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A review and critique of UK housing stock energy models, modelling approaches, and data sources

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Abstract

The UK housing stock is responsible for some 27% of national energy demand and associated carbon dioxide emissions. 80% of this energy demand is due to heating (60%) and domestic hot water (20%), the former reflecting the poor average thermal integrity of the envelope of the homes comprising this stock. To support the formulation of policies and strategies to decarbonise the UK housing stock, a large number of increasingly sophisticated Housing Stock Energy Models (HSEMs) have been developed throughout the past 25 years. After describing the sources of data and the spatio-temporal granularity with which these data are available to represent this stock, as well as the physical and social phenomena that are modelled and the range of strategies employed to do so, this paper evaluates the 29 HSEMs that have been developed and deployed in the UK. In this we consider the models' predictive accuracy, predictive sensitivity to design parameters, versatility, computational efficiency, the reproducibility of predictions and software usability as well as the models' transparency (how open they are) and modularity. We also discuss their comprehensiveness. From this evaluation, we conclude that current HSEMs are lacking in transparency and modularity, they are limited in their scope and employ simplistic models that limit their utility; in particular, relating to the modelling of heat flow and in the modelling of household behaviours relating to investment decisions and energy using practices. There is a need for an open-source and modular dynamic housing stock energy modelling platform that addresses current limitations, can be readily updated as new (e.g. housing survey) calibration data is released and be readily extended by the modelling community at large: improving upon the utilisation of scarce developmental resources. This would represent a considerable step forward in the formulation of housing stock decarbonisation policy that is informed by sound evidence.

Keywords: residential buildings, modularity, energy modelling, policy support

1. Introduction

Building stocks are responsible for a significant proportion of the energy demands and Greenhouse Gas (GHG) emissions of most countries [1]. In the UK, the domestic sector is responsible for 27% of national energy demand [2]. A first step towards reducing the energy demand of dwellings is to measure that demand precisely. Measurements of energy demand should deepen our understanding of the relationships between elements of the dynamic system that comprise a dwelling. These measurements can then be analysed to target policies promoting new energy technologies (e.g. smart meters), behaviour change (e.g. reducing standby power), or financial incentives to encourage investments (e.g. energy-related taxes) [3, 4, 5, 6]. Crucially such measurements can also be used to calibrate models with which to evaluate the effectiveness of alternative policies destined to decarbonise the housing stock [7, 8].

It is useful to identify the principal component parts of the energy system, in terms of energy supplied (S) and energy demanded (D), which in turn may be split into energy used (U) and energy lost via transformation (L). Gas is the most common supply of domestic energy (68%), which in the UK became prominent in the 1990s when electricity generation switched from using coal to natural gas. Electricity is also a prominent supply (24%) and is generated by nuclear, wind, and hydro-power plants; other fuels include petroleum, coal, coke and breeze, and with minor share solid fuels such as bio-energy and waste [9]. By contrast, the energy demand of dwellings is shaped by the needs of individual households, which in turn are a function of their socio-demographic characteristics and associated activities. In dwellings, this energy demand is attributable to four key services: 60% to space-heating, 20% to domestic hot water, 17% to lighting and appliances, and 3% to cooking. Satisfying an energy demand generally implies the emission of pollutants to the environment when combustion is involved, but is dependent on the fuel properties and the processes required to deliver that energy to the 27 million dwellings that comprise the UK housing stock. The UK's Climate Change Act aims to reduce national GHG emissions to 80% below 1990 levels by 2050 [10]. Before formulating policies to help meet this ambitious target, a full understanding of a dwelling's energy system is required, which can be scaled up to consider stocks of dwellings.

The development of a Housing Stock Energy Model (HSEM) starts with a basic abstraction that captures the energy flow pathways in a single dwelling. This mainly comprises the heat transfer through the envelope (to or from the external environment or conjoined buildings), via conduction and associated surface convective and radiative transfers and by infiltration and exfiltration, as well as the thermal gains from occupants and appliances. A key example of this abstraction is the Building Research Establishment Domestic Energy Model (BREDEM), which forms the basis of many other UK dwelling energy models. This abstraction for a single dwelling can be replicated for a given housing stock, to capture the variation in dwelling geometry, age, and context. When dwellings share properties they can be allocated to *groups*, *clusters*, or *typologies* that make a dataset more manageable and can be used to study a stock of dwelling through extrapolation [11, 12, 13, 14]. However, this implies that some of the unique properties of each dwelling are replaced by a representative value when they are allocated to a specific group. This loss of information increases uncertainty in the stock model [15] and so tracing it is important.

