Targeting household energy efficiency measures using sensitivity analysis

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Abstract

The Community Domestic Energy Model (CDEM) has been developed to explore potential routes to reduce CO_2 emissions and the model is used to predict the CO_2 emissions of the existing English housing stock. The average dwelling CO_2 emissions are estimated as 5,827 kgCO_2 per year, of which space heating accounts for 53%, water heating 20%, cooking 5% and lights and appliance 22%. Local sensitivity analysis is undertaken for dwellings of different age and type, to investigate the effect on predicted emissions of uncertainty in the model's inputs. High normalised sensitivity coefficients were calculated for parameters that affect the space heating energy use. The effects of the input uncertainties were linear and superposable, so the impact of multiple uncertainties could be easily determined. The results show that the accumulated impact on national CO_2 emissions of the underperformance of energy efficiency measures could be very large. Quality control of the complete energy system in new and refurbished dwellings is essential if national CO_2 targets are to be met. Quality control needs to prioritise detached dwellings because their emissions are both the greatest and the most sensitive to all energy efficiency measures. The work demonstrates that the uncertainty in the predictions of stock models can be large; failure to acknowledge this can lead to a false sense of their reliability.

Keywords: Building stock, Domestic; housing; energy model; carbon model;CO2 emissions;, energy efficiency

1. Introduction

In 2006 the CO_2 emissions from the UK residential sector, principally arising from gas, electricity, coal and oil consumed for heating and powering domestic buildings, were 149 million tonnes (DEFRA, 2007a). This was 26.9% of the UK's total CO_2 emissions and average CO_2 emissions per dwelling in 2006 were around 6.1 tonnes. The UK Government's Climate Change Bill 2008 commits the country to a legally-binding reduction in CO_2 emissions of 80% by 2050 based on 1990 levels (DEFRA, 2009). This is to be achieved through a series of five year targets and will require CO_2 emission reductions in most if not all sectors of the economy. For some sectors, such as transport, CO_2 reductions are difficult and the burden of achieving the reductions targets may fall on those sectors where CO_2 emission reductions can be more easily implemented. The UK residential sector has long been considered to have great potential for CO_2 emission reductions through the use of energy efficiency and renewable energy technologies. However the UK residential sector is complex and in making any changes there are many technical, social and economic barriers to overcome. For this reason a thorough understanding of the nature of energy consumption and

CO_2 emissions in UK dwellings is required to formulate successful strategies and policies to achieve significant emission reductions.

The complexity of the UK domestic built environment arises from variations in its physical form, the climatic conditions it is subjected to and the behaviour of the building occupants. There are over 20 million dwellings in the UK and there is a great variation in the size, shape and construction of these buildings. The UK housing stock has been constructed over a long period of time and there are many different building materials and techniques used, from stone and solid brick walls to highly-insulated cavity wall construction. Within the homes the space and water heating provision can vary widely in terms of types of systems, fuels used and efficiency. Each of these buildings is subjected to climatic conditions, including ambient air temperature and solar irradiation, which can vary spatially as well as containing short-term fluctuations and long-term trends. In particular the local micro-climate can vary considerably across the housing stock from highly exposed rural locations to city centres affected by the urban heat island effect. The behaviour of the occupants in the homes is a further complexity and is dependent on the number of people in the household, their ages, the occupancy patterns and many other factors. In particular the space and hot water heating demands, and the patterns of use of household electrical appliances, is largely determined by building occupant behaviour.

Measured data on the English housing stock is mainly provided by a number of large government surveys. The English House Condition Survey reports on the building construction and the building services provision for English housing and is based on an annual survey of thousands of dwellings (DCLG, 2007). The UK Census provides the number and type of dwellings for a range of different administrative boundaries throughout England (ONS, 2007). National statistics are also available from the UK government for the energy consumption by fuel type at the national, regional, local authority and sub-local authority levels based on aggregated totals of consumer fuel bills (BERR, 2008). Climate data is available through the Meteorological Office (Met Office, 2007) and, to a limited extent, household behaviour through surveys such as the Family Expenditure Survey (ONS, 2008). However this measured data cannot alone provide the information needed to investigate CO_2 reduction strategies for the housing stock and, to fill the missing information gap, accurate and comprehensive energy and carbon models of the housing stock are required.

Housing stock models provide several benefits. They reduce the need to make time-consuming measurements of large numbers of dwellings and can be used to estimate current information, whereas measured data quickly becomes out of date. Models can provide information on hard to measure quantities, such as heat loss coefficients or ventilation rates of buildings. Once constructed, a housing stock model can be used for scenario planning to estimate the effects of technologies, policies and future climates on overall energy consumption and CO_2 emissions. By employing a variety of scenarios, and varying the input parameters to the scenarios, optimum CO_2 reduction strategies can be identified. However for such results to be of use in policy formation the model must accurately describe the complexities of the housing stock including the physical, climatic and household behavioural aspects. Any model must be thoroughly validated against existing datasets and the uncertainties within the model be fully quantified. Without rigorous testing the model predictions will lack credibility and the impact of the results will be limited. In particular, as inputs to a housing stock model will, by their very nature, be inferred or estimated values (due to the size and complexity of the built environment, the limited data available and the difficulty in making many of the necessary measurements), the model should clearly demonstrate the effect of the uncertainty in the model inputs on the model predictions. This process ensures that any recommendations based on model predictions can be fully qualified according to the knowledge of the housing stock and the buildings' physical properties available at the time of modelling. It also shows which input parameters cause the greatest uncertainty in the model predictions and if further field measurements of these parameters would be beneficial.

The standard approach to modelling the English housing stock has been to simplify the physical complexity by adopting a number of house archetypes which together represent all dwellings in the stock. House types may be defined by built form (such as detached or semi-detached), building age (usually placed into age bands based on building regulation changes), space heating systems and several other factors. For each house type nominal average physical parameters (such as size, shape and construction materials) are generated. A core building energy model (based on the principles of heat transfer as well as empirical relationships) takes the average physical parameters as inputs and is used to predict the energy consumption for each house archetype. Aggregating the predictions for each house type gives the overall housing stock energy consumption.

The house archetype approach has been used by four prominent national housing stock models: the BREHOMES model developed by the Building Research Establishment (Shorrock and Dunster, 1997); the UK Domestic Carbon Model (UKDCM) reported by Boardman (2007); the model developed by Johnston et al. (2005) (hereafter referred to as the Johnston model); and the DECarb model by Natarajan and Levermore (2007). All these models use the Building Research Establishment Domestic Energy Model (BREDEM) as the building energy model to calculate energy consumption based on supplied input parameters (Anderson et al., 2002). The number of house archetypes used varies from two archetypes (in the Johnston model based on pre- and post-1996 construction) to over 1000 archetypes (in the BREHOMES model based on built form, age, tenure and central heating ownership). In most cases validation has been carried out by comparing a single prediction for the total annual energy consumption of the housing stock against UK government statistics (for a single year or a series of years) or by comparison to an energy study of dwellings carried out by the English House Condition Survey in 1996. Rarely has the uncertainty in the predictions of the models been studied or accounted for in the validation exercises, and a study of this uncertainty is the primary aim of this paper.

The accessibility of these four housing stock models is severely limited; either the models are not available publicly or the implementation of the models is very complex and not transparent (in part as a result of the complexity of the modelling task itself). This lack of accessibility makes any analysis of the four models themselves, in particular an investigation of the assumptions used and the algorithms employed, impractical. One of the aims of this paper is to lay the ground for greater transparency in UK domestic energy modelling.

All four models have been used to make forward predictions to the year 2050 to investigate potential routes to a low-carbon UK domestic built environment. This process by its very nature is intensely challenging and involves the estimation of current and future trends, technological advancement, policy initiatives and many other determining factors. Less attention has been given to the models' accuracy in describing the variation in current energy consumption and CO_2 emissions across the housing stock and in no case has the effect of uncertainty within the model inputs on predictions been investigated. This is highly important as all four housing models use the same core building energy model (BREDEM) and will therefore contain many of the same base assumptions for calculating parameters such as wall U-values, ventilation rates and boiler efficiencies. These types of parameters are difficult to measure directly, and more difficult to estimate across the entire housing stock, and so the uncertainty contained within these parameters could be highly influential in the models' predictions, for predicting the impact of energy intervention and for other energy and CO_2 emission scenario investigations.

