A review of bottom-up building stock models for energy consumption in the residential sector

Article *in* Building and Environment · July 2010

DOI: 10.1016/j.buildenv.2010.01.021

6 authors, including:

Miroslava Kavgic
University of Ottawa

Anna Mavrogianni
University College London

D. Mumovic
University College London

A.J. Summerfield
University College London

Building and Environment 45 (2010) 1683–1697

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

A review of bottom-up building stock models for energy consumption in the residential sector

M. Kavgic [a,*], A. Mavrogianni [a], D. Mumovic [a], A. Summerfield [b], Z. Stevanovic [c], M. Djurovic-Petrovic [d]

[a] The Bartlett School of Graduate Studies, University College London, London, UK
[b] UCL Energy Institute, University College London, London, UK
[c] Institute of Nuclear Sciences Vinca, University of Belgrade, Serbia
[d] Ministry of Science and Technological Development, Serbia

ARTICLE INFO

Article history:
Received 20 September 2009
Received in revised form
4 January 2010
Accepted 21 January 2010

Keywords:
Bottom-up building physics stock models
Residential energy use
CO_2 emission reduction strategies

ABSTRACT

Efficient and rational implementation of building stock CO_2 emission reduction strategies and policies requires the application of comprehensive building stock models that have the ability to: (a) estimate the baseline energy demand of the existing building stock, (b) explore the technical and economic effects of different CO_2 emission reduction strategies over time, including the impact of new technologies, and (c) to identify the effect of emission reduction strategies on indoor environmental quality.

The aims of this paper are fourfold: (a) to briefly describe bottom-up and top-down methods and overview common bottom-up modelling techniques (statistical and building physics based), (b) to critically analyse the existing bottom-up building physics based residential energy models focusing on their purposes, strengths, and shortcomings, (c) to compare five building physics based bottom-up models focusing on the same building stock – UK case study, and (d) to identify the next generation of coupled energy–health bottom-up building stock models.

This paper has identified three major issues which need to be addressed: a) the lack of publicly available detailed data relating to inputs and assumptions, as well as underlying algorithms, renders any attempt to reproduce their outcomes problematic, b) lack of data on the relative importance of input parameter variations on the predicted demand outputs, and c) uncertainty as to the socio-technical drivers of energy consumption – how people use energy and how they react to changes in their home as a result of energy conservation measures.

1. Introduction

In the EU, the residential building sector is responsible for about 22% of total energy consumption [1]. Over the last decade policy-makers, as elsewhere, have increasingly recognised the potential of the sector to contribute towards reductions in energy consumption and CO_2 emissions. Among a diverse array of initiatives operating in the EU, one of the most significant is the Directive on the Energy Performance of Buildings (Directive 2002/91/EC) that came into force in 2002 with legislation in member states by 2006 [2]. The main aim is to promote the improvement of energy performance in buildings via four requirements: (a) a general framework for a methodology of calculation of the integrated performance of buildings, (b) application of minimum standards in new buildings and certain renovated buildings, (c) energy certification and advice for new and existing buildings, and (d) inspection and assessment of boilers and heating/cooling systems [2].

In the UK, a legally binding target was set for CO_2 emission reductions of at least 26% by 2020 and 80% by 2050, compared to 1990 levels [3]. This has been accompanied by the work of the Committee on Climate Change (CCC) which has released a series of carbon budgets to delineate a pathway to the 2050 carbon target by identifying contributions from each sector, and within these the reductions expected from specific policy measures. From the existing residential stock, the CCC expects carbon reductions by 2020 that correspond to savings of 10–12% from 2005 due to energy efficiency measures alone, and it prescribes no addition carbon emissions should occur from new build [4]. Meanwhile the UK government, like many others, is applying a range of policy leavers via various mechanisms, from improvements in building regulations to obligations on utilities to facilitate energy efficiency improvements for households and on local government to reduce energy consumption in their social housing stock.

* Corresponding author.
E-mail address: miroslava.kavgic@gmail.com (M. Kavgic).

0360-1323/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.buildenv.2010.01.021

In this policy environment for rapid and substantial improvement in energy performance across all levels of governance (and which is similar in its multifaceted character to what already exists or is likely to occur in many nations), it is essential that robust and accurate models are available to inform and evaluate specific policy measures. Building stock models for energy consumption represent a key tool to assist with the efficient and rational implementation of policy. Among other criteria, these models should ideally have the ability to:

a) estimate the 'baseline' energy consumption of the residential housing sector, disaggregated by building or social categories and energy end-uses.
b) explore the technical and economic effects of different CO_2 emission reduction strategies over time, including the impact of new technologies, such as renewables and smart metering.
c) not be confined to issues directly related to energy, but identify the effect of emission reduction strategies on indoor environmental quality.

In recent years, a plethora of disaggregated national level energy demand models has been developed that vary considerably in terms of their data input requirement and disaggregation levels, the socio-technical assumptions that are made about building operation, and hence in the type of results and scenarios they can reliably evaluate. Both policy developers and building scientists would benefit from a better understanding of the appropriate application and limitations of these models. Policymakers would gain by establishing which building parameters are key for national carbon reduction strategies for dwellings and highlighting policy challenges for climate and building stock [5,6]. Those in the construction industry could also benefit by improving their detailed knowledge of the existing stock and develop business strategies and techniques for sustainable refurbishment.

The aim of this paper is to provide a comparison of bottom-up building physics stock models, one of the main groups of models used to analyse the residential sector. With knowledge of the extent that the model structure and assumptions affect its prediction outcomes [7,8], potential users of the models will be able to take an informed decision on which model to use for a specific purpose. For example, the resolution of a given model might render it suitable for national level predictions, but not at a finer spatial resolution, such as at the local authority level. After placing bottom-up building physics stock models in the context of other methodologies (Section 2), we give a critical evaluation of these models with respect to their purpose, strengths and shortcomings (Section 3), and use the UK as a case study for the comparison of five existing models (Section 4). We then illustrate the future direction of building stock models in coupling energy consumption with other outcomes, such as health impacts (Section 5). The paper concludes with a discussion of the issues raised and of the main ways these models could be improved as tools for policymakers (Section 6).

2. Overview of modelling approaches

This section is only intended as an outline description of the methodologies and the underlying techniques available for modelling residential sector, as this has already been given elsewhere [9–12] and particularly the review of Swan and Ugursal [13]. Broadly, there are two fundamental classes of modelling methods used to predict and analyse various aspects of the overall building stock energy use performance and associated CO_2 emissions: the top-down and bottom-up approaches [14]. Fig. 1, as developed by IEA [15], schematically displays the general methodological philosophy behind the bottom-up and top-down models and their main characteristics are described in Table 1. However, it is also the case that some of the more sophisticated models can combine components where each of these approaches has been used.

2.1. Top-down approach

The top-down modelling approach works at an aggregated level, typically aimed at fitting a historical time series of national energy consumption or CO_2 emissions data. Such models tend to be used to investigate the inter-relationships between the energy sector and the economy at large, and could be broadly categorised as econometric and technological top-down models.

The econometric top-down models are primarily based on energy use in relationship to variables such as income, fuel prices, and gross domestic product to express the connection between the energy sector and economic output. They can also include general climatic conditions, such as population-weighted temperature, for a nation. As such, the econometric top-down models often lack details on current and future technological options as they rather place the emphasis on the macroeconomic trends and relationships observed in the past, rather than on the individual physical factors in buildings that can influence energy demand [16]. More importantly, the reliance on past energy–economy interactions might also not be appropriate when dealing with climate change issues where environmental, social, and economic conditions might be entirely different to those previously experienced. They have no inherent capability to model discontinuous changes in technology. The technological top-down models include a range of other factors that influence energy use (i.e. saturation effects, technological progress, and structural change), however they are not described explicitly within the models [17].

As an example of a simple top-down model, the annual delivered energy price and temperature (ADEPT) was recently developed for annual household energy consumption in the UK since 1970 [18]. This is a regression model based on average heating season temperature and an inflation adjusted energy price. The aim of the ADEPT model is just to allow yearly consumption data to be compared with what might be expected after allowing for the prevailing temperature and price settings. It provides policymakers and the public a straightforward way of determining if changes are outside that expected from these basic drivers (and as might be anticipated to occur from major changes in the energy performance of the stock). So while the model acts to prevent any reductions in national energy consumption that are associated with warmer conditions or price changes from being automatically ascribed to fundamental improvements in the sector, it is not intended to explain consumption in more detail, such as quantifying the role of other factors and the effectiveness of specific policy measures.

2.2. Bottom-up approach

Bottom-up methods are built up from data on a hierarchy of disaggregated components, that are then combined according to some estimate for their individual impact on energy usage, for instance in the UK the contribution from Victorian terrace housing might be weighted according to their prevalence in the stock. This implies that they may be useful for estimating how various individual energy efficiency measures impact on CO_2 emission reduction, such as by replacing one type of heating systems with another. Often these models are seen as a way to identify the most cost-effective options to achieve given carbon reduction targets based on the best available technologies and processes [19].