The first attempts to model energy flows in dwellings were made in the mid-1970s [16, 13], but were constrained by computing power, availability of dwelling information, and the ability to process it [12]. More recently, the adoption of more sophisticated algorithms, facilitated by improved computing power, and the increased availability and resolution of representative data have improved the accuracy and usability of HSEMs [17, 18]. However, as HSEMs have become more sophisticated they require more inputs, which increases the likelihood of data input errors [19]. Therefore, a sound understanding of domestic energy flow pathways and the factors influencing them (both housing and household factors) is essential in formulating policies designed to reduce the energy demand and associated carbon emissions of any housing stock. It is then imperative to identify a parsimonious housing stock energy modelling strategy.

Stock modelling strategies are shaped by two key aspects. The first is the information (or stock data) required to achieve satisfactory levels of predictive accuracy and consistency. Such data might describe the physicality of dwellings (fabric, shape, location), their components and systems (fuel, water, technology), and their occupancy and use (household composition, patterns of presence and behaviour). The second aspect relates to the faithfulness with which the underlying energy model represents reality: the rigour of its modelling of energy flow pathways. The level of disaggregation required to represent a stock, the energy flow pathways within it, and the reliability of any of the adopted assumptions [20, 21] are important factors. It is relatively straightforward to assign individual dwellings to a group, but the energy-modelling of the housing stock is complicated by the fact that most dwellings display heterogeneity, both physically (the housing) and socio-economically (the household behaviour)[1], and so can also be considered unique. Household behaviour is a known area of modelling uncertainty, and may be influenced by collective (peer pressure influencing the penetration of technology), circumstantial (environmental responses or local incentives to acquire devices), biological (occupants' needs according to age and health conditions), or cultural (habits and patterns) factors [23, 24, 25, 26]. Some of these drivers are strongly interrelated. HSEMs should ideally consider the influence of these socio-economic factors on the underlying energy flow pathways being modelled, and be regularly updated as housing and household stock composition changes. This requires an evaluation of the descriptive data sources and the employed modelling strategies so that they can be accessed and used by different developers and stakeholders [27].

The aim of this paper is to review existing HSEMs used to estimate the energy demand of UK housing stocks for a range of scenarios, utilising existing and possible future sources of input data. Section 2 describes the composition of the current UK housing stock and discusses sources of information that are

[1] A household is defined as one or more persons sharing living accommodation and who are not necessarily related by blood or marriage [22]

used by HSEMs to characterise it. Section 3 catalogues the evolution of UK HSEMs and summarises their relative advantages and disadvantages. Finally, Section 4 describes a method for evaluating the functionality of HSEMs and applies it to 29 existing models. This exercise is used to highlight significant anomalies in, and omissions from, HSEMs and to show where research should be focussed to ensure that future HSEMs are simultaneously more rigorous and useful for formulating policies and strategies to decarbonise the UK housing stock. These recommendations are general in character, and as such should be of value to modellers and policy-makers that are concerned with housing stock decarbonisation, whichever their country of focus.

2. The Composition and Evolution of the UK Housing Stock

2.1. Stock Structure

As of 2011[2], the UK housing stock was comprised of 27.4 million dwellings (83.3% England, 5.1% Wales, 8.9% Scotland and 2.7% Northern Ireland). It has homogeneity in its physical features and can be divided into five groups: 28% terraced, 9% bungalow, 26% semi-detached, 17% detached, and 20% apartments [28] (see Figure 1:a). In the last forty years, the number of detached dwellings and apartments increased by 124% and 75%, respectively [28, 29], but this increase does not correlate well with the number of householders. The number of UK households is rising at around 1% per annum [30, 28], but the average household size of 2.2 is gradually falling because of increased family fragmentation and reduced fertility rates (see Figure 1:b). Concurrently, changes in the ownership and use of appliances and systems are causing fluctuations in dwelling energy demand [31, 32, 33], despite improvements in their efficiency[3]. The energy demand of some systems, especially those for heating, is correlated

[2]This document uses 2011 data as a reference because: (1) it is the same year of the last Census; (2) the CHM, a reference HSEM for national documents, also uses 2011; and (3) Super Output Areas, the sample units of many HSEMs, are constructed for this year.