This work seeks to address the current lack of knowledge concerning the accuracy of national domestic stock models and the uncertainty in their predictions, to quantify the relative impact of different CO_2 reduction measures and to pave the way to greater transparency in energy modelling through the development of simple models. To achieve these aims it is important to understand the sensitivity of BREDEM models' predictions to the primary input parameters, the uncertainty in predictions due to the uncertainty in each model input and the way these uncertainties aggregate to give the overall uncertainty in the model predictions.

To undertake the work, a new housing stock model has been developed based on the same principles as previous models (the use of house archetypes and the same core building energy model). The new model is named the Community Domestic Energy Model (CDEM) as future implementations are intended to model not only the national housing stock but also regions, local authorities, cities and other sub-national areas. The model development forms part of the Carbon Reduction in Buildings (CaRB) project, a wider study investigating energy use and CO_2 emissions from UK domestic and non-domestic buildings (Lomas et al., 2006). The development and method of CDEM is described and initial results for the English housing stock are presented. Local sensitivity analysis (SA) is then carried out on the CDEM predictions and is used to identify, from the large number of model input parameters, which ones are highly influential on the model predictions. Such an approach has been employed previously by Lomas et al. to investigate uncertainties in building thermal simulation programs (Lomas and Eppel, 1992). The testing and sensitivity analysis of the housing stock model described in this paper leads to a much better understanding of the determining factors for energy consumption and CO_2 emissions in English homes.

2. Modelling methods

2.1. Use of house archetypes

The CDEM model consists of two main components: a house archetype calculation engine and a core building energy model (Figure 1). The house archetype calculation engine defines the characteristics of 47 individual house archetypes which together were used to represent all dwelling types in the housing stock. The house archetypes were chosen primarily to capture the variation in space heating, as space heating in dwellings represents the largest proportion of domestic energy consumption (around 61% of overall household energy consumption in 2004 (BERR, 2007). Built form is a key factor in space heating as it determines the number of exposed walls and the average floor area (both of which affect the dwelling heat loss). The age of the dwelling is also a key determinant as older buildings are constructed to lower thermal standards (for example using solid walls, unfilled cavity wall and single glazing) than modern buildings. The house archetypes in CDEM were therefore based on combinations of built form and dwelling age. Six built form categories and nine age band categories were used and the 47 CDEM house archetypes are defined in Table 1. Pre-1900 purpose built flats and post-1945 other flats were not considered as these combinations occur very infrequently in the housing stock.

In the CDEM model each of the 47 dwellings is designed to be an average example of its archetype. In cases where more than one construction technique is present in an archetype, and a direct calculation of an average value is not possible, the physical properties are calculated from a weighted average. For example, a number of different wall constructions (such as solid wall, cavity wall and timber frame) exist for 1940s semi-detached English houses and the house archetype average wall U-value is calculated from a weighted average of the different wall construction U-values and the percentage of houses with each type of wall construction. For each archetype, the dwelling heat loss coefficient (the rate of fabric and ventilation heat loss in steady state conditions) is calculated. The 47 dwellings are subjected to the same weather conditions and initial calculations are made for solar gains, water heating energy consumption, cooking energy consumption and lights and appliances energy consumption. Again weighted averages are used to account for variations within each archetype, for example different building orientations when calculating solar gains or different water heating systems when calculating water heating energy consumption. The average internal heat gains for the dwellings are then estimated (based on the weighted average values just calculated) and, along with the dwellings' heat loss coefficients, used to calculate the space heating energy requirements of the buildings. This is also calculated as a weighted average, to take into account the distribution of different space heating systems, their efficiencies and the different fuels used. From the energy predictions made for the 47 house archetypes, the annual energy consumption for a community of dwellings (such as the English housing stock) can be expressed as:

$$E_{COM} = \sum_{i=1}^{n} E_i \times N_i$$

where E_{COM} is the overall predicted annual energy consumption for a community of dwellings (kWh), n is the total number of house archetypes, E_i is the predicted annual energy consumption for house archetype i (kWh), and N_i is the total number of dwellings of house archetype i in the community.

2.2. Derivation of input parameters

CDEM has many input parameters which describe the characteristics of UK dwellings including geometric properties of dwellings, physical properties of construction materials, the composition of households and climatic variables. For the sensitivity analysis undertaken later in this paper a specific set of input parameters was used. These were defined as *primary input parameters* and consisted of numerical inputs which fed directly into the core building energy model. The remaining input parameters were defined as *secondary input parameters* as these were not directly used by the core building energy model but instead were used to calculate the primary input parameters. As an example, average wall U-value (for each house archetype) is a primary input parameter. The secondary input parameters which are used to calculate average wall U-value are: distribution of wall types (solid, cavity, timber); construction age band; default wall U-values for different constructions and ages (based on BREDEM tables);

percentage of dwellings with solid wall insulation; and percentage of dwellings with cavity wall insulation. It was not considered necessary to perform sensitivity analysis on each of these secondary input parameters individually as their effects are all encapsulated in the primary input parameter (the overall wall U-value in this example).

There were 27 primary input parameters to CDEM and these were classified in the following categories: location, geometry, construction, services and occupancy. Location parameters included climate data (monthly external temperatures and solar radiation) sourced from the UK Meteorological Office (Met Office, 2007), the site latitude and the number of dwellings for each built form, derived from Census 2001 data (ONS, 2007). Geometry input parameters describe the size and shape of the house archetypes and were based on standard house descriptions by Allen and Pinney (1990). Average floor area, storey height and window area data, taken from the 2001 English House Condition Survey (EHCS) (DCLG, 2007) and reference tables in SAP 2005 (DEFRA, 2007b), was used to scale the Allen and Pinney house descriptions to generate unique geometries for each house archetype. Construction input parameters consist of average U-values for the building envelope elements (walls, windows, roofs and floors) and average infiltration rates for each house archetype. These were calculated from the construction information provided in the EHCS 2001 (for example the distribution of wall construction type), average U-values given in SAP 2005 and BREDEM default tables and procedures. Similarly the services input parameters (which described the equipment used to provide heat and power to the building) were sourced from EHCS 2001, SAP 2005 and BREDEM default tables. The EHCS did not include data on the proportion of low energy lighting or the distribution of cooker type and information from the Market Transformation Programme (MTP, 2007a and MTP, 2007b) was used to derive estimates for these values. Occupancy input parameters included the average number of occupants for each house archetype (again taken from the 2001 EHCS) and the average heating patterns used in the households. In this work the standard BREDEM default heating pattern was assumed (a thermostat setting of 21ºC and a heating period of 9 hours on weekdays and 16 hours on weekends). As an example, all important values of primary and secondary input parameters for the 1945 to 1964 semi-detached house archetype, along with their data sources and sample values, are shown in Table 2.

2.3. Energy and carbon calculations

The core building energy model is based on the calculation algorithms of BREDEM-8, a monthly version of the physically-based BREDEM model (Figure 1). This calculates the energy consumption for four end use categories: space heating; water heating; cooking; and lights and appliances (Anderson et al., 2002). It has an extensive history of testing and validation (Shorrock et al., 1994 and Dickson et al., 1996) and is used in many applications including the

UK Government's Standard Assessment Procedure (SAP) for dwellings (DEFRA, 2007b) and in commercial energy rating schemes such as the National Home Energy Rating (NHER, 2007). BREDEM-8 uses a combination of physical and empirical relationships to calculate a dwelling's energy consumption.