The bottom-up models work at a disaggregated level, and thus need extensive databases of empirical data to support the description of each component [20]. Contingent upon the type of

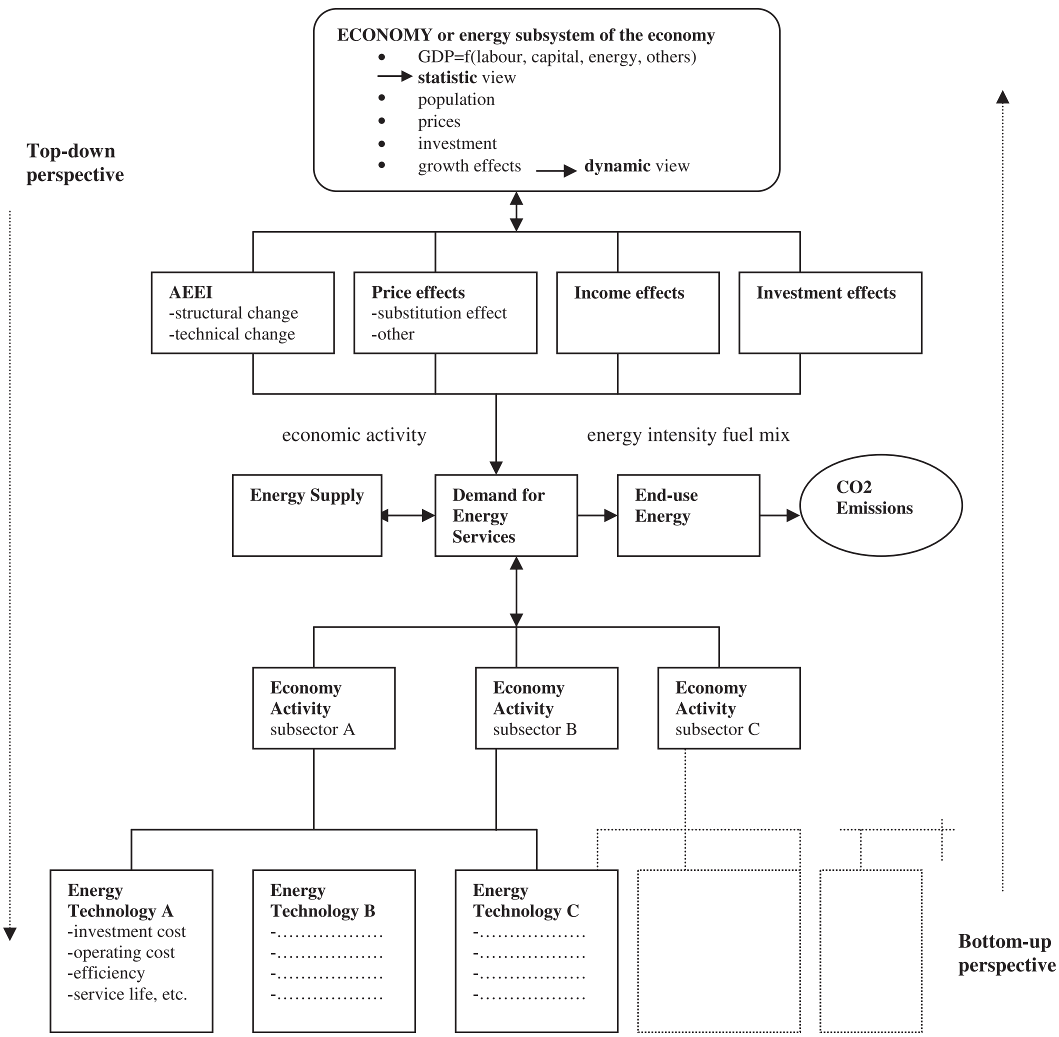

Fig. 1. Top-down and bottom-up modelling approaches (adapted from [15]).

data input and structure, statistical and building physics based methods represent two distinct approaches applied in the bottom-up models to determine the energy consumption of specified end-uses [13].

2.2.1. Approach based on building physics

Building physics based modelling techniques generally include the consideration of a sample of houses representative of the national housing stock and utilization of a building energy calculation method to estimate the delivered energy consumption [21]. Therefore, they require data input composed of quantitative data on physically measurable variables such as the efficiency of space heating systems and their characteristics, information on the areas of the different dwelling elements (walls, roof, floor, windows, doors) along with their thermal characteristics (*U*-values), internal temperatures and heating patterns, ventilation rates, energy consumption of appliances, number of occupants, external temperatures, etc. [17].

The combination of building physics and empirical data from housing surveys and other data sets, as well as assumptions about buildings operation, give modellers the means to estimate energy consumption in dwellings for the past, present, and future. By developing different scenarios, the bottom-up models appear to have the potential to be used to assess the impact of specific carbon reduction measures on the overall energy demand [22], which can be used as part of an evidence based approach to medium to long-term energy supply strategy. In Europe, bottom-up building physics stock models are seen as useful tools to provide for policymakers with estimates for the effectiveness of policies and can help to identify technological measures that end-use efficiencies.

A level of building physics stock model's complexity is determined by their core calculation engines. In the UK, for example, the most widely used physically based model for the calculation of domestic energy demand is BREDEM (The Building Research Establishment's Domestic Energy Model) [23–26]. It consists of a series of heat balance equations and empirical relationships to produce an estimate of the annual (BREDEM-12 [24]) or monthly (BREDEM-8 [25,26]) energy consumption of an individual dwelling. Importantly, an annual modified version of BREDEM (BREDEM-9) forms the basis of the UK Government's Standard Assessment Procedure (SAP [27]) which is used for the energy rating of dwellings. One of the main advantages of the BREDEM algorithms for model developers is their overall modular structure so that they can be easily modified to suit particular needs. For instance, BREDEM determines the electricity use for lights and appliances using simple relationships based on floor area and occupant numbers, which can easily be replaced by a more sophisticated approach if needed.

Table 1
Benefits and limitations of bottom-up and top-down modelling approaches.

Characteristics	Top-down	Bottom-up statistical	Bottom-up building physics
Benefits	- Focus on the interaction between the energy sector and the economy at large - Capable of modelling the relationships between different economic variables an energy demand - Avoid detailed technology descriptions - Able to model the impact of different social cost-benefit energy and emission policies and scenarios - Use aggregated economic data	- Include macroeconomic and socioeconomic effects - Able to determinate a typical end-use energy consumption - Easier to develop and use - Do not require detailed data (only billing data and simple survey information)	- Describe current and prospective technologies in detail - Use physically measurable data - Enable policy to be more effectively targeted at consumption - Assess and quantify the impact of different combination of technologies on delivered energy - Estimate the least-cost combination of technological measures to meet given demand
Limitations	- Depend on past energy economy interactions to project future trends - Lack the level of technological detail - Less suitable for examining technology-specific policies - Typically assume efficient markets, and no efficiency gaps	- Do not provide much data and flexibility - Have limited capacity to assess the impact of energy conservation measures - Rely on historical consumption data - Require large sample - Multicollinearity	- Poorly describe market interactions - Neglect the relationships between energy use and macroeconomic activity - Require a large amount of technical data - Do not determinate human behaviour within the model but by external assumptions

One of the main weaknesses of building physics models, lies in the many assumptions made regarding the role of behavioural factors on energy consumption, for instance in estimating the impact of changing demographic factors related to an aging population and hours of occupancy and heating system use. These issues, among others, are discussed in more detail in subsequent sections.

2.2.2. Statistical models

A detailed review of the statistical techniques used for modelling energy consumption of the residential sector can be found elsewhere [13]. Even though, there is a wide array of statistical modelling techniques available, most of the bottom-up statistical models are based on regression techniques [13,28,29]

Even though, all of these methods can be used to model residential energy consumption they do not provide much detail and flexibility and therefore have restricted capacity to evaluate the impact of a wide range of energy conservation scenarios [28]. For example, the Princeton scorekeeping method (PRISM) has been used broadly in the US by many governments, utilities and research organisations to analyse conservation and refurbishment measures in buildings. PRISM is a two variable (a constant and a slope) linear regression model that uses a year of monthly billing data from a dwelling to create a weather-adjusted Normalised Annual Consumption (NAC) index of consumption [29]. It has been applied to characterise energy conservation measures in a number of US regions, such as New Jersey and St. Louis, by developing a simple models for monitoring natural gas consumption in large aggregates of houses based on the individual-house scorekeeping approach.

2.2.3. Hybrid models

While it is the case that building physics based models also rely on statistics for much of their empirical data, for instance average hot water demand per person. Some of the more sophisticated models combine, in a more fundamental way, components where both building physics and statistical approaches have been applied. The Canadian Hybrid Residential End-use Energy and Emission Model (CHREM) is a typical example of a hybrid model. CHREM, which relies on the 17,000 detailed house records, implements the neural networks technique [30,31]. This model consists of two energy modelling components, statistical and physics based component that are used to estimate the energy consumption of the major end-use groups: a) domestic appliances and lighting, b) domestic hot water and c) space heating and cooling. The CHREM employs a calibrated neural network model as the statistical half of the model for use in estimating the annual energy consumption for appliances, lighting and domestic hot water loads as they are predominately influenced by occupant behaviour [32,33]. Estimation of space heating and cooling loads is accomplished using the high-resolution building performance simulation package ESP-r as there is no relevant historic data for statistical analysis of new technologies.

3. Bottom-up building physics residential stock models

In recent years, a wide range of bottom-up building physics based residential stock models have been developed aiming to enable policymakers to establish the long-term targets related to housing stock energy consumption and associated CO_2 emissions. We have selected four models focusing on residential building stocks in Canada [34], Finland [35], USA [36], and Belgium [37] that have distinct characteristics, with a further five from the UK for a more detailed comparison [8,17,20,38,39] and are discussed in more detail in Section 4. Although each of the selected models differs in their level of complexity, data input requirements, and structure, all of them have been used to analyse the potential impact of various energy efficiency measures and policy scenarios on the future energy consumption of specific housing stocks. Comparative analysis of the selected bottom-up models is presented in Table 2.

3.1. Four selected residential stock models (outside of the UK)

The Canadian Residential Energy End-use Model (CREEM) [34] was primarily developed to investigate the impact of various carbon reduction strategies included within two standards, the R-2000 [40] and NECH standard [41]. The Canadian residential stock comprises of five major types of dwellings: single-detached, single-attached (i.e. houses but with at least one wall shared with a neighbour), apartments (less than five storeys), high-rise apartments (five storeys and more), and mobile homes. However, single-detached and single-attached houses account for about 60% of the households in Canada and are responsible for the largest share of residential energy consumption [34]. For this reason, only single-detached and single-attached dwellings are considered in this study. Although the residential building stock was primarily divided into four age categories: pre 1941, 1941–1966, 1967–1978, 1978 or later, the impact of energy efficiency measures prescribed

Table 2
Comparative analysis of bottom-up models.