[3]The same phenomenon was pointed out more than a hundred years ago by Jevons [34], although specifically for coal. This has recently been termed the rebound effect [35] and is a relevant phenomenon that affects the energy performance at stock level.

with the associated housing typologies [9, 36]. This is due to façade elements and construction technologies adopted in their period of construction.

Six age bands are traditionally used to characterise the UK housing stock: pre 1919, inter-war, post-war 1950s, industrial 1970s, modern 1980s and post 2000 (see Figure 1:c). More than one-third of the stock date from the first two bands, in which most of the constructions employ solid masonry (see Figure 1:d) and the floor area is significantly larger than the average size of 92 sqm [29]. The housing stock increased by 45% between 1970 and 2011, with a majority of these dwellings built with cavity walls. Changes in construction methods during this period were, in general, intended to reduce the thermal transmittance of the envelope as well as uncontrolled air leakage. The registered age of construction provides thus an indication of the energy performance of the current housing stock, considering that energy conservation standards for dwellings were developed in response to the 1973 oil crisis and were maintained in the 1980s by the Housing Act [37, 38, 29]. In addition, the conformation of typologies within these bands is complemented by changes in the tenure composition. These changes reflect government (in particular monetarist) policies to encourage home ownership and the associated transfer of ownership of local authority housing [39]. By 1970, 47% of properties were owner-occupied; by 2011, this tenure increased to 65% of the stock (see Figure 1:e) [28, 40]. As a result, not only these compositional changes affected services and energy usage, but also indoor conditions, although not always positively [23].

[Figure 1 about here.]

Since 1970, the mean external air temperature has increased by around 1 K whereas the mean indoor air temperature has risen by around 6 K [9] (see Figure 1:f). This significant increase is attributable to improvements in fabric properties, the prevalence of central heating systems, an increase in acceptable comfort temperatures [23], and more onerous regulations relating to the conservation of heat and power. Some of these changes have delivered improved indoor comfort and health co-benefits [41], but have not significantly reduced fuel bills or lowered carbon emissions.

[Figure 2 about here.]

2.1.1. Evolution of Domestic Services

Figures 1:g-h highlight the significant changes in installed space heating systems supplied by gas, and in the Domestic Hot Water (DHW) technologies found in UK dwellings [2, 42]. Incidentally, gas is also the most common source of energy used by UK power stations to generate electricity and for district heating, especially since the 1990s, by the supply shift from coal to natural gas in power stations. This shift helped to reduce carbon emissions significantly (see Figure 1:i). Figure 2 shows that gas is, directly and indirectly, responsible for some 73% of all space heating, 79% of all DHW, 36% of all lighting and appliance energy, and 55% of all cooking energy [2]. Some houses in rural locations use petroleum or oil and Figure 2 shows that they satisfy 8% of total demand for space heating. Together, heating systems (space and water) represent around three-quarters of the energy demand and so are significant. For that reason, highly disaggregated information about these systems should be included in datasets so that they can be modelled accurately by HSEMs.

Since 1970, the ownership of household appliances and its aggregate energy demand has experienced continuous growth, having doubled in size [43, 44, 45, 28]. Meanwhile, significant improvements have been made in appliance energy efficiency over the same period [46, 45]. Increased ownership is partly attributable to population growth, consumer-biased lifestyles and the rebound effect, where improvements in appliance efficiency have created a gap in dwelling energy demand that is filled by the acquisition of more appliances, or their more intense use [23, 47].