For space heating, monthly energy consumption is calculated using the BREDEM steady-state physical equation based on the difference between the monthly average external air temperature and monthly average internal air temperature (the average internal temperature is calculated using a complex procedure within the model), the estimated heat loss parameters of the dwelling (including fabric and infiltration heat loss) and the dwelling heat gains (including solar gains and internal heat gains) (Anderson et al., 2002). Empirical relationships are used to calculate the remaining energy end uses of water heating, cooking and lights and appliances. The empirical algorithms used make use of descriptive variables such as the total floor area of the dwelling and the number of occupants and do not directly represent any physical processes. For example, the amount of hot water used by the occupants per day (in litres) is calculated using a simple linear function of the number of occupants in the household. CO_2 emissions are derived from energy predictions using standard energy to CO_2 emission factors sourced from the Carbon Trust (2007). For the four main fuel types considered in CDEM these are: gas 0.19 $kgCO_2/kWh$; electricity 0.43 $kgCO_2/kWh$; oil 0.26 $kgCO_2/kWh$; and solid fuel (coal) 0.3 $kgCO_2/kWh$.

CDEM is constructed using spreadsheet software (Microsoft Excel) so it is possible to see the intermediate workings of the model calculations, such as the solar gains or internal temperatures. The BREDEM algorithms are implemented in a batch processing format so that predictions for each house archetype can be made simultaneously. The open structure of the model will allow ongoing data being collected in other studies within the CaRB project, to be easily incorporated into the model inputs and calculation algorithms. These studies include: a nationally representative survey of around 500 English dwellings which is collecting information on heating practices and is monitoring energy use and internal temperatures (Shipworth et al., 2008); a study monitoring appliance energy use trends in domestic buildings (Firth et al., 2008); a study monitoring the energy consumption of individual appliances in a sample of dwellings with a focus on 'infotainment' appliances (such as televisions, computers and games consoles); and an investigation of domestic lighting energy use from a socio-technical perspective (Wall and Crosbie, 2007).

3. Initial predictions of energy consumption and CO_2 emissions

Predictions for the energy consumption and CO_2 emissions for the 2001 English housing stock were made using 1971 to 2000 average climate data so the results would not be skewed by the weather patterns of one particular year.

Predictions for six built form types are summarised in Table 3. The energy consumption predictions are broken down by fuel type and the CO_2 emission predictions by fuel type and by end use. Descriptive statistics are also given for the numbers and average size of the dwellings, the average number of occupants, the average dwelling heat losses and the average annual internal temperatures. The CO_2 emissions of the average English dwelling, based on the 30 year average climate data, is predicted to be 5,827 $kgCO_2$. This is comparable to the UK average figure of 6.1 tonnes CO_2 in 2004 (DEFRA, 2007a).

Detached houses have the largest CO_2 emissions (8,220 $kgCO_2$) followed by end terraces (5,811 $kgCO_2$) and semi-detached houses (5,776 $kgCO_2$). Purpose-built flats have the lowest CO_2 emissions (3,642 $kgCO_2$). The distribution of CO_2 emissions from end use consumption is: space heating 53%; water heating 20%; cooking 5%; and lights and appliances 22%. These figures match exactly estimates given by the UK Government for CO_2 emissions end-use in UK dwellings in 2003 (DEFRA, 2006). Detached houses have the largest space heating CO_2 emissions (5,128 $kgCO_2$) and lights and appliances CO_2 emissions (1,629 $kgCO_2$), due to the high dwelling heat loss and large total floor area. The consumption of gas accounts for 73% of all energy use but only 57% of CO_2 emissions due to its relatively low carbon intensity (0.19 $kgCO_2$/kWh) compared to the other fuels. Electricity, with its high carbon intensity (0.43 $kgCO_2$/kWh), accounts for 19% of overall energy consumption but 34% of CO_2 emissions. The percentage of CO_2 emissions from oil consumption (5%) and solid fuel consumption (4%) represents a small proportion of overall CO_2 emissions. The total annual CO_2 emissions per person are highest in detached houses (3,088 $kgCO_2$ per person) and are lowest in mid terraces (1,811 $kgCO_2$ per person). The combination of relatively high CO_2 emissions and low occupancy means the other flats have the second highest per person CO_2 emissions (2,643 $kgCO_2$ per person).

4. Local sensitivity analysis

4.1. Theoretical basis

Local sensitivity analysis investigates the changes in a model's output variables based on small changes in the model's input parameters (Saltelli et al., 2000). It is the first step in the sensitivity analysis process and begins to provide information on the relative importance of the input parameters. The technique is particularly useful when a model contains a large number of input parameters and it is not immediately apparent which of these should be included, and which (if any) can be ignored, in subsequent analysis. Local sensitivity analysis has the following steps: a) each input parameters is assigned a set value k_j (typically based on the average or expected value for the parameter of the system under study); b) each input parameter in turn is subjected to a small change Δk_j whilst the other input parameters are held constant at their set values; c) for each change in the input parameters in step b) the model is run and the new output variables are used to calculate a series of sensitivity coefficients; and d) normalised sensitivity coefficients are calculated to allow comparisons between the effects of different input parameters.

The sensitivity coefficients represent the partial derivatives of output variables to input parameters and can be calculated using finite-difference approximation based on central differences. For a model with *n* output variables and *m* input parameters, the sensitivity coefficients are given by:

$$\frac{\partial y_i}{\partial k_j} \approx \frac{y_i(k_j + \Delta k_j) - y_i(k_j - \Delta k_j)}{2\Delta k_j}, \qquad i = 1,\ldots,n \text{ and } j = 1,\ldots,m$$

where y_i is the ith output variable; k_j is jth input parameter; $\partial y_i / \partial k_j$ is the sensitivity coefficient for output value y_i and input parameter k_j; and $y_i(k_j + \Delta k_j)$ denotes the value of y_i when the input parameter k_j is increased by a small increment Δk_j. In this work 27 input parameters are considered (m=27) and a single output variable, average dwelling annual CO_2 emissions (n=1).

If the model is non-linear then the sensitivity coefficients will be affected by two factors. Firstly using different set values to initially populate the input parameters will give different results, as the sensitivity coefficients will be describing a new parameter space. Secondly the size of the small increment used to change the input parameters (Δk_j) will have an effect. An increment that is too small will be subjected to potential rounding errors in the output variables. An increment that is too large will be unduly affected by the non-linearity of the model. Following suggestions from the literature, in this work an increment of a ±1% change in the input parameter is used (Saltelli et al., 2000).

The final step is to calculate normalised sensitivity coefficients which allows the comparison of sensitivity coefficients based on input parameters with different units. The normalised sensitivity coefficients $S_{i,j}$ represent the percentage change in the output variables given a one percent change in the input parameters. For each input parameter and output variable combination, the normalised sensitivity coefficients are given by:

$$S_{i,j} = \frac{k_j}{y_i}\frac{\partial y_i}{\partial k_i}, \qquad i = 1,\ldots,n \text{ and } j = 1,\ldots,m$$

4.2. CDEM predictions of average dwelling CO_2 emissions

Local sensitivity analysis was carried out on the CDEM model by varying the 27 primary input parameters and recording the change in average dwelling CO_2 emissions. Table 4 shows the results for the local sensitivity analysis for CDEM based on initial set values of the 2001 English housing stock and 1971 to 2000 climate data (the same values used to generate the results shown in Section 3). The sensitivity coefficients for 27 primary input parameters were calculated. A single output variable, average dwelling annual CO_2 emissions for all dwellings in the stock, was used in the analysis. The values shown in Table 4 are the weighted average value for all 47 house archetypes. Where the set values for an input parameter varied across the house archetypes (for example total floor area was different for each archetype) then the input parameter of each archetype was individually adjusted. The resulting overall change in the output variable (y_i) is shown in the table together with the sensitivity coefficients and normalised sensitivity coefficients ($S_{i,j}$). The results are presented in order of the absolute value of the normalised sensitivity coefficients within each parameter group: location; geometry; construction; services; and occupancy.