Name	BREHOMES	CREEM	Regional engineering model	A Bottom-up Engineering Estimate of the Aggregate Heating and Cooling Loads for the Entire U.S. Building Stock	Software package VerbCO_2M	Johnston	UKDCM	DECarb	CDEM
Developer	Building Research Establishment (BRE)	Canadian Residential Energy End-use Data and Analysis Centre (CREEDAC)	University of Joensuu, Finland	Lawrence Berkeley National Laboratory, U.S. Department of Energy (USDOE)	Department of Civil Engineering, Laboratory for Buildings Physics, Leuven, Belgium	PhD thesis (Leeds University)	Environmental Change Institute (ECI), Oxford University	University of Bath, University of Manchester	Department of Civil and Building Engineering, Loughborough University, Loughborough, UK
Year	Early 1990s	1998	1999	2000	2001	2003	2006	2007	2009
Embedded calculation model	BREDEM-12	HOT200 Batch v7.14 energy simulation program	–	DOE-2.1E	VerbCO_2M	BREDEM-9 (modified version)	BREDEM-8	BREDEM-8	BREDEM-8
Data output and temporal resolution	Annual energy consumption	Annual energy consumption	Annual energy and emission estimates and related heating energy costs based on 1996 prises	Heating and cooling energy consumption of the national building stock	Annual energy consumption and CO_2 emissions	Annual energy consumption and CO_2 emissions	Monthly energy consumption and CO_2	Monthly energy consumption	Monthly energy consumption and CO_2 emissions
Level of disaggregation (spatial resolution)	1000 dwelling types (defined by age group, built form, tenure type and the ownership of central heating)	8767 dwellings (defined by type, space heating fuels, vintage and province)	4163 calculation units (municipally aggregated groups of buildings with similar heat consumption features)	80 single-family, 60 multi-family buildings and 120 commercial buildings	A set of 960 dwellings for the period up to 1990	Two dwelling types (pre- and post-1996)	20000 dwelling types by 2050	8064 unique combinations for 6 age bands	47 house archetypes, derived from unique combinations of built form type and dwelling age
Level of data input requirement	Medium (national statistics)	Medium (national statistics)	Low (national statistics)	Medium (national statistics)	Medium (national statistics)	Medium (national statistics)	Medium (national statistics)	Low (defaults from national statistics)	Medium (national statistics)
Time dimension (projections to the future)	Two scenarios until 2020: (a) reference (business-as-usual), (b) efficiency	Two scenarios: (a) R-2000 standards, (b) NECH standards	–	–	Three scenarios: (a) business-as-usual, (b) an explicit shift towards retrofits and reconstruction, restricted expansion of the housing stock, (c) a demand guided retrofit and reconstruction, no expansion of the housing stock beyond 2010	Three scenarios until 2050: (a) business-as-usual, (b) demand side, (c) integrated	Three scenarios until 2050: (a) business-as-usual, (b) 44% emission reduction, (c) 25% emission reduction below 1990 levels	Back-cast scenario from 1970 to 1996 and UKCIP02 climate change scenarios and additional runs to test the BREHOMES, Johnston and UKDCM scenarios	Predictions only for one point in time (2001 housing stock)
Aggregation level of data output (spatial coverage)	National	National	National	National	National	National	National	National	National, City, Neighbourhood
Inter-model comparison	Extensive	Comparison with Aydinalp's (2002) two district data-driven models based on the Neural Network (NN) and Conditional Demand Analysis (CDA) techniques.	–	–	Comparison with top-down analysis for the Walloon region	Comparison with results obtained from BREHOMES	Comparison with regional statistics provided by BERR	Comparison with results obtained from BREHOMES	Local sensitivity analysis, linearity and superimposition tests to quantify the impact of input parameters on output uncertainties

(*continued on next page*)

Table 2 (*continued*)

Name	BREHOMES	CREEM	Regional engineering model	A Bottom-up Engineering Estimate of the Aggregate Heating and Cooling Loads for the Entire U.S. Building Stock	Software package $VerbCO_2M$	Johnston	UKDCM	DECarb	CDEM
Empirical validation with existing data	Extensive	Validation with 3248 energy billing records from28 11 houses.	Comparison with national l statistics provided by SENER	Residential Energy Consumption survey (1982) and Non-residential Buildings Energy Consumption Survey (1989)	–	Comparison with empirical data from the BRE Domestic Energy Fact File	Comparison with regional statistics provided by BERR	Comparison with DUKES provided by BERR and the BRE Domestic Energy Fact File	Comparison with DEFRA aggregate domestic space heating consumption figure for 2001
Application	Policy advice tool (used by DEFRA)	Policy advice tool	Policy advice tool	To assess current research, development and deployment activities and prioritize future actions	Policy advice tool	Policy advice tool	Policy advice tool (Oxford)	Policy advice tool	Policy advice tool
Current availability		Used only by the developers	Used only by the developer	Freely available	Used only by the developer	Used only by the developer	Freely available	Open framework	Open structure

by NECH and R-2000 standards was analysed by 'implementing' measures to 10, 20, 30, 50 and 90% of the houses built in 1966 or later. The delivered energy use attributable to low-rise family residential stock is calculated by HOT2000, a simulation programme used for the ecoENERGY Housing Retrofit Program, the EnerGuide New Housing Program, and Canadian public policy on energy efficiency in housing.

CREEM is used to conduct comparative techno-economic analysis for a wide range of building retrofit and fuel switching scenarios and capability to assess the energetic and emissions impact of changes to the building code [42]. The main limitations of the model are related to the omission of mid and high-rise multi-family residential buildings (30% of Canadian residential stock), and that the scenarios do not include older dwellings (pre 1967) in the evaluation of energy efficiency policies. This reflects a lack of empirical data for these parts of the stock.

The North Karelia, Finland model [35] is a regional building stock model that was developed to improve the quality and quantity of heating energy and emission data, especially for the benefit of local decision making authorities. This is a non-dynamic, bottom-up numerical model for producing annual energy and CO_2 emission estimates, as well as associated heating energy costs. The model comprises of calculation units that represent municipally aggregated groups of all buildings in the area. The buildings are clustered according to the type of building (detached houses, semi-detached houses, apartments, commercial, educational, offices, hospitals and clinics, traffic, conventional, storage, industrial, and others), heat distribution type (hot water heating, hot-air heating, direct electric heating, stove/fireplace, no stationary heating devices, and unknown), primary heat/energy source (district heating, coal, wood, peat, electricity and other), and construction or refurbishment year (1920 or earlier, 1921–1939, 1940–1959, 1960–1969, 1970–1979, 1980–1989, 1990 or later and unknown).

The developed model produced extensive municipal estimates of heating energy and related greenhouse gas emission and introduced new indicators characterising the sustainability of heating energy use (i.e. municipal per capita estimates of heating energy and emissions and the determination of the shares of domestic and renewable energies in space heating). The main limitations of this model are concerned with limitation in the supporting data on fuel use, such as the use of biomass for space heating, which lead to major assumptions in modelling energy and emissions scenarios. Secondly, as this is a steady-state physics model rather than a dynamic model, it is unable to address the temporal changes in demand that result from heating loads due to occupants, appliance usage, and solar gains which might be of particular value to local authorities.

The Huang and Brodick model [36] for the US building stock is not based on dwellings per se, but on the aggregated cooling and heating loads attributable to different building envelope components in the stock, such as windows, roofs, walls, internal processes, and space conditioning systems. The model is used to estimate the national potential for improvements for U.S. Department of Energy's (DOE) Office research and market transformation activities in building energy efficiency [36]. The examined building stock comprised of 112 single-family, 66 multi-family housing and 481 commercial buildings. With the information on age (pre-1940s, 1950–1959, etc.), dwelling type (single-family, small multi-family with less than four units, large multi-family with more than 20 units, etc.), and total building stock in each region, the overall energy use of the US housing stock was calculated using the DOE-2.1E simulation tool.

The developed model produced aggregated estimates of residential and commercial building energy use that are generally consistent with top-down statistical approaches. Moreover, the detailed hourly load shapes from this project can also be useful for evaluating energy service contracts, energy pricing alternatives, or selecting energy efficiency program needs [36]. Nevertheless, users of the model need to be aware of some key issues. As the authors of this model acknowledge, the totals for the non-space conditioning end-use such as water heating, lighting were modelled very simply. Only gas was included as the primary fuel source for space and water heating, even though electricity (space heating: 29.1%, water heating: 39%) and other fuels are also used as a primary energy source [43]. These fuel sources may occur in buildings with certain characteristics, rather than across the whole stock. So the model provides information on potential improvements in certain building components, such as shifting from single to double-glazing, but not in which parts of the stock these gains would occur or would benefit most from the change.

The Hens et al. model [37] for the Belgian residential sector addressed the question: "*Which improvement could generate the reduction needed?*" It is based on a set of 960 reference dwellings using five key variables: age (before 1945, 1946–1979, 1971–1980, 1981–1990), building type (terraced, double, individual flat), total floor area (up to 64, 65–104, and above 105 m^2), primary energy (oil, gas, butane, electricity, other), and the presence or otherwise of central heating. The energy consumption for an individual reference dwelling is split into three main parts: heating, hot water, and general household energy consumption, while cooling was not considered. These dwellings were then used to represent the energy consumption of building stock for the period up to 1990, according to a weighted average consumption for each.

The model's results indicate that incremental improvement of energy efficiency of new buildings and retrofits of old building are not sufficient and major efforts will be needed to reach the emission reduction objectives [37]. In addition, housing policy should be more dedicated to retrofitting than is the case today. Nevertheless, a number important issues need to be considered when interpreting results from this model. Energy consumption associated with appliances and lighting is not currently part of the calculation for individual reference dwellings [44]. The energy conservation measures considered do not go beyond improvements to the building envelope. Cooling loads, which are also not currently included in the energy calculation, may become increasingly important with climate change and improvements to the stock.