Correspondingly, cold appliances (fridges, freezers) are responsible for 4% of overall domestic annual energy demand, wet appliances (washing machines, dishwashers) use 5%, lighting uses 3%, cooking (ovens, stoves, cookers) uses 2%, and brown electronics (TV, audio systems, PCs) use 5%. Cold and wet appliances may be associated with dwelling typologies because of their relationship with household size, and their overall energy demand can be described well by their energy efficiency labels. However, the energy demand for lighting, cooking, brown appliances, and to some extent wet appliances, is more related to users' activities and interactions [30, 11, 12], which is subject to stochasticity. Given that the relative proportion of total energy demand due to these services will increase as the thermal integrity of housing improves, explicit modelling of these services and the socio-demographic factors influencing them would be merited; though this implies that data representing the housing stock be augmented with that representing household characteristics [11, 48].

[Table 1 about here.]

2.2. Sources of Information: Scope and Quantity

In the UK, a national census is conducted every ten years, providing a rich picture of the population by household, giving the number of inhabitants, their education, employment and social affairs, and building information including tenure, size and installed heating system[4]. However, the accuracy of the data may deteriorate over time as household composition and characteristics evolve. To address this, the census is updated annually using information from specific topical surveys and regional data, such as the Annual Population Surveys (APSs) [49]. Census data is also enriched with estimates and direct measures from electricity and gas sales in the domestic sector [40], to increase the resolution of energy-related information. For example, the UK Government's Department for Environment, Food and Rural Affairs (DEFRA)'s Market Transformation Programme (MTP) can model the energy demand of domestic appliances, and make detailed estimations of their usage by calibrating ownership with energy demand [45] although the level of disaggregation is constrained by the available supply subtotals, and cannot describe behaviours affecting the energy use in dwellings.

[4]The collection of national and regional statistics is conducted by Office for National Statistics (ONS), National Records of Scotland (NRS), Statistics for Wales (SW), and Northern Ireland Statistics and Research Agency (NISRA), respectively

Limited attempts have been made to identify environmental attitudes and energy-using behaviours. For example, a highly disaggregated study regarding appliances' energy demand was conducted in the 1990s [50], and was extrapolated and calibrated for an estimation of national energy demand but limited to a small sample in the south of the UK. More recently, DEFRA, the Department of Energy and Climate Change (DECC) and the Energy Saving Trust (EST) commissioned a detailed field study of electricity use by 251 households at a one-minute resolution [46, 32, 51]. DECC published these studies as cross-tabulated data [2], which is a source for the Digest of UK Energy Statistics (DUKES). These data calibrate and reconcile HSEMs [52, 53, 54] for a sample of the national housing stock.

Common approaches used to reconcile a representative and statistically valid sample of the housing stock are sampling and clustering. Sampling involves random or systematic selection of units (e.g., households, dwellings, neighbourhoods) amongst the population, whereas clustering involves the identification of groups that share characteristics. Both methods use weights to then match the population totals. Table 1 identifies the characteristics of the three clustering strategies that are most commonly used to describe the UK population, and to account for dwellings and households: Local Authority (LA), Nomenclature of Territorial Units for Statistics (NUTS) and Super Output Area (SOA).

Firstly, the LA classification are helpful in that they represent administrative areas, and thus express relationship with the government and its structures. An LA may have access to specific datasets (public and private), which enhance the calibration of the stock weights [55, 56]. Secondly, NUTS is a geocode standard used for referencing the subdivisions of countries for statistical purposes and is regulated by the European Union. Its different layers align with UK regions; for example, the former Government Office Regions are equivalent to NUTS-1 [40]. Finally, the SOA is designed to improve the reporting of small area statistics and are made up of groups of output areas and LAs [55]. They are constructed by clustering households by socio-economic status. These clusters have been used to support the development of national housing surveys because they maintain characteristic attributes (demographic, household composition, housing, socio-economic and employment) and so can be considered as representative subsets of the population.

Furthermore, for the analysis of very specific dwelling properties, reference typologies have been deployed with representative attributes associated with them [57, 58, 59]. Reference typologies include the variability among dwellings and can be linked to the stock typologies, even though their attributes result from extrapolation. Nevertheless, they can also be useful for the calibration and reconciliation of HSEMs with the different sources of information. Besides, one advantage of this approach is that the typologies can be scaled, although the procedure for each subset needs to be correspondingly refined [57, 60, 14]. By contrast, representative sampling provides real examples of the housing stock and can be used to study performance under realistic constraints; for instance, they can support cost-effective analyses based on household energy expenditure. An example of this type is the English Housing Survey (EHS).