The largest $S_{i,j}$ values in Table 4 are all based on input parameters which almost exclusively influence space heating energy consumption in dwellings. Space heating accounts for the largest proportion of CO_2 emissions in dwellings (predicted as an average of 53% in Table 3) and therefore changes in space heating energy consumption will strongly influence overall CO_2 emissions. The heating demand temperature (which in most cases is the thermostat set point temperature used in the dwelling to control the heating system) results in the most sensitivity ($S_{i,j} = 1.55$). This can be interpreted as a 1% rise in the heating demand temperature in an average dwelling results in a 1.55% increase in the CO_2 emissions of that dwelling. This is significantly higher than the other $S_{i,j}$ values and suggests that heating demand temperature is the key determinant of CO_2 emissions in housing. The length of the daily heating period has the second highest sensitivity ($S_{i,j} = 0.62$) and external air temperature has, in magnitude, the third highest ($S_{i,j} = -0.58$). The negative sensitivity for external air temperature is because an increase in external air temperature will cause a decrease in space heating energy consumption (and therefore overall CO_2 emissions). Together the heating demand temperature, length of heating period and the external air temperature determine the temperature difference across a building’s envelope so it is not surprising that energy use is rather sensitive to these values. Certainly external air temperature, and also to a large extent heating demand temperature and heating period length, are not amenable to energy efficiency initiatives.

The results of the local sensitivity analysis require careful interpretation due to the nature of the model calculations. For example, total floor area is often cited as a key parameter in determining space heating, and indeed

CO_2 emissions are sensitive to floor area and to storey height. However in the core building energy model, total floor area is also used to calculate the energy used by lights and appliances (as described in Section 2.3) and the total glazing area, so an increase in floor area also results in increased heat gains from appliances and from solar gains. This means slightly less space heating is needed and thus makes overall CO_2 emissions less sensitive to total floor area than might be expected. A second example is the negative $S_{i,j}$ value given for site latitude ($S_{i,j}$ = -0.10) which seems strange as an increase in site latitude would result in lower temperatures and so an increase in space heating energy consumption and CO_2 emissions. However, in the model the site latitude is only used for the solar gains calculations (and is not coupled to the external temperature or solar radiation). Thus an increase in latitude only results in a lower solar elevation which increases the solar gains to the dwelling reducing the space heating energy consumption and the CO_2 emissions.

The technique of using average values for the 47 house archetypes can also potentially obscure the detail of some of the results. For example, the window area input parameter is shown to have a relatively low sensitivity value ($S_{i,j}$ = -0.10). This is because a larger window area will result in increased solar gains (which reduces the space heating energy use) but also increased heat losses (due to the higher U-values of windows compared to walls). Whilst the net result of these opposite effects gives, on average, a low sensitivity, it is clear that this might not be the case for individual dwellings with certain combinations of wall and window U-values, window areas and orientations.

4.3. Built form type and building age band

The normalised sensitivity coefficients in Table 4 were the average values calculated for the 47 house archetypes. Figure 2 shows, for the eight input parameters with the highest sensitivities in Table 4, the individual $S_{i,j}$ values for each house archetype. This illustrates, for each input parameter, the variation in sensitivity caused by built form type and building age band. In all cases the $S_{i,j}$ are widely distributed and there are large differences between the built form types (notably detached houses and flats) and between older dwellings (pre 1850) and newer dwellings (1991 to 2001). In many cases detached houses have the largest $S_{i,j}$ values (either the highest for positive sensitivities such as demand temperature or the lowest for negative sensitivities such as external air temperature). Mid terraces, purpose built flats and other flats generally have the lowest $S_{i,j}$ values. Semi-detached houses and end terraces appear to be very similar in most cases. This suggests that the area of building envelope is an important factor when considering the relative sensitivities of different built form types.

For the majority of the input parameters the $S_{i,j}$ values become smaller with increasing building age. This might be expected as modern housing has increased insulation and higher air tightness, and therefore will be less sensitive to the same change in an input parameter (such as heating demand temperature) than older housing. For gas boiler efficiency there is a very different pattern where the $S_{i,j}$ values initially become larger as building age increases before either remaining relatively constant or decreasing slightly. This effect is likely to be due to the fact that not all dwellings, especially older dwellings, have gas boilers installed. The average $S_{i,j}$ is less for older dwellings as there are fewer gas boilers present in this category of dwellings. Similarly for window U-values there is, overall, an increase in $S_{i,j}$ values between 1851 and 1990. One explanation for this is because as walls becomes better insulated over this time period the effect of window U-values become more significant for CO_2 emissions.

4.4. Testing for linearity and superposition

The normalised sensitivity coefficients illustrate the sensitivity of the model around small changes in the model input parameters (±1% for the $S_{i,j}$ values calculated in Sections 4.1 and 4.2). If the sensitivity of the model is linear then the effects of larger changes in the input parameters can be estimated from the calculated $S_{i,j}$ values. Linearity is defined as meaning that multiplying some input Δk by a scaling factor α yields the same scaled output αy:

$$y(\alpha.\Delta k) = \alpha.y(\Delta k)$$

Figure 3 shows, for the five input parameters with the highest sensitivities, the effect on average dwelling CO_2 emissions for changes in the input parameters of ±10%. It can be seen that for each input parameter the change in CO_2 emissions is approximately linear. This result is also observed in many of the other input parameters given in Table 4.

A second important test is to check if the sensitivity coefficients can be superimposed and give reliable results. For example, heating demand temperature has an average $S_{i,j}$ of 1.55 and external air temperature has an average $S_{i,j}$ of -0.58. If the combined effect of a 1% increase in demand temperature and a 1% increase in external air temperature results is equal to the sum of the two $S_{i,j}$ values then this would show that superposition can be applied in this case. If this is true then the effects of changes in several input parameters, occurring at the same time, can be estimated from the individual normalised sensitivity coefficients given in Table 4. Superposition is defined as meaning that adding two input variables Δk_1 and Δk_2 yields the sum of the two outputs:

$$y(\Delta k_1 + \Delta k_2) = y(\Delta k_1) + y(\Delta k_2)$$

The results of a superposition test for the nine input parameters with the largest sensitivity is shown in Figure 4. The change in input parameter is chosen such that a positive change in average dwelling CO_2 emissions always results (all the input parameters are increased by 1% apart from external air temperature and gas boiler efficiency which are decreased by 1%). In the first case the overall change in average dwelling CO_2 emissions is simply calculated from the sum of individual $S_{i,j}$ values as given in Table 4 (shown by the solid black line). In the second case the 1% changes in the input parameters are applied cumulatively to the model to give the overall change in average dwelling CO_2 emissions (shown by the dashed black line). The percentage change in average dwelling CO_2 emissions for the two approaches are very similar which suggests that superposition of the $S_{i,j}$ values is valid for the housing stock model at least over a limited change of parameter values.

The tests for linearity and superposition (shown in Figures 3 and 4) show that the normalised sensitivity coefficients calculated in Table 4 may be used to estimate the effects on CO_2 emissions of changes within the housing stock. For example, a 2% reduction in space heating demand temperatures ($S_{i,j}$ = 1.55) will, according to the model predictions, result in an approximate CO_2 emissions reduction, for the average dwelling, of 3.1%. If this was combined with a 10% reduction in wall U-values ($S_{i,j}$ = 0.27), the overall CO_2 reductions would be approximately 5.8%. This approach has the potential to provide a simple and effective method of calculating potential CO_2 emission reductions in dwellings. It can also be used to test the impact on energy demands of any failures to meet expected U-values or in situ boiler efficiencies etc during dwelling refurbishment works.

5. Discussions

The sensitivity analysis described in this work clearly illustrates the relative influence of input parameters on overall housing stock CO_2 emissions. The findings are also relevant for three areas of further work: the uncertainty associated with predictions of domestic stock CO_2 emissions; the development of more targeted CO_2 intervention strategies; and the development of simpler and more transparent domestic stock models.