3.2. Common and underlying issues

Before proceeding with the comparison of the UK models, it is worth reflecting on some of the issues that have emerged already. First is the influence of data, or more precisely the lack of data, in determining the structure of the models, such as omissions of certain sectors of the residential stock or types of energy use from the models. This has a further impact on the type of methodology used in the model to quantify certain aspects of energy use, such as applying very simple approximations for solid fuels burnt or appliance usage. Such limitations may be appropriate within the specific scenarios tested in the papers and when their results are accompanied by caveats. However the temptation is that once these tools become embedded with a policy evaluation process (and given that scientific papers are often used to establish a model's credentials), the underlying assumptions and inadequacies of data may be overlooked and policymakers end up using the models beyond their realm of validity. For instance, they may not be aware that the models were only appropriate for comparative analysis for only certain types of measures (such as fabric improvements) and that these were applied to only specific parts of the stock (such as building constructed since some year). This leads to the broader point that these models typically draw upon a wide range of sources for their input data, including building surveys, occupant reports, and industry data on installation rates, that all have varying degrees of representativeness and accuracy. For all the models this renders it difficult for other researchers, let alone policymakers, to identify the limitations of data and methodologies and understand the implications of these on the estimates and policy comparisons.

4. UK building physics residential stock models

In the UK a number of physics based energy models have been developed in recent years aiming to estimate the baseline energy consumption of the existing residential stock as well as to provide insight on the future of residential energy demand. This provides the unique opportunity to examine the advantages and disadvantages of various methodological approaches tested for the same building stock. The key characteristics of each model are given in Table 3, with structure of each shown in a corresponding figure.

1. **The Building Research Establishment's Housing Model for Energy Studies** (BREHOMES) developed by Shorrock and Dunster [20,45,46], Fig. 2;
2. **The Johnston model** [17,47], developed by Johnston, Fig. 3;
3. **The UK Carbon Domestic Model** (UKDCM) developed by Boardman et al. [38] as part of the 40% House project, Fig. 4;
4. **The DECarb model** developed by Natarajan and Levermore [39,48], Fig. 5
5. **The Community Domestic Energy Model** (CDEM) developed by Firth et al. [8], Fig. 6.

The five models selected for this comparative analysis all share the same core calculation engine, BREDEM, modified to varying degrees; the annual version BREDEM-12 is integrated in BREHOMES, a simplified version of the annual BREDEM-9 is used by Johnston, whereas UKDCM, DECarb and CDEM are all based on the monthly BREDEM-8. In four out of five models (BREHOMES, Johnston, UKDCM, and DECarb) these original BREDEM algorithms are substituted by the more sophisticated algorithms developed by the Domestic Equipment and Carbon Dioxide Emissions (DECADE) Team at the University of Oxford [49].

4.1. Disaggregation levels

The level of disaggregation differs significantly among the five models. DECarb is a highly disaggregated model using a relational data set to delineate 8064 unique combinations for 6 age bands. UKDCM similarly comprises over 20,000 dwelling types by 2050, defined by geographical areas, age classes, types of construction, number of floors, tenure and construction method, with each type given an appropriate weighting to describe the overall carbon and energy profile for a given scenario. BREHOMES disaggregates the housing stock into over 1000 categories, defined by built form, construction age, tenure and the central heating ownership. However, it uses a single composite dwelling to predict future trends in the overall stock, resulting in simplified calculations at the cost of the full diversity [39]. CDEM aggregates annual energy consumption of only 47 house archetypes, derived from unique combinations of built form type and dwelling age. At the other end of the scale, the Johnston model has been constructed around only two 'notional' dwelling types (pre- and post-1996).

One of the main criticisms of models that function at relatively low disaggregation levels is that the model provides only broad or indicative results for relative differences when comparing efficiency measures [48]. Johnston, for instance, acknowledges that the two 'notional' dwelling types approach makes it difficult "*to explore*

Table 3
Summary of BREHOMES, Johnston's, UKDCM, DECarb and CDEM models.

Models	Name of model and summary
BREHOMES	- Earliest UK residential energy model - Physically based bottom-up model of the energy use of the UK housing stock - Incorporates over 1000 dwelling categories to define historical housing stock - Uses weighted average stock transformation method - Uses 1993 as base year - Utilize BREDEM (building research establishment domestic energy model) to calculate energy use for dwelling - BREDEM requires data on the area of the different dwelling elements, their thermal characteristics, characteristics of heating system, internal temperatures and external temperatures, heating patterns, number of occupants, and solar gains - Ten heating patterns are defined - The energy use for lights and appliances are at an aggregated level - Includes marginal or incremental or full cost of energy conservation measures - Two scenarios have been developed, namely: reference and efficiency scenario
Johnston	- Physically based bottom-up model of the energy use of the UK housing stock - Data module has adopted a selectively disaggregated approach - Constructed around two components: a data module and a BREDEM based energy and CO_2 emission model - Uses weighted average stock transformation method - Uses 1996 as the base year - Incorporates two "notional" dwelling types (pre-and post-1996) - Three scenarios have been developed namely business-as-usual, demand side and integrated - Calculates annual energy consumption and CO_2 emissions
UKDCM	- Physically based bottom-up model of the energy use of the UK housing stock - Uses a highly disaggregated housing stock approach - Comprises over 20,000 dwelling types by 2050 - Uses weighted average stock transformation method - Uses 1996 as base year - Dwellings are classified by age, dwelling type, construction type, number of floors and floor area - 40% scenario - Calculates monthly demand for space heating using BREDEM heat flux approach
DECarb	- Physically based bottom-up model of the energy use of the UK housing stock - Uses a highly disaggregated housing stock approach - Comprises 8064 unique combinations for each of 6 historical age classes - Uses an iterative stock transformation method - Uses 1996 as base year - Data set consists of 6 files (1 file for each of 6 age classes), while these data are composed of 7 variables (dwelling type, insulation characteristics, etc) - Energy consumption is based on modified version of BREDEM model - Calculates annual energy consumption and CO_2 emissions
CDEM	- Physically based bottom-up model of the energy use of the UK housing stock - Uses a highly disaggregated housing stock approach - Comprises 47 house archetypes, derived from unique combinations of built form type and dwelling age - Uses weighted average stock transformation method - Estimates the energy demand of the 2001 English housing stock based on 1971–2000 average climate data - Assigns uncertainty sensitivity coefficients to input parameters - Energy consumption is based on the BREDEM model - Calculates annual energy consumption and CO_2 emissions

what reductions in energy consumption and CO_2 emission could be achieved if different age classes of the UK housing stock were selectively upgraded or demolished" [17]. On the other hand, models that disaggregate the stock to a high degree risk not having sufficient supporting data for each category. For instance, surveys may identify that central heating has a certain impact on average internal temperature and this may need to be assumed to occur across all dwelling categories without direct empirical evidence that this is the case. Secondly, the disaggregation provides the opportunity to adjust numerous variables so as to fit national statistics better over time, for instance in the uptake of condensing gas boilers across the stock. Whilst each adjustment may appear justified, having so many degrees of freedom in the model with relatively limited records of national energy consumption, without strong supporting data they risk loosing validity for the predictive power of the model.

Furthermore, all the models apart from DECarb use a weighted average stock transformation method, that takes into account the proportional relevance of each component, rather than treating each component equally. For example, "*if the scenario specified the distribution of solid walls and cavity walls as 40% and 60% with 10% and 30% of total walls being insulated, respectively, then solid wall (insulated) is determined as: 40% × 10% = 4% of dwellings. Similarly cavity wall (insulated) as: 60% × 30% = 18% of dwellings*" [39]. For the DECarb model [50], Natarajan and Levermore developed a two-step iterative stock transformation method as an alternative to deal with this limitation.

4.2. Input data assumptions and uncertainty analysis

All the models require assumptions to construct the models, both in the absence of direct data and in the application of input values where some supporting data are available. As was the case for the international models, diverse sources are relied upon for information to describe the building stock and its rate of change. Nevertheless, of the five UK models only CDEM was investigated in terms of the relative influence of the uncertainties on the results associated with the input variables [8]. Frith et al. carried out an extensive local sensitivity analysis and assigned sensitivity coefficients to the primary input parameters of the model. They found that the various input parameters have widely varying effects on the prediction outputs. The characteristics and usage patterns of heating systems (such as the thermostat temperature and hours of heating use) and the heat losses of the dwellings were pinpointed as highly determining factors of domestic space heating demand. For instance, a sensitivity coefficient of 1.55 was assigned to the input parameter for heating demand temperature, which means that an increase of 10% in this value leads to 15.5% increase in the estimated CO_2 emissions. The authors also demonstrated that the effects on CO_2 emissions of the assigned sensitivity coefficients may be added linearly to calculate reliable estimates of the cumulative effect of a series of uncertainties. From this, they highlight the potential for constructing simpler domestic energy models functioning only with a set of limited input parameters and associated sensitivity coefficients.

4.3. Applications

One of the difficulties in comparing the various UK models is due to the range of baselines used for estimating energy consumption, both in terms of the year and the external conditions. Thus far CDEM has not been used to test scenarios, but to estimate the energy demand of the 2001 English housing stock under 1971–2000 average climate conditions. The Johnston model, UKDCM, and DECarb have 1996 as their base year and projected scenarios to

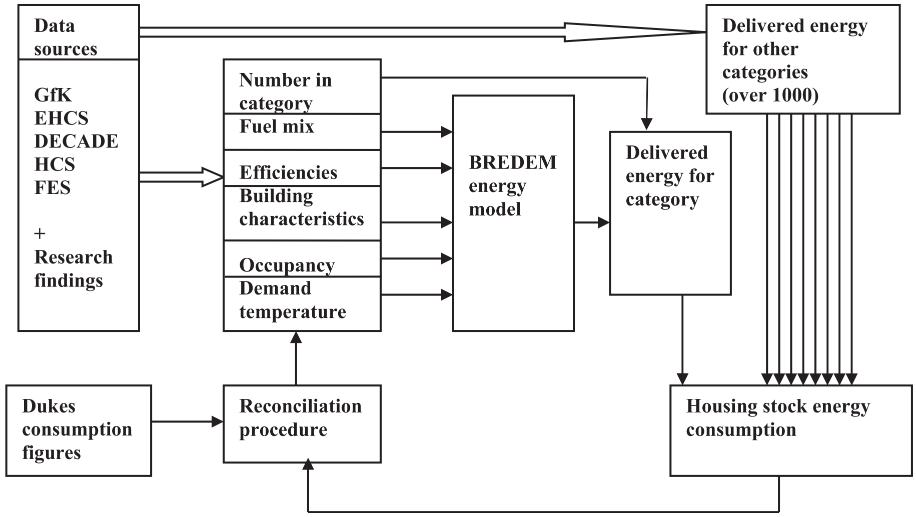

Fig. 2. Structure and form of BREHOMES model (adapted from [20]).