The EHS [61][5] is a particularly valuable source of data for the purposes of UK housing stock modelling (representing 83.3% of the UK stock). It adopts a clustering method to select a statistically representative sample of more than 14 thousand English dwellings. The data collected includes a household questionnaire and a visual survey of dwellings' physical properties. The EHS samples are calibrated with SOAs. Hence, by using the EHS, it is possible to limit the analysis to a specific group of typologies defined by epoch of construction, dwelling type, location, tenure and floor areas. Many HSEMs have directly used this dataset to develop their studies, such as: Building Research Establishment's Housing Model for Energy Studies (BREHOMES) [62], Johnston's model [57], Domestic Energy and Carbon Model (DeCarb)[63], Cambridge Housing Model (CHM) [54], Domestic Energy and Carbon Model (DECM) [52], Domestic Ventilation Model (DOMVENT) [64], and Lorimer's model [53]. Likewise, the

[5] In April 2008 the EHS was created by merging the English House Condition Survey with the Survey of English Housing `www.gov.uk/government/collections/english-housing-survey`

Living in Wales survey (succeeded by the National Survey for Wales), the Northern Ireland House Condition Survey and the Scottish House Condition Survey, all contain equivalent information describing the dwellings of their respective countries, and apply similar sampling and weighting methods to those of the EHS.

Other surveys and databases used to characterise the housing stock are contained in Table 2. Sources with smaller samples improve the resolution of the collected information. For example, the Energy Follow Up Survey (EFUS) measures indoor temperature and provides additional socio-demographic information. Furthermore, both the National Energy Efficiency Data-framework (NEED) and the Homes Energy Efficiency Database (HEED) analyse and forecast the adoption of retrofit measures across the stock, but reduce their own resolutions. The HEED [65] specifically gives information on retrofitted energy efficiency measures and a wealth of physical dwelling characteristics (property age, property tenure, glazing type, heating system or insulation), but its data is limited to a number of UK regions and so suffers from sampling biases and reductions.

[Table 2 about here.]

2.3. Reductions and Imputations: Common Assumptions in Stock Data

In the context of building performance modelling, it has been argued that as the quantity of required input data increases, so the average quality of this data reduces and the risk of input errors increases[19]. Whilst it may be theoretically possible to acquire data for the 27 million dwellings that comprise the UK housing stock, this is neither viable nor is it necessarily desirable. Conversely, a sampling process may over-simplify the data, if it is not repeated when updates are made. Furthermore, surveyors are constrained by limits on budget, time, or personnel, but computational advances can offset these limitations by increasing the speed of data collection and by improving the number of variables collected.

Sampling is required to form representative datasets of the entire housing stock, with inherent risks of bias and errors needing to be managed. Sampling bias is related to the procedures, criteria, and strategies taken when selecting samples, and is commonly compensated by a weighting process. Buckley et al. [66] describe one such method for weighting nationwide surveys. Sampling errors occur during the process of collecting data and can be random (false occupant responses, survey mistakes, typographic errors) or systematic (instrument error, inaccurate resolution, conversion errors) [67, 18]. When combined with confidentiality issues, these errors may impose limitations on the use of the datasets. Nevertheless, the process of sampling an entire stock is of such a magnitude that some information must be absent (the data has gaps).

The process of reducing gaps in the collected dataset is tackled either by retaining missing values or by applying imputations: assumptions about values used to fill gaps. Imputations can be arbitrary or systematic, but any replacements can introduce errors. However, these replacements can be calibrated using derived census data, manufacturer specifications, and *in-situ* measurements. But their availability needs to be standardised and centralised based for example on CIBSE guidelines [68] or the Standard Assessment Procedure (SAP)—the UK government's method of assessing the energy performance of dwellings [69].

The SOAs that provide a robust basis for sampling socio-economic clusters in the UK cover around 1500 households per cluster, so that some details are missed or are over-simplified. Here, fabric properties can be inferred statistically for a given SOA, but other properties may differ significantly, even though these details are regulated at LA and ward level where homogeneity can be expected. These differences arise due to locale-specific construction practices. Other properties that are extrapolated (and hence simplified) in SOAs are location, orientation, geometry, and household-specific information. Nevertheless, SOAs provide a sound starting point to study homogeneous groups and to link them with more granular and spatially detailed data.