There will always be uncertainty associated with models which seek to predict the energy consumption and carbon emissions of the housing stock due to the complex nature of the domestic built environment and the many assumptions needed in order to make predictions. However in all the previous models surveyed in the literature, none have attempted to quantify the uncertainty in their predictions. The main difficulty with uncertainty analysis is in sourcing the uncertainty associated with the input parameters, for example the 95% confidence interval (CI) associated with, say, average wall U-values. In this work the sensitivity coefficients $\partial y_i/\partial k_j$ given in Table 4 show how CO_2 emissions will vary with uncertainty in the input parameters. For example if the infiltration rate (average value of 0.7 ach) has a 95% CI of ±0.1 ach then the resulting uncertainty in average dwelling CO_2 emissions would be, at the 95% CI level, ±101 $kgCO_2$ (±0.1 ach x 1010.4 $kgCO_2$/ach).

A rough estimate of the potential uncertainty in the model can be made without sourcing (or measuring directly if the information is not available) the exact uncertainty in the input parameters. For example, suppose the 95% CIs for five of the important input parameters are: wall U-value 0.0 to 0.2 W/m^2K; window U-value 0.0 to 0.1 W/m^2K; infiltration rate 0.0 to 0.1 ach; boiler efficiency -0.1 to 0.05; and heating demand temperature -0.25 to 0.5 ºC. In the case of U-values it is more likely that the range of uncertainty will be larger, but not smaller, than the original set values due to factors such as gaps in insulation, unexpected heat bridging, etc. Likewise, in practice, boilers are likely to be less, rather than more, efficient when installed than expected. Using the estimated CIs for the input parameters, the uncertainty for average dwelling CO_2 emissions would be, at the 95% CI level, -304 to 977 $kgCO_2$, which is a significant proportion of the predicted value of 5,827 $kgCO_2$ (Table 3).

More work is needed in the area of the predictive uncertainty of stock models: the transparent easy-to-run model presented here will enable this. From these illustrative results some useful observations can however be made. Firstly, that the uncertainty in the predictions of stock models could be rather large for example here the CI is -5% to +17% of the basic value. Most UK stock modelling work has ignored the issue of uncertainty, but to do so is to convey a false sense of the reliability of the predictions[1]. Related to this is the need to better understand what the variability of key model parameters is in practice and if and how these variations might differ with house type and age. For example, the efficiency of older boilers in larger and older houses might be rather more uncertain and have a bigger impact on CO_2 emissions than the efficiency of boilers in modern homes. Thus the uncertainty in predictions might be much greater for some house types than for others.

Secondly, knowing the factors that most influence energy demand in different dwelling types, quality control efforts can be more effectively focussed. The results here show, for example, an obvious need to achieve target wall U-values in practice and for boiler efficiencies to match expectations. In contrast, there is ample evidence, e.g. from thermographic surveys, that heat bridging, missing insulation and air leakage is common in new dwellings and refurbishment studies tend to show, partly for similar reasons, that energy savings are less than expected.

Thirdly, the uncertainty in the predicted emissions is markedly skewed. In dwellings that produce higher than anticipated (predicted) CO_2 emissions, e.g. due to faulty wall insulation, low boiler efficiency etc, the emissions can be much higher. In contrast dwellings that cause lower than predicted emissions produce only a little less. The skewed overall uncertainty arises because for many of the energy efficiency measures to which the model is sensitive,

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[1] However it does need to be recognised that the energy use of the national housing stock is known quite accurately from official statistics on delivered energy. Thus, a stock model will often be run such that its predictions are matched to the official statistics, thereby effectively greatly reducing the uncertainties in the predictions.

performance is unlikely to be better than the idealistic calculated value but it can very easily be much worse. What is surprising perhaps is just how skewed the overall uncertainty in the CO_2 emissions becomes. This clearly suggests that avoiding the accumulation of defects in the complete energy system (plant, fabric, etc) is critical to achieving predicted CO_2 reductions in practice. This quality control, by builders, refurbishment companies, and building inspectors needs to consider the complete energy system and not just isolated components of it. Furthermore, because sensitivities differ substantially with dwelling type (see Figure 2) attention ought to be focussed on those for which sensitivities are greatest. In this regard, detached houses are more sensitive to under-performance in virtually all the factors studied than any of the other house types: because of their greater envelope area and higher intrinsic heating demands (Table 3). There is therefore an argument for prioritising quality control on new and refurbished detached dwellings.

It is also useful to consider the implications of the sensitivity analysis results for energy and CO_2 reduction policies. Clearly, it is more useful to address those factors that have a big impact on emissions and that are amenable to intervention than those that are not. This is demonstrated for different built form types and building ages in Figure 2. For example it can be observed that promoting the reduction of demand temperatures (i.e. thermostat settings) in detached houses will result in larger CO_2 reductions that in purpose built flats. Similarly measures targeted at older dwellings will, in general, have a larger effect than those in modern dwellings. It is also detached houses for which changes in physical size (as represented by floor area and storey height) have the greatest impact on CO_2 emissions. In this regard we might also observe that the potential for extensions tends to be much greater in detached dwellings than in most other dwelling types. In passing it is worth noting that results for external air temperature begin to illustrate the emissions impact of future climate change.

Finally, from the stock modelling perspective, the linearity and superposition tests carried out on the sensitivity coefficients suggests that there is potential to develop simpler and more transparent domestic stock models. Rather than use complex, physical models (such as the CDEM model described in this work), it may be possible to construct models for estimating CO_2 reductions which are based on a set of basic parameters with associated sensitivity coefficients. Such models could be framed as a set of simple linear equations with the coefficients defined by the uncertainties. These models would be straightforward to use, operate very quickly and thus provide policy makers with access to very simple tools with which to investigate methods of reducing CO_2 emissions in housing. Although this paper has developed sensitivity coefficients for the English housing stock similar coefficients could be developed for smaller areas of interest such as regions or local authority areas. An initial step in developing such a tool would be to fully determine the range of applicability of the linearity and superposition principles of the stock model.

6. Conclusions

This work has described the development of a new model, the Community Domestic Energy Model (CDEM), to predict energy consumption and CO_2 emissions in dwellings. The CDEM modelling method has been described in detail and predictions for the existing 2001 English housing stock have been presented based on 1971 to 2000 average climate data. The predictions are made using 47 house archetypes, unique dwelling types based on the built form type and the dwelling age. Local sensitivity analysis, including linearity and superposition tests, has been carried out on the CDEM predictions to understand the influence of the model input parameters.

- The overall average dwelling annual CO_2 emissions for the 2001 English housing stock, using average climate data from 1971 to 2000, was predicted as 5,827 $kgCO_2$. Detached houses had the largest annual CO_2 emissions (8,220 $kgCO_2$), followed by end terraces (5,811 $kgCO_2$) and semi-detached houses (5,776 $kgCO_2$). Purpose-built flats had the lowest annual CO_2 emissions (3,642 $kgCO_2$). Space heating usage contributed 53% of overall CO_2 emissions, water heating 20%, cooking 5% and lights and appliances 21%. Gas consumption accounted for 73% of overall total energy consumption but only 57% of overall CO_2 emissions due to the low carbon intensity of mains gas. Similarly electricity consumption accounted for 19% of energy consumption but 34% of overall CO_2 emissions due to the high carbon intensity of centrally-generated grid electricity.
- The characteristics and use of heating systems, and the heat losses of buildings, are the most influential factors of dwelling CO_2 emissions. In particular the heating demand temperature was calculated, for the average dwelling in the 2001 English housing stock, to have a normalised sensitivity coefficient of 1.55 on dwelling CO_2 emissions. This means that for every 1% increase in the heating demand temperature, a 1.55% increase in average dwelling CO_2 emissions will result. Other factors with high normalised sensitivity coefficients included length of heating period (0.62), the dwelling size, as reflected in the average storey height (0.48) and floor area (0.34), gas boiler efficiency (-0.45), and wall U-value (0.27). All of these factors relate strongly to the space heating energy consumption and this analysis shows that a sound knowledge of these factors is essential when modelling CO_2 emissions in dwellings.
- There can be a large difference in the influence of input parameters depending on the built form and age of a dwelling. In general, detached houses and older dwellings are shown to be most susceptible to changes in their input parameters. Mid-terraces, flats, and newer dwellings are, in general, the least susceptible. For example, all

the factors with high normalised sensitivity coefficients (listed above) have two to four times more influence on the CO_2 emissions of 1900-1918 detached houses than on the emissions from 1991 to 2001 purpose built flats. Thus interventions to reduce CO_2 emissions are more effective in some dwellings, such as older detached houses, than others; conversely these dwellings are more susceptible to the underperformance of installed energy efficiency measures.