2050. An earlier version of BREHOMES made technical projections from the base year 1990 up to the year 2020 [20,45], whereas a more recent version [46] used 1993 as its base year to make projections to the year 2050.

Different future scenarios have been constructed within these studies. Two illustrative scenarios were tested in BREHOMES, namely: '*Reference*' scenario (business-as-usual based on current population and consumption trends) and '*Efficiency*' scenario (the same, but the uptake of efficiency measures, such as loft insulation, is increased). As BREHOMES is the only model that gives an account of energy saving and costs from conservation measures, this aspect of the various scenarios cannot be compared across models. Also the result of this is component of the analysis is limited as it does not include any related impact of change to energy price in its calculation.

In addition to a '*Business-as-Usual*' scenario (a continuation of the current trends in fabric, end-use efficiency and carbon intensity trends for electricity generation), the Johnston model has been used to investigate two low carbon scenarios: the '*Demand Side*' and the '*Integrated*' scenario. The '*Demand Side*' represents what could happen if the current rate of uptake of fabric and end-use efficiency measures is increased. The '*Integrated*' scenario is similar, but is the only scenario also to examine the implications of additional measures on the energy supply side. The supply side model is based around two fuels, natural gas and electricity, and is defined via the carbon intensity of these fuels. A wide range of technological measures capable of reducing the carbon intensity of electricity are introduced and classified into three related groups: (1) technologies that are capable of increasing the efficiency of energy conversion, (2) technologies that either have very low or zero net CO_2 emissions, and (3) technologies that are capable of capturing and storing the CO_2 emissions associated with the combustion of fossil fuels. Therefore, the main difference from the '*Demand Side*' is the lower carbon intensity of electricity specified in the '*Integrated*' scenario.

The 40% House scenario tested in UKDCM (where domestic sector emissions are targeted as being 60% lower by 2050) presents energy efficiency measures and a shift towards low and zero carbon technologies that are retrofitted or integrated to the building or community. These include: heat-only technologies (heat pumps, solar hot water, biomass and geothermal), heat and electricity technologies (gas fired CHP, gas fired micro-CHP-Stirling engine, gas fired micro-CHP-fuel cells, energy from waste or biomass, CHP biomass in community heating, biomass in micro-CHP), and electricity only technologies (photovoltaic and wind).

Rather than adding further scenarios, the DECarb model has examined the scenarios developed by BREHOMES, Johnston, and UKDCM. The findings suggest that neither of the two low carbon scenarios tested with the Johnston model would reach the target of 50% reduction in carbon emissions by 2050 [48]. Whereas results from the DECarb model agree with the UKDCM's 40% scenario of generating the targeted 60% CO_2 emission reduction by 2050. However, DECarb also revealed that delays in implementation of any carbon saving measures greatly affect the 40% scenario, due to the longer transformation of housing stock through retrofitting and demolition. This leads Natarajan and Levermore to conclude that if the 40% House scenario were to be accepted major changes to the existing housing stock would need to take place soon [48].

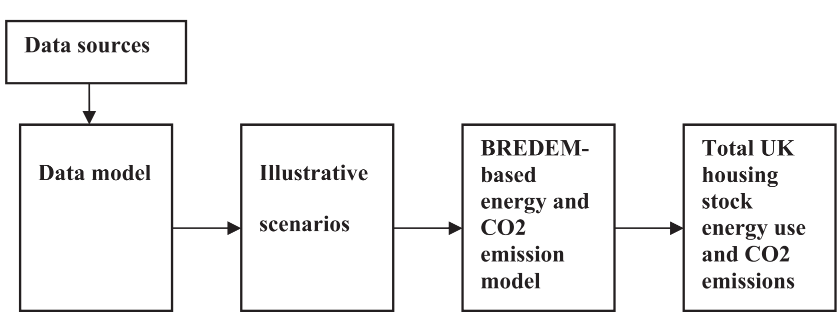

Fig. 3. Structure and form of Johnston's model (adapted from [17]).

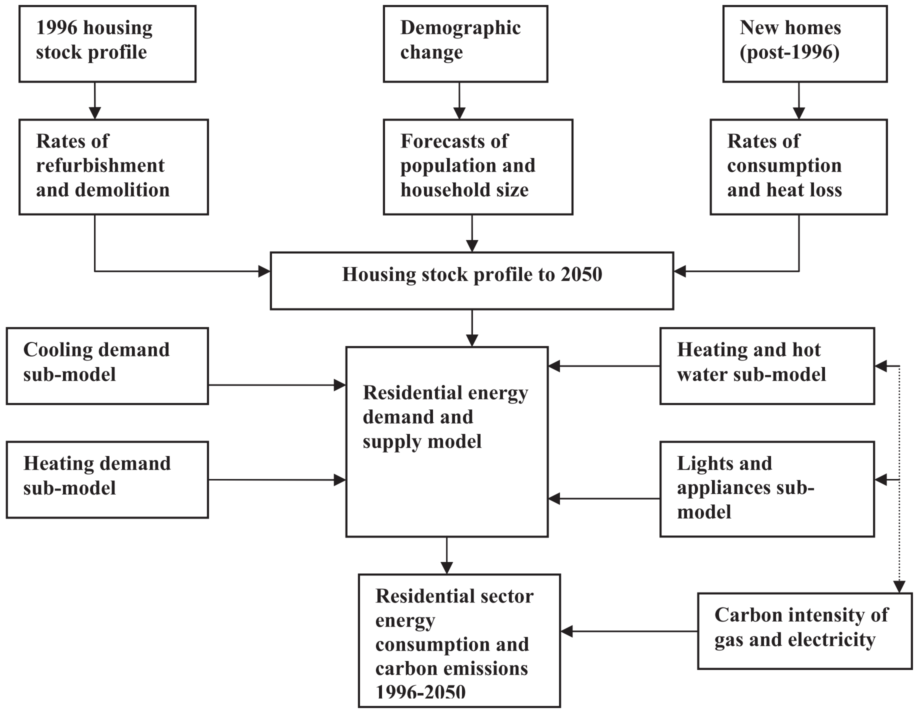

Fig. 4. Structure and form of UKDCM model (adapted from [38]).

4.4. Transparency

The transparency of both data sources and model structures has been recognised by most authors as a crucial issue for the future deployment of the models as policy-making tools. Unfortunately, access to either the raw input data or the model algorithms is currently limited for the majority of the models. As a result, their outputs cannot be accurately replicated. This problem has been acknowledged by Natarajan and Levermore [48] who essentially developed DECarb as a platform which would enable the inter-model comparison of future scenarios already tested in BREHOMES, Johnston's model and UKDCM. The disparity in the results they produced and the uncertainty regarding how these differences arise reflect this lack of transparency.

In terms of access to the input data sources of the models examined, the majority of them derive building fabric data from the publicly available English House Condition Survey database (EHCS) [51,52] and, in some cases, housing surveys for other countries in the UK (Wales, Scotland and Northern Ireland). BREHOMES also makes use of a Market Research survey (GfK), which is not accessible due to commercial issues. Other input sources used by the models include publicly available data from the Family Expenditure Survey, Office for National Statistics (ONS) Neighbourhood Statistics, and the Market Transformation Programme.

In almost all cases and for whatever reasons, no access is available to the core calculation algorithms of almost all the models, including the modified BREDEM-type modules. However, there are recent improvements to transparency in this area. UKDCM2 has been made available to download online, together with spreadsheets including the assumptions made in the scenarios tested [53]. Developers of both DECarb and CDEM have also attempted to increase the transparency of their models: DECarb has an object-oriented open framework which could potentially allow modifications by other users whereas CDEM's open structure will allow the input of ongoing data from other researchers.

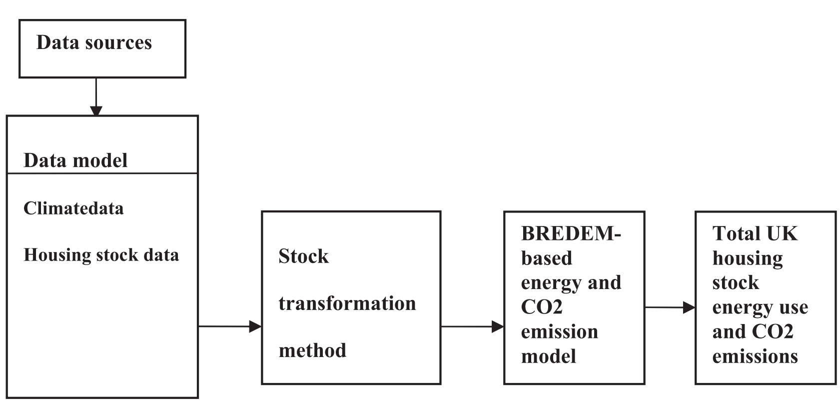

Fig. 5. Structure and form of DECarb model.