In summary, the impacts of information loss from sampling biases have been widely studied and discussed in the literature [70, 71, 72, 18], but little attention has been given to the magnitude of errors attributable to sampling methods. A high level of inaccuracy may be present in datasets generated from censuses and nationwide surveys. Therefore, it is important to track error propagation through each layer of the data, so that specific criteria can be adopted to maintain a workable source of information. An example of this tracking is achieved via *monitoring indicators* that identify the most influential parameters in the composition of a stock of dwellings [60, 14]. *Monitoring indicators* are used to help validate model outcomes. They may be available directly from survey data, or else are derived directly from this data, but without requiring uncertain assumptions. Parsimony is imperative.

3. The Conformation of Housing Stock Energy Models

Generally, domestic energy demand models can be categorised as *top-down* or *bottom-up*. Top-down approaches follow a deductive method, and start at a macroscopic level by considering measures such as appliance efficiency labels, energy price, or weather conditions. Bottom-up approaches follow an inductive method, considering measures such as internal conditions, building properties, or system usage. Each approach can be further categorised by statistical and physical modelling methods. Statistical methods generally apply regression techniques to describe and predict phenomena, whereas physical methods typically utilise simplified analytical models of physical phenomena [73, 12, 74, 13]. It is common for HSEMs to combine the virtues of these two approaches, by calibrating the predictions of physical models with statistical data that describes a stock; primarily employing bottom-up strategies [8].

[Figure 3 about here.]

In the UK, the first HSEMs were developed in the 1970s in response to the oil crisis [40]. They supported the identification and testing of strategies to reduce building energy demand and the formulation of building regulations to enforce them. Subsequently, many new approaches have developed. Figure 3 displays the temporal evolution of UK HSEMs, and shows the underlying energy-related policies, guidelines, and national programmes that motivated their incremental evolution. Most models predict the energy required by systems and appliances to satisfy occupant demands for comfort and services.

There are three important elements that are common to many HSEMs: 1) descriptions of building geometry and fabric; 2) analysis of the inter-relationships between dwelling components and zones; and 3) representation of occupancy and appliance usage within dwellings. The latter element is particularly complex and is neglected by many models.

3.1. Building Geometry and Fabric

When modelling a single dwelling, it is possible to describe the attributes of the building with a high level of resolution. However, when modelling a stock of dwellings, only the most relevant properties, such as those for geometry and fabric, are used to describe physical attributes, because they are essential for understanding the energy flows in any building. It is also important to understand their composition (arrangement, layout) and their context (environment, climate).

BREDEM (see Section 1) does not require an explicit three-dimensional representation of building geometry. Its energy balance calculation requires that heat gains and losses across each element of the envelope, infiltration, and internal heat gains, are represented as parameters [75]. Thus the envelope is described by a series of elemental areas and properties supplemented by total floor area, A_T, and height, to determine the internal volume. The CHM [76] improves BREDEM's geometric representation of dwellings by including multiple stories and additional spaces, such as attics and basements. Consequently, additional parameters are derived to describe the physical space, such as living area fractions (allowing heating demand to be allocated more specifically) and linear scalar factors (used to calibrate the solar radiation gains).

The physical space is enclosed by surfaces constructed of materials with different properties. These elemental properties include heat transfer coefficients, solar reflectance values, and thicknesses. If they are unspecified then default values can be assigned from guidelines (e.g. [77, 78, 68]). In BREDEM, the wall thickness is not a direct input, but it is indirectly included in a general thermal mass parameter, which is used to account for thermal storage of solar gains and gains from intermittently used heating systems. The CHM derives wall thicknesses and material properties from the age of construction and thus provides more detailed building fabric properties than BREDEM.

The resulting heat transfer is a direct function of the (unintentional) infiltration and (intentional) ventilation rates, which are represented by a number of different approaches. BREDEM uses a simple air exchange rate associated with both infiltration and ventilation that is a function of the average regional wind speed. The algorithm for ventilation is improved by the CHM, which includes the number of sheltered sides and a draught factor. More recently, the DOMVENT improved the prediction of infiltration in dwellings by generating façades and including detailed parameters that account for local surroundings [79]. This can in principle be used by HSEMs.