- Tests have shown that the effects on CO_2 emissions of the calculated sensitivity coefficients can be added in a linear fashion and superimposed to reliably estimate the cumulative effect of multiple uncertainties. This means that the local sensitivities can be used to make rapid estimates of the CO_2 savings that arise from implementing multiple energy efficiency measures and, conversely, for estimating the effects of the underperformance of multiple energy efficiency interventions.
- A preliminary investigation has shown that the cumulative uncertainty in stock model predictions, due to the uncertainties in just a few key model input parameters, could be large. Failure to reflect this, when predicting the impact of past energy efficiency interventions and the possible effect of future proposed interventions, leads to a false impression of the reliability of stock model predictions and, more seriously, a false impression that the intended effects of the interventions will be actually be achieved in practice. More work is needed to quantify the real in-situ performance of energy efficiency measures in dwellings of different type and age.
- Because the cumulative effect of the underperformance of a small number of energy efficiency measures is so large, and much larger than the additional emissions reduction that unexpectedly higher performance might yield, it is very easy, in practice, for expected emissions reductions not to be realised.
- There is a need for rigorous quality control by builders, those undertaking refurbishment measures and quality control officers if desired CO_2 emissions targets are to be met. Such quality control is particularly important for larger, older detached dwellings.

The applicability of the CDEM modelling approach to the problem of reducing national domestic building CO_2 emissions has been clearly demonstrated. The findings have established the need for further modelling work to explore the uncertainties associated with the key input parameters used to describe the housing stock. Further work in the CaRB project will incorporate the results of several field studies of domestic buildings into the modelling process. This will be used to undertake a full validation of the model, using known uncertainties within the model inputs. The impact of the underperformance of energy efficiency interventions on the emissions of the national domestic stock will be more thoroughly explored.

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7. Tables

Table 1: House archetype category combinations

Built form categories	Dwelling age band categories
End terrace Mid terrace Semi detached Detached	pre 1850, 1851 - 1899, 1900 - 1918, 1919 - 1944, 1945 - 1964, 1965 -1974, 1975 - 1980, 1980 - 1990, 1991 - 2001
Flat: purpose built	1900 - 1918, 1919 - 1944, 1945 - 1964, 1965 - 1974, 1975 - 1980, 1980 - 1990, 1991 - 2001
Flat: other (converted or in commercial building)	pre 1850, 1851 - 1899, 1900 - 1918, 1919 - 1944

Table 2: Sample values of primary and secondary input parameters for the 1945 to 1964 semi-detached house archetype

Input parameter	Category [1]	Input data source(s)	Sample values for the 1945 to 1964 semi-detached house archetype
Number of dwellings in 2001 English housing stock	L	Census 2001, EHCS	2.4 million
Average total floor area	G	EHCS	78.4 m^2
Building geometry	G	Allen and Pinney, EHCS, SAP 2005	many values e.g. exposed wall area: 67.6 m^2
Average wall U-value	C	EHCS, BREDEM, SAP 2005	1.2 W/m^2K [3]
Average roof U-value	C	EHCS, BREDEM	0.44 W/m^2K [4]
Hot water heating system type distribution	S	EHCS	combi boiler: 18% other boiler: 72% electric immersion: 9% instantaneous: 1%
Hot water cylinder insulation distribution	S	EHCS	foam: 50% jacket: 48% none: 2%
Probability of hot water cylinder thermostat present	S	EHCS	56%
Average fraction of low energy lights [2]	S	MTP	3%
Cooker type distribution [2]	S	MTP	electric: 46% gas: 40% kitchen range: 2% gas hob and electric oven: 12%
Space heating system type distribution	S	EHCS	gas central heating single purpose: 49% oil central heating: 1% solid fuel central heating: 6% electric storage heaters: 4% gas room heaters: 5% solid fuel room heaters: 1% gas central heating back boiler: 32%
Probability of thermostatic radiator valves (TRVs) present	S	EHCS	31%
Average gas boiler efficiency	S	EHCS, BREDEM	67% [5]
Set point temperature for space heating [2]	O	BREDEM	21ºC
Average number of occupants	O	EHCS	2.6

[1] input parameter categories are defined as: location (L), geometry (G), construction (C), services (S) and occupancy (O)
[2] these values will be updated by field measurements from the other CaRB studies currently in progress
[3] based on distribution of wall types: solid 5% (U-value 2.1 W/m^2K); unfilled cavity 61% (U-value 1.6 W/m^2K); and filled cavity 34% (U-value 0.5 W/m^2K)
[4] based on an average roof insulation thickness of 0.109m
[5] based on distribution of gas boiler: condensing fan assisted 5% (with efficiency 81%); non-condensing fan assisted 36% (with efficiency 71%); wall mounted open flue 45% (with efficiency 65%); and floor mounted open flue 15% (with efficiency 60%)

Table 3: CDEM energy and CO_2 emission predictions by built form type for the 2001 English housing stock

		End terrace	Mid terrace	Semi-detached	Detached	Flat: purpose built	Flat: other	All dwellings
Number of dwellings (thousands)		1,374	4,121	6,713	4,786	2,968	1,212	21,263
Average dwelling total floor area (m^2)		79.9	77.1	83.6	131.2	57.1	68.3	87.9
Average number of occupants		2.71	2.77	2.69	2.66	1.79	1.95	2.52
Average dwelling heat loss (W/K)		270	225	262	386	134	208	261
Average annual internal temperature (°C)		18.0	18.3	18.1	18.0	19.4	18.7	18.3
Average annual energy consumption by fuel (kWh)	**Gas**	18,788	15,531	17,727	24,175	9,416	15,300	17,449
	Electricity	4,528	4,448	4,439	5,084	4,248	4,931	4,574
	Oil	173	82	498	4,168	41	229	1,141
	Solid Fuel	830	462	1,233	1,189	53	306	825
Percentage of total energy consumption by fuel	**Gas**	77%	76%	74%	70%	68%	74%	73%
	Electricity	19%	22%	19%	15%	31%	24%	19%
	Oil	1%	0%	2%	12%	0%	1%	5%
	Solid Fuel	3%	2%	5%	3%	0%	1%	3%
Average annual CO_2 emissions by fuel ($kgCO_2$)	**Gas**	3,570	2,951	3,368	4,593	1,789	2,907	3,315
	Electricity	1,947	1,913	1,909	2,186	1,826	2,121	1,967
	Oil	45	21	129	1,084	11	60	297
	Solid Fuel	249	139	370	357	16	92	248
Percentage of total CO_2 emissions by fuel	**Gas**	61%	59%	58%	56%	49%	56%	57%
	Electricity	34%	38%	33%	27%	50%	41%	34%
	Oil	1%	0%	2%	13%	0%	1%	5%
	Solid Fuel	4%	3%	6%	4%	0%	2%	4%
Average annual CO_2 emissions by end use ($kgCO_2$)	**Space heating**	3,074	2,293	2,971	5,128	1,456	2,829	3,100
	Water heating	1,180	1,172	1,229	1,183	980	1,017	1,153
	Cooking	281	283	280	279	248	254	274
	Lights and appliances	1,276	1,275	1,296	1,629	958	1,080	1,301
Percentage of total CO_2 emissions by end use	**Space heating**	53%	46%	51%	62%	40%	55%	53%
	Water heating	20%	23%	21%	14%	27%	20%	20%
	Cooking	5%	6%	5%	3%	7%	5%	5%
	Lights and appliances	22%	25%	22%	20%	26%	21%	22%
Average annual total CO_2 emissions ($kgCO_2$)		5,811	5,024	5,776	8,220	3,642	5,179	5,827
Average annual total CO_2 emissions per person ($kgCO_2$)		2,138	1,811	2,148	3,088	2,024	2,643	2,308

Table 4: Results for local sensitivity analysis of CDEM primary input parameters to the average dwelling CO_2 emissions output variable for the 2001 English housing stock using 1971 to 2000 climate data. All values in this table are average English housing stock values based on weighted averages of the individual 47 house archetype values.