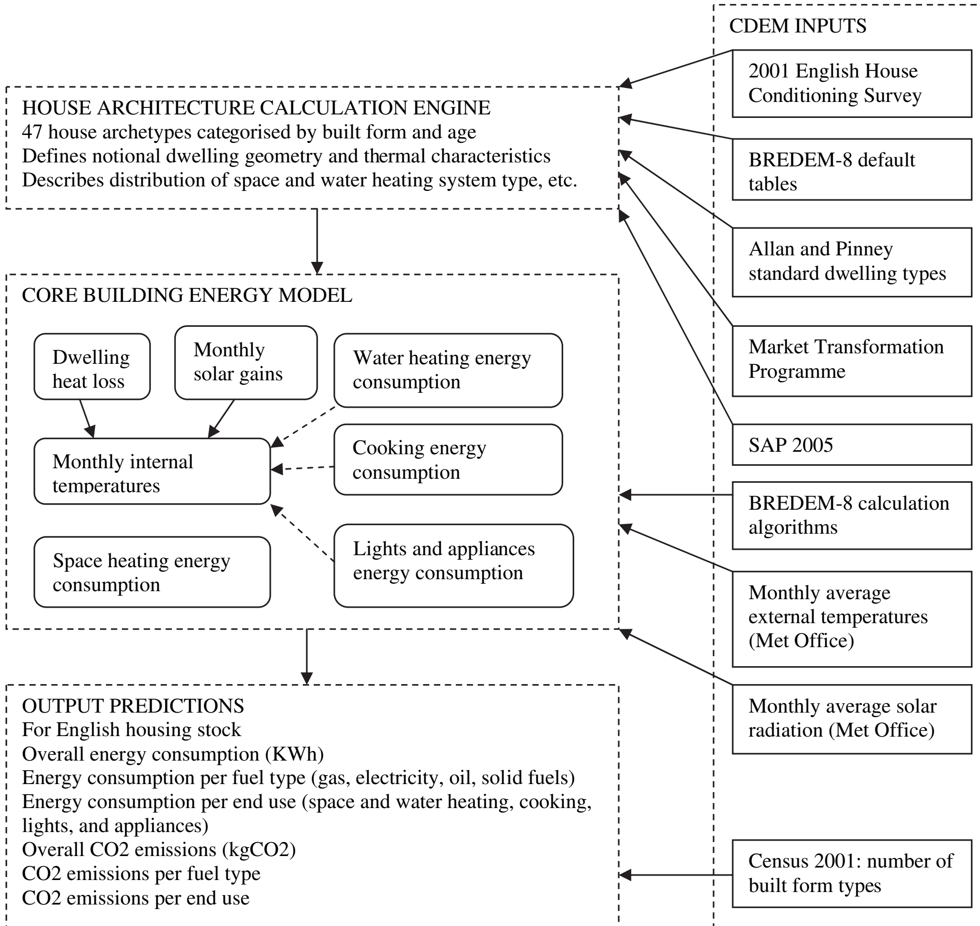

Fig. 6. Structure and form of the CDEM model (adapted from [8]).

5. Coupled energy–health dynamic models

In spite of the issues raised, the increasing needs of policy-makers in wide ranging areas beyond energy and carbon emissions and rapid technological progress, point to a future of continuing development of more sophisticated building stock models, especially those that incorporate multidisciplinary aspects in their analysis. The Energy and Environmental Prediction (EEP) tool is a recent exemplar of this integrated approach that incorporates building energy use, traffic flow, and health parameters [54]. In this section, we describe a recent extension of the EEP approach for assessing health impacts with development under the LUCID project of a model that includes dynamic responses to climatic conditions so as to construct a heat vulnerability index for London [55].

The EEP model has previously been applied in a number of cities in the UK and Australia, but it could be easily transferred to other urban areas. Its main aim is to explore the interactive processes between built form, transport, industry, their associated energy demand, and the health burden they potentially inflict on urban dwellers. The model makes use of Geographical Information Systems (GIS). Data are processed at the individual building level and are subsequently aggregated at an intermediate geographic level, i.e. unit postcode level. These data, in conjunction with additional health-related surveys, are subsequently fed into the public health sub-model, which investigates the impact of indoor environmental conditions, interior house layout and neighbourhood quality on cardio-vascular disease, mental health, and home injuries of the resident population.

Importantly, however, cross-disciplinary building stock models need to take a dynamic, rather than steady-state approach, in order to allow for the assessment of the sustainability of existing and new urban developments. Building stocks, as well as their associated heating/cooling needs and impacts on human health, are climate-sensitive systems. The majority of urban areas worldwide face an increasing risk of overheating due to the combined effect of global warming-induced climate change and the intensification of the Urban Heat Island (UHI) [56]. The severe 2003 heat wave in Europe is an example of an extreme weather event that posed a significant risk to the health and comfort of urban populations and caused deaths and economic losses. According to current projections, it is likely that similar extreme weather events will take place every two or three years by the 2050s in Europe [57,58]. This means that the heating and cooling requirements of buildings will need to be reviewed as overheating is set to become a crucial design issue in the future.

A considerable amount of literature has been published on the impact of excess outdoor temperature on heat-related mortality, as well as the potential modifiers of this relationship e.g. age, health and socioeconomic status of the population [59,60]. A number of UK studies indicated that excess heat-related mortality during the heat wave increased in London and other urban areas [61], among those aged 75 and over and among those suffering from severe and chronic illnesses [62]. Increased air temperatures are also associated with poor air quality and high levels of ozone and other pollutant concentrations e.g. PM_{10}, which are subsequently linked to respiratory and cardio-vascular mortality [63]. Contrary to other climate change-induced risks (e.g. floods), heat waves cannot be prevented and have no tightly defined physical boundaries [58,63]. The extent of the climate change impacts, and whether their net effects will be harmful or beneficial varies greatly by region, urban built form texture, and socioeconomic structure of a given area. For instance, in temperate climates the increased cooling requirements and summertime health morbidity might, or might not, be offset by reduced heating season loads and lower cold-related mortality rates [64,65]. Therefore, in the context of a changing climate, disaggregated physically based stock models will be necessary in order to assess whether the existing and new urban fabrics are resilient to climate change impacts. This could be achieved by the development of coupled energy–health bottom-up building stock models as part of the risk identification process.

A 'heat vulnerability index', which determines the combination of factors that render urban populations and communities more at risk of heat stress, is currently under development [66], within the framework of the LUCID project [55]. It is a sub-model of a GIS-based integrated model that aims to explore the impact of urban built form and the heat island phenomenon on domestic energy consumption and heat-related mortality. This profiling tool is showcased for the Greater London Area and will be used to rank London areas according to both their domestic energy use and heat-related health risk within a reduced level of disaggregation (unit areas of approximately 3000 households). The model builds on previous work on GIS data extraction methods from a number of existing building databases [54,67,68]. Similarly to the UK-focused domestic energy models analysed above, it calculates the domestic heat demand of the case study areas through an automated BREDEM calculation procedure at individual dwelling level and then aggregates these data to a given output area. An innovative element of the study, however, is the development of an epidemiological model in conjunction with the energy use model. The principal objective of the health sub-model is to quantify the variations in heat-related mortality within the case study London areas and the extent to which such variation could be attributed to micro-variations in outdoor and indoor environmental characteristics.

The first stage of the study included multi-variable analysis of deaths at unit postcode level during heat wave and non-heat wave days in order to examine the influence on risk of heat-related mortality of local urban built form characteristics, such as built space ratio, urban volumetric density and green coverage ratio. The excess number of deaths was linked to the area characteristics based on unit postcode of residence. The data were normalised for a series of socioeconomic characteristics, such as age, sex and quartile of socioeconomic deprivation. The preliminary results obtained from the epidemiological model indicated that built density and average height may prove to be proxies for heat-related mortality risk, in accordance with studies that suggested that an individual's risk to overheating increases with overexposure to heat i.e. living in urban areas and south facing top floor flats. Further steps of the model development will entail modelling indoor air temperatures and assessing the joint external temperature/pollutant impact on health and energy demand by overlaying air pollution data (NO_2, PM_{10}, $PM_{2.5}$ and ozone predicted concentrations), air temperature data and summertime mortality records across London. The model could potentially be of use to energy and health policymakers in order to identify 'hotspots', i.e. the areas in which energy efficient retrofit measures and heat wave mitigations plans should be prioritised.

6. Discussion

In the previous sections we have examined a range of approached to building stock models, and have focussed on the key features of building physics models, with particular reference to their use in the UK. By disaggregating the building stock into different components of energy usage within dwelling types, physics based bottom-up models provide a framework for a detailed description of energy losses and the effect of technologies, such as the thermal performance of building fabric or the efficiency of heating systems. If the calculation engine (the algorithm described by the software) is constructed in a modular form, such as in BREDEM, it becomes relatively straightforward to examine the effect of altering energy technologies used in the model and for even whole modules to be replaced to capture other effects or new technologies. Thus, given a set of assumptions about operation and installation, these models appear to be a valuable tool to provide a strong indication of where the main potential for technological and performance related saving can be made in specific sectors of the building stock, and that is useful in setting the physical limits of what can be expected from a policy measure. For instance, given internal temperatures and heating patterns remaining unchanged, this could provide an indication of the absolute potential benefit of replacing certain heating systems in specific categories of dwellings.

Another aspect is the way this physics based core can be extended to encompass other aspects of analysis or to include interrelationships between effects, indeed most of the UK models examined here have adapted the BREDEM modules to that effect. For example, if efficiency measures are analysed in terms of their capital costs and the energy saving generated, then economic comparison can be included so that carbon savings may be identified in terms of the optimum-cost mitigation options [15]. With BREHOMES, Shorrock summarised the result of the potential savings analysis and their cost-effectiveness under various assumptions about prices, discount rates, etc., and presented it in terms of the net costs of carbon savings [69]. Also in terms of interrelated effects, these models can include complex relationships between the different end-uses of energy and *changes in ownership and saturation effects* [17]. For instance Shorrock and Dunster [20,45,46] develop scenarios with the use of S-curves to describe the rate of uptake over time of individual energy related measures, such a loft and cavity insulation, double-glazing, central heating and tank insulation, in terms of the total potential available for their installation in the stock.

In many ways the limitations of physics based bottom-up models are a reflection of their ease of use and apparent simplicity. The capability to calculate energy consumption precisely can lead modellers and policymakers to overlook the extent that these models often are reliant on assumptions for input values. For instance, for accurate data on the thermal performance of different types of building fabric requires more than just calculations based on laboratory values for individual components, but their combined in-situ performance that allows for vagaries of construction methods, compliance, and external conditions. Thus it should be expected that the thermal conductivity for damp masonry cavity walls with insulation (that may well not reach corners and results in thermal bridging) will be higher than otherwise expected. Moreover such issues will not be consistent across all parts of the stock, but will apply in vary degrees to specific types and age ranges of dwellings.