The context of a stock of dwellings defines the general composition of each of the buildings, and the external conditions that interact with them. The Domestic Energy, Carbon Counting and Carbon Reduction model (DECoRuM) correlates the shape of a stock of dwellings with their energy demand. It uses a Geographical Information System (GIS) to estimate energy demand as a function of dwelling size and location and estimates the risk of overheating. However, its ability to model the energy demand of dwellings is constrained by limited data and simplistic algorithms [80]. Similarly, the Domestic Dwelling Model (DDM) model [81] links aerial imagery with census data. Both models improve the efficiency with which energy-related measures may be assessed and, by using GIS, can link detailed regional information about dwelling fabric and its context. Steadman's model also includes a built form parameter to explore general retrofits, but this is limited to Middle-SOAs and a very limited stock size [82, 65, 83].

Although dwelling geometry and orientation are both essential for an initial estimate of solar gains, the latter is only considered by BREDEM when estimating the energy contribution of photovoltaic cells, as a correction factor for incident solar irradiation. In contrast, the CHM explicitly considers gains through two theoretical windows to represents daylight-responsive artificial lighting use. Solar loads through walls are not represented by the BREDEM algorithm because of its simplified representation of dwelling geometry and of heat flow.

3.2. System Components and Inter-Relationships

Section 3.1 described the conceptual approximations of energy flows used by HSEMs as a function of dwelling geometry and fabric properties. We now describe the abstract representation of dwelling gains and losses to explore in more detail the performance of a single building that can be extrapolated to a housing stock.

3.2.1. Abstraction of Energy Flow Pathways

A classic representation of dwelling energy flow pathways includes the sum of external heat gains $Q_{ext}[W]$ (net solar radiation gains and transmitted heat from the surroundings) and internal heat gains $Q_{int}[W]$ (occupants, appliances and systems), balanced with the energy lost to the environment $Q_{out}[W]$.

$$Q_{ext} + Q_{int} = Q_{out} \tag{1}$$

External gains are mostly caused by radiation (direct solar gains Q_{sg} and long-wave radiation Q_{lwg}). Other external gains gains are attributable to adjacent connected buildings Q_{bg} as transmitted heat from the local environment Q_{xg}.

$$Q_{ext} = (Q_{sg} + Q_{lwg}) + Q_{bg} + Q_{xg} \tag{2}$$

Internal gains comprise the indirect effects of lighting Q_{lg}, appliances Q_{ag}, cooking Q_{cg}, occupants Q_{og} and, more substantially, the direct effects of heating systems Q_{hg}.

$$Q_{int} = Q_{lg} + Q_{ag} + Q_{cg} + Q_{og} + Q_{hg} \tag{3}$$

The right side of Figure 2 disaggregates end-use energy demand and in so doing identifies the relative contributions of internal gains to Q_{int}.

The losses, Q_{out}, can be directly transmitted through the fabric, Q_{fl}, lost to the environment via purpose-provided ventilation, Q_{vl}, and infiltration, Q_{il}, or stored by thermal mass, Q_{tm}. In addition, the fabric losses Q_{fl} occur via transmission through those parts of the envelope in contact with the outside air, Q_{ftl}, thermal bridges, Q_{tbl}, and floors in contact with the ground, Q_{gl}.

$$Q_{out} = Q_{fl} + (Q_{vl} + Q_{il}) + Q_{tm} \tag{4}$$

$$Q_{fl} = Q_{ftl} + Q_{tbl} + Q_{gl} \tag{5}$$

This energy balance is specified by [84] and by BREDEM [77], and is simplified or further elaborated depending on the desired accuracy of a model and the availability of calibration data. Therefore, algorithms vary in each HSEM according to the complexity of the chosen energy flow pathways. A number of notable anomalies and omissions are discussed in Section 4.1.1.