Primary input parameter	Category [1]	Initial set value for input parameter (k_j)	Overall change in input parameter ($2\Delta k_j$)	Overall change in output variable [2] (change in y_i)	Sensitivity coefficient $\partial y_i/\partial k_j$	Normalised sensitivity coefficient $S_{i,j}$ [3]
External air temperature (°C) [4]	L	9.3	0.19	-67.5	-362.4	-0.58
External solar radiation (W/m^2) [4]	L	110.2	2.20	-13.3	-6.0	-0.11
Site latitude (°)	L	52.4	1.05	-11.5	-11.0	-0.10
Average storey height (m)	G	2.5	0.05	55.7	1132.9	0.48
Total floor area (m^2)	G	87.7	1.75	39.7	22.6	0.34
Number of storeys	G	1.8	0.04	7.6	215.8	0.07
Door area (m^2)	G	1.5	0.03	1.9	65.3	0.02
Window area (m^2)	G	17.5	0.35	-0.8	-2.2	-0.01
Wall U-value (W/m^2K)	C	1.3	0.03	31.4	1172.3	0.27
Window U-value (W/m^2K)	C	3.2	0.06	21.7	340.0	0.19
Infiltration rate (ach)	C	0.7	0.01	14.1	1010.4	0.12
Overshading factor [5]	C	0.7	0.01	-13.3	-955.2	-0.11
Proportion of glass [5]	C	0.8	0.02	-13.3	-835.8	-0.11
Transmission factor [5]	C	0.8	0.02	-13.3	-844.5	-0.11
Floor U-value (W/m^2K)	C	0.5	0.01	8.1	810.1	0.07
Roof U-value (W/m^2K)	C	0.4	0.01	5.8	716.0	0.05
Door U-value (W/m^2K)	C	2.5	0.05	2.3	45.9	0.02
Boiler efficiency	S	0.7	0.01	-52.3	-3923.6	-0.45
Hot water cylinder size (l)	S	131.0	2.62	2.3	0.9	0.02
Hot water cylinder jacket insulation thickness (mm)	S	29.5	0.59	-2.2	-3.8	-0.02
Hot water cylinder foam insulation thickness (mm)	S	29.3	0.59	-0.9	-1.6	-0.01
Proportion of radiators with thermostatic radiator valves	S	0.3	0.01	-0.8	-120.5	-0.01
Proportion of hot water cylinders with thermostats	S	0.6	0.01	-0.3	-21.9	0.00
Proportion of lights with low energy bulbs	S	0.03	0.00	-0.1	-84.9	0.00
Heating demand temperature (°C)	O	21.0	0.42	179.8	429.9	1.55
Length of daily heating period (hours)	O	11.0	0.22	36.4	330.9	0.62
Number of occupants	O	2.5	0.05	9.9	195.6	0.08

[1] input parameter categories are defined as: location (L), geometry (G), construction (C), services (S) and occupancy (O)
[2] the output variable used in this local sensitivity analysis is average dwelling CO_2 emissions ($kgCO_2$). The initial set value for the output variable (y_i) was 5827 $kgCO_2$ (as given in Table 3)
[3] equivalent to the percentage increase in the output variable when the input parameter is increased by 1%
[4] the temperature and solar radiation values in this table are the average of the 12 monthly input parameter values
[5] these three input parameters are all directly proportional to solar gains (a value calculated internally in the energy model) and therefore they have the same normalised sensitivity coefficient values

8. Figures

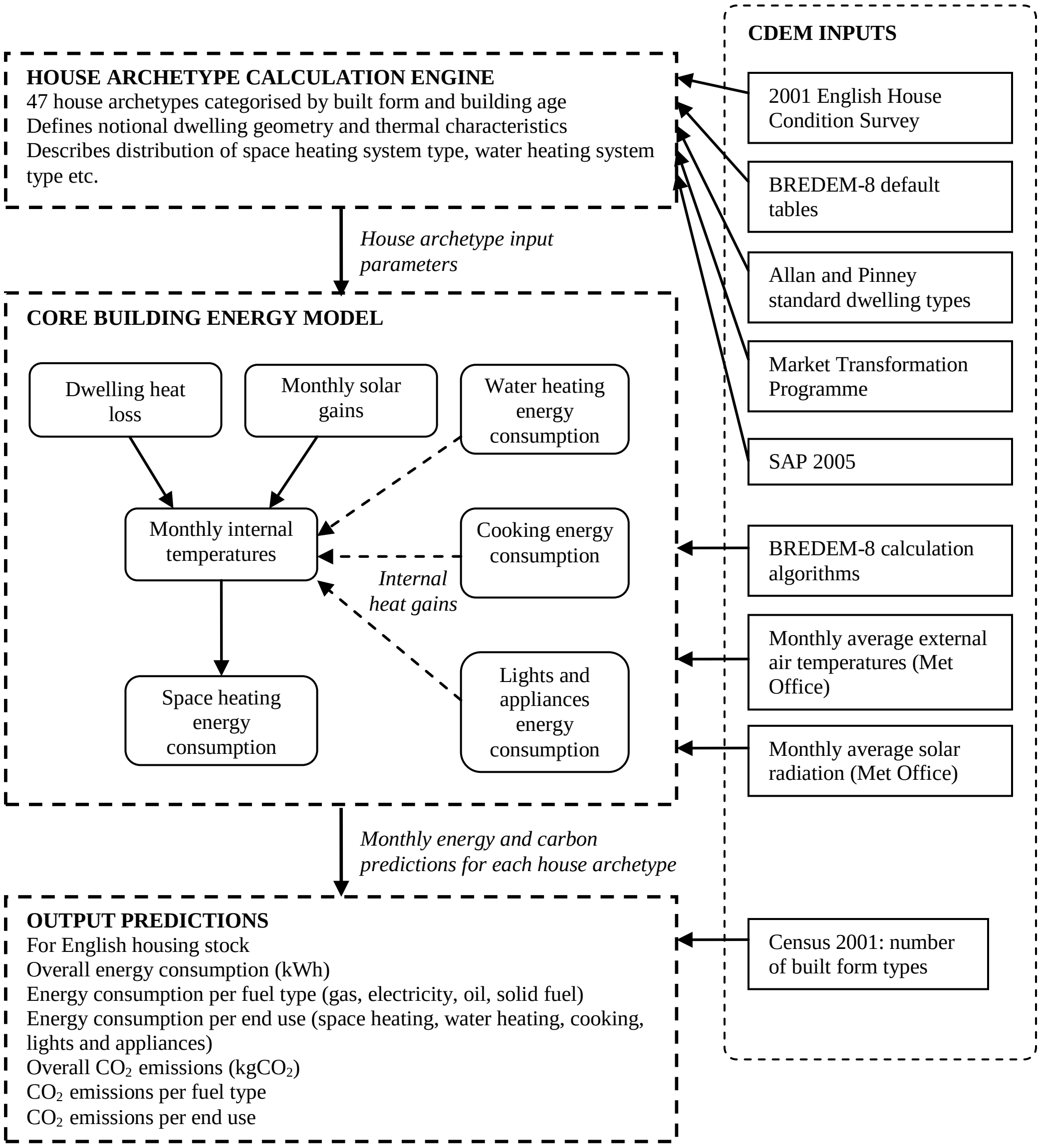

Figure 1: Schematic of the Community Domestic Energy Model (CDEM) modelling process