The models may also completely neglect important interactions between technologies and occupants. For instance, installing a more efficient heating systems may also lead to an increase in average indoor temperate. In this case BREDEM allows for such an increase with for example the shift from portable heating to gas central heating. But it specifies a temperature for each heating system type, and this is not a function of dwelling type, socioeconomic status, or age demographics of occupants. Nor is it clear to what extent that the adjustment given is based on empirical data. Moreover installing gas central heating system may impact other aspects of energy performance, since in practice the adding piping for water around the building (penetrating the building fabric) can increase infiltration rates.

One example to illustrate the issue further is to consider the role of conservatories in UK dwellings that in the 1980s were intended as passive solar spaces added on to the dwelling [70]. It was subsequently identified that they were not producing the expected energy savings in the building stock. The building physics based approach suggests that policies to mandate double rather than single-glazing in conservatories should solve the issue and improve the energy performance. However subsequent occupant survey evidence indicates that completely the opposite outcome occurs, since the double-glazing renders the spaces more affordable to heat and has resulted in greatly increased usage throughout the winter [71,72]. Occupants report heating these spaces more either directly or by leaving the internal doors open and using central heating. Thus contrary to the original intention of having passive solar spaces as an energy efficiency feature, conservatories in the UK have in effect become integrated as highly glazed parts of the dwelling, with all the associated heat losses and increased energy consumption. Models using a physics based or some other technical approach are simply unable to predict such outcomes without empirical evidence to quantify and incorporate into their algorithms the expected changes in occupant usage behaviour.

Another critical limitation concerns omitting external drivers of household energy consumption from consideration in the model. The most glaring example would be the lack the feedback from the economic context [16]. Generally, these models do not include market interactions [22] and tend to neglect the correlations between energy consumption and macroeconomic activity [17]. Therefore, they are unable to provide a description of either the macroeconomic feedbacks of different energy strategies and policies in terms of economic structure changes, economic growth, productivity and trade that would influence the rate or the macroeconomic decision making by consumers. This has been clearly illustrated since 2005 in the UK, where there has been a significant decline in residential energy consumption that is strongly associated with a marked increase in energy price [18] (and that was market driven rather than directly the result of energy policies, such as a carbon tax). Yet the UK models, such as BREHOMES and others, do not predict any such decline as they do not include any data for price elasticity for different fuels or how this varies across social groups.

Given the range of assumptions and approximations, as well as omissions, at work in these models there is both an explicit and implicit opportunity to tune the predictions to match national energy data. During model development, an understandable process of testing, optimisation, and revision typically occurs, which leads modellers to select and adjust the model inputs and interactions in a way that 'improves' the results. In BREHOMES, one way results are explicitly adjusted is via changes in average internal temperatures in the residential stock from year to year, but other factors such as average heating system efficiency may also change [20]. As was mentioned previously, the combination of highly disaggregated models combined with sparse empirical data to support the assumptions made across and within categories, renders the model with so many degrees of freedom relative to the limited national statistics for energy consumption that it greatly reduces the predictive power of the model. It might have been expected that if the models were highly predictive, then they should have been able to identify the occurrence of major anomalies in consumption (even if not exactly the cause), such as have come to light with conservatories in the UK or more recently that uncapped party walls in some terrace housing (which leads to large heat losses to the roof space) being effectively the same as un-insulated external walls [73].

The most immediate solution to address many of the issues raised here is for models to be supported by an annual publicly funded building and household survey that is representative of the stock and includes energy consumption data (preferably at least on a quarterly basis so that seasonal variation, and hence heating and cooling, can be identified). This would provide the accessible empirical data to help detect the impact of new social and technological trends, for instance the ownership of new appliances such as large flat screen televisions or the increasing use of 'power showers'. It would also identify if specific energy efficiency measures were having an effect on energy consumption and the extent that this varied according to dwelling or household type. In the UK, the new annual English Housing Survey (including the physical survey of 8000 dwellings by trained assessors) [74] has been formed out of English House Condition Survey (that has previously been used in the models) and the Survey of English Housing (that has a far more detailed social survey). This new survey could potentially provide much of the detail to support the further methodological development of residential building stock models. Unfortunately this potential is profoundly limited, as the survey does not currently include the collection of empirical data on household energy use. Given the need for energy policy formulation and evaluation supported by accurate building stock models, this seems a missed opportunity that should be urgently reviewed.

This additional public data should be viewed as part of a much great focus on transparency and accessibility to the underlying workings of the models. Fortunately this area appears to be changing rapidly, with transparency becoming part of publicly funded research projects. Models should also run standard agreed scenarios in addition to specific ones developed by model authors, so the findings can be easily compared. Then the effects of uncertainties in the data should be investigated through sensitivity analysis, as a matter of course, in any presentation of findings. It is only on these much stronger foundations can these model provide the confidence in their findings and fully contribute to the type of policy developments required in the context of rapid emissions reductions.

The other future direction to strength these models will be to broaden their scope and level of interaction with other influences and outcomes. Model development is already moving towards greater sophistication with the integration of complex dynamics of the building stock transformations into the modelling process. Further arguments supporting this approach have been summarised by Kohler and Hassler [75], where they highlight the need to adopt a more interdisciplinary approach that encompasses the study of socioeconomic factors, and life cycle analysis. We have briefly illustrated such an approach with the recent development of a dynamic model for the health consequences of modifications in the urban microclimate. So while the future applications of these models are very promising, it gives all the more reason for modellers to ensure that policymakers and other users of the model are mindful of the assumptions and limitations in the energy algorithms that underlie any findings.

7. Conclusion

Although bottom-up building physics stock models are used to explicitly determine and quantify the impact of different combinations of technological measures on delivered energy use and CO_2 emissions, and therefore represent an important tool for policymakers, there are a number of different limitations associated with the models. The most important shortcoming of all these models is their lack of transparency and quantification of inherent uncertainties. The lack of publicly available detailed data on the models' inputs and outputs, as well as underlying algorithms renders any attempt to reproduce their outcomes problematic. In addition, the relative importance of input parameter variations on the predicted demand outputs needs to be quantified as a matter of course. Currently, models often fail to deal adequately with the interactions that occur with different aspects of energy demand, particularly socio-technical factors. Specifically this reflects our lack of knowledge of how different people consume energy in their homes, how they use domestic technologies, and how they react to changes in the dwelling as a result of energy performance measures. Last but not least, the new generation of bottom-up building stock models should include multidisciplinary and dynamic approaches, so that for instance they can improve the synergy in policy development on energy efficiency, comfort, and health.

References

[1] International Energy Agency (IEA). Energy consumption by sector [Online]. Available: http://www.eia.doe.gov/emeu/aer/pdf/pages/sec2.pdf [accessed 21.12.09].

[2] EPBD Directive 2002/91/EC. Directive of the European parliament and of the council on the energy performance of buildings. The European Community Official Journal 2003;L001:0065–71.

[3] Department of Energy and Climate Change. Climate change act 2009 impact assessment; March 2009.

[4] Committee on Climate Change (CCC). Building a low-carbon economy – the UK's contribution to tackling climate change. London: The Stationery Office; 2008.

[5] Lowe R. Technical options and strategies for decarbonizing UK housing. Building Research & Information 2007;35(4):412–25.

[6] Lowe R. Policy and strategy challenges for climate change and building stocks. Building Research & Information 2009;37(2):206–12.

[7] da Costa RC. Do model structures affect findings? Two energy consumption and CO_2 emission scenarios for Brazil in 2010. Energy Policy 2001;29(10):777–85.

[8] Firth SK, Lomas KJ, Wright AJ. Targeting household energy-efficiency measures using sensitivity analysis. Building Research & Information 2010;38(1):25.

[9] Tuladhar SD, Yuan M, Bernstein P, Montgomery WD, Smith A. A top-down bottom-up modeling approach to climate change policy analysis. Energy Economics 2009;31:S223–34.

[10] Böhringer C, Rutherford TF. Combining bottom-up and top-down. Energy Economics 2008;30:574–96.

[11] Böhringer C, Rutherford TF. Integrated assessment of energy policies: decomposing top-down and bottom-up. Journal of Economic Dynamics and Control 2009;33:1648–61.

[12] Strachan N, Kannan R. Hybrid modelling of long-term carbon reduction scenarios for the UK. Energy Economics 2008;30:2947–63.

[13] Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: a review of modeling techniques. Renewable and Sustainable Energy Reviews 2009;13:1819–35.

[14] Böhringer C, Rutherford TF, Arbor A. Combining bottom-up and top-down; revised March 2007.

[15] IEA. Mapping the energy future: energy modelling and climate change policy. In: Energy and environment policy analysis series. Paris, France: International Energy Agency/Organisation for Economic Co-operation and Development; 1998.

[16] MIT. Energy technology availability: review of longer term scenarios for development and deployment of climate-friendly technologies. Cambridge, Massachusetts, USA: Massachusetts Institute of Technology Energy Laboratory; 1997.

[17] Johnston D. A physically based energy and carbon dioxide emission model of the UK housing stock. Ph.D. thesis. Leeds Metropolitan University, UK; 2003.

[18] Summerfield AJ, Lowe RJ, Oreszczyn T. Two models for benchmarking UK domestic delivered energy. Building Research & Information 2010;38:12–24.

[19] Rivers N, Jaccard M. Combining top-down and bottom-up approaches to energy–economy modeling using discrete choice methods. The Energy Journal 2005;26(11):83–106.

[20] Shorrock LD, Dunster JE. The physically-based model BREHOMES and its use in deriving scenarios for the energy use and carbon dioxide emissions of the UK housing stock. Energy Policy 1997;25(12):1027–37.

[21] Aydinalp-Koksal M, Ugursal VI. Comparison of neural network, conditional demand analysis, and engineering approaches for modeling end-use energy consumption in the residential sector. Applied Energy 2008;85(4):271–96.