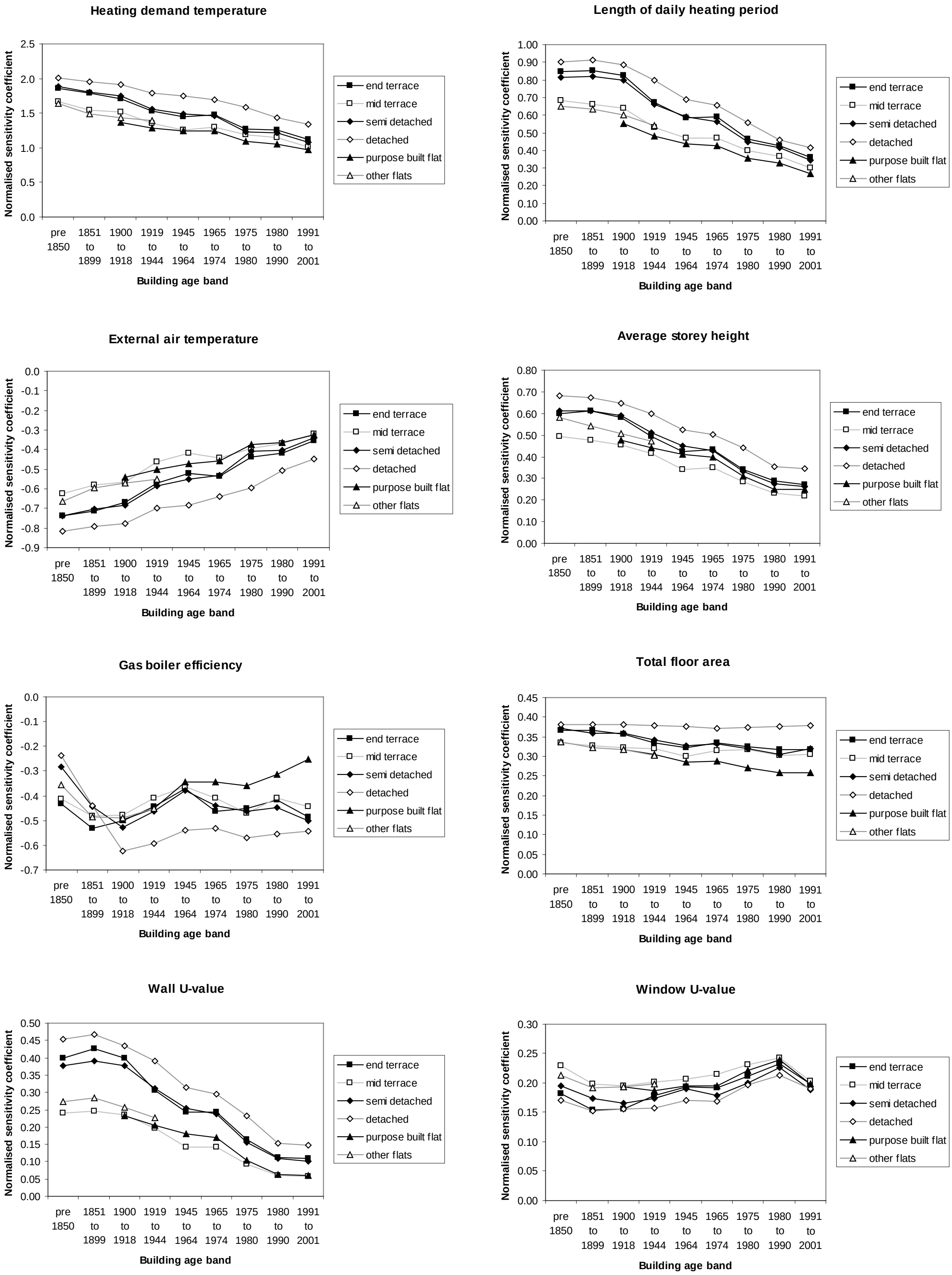

Figure 2: Normalised sensitivity coefficients by built form type and building age band for the eight most influential input parameters

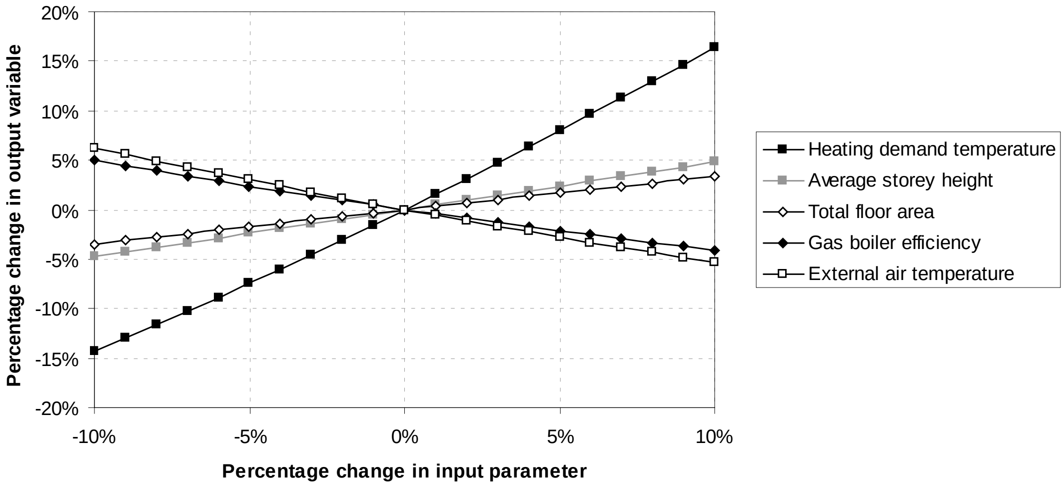

Figure 3: Linearity test showing the percentage change in the output variable (average dwelling CO_2 emissions) resulting from a percentage change of ±10% in the five most influential input parameters

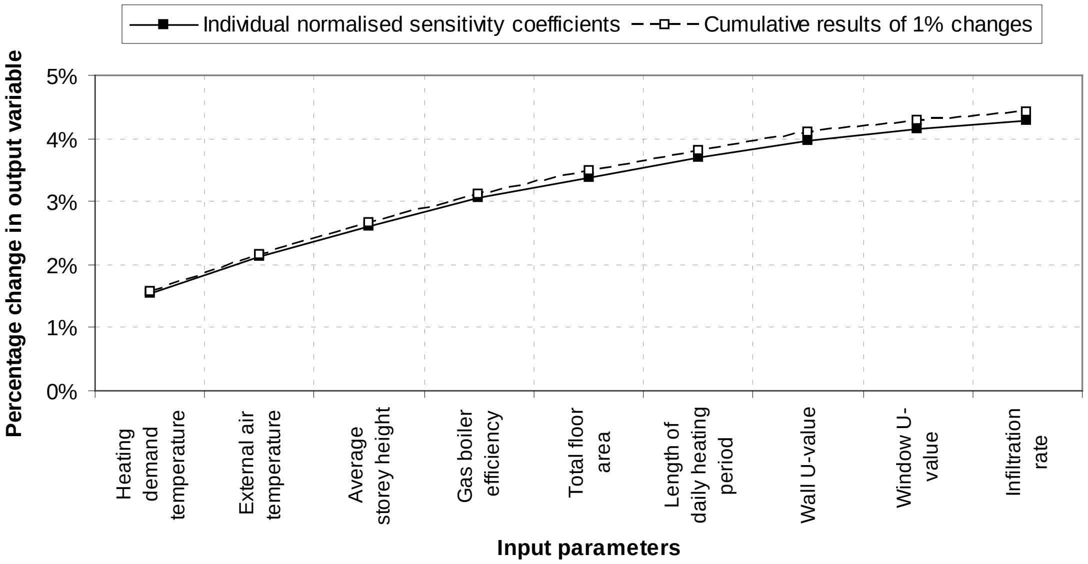

Figure 4: Superposition test showing the total percentage change in the output variable (average dwelling CO_2 emissions) resulting from normalized sensitivity coefficients and cumulative 1% changes in the nine most influential input parameters