[22] Wilson D, Swisher J. Exploring the gap: top-down versus bottom-up analyses of the cost of mitigating global warming. Energy Policy; 1993:249–63.

[23] Dickson CM, Dunster JE, Lafferty SZ, Shorrock LD. BREDEM: testing monthly and seasonal versions against measurements and against detailed simulation models. Building Services Engineering Research and Technology 1996;17(3):135–40.

[24] Anderson BR, Chapman PF, Cutland NG, Dickson CM, Henderson G, Henderson JH, et al. BREDEM-12-model description: 2001 Update. Watford, UK: BRE; 2002.

[25] Shorrock LD, MacMillan S, Clark J, Moore G. BREDEM 8, a monthly calculation method for energy use in dwellings: testing and development. In: Proceedings of the building environmental performance '91, London, 10th–11th April; 1991.

[26] Anderson BR, Chapman PF, Cutland NG, Dickson CM, Doran SM, Henderson G, et al. BREDEM-8-model description: 2001 Update. Watford, UK: BRE; 2002.

[27] BRE. The UK government's standard assessment procedure. Available: http://projects.bre.co.uk/sap2005; 2005 [accessed 19.12.09].

[28] Fung AS. Modeling of national and regional residential energy consumption and associated greenhouse gas emissions. Ph.D. thesis. Dalhousie University; 2003.

[29] Fels M. PRISM: an introduction. Energy and Buildings 1986;9(1–2):5–18.

[30] Swan L, Ugursal VI, Beausoleil-Morrison I. Implementation of a Canadian residential energy end-use model for assessing new technology impact. In: Proceedings of the eleventh international IBPSA conference, Glasgow, 27th–30th July; 2009.

[31] Mohmed A, Ugursal VI, Beausoleil-Morrison I. A new methodology to predict the GHG emission reductions due to electricity savings in the residential sector. In: Proceedings of the third Canadian solar buildings conference, Fredericton, 20th–22nd August; 2008.

[32] Aydinalp M, Ugursal VI, Fung AS. Modeling of the appliance, lighting, and space cooling energy consumption in the residential sector using neural networks. Applied Energy 2002;71(2):87–110.

[33] Aydinalp M, Ugursal VI, Fung AS. Modeling of the space and domestic hot water energy consumption in the residential sector using neural networks. Applied Energy 2004;79(2):159–78.

[34] Farahbakhsh H, Ugursal VI, Fung AS. A residential end-use energy consumption model for Canada. International Journal of Energy Research 1998;22(13):1133–43.

[35] Snakin JPA. An engineering model for heating energy and emission assessment: the case of North Karelia, Finland. Applied Energy 2000;67:353–81.

[36] Huang YJ, Brodrick J. A bottom-up engineering estimate of the aggregate heating and cooling loads of the entire building stock. In: Proceedings of the 2000 ACEEE summer study on energy efficiency in buildings, Pacific Grove, 20th–25th August; 2000.

[37] Hens H, Verbeeck G, Verdonck B. Impact of energy efficiency measures on the CO_2 emissions in the residential sector, a large scale analysis. Energy and Buildings 2001;33:275–81.

[38] Boardman B, Darby S, Killip G, Hinnells M, Jardine C, Palmer S, Sinden G, et al. 40% house. Oxford: ECI, University of Oxford; 2005.

[39] Natarajan S, Levermore GJ. Predicting future UK housing stock and carbon emissions. Energy Policy 2007;35(1):5719–27.

[40] CHBA/NRCan. R-2000 home program technical requirement. Ottawa: Canadian Home Builders Association (CHBA) and Natural Resources Canada (NRCan); 1994.

[41] NRC. The national energy code for housing. Draft 6.1, Canadian commission on building and fire codes. Ottawa: National Research Council; 1996.

[42] Canadian Residential Energy End-use Data and Analysis Centre (CREEDAC). Development of Canadian residential energy end-use and emission model; September 2000.

[43] The Residential Energy Consumption Survey (RECS). Energy information administration official energy statistics from the US government; 2001.

[44] Fawcett T, Lane K, Boardman B. Lower carbon futures, for European households. Energy and environment programme. UK: Environmental Change Institute, University of Oxford; 2000.

[45] Shorrock LD, Dunster JE. Energy use and carbon dioxide emissions for UK housing: two possible scenarios. In: Building research establishment, information paper 7/97. Watford, UK: BRE; 1997.

[46] Shorrock LD, Henderson J, Utley JI. Reducing carbon emissions from the UK housing stock. Watford, UK: Building Research Establishment, BRE; 2005. p. 80.

[47] Johnston D, Lowe R, Bell M. An exploration of the technical feasibility of achieving CO_2 emission reductions in excess of 60% within the UK housing stock by the year 2050. Energy Policy 2005;33:1643–59.

[48] Natarajan S, Levermore GJ. Domestic futures – which way to a low-carbon housing stock? Energy Policy 2007;35(11):5728–36.

[49] Environmental Change Unit (ECI). DECADE: Domestic Equipment and Carbon Dioxide Emissions, second year report 1995. Energy and environment programme. University of Oxford, UK. Environmental Change Unit. Decision No 1230/2003 of the European Parliament and of the Council of 26 June 2003 adopting a multiannual programme for action in the field of energy "Intelligent Energy – Europe" (2003–2006), OJ L 176, of 15.7.2003, p. 29.

[50] Natarajan S. Modelling energy use and carbon emissions from the UK domestic sector. Manchester: School of Mechanical Aerospace and Civil Engineering, University of Manchester; 2006. p. 287.

[51] Department for Communities and Local Government (DCLG). The English house condition survey 1996. Headline report. London: DCLG Publications; 1996.

[52] Department for Communities and Local Government (DCLG). The English house condition survey 2001. Headline report. London: DCLG Publications; 2001.
[53] Environmental Change Unit (ECI). UKDCM2 model. Environmental Change Unit (ECI). Oxford: University of Oxford. Available: http://www.eci.ox.ac.uk/research/energy/bmtmodelling.php; 2009 [accessed 19.12.09].
[54] Jones P, Patterson J, Lannon S. Modelling the built environment at an urban scale – energy and health impacts in relation to housing. Landscape and Urban Planning 2007;83:39–49.
[55] LUCID. The development of a local urban climate model and its application to the intelligent design of cities [Online]. Available: http://www.lucid-project.org.uk [accessed 19.12.09].
[56] Mayor of London. London's Urban Heat Island, a summary for policy makers. London: Greater London Authority; 2006.
[57] Beniston M, Diaz HF. The 2003 heat wave as an example of summers in a greenhouse climate? Observations and climate model simulations for Basel, Switzerland. Global and Planetary Change 2004;44:73–81.
[58] Mayor of London. The London climate change adaptation strategy. Draft report. London: Greater London Authority; 2008.
[59] Hajat S, Armstrong B, Baccini M, Biggeri A, Bisanti L, Russo A, et al. Impact of high temperatures on mortality: is there an added heat wave effect? Epidemiology 2006;17:632–8.
[60] Ishigami A, Hajat S, Kovats RS, Bisanti L, Rognoni M, Russo A, et al. An ecological time-series study of heat-related mortality in three European cities. Environmental Health 2008;28(7):5.
[61] Kovats RS, Johnson H, Griffiths C. Mortality in southern England during the 2003 heat wave by place of death. Health Statistics Quarterly 2006; 29:6–8.
[62] Hajat S, Kovats RS, Lachowycz K. Heat-related and cold-related deaths in England and Wales: who is at risk? Occupational and Environmental Medicine 2007;64:93–100.
[63] National Health Service. Heatwave, plan for England. UK: Crown; 2008.
[64] Kolokotroni M, Giannitsaris I, Watkins R. The effect of the London heat island and building summer cooling demand and night ventilation strategies. Solar Energy 2006;80(4):383–92.
[65] Medina-Ramón M, Schwartz J. Temperature, temperature extremes, and mortality: a study of acclimatisation and effect modification in 50 US cities. Occupational and Environmental Medicine 2007;64:827–33.
[66] Mavrogianni A, Davies M, Chalabi Z, Wilkinson P, Kolokotroni M, Milner J. Space heating demand and heatwave vulnerability: London domestic stock. Building Research & Information 2009;37(5–6):583–97.
[67] Rylatt RM, Gadsden SJ, Lomas KJ. Methods of predicting urban domestic energy demand with reduced datasets. Building Services Engineering Research and Technology 2003;24:93–102.
[68] Gupta R. Investigating the potential for local carbon emission reductions: developing a GIS-based domestic energy. Carbon-counting and carbon-reduction model (DECoRuM). In: Proceedings of solar world congress, USA, Florida, Orlando, 6th–12th August; 2005.
[69] Shorrock L. Potential carbon emission savings from energy efficient housing. BRE Information Paper IP 15/95. Watford, UK: BRE; 1995.
[70] Oreszczyn T. The energy duality of conservatory use. In: Proceedings of the third European conference on architecture: solar energy in architecture and planning, Florence, Italy, 17th–21st May; 1993.
[71] Summerfield AJ, Pathan A, Hong SH, Oreszczyn T. Energy, ventilation, and occupant behaviour. In: Mumovic D, Santamouris M, editors. A handbook of sustainable building design and engineering: an integrated approach to energy, health, and operational performance, buildings, energy and solar technology series. London: Earthscan; 2008.
[72] Pathan A, Summerfield AJ, Oreszczyn T, Lowe RJ, Young A. Trends in conservatory use: a comparison between the 1991 conservatory association survey and the UCL 2004 survey. London: University College London (UCL) for the Energy Saving Trust; 2007.
[73] Lowe R, Wingfield J, Bell M, Bell J. Evidence for heat losses via party wall cavities in masonry construction. Building Services Engineering Research and Technology 2007;28(2):161–81.
[74] English Housing Survey (EHS) [Online]. Available: http://www.communities.gov.uk/housing/housingresearch/housingsurveys/englishhousingsurvey/ [accessed 4.01.10].
[75] Kohler N, Hassler U. The building stock as a research project. Building Research & Information 2002;30(4):226–36.