3.2.2. Abstraction of Energy Inputs

External gains (Equation 2) are commonly calculated in HSEMs using monthly factors as well as adjustments to represent transmitted gains from solar and long-wave radiation. These typological and contextual properties also relate to the heating systems and, in some cases, households activities (use of appliances, utilisation of spaces in houses that are frugally heated). The consideration of the external environment (Q_{bg} and Q_{xg} in Equation 2) and its influence on dwelling energy demand is limited in most HSEMs; for example, BREDEM only considers an over-shading factor. The Local Area Resource Analysis (LARA) model includes regional information at SOA resolution but focusses on the estimations of fuel use and associated GHG [85]. Furthermore, the Energy and Environment Predictions (EEP) model uses local neighbourhood and home hazard information from the EHS to estimate negative health consequences of poor indoor air quality, such as respiratory diseases [86]. Yet the extent to which it applies Equation 2 is poorly defined.

The main contributor to Q_{int} (Equation 3) is the heating system (Q_{hg}). Its output is usually estimated as a function of the local climatic conditions and the number of heating degree days using a base temperature (also known as a balance-point temperature). This estimate is then scaled by the variation of the external air temperature over a year. Modern heating systems can improve their performance by adding semi-automatic controls, but their operation is typically seasonal. The CHM includes the SAP catalogue and increases the number of heating systems and their properties to provide a more detailed estimate of the direct heat gains from them. Furthermore, BREDEM estimates an overall monthly water demand that can differentiate between hot and cold water use. The Domestic Hot Water (DHW) demand is estimated using a typical number of heating systems and their corresponding fuel type, and is adjusted by the number of occupants N.

If N is unknown then BREDEM estimates the value as a function of the total floor area, A_T, [87] where

$$N = 1 + 1.76(1 - e^{-0.00035(A_T - 13.9)^2} + 0.0013(A_T - 13.9); \quad A_T \geq 13.9 \tag{6}$$

N is also used to estimate average metabolic heat gains (Q_{og}).

In BREDEM, lighting L and appliances A, and later their corresponding heat gains (Q_{lg} and Q_{ag}), are estimated by assuming a correlation between A_T and N [69]. The power law relationship described by Equation 7 has been estimated from electricity meter readings. These lumped gains are then allocated according to the weights of L (0.21) and A (0.79) [88].

$$L + A = 263 \cdot (A_T \cdot N)^{0.47} \tag{7}$$

However, this model for L and A cannot replicate the large variations in appliance energy use that are observed in practice [89]. Lorimer [53] has developed a more disaggregated model of lighting and appliance energy demand, but its scope is limited to the HEED and therefore a limited number of UK regions.

In particular, the energy used for cooking tends to be highly simplified in HSEMs, because it is generally only responsible for a minor proportion of dwelling energy demand (see Figure 2). In BREDEM, cooking type coefficients are derived to estimate yearly demands aggregated by fuel types. This lack of detail may be problematic, because cooking directly affects indoor air quality and the responses of ventilation systems and householders to it, with corresponding impacts on ventilation losses.

Finally, the losses described by Equation 4 are varied in HSEMs. Infiltration (Q_{il}) is represented in BREDEM as a correlation factor derived from material properties. Purpose-provided ventilation (Q_{vl}) is calculated monthly using an adjustment factor that accounts for internal flues and an exposure factor. The CHM ascribes ventilation losses to different ventilation systems (mechanical and forced), thus increasing its variability across the stock, although there are only a limited number of these systems in the model. More detailed descriptions of ventilation are developed in the Health Impact of Domestic Energy Efficiency Measures (HIDEEM) [90] and the DOMVENT models [91, 64]. Energy transmission through the envelope (Q_{fl}) and thermal bridges (Q_{tm}) are simplified to average values, which result as a function of the materials and the estimated dwelling geometry.

So although Equations 1-5 are simplified representations of heat flows in dwellings, they do nevertheless represent the principal factors influencing them. Many of the underlying drivers of operational and investment behaviours that directly affect energy flow pathways could and should be linked to them. An HSEM can in principle be used to assess the consequences of householder behaviours that influence decision-making on dwelling energy performance; although reliably predicting the consequences of operational behaviours in the absence of the prediction of the dynamic stimuli influencing them would not be straightforward.

3.3. Decision Making in HSEMs

HSEMs poorly describe the influence of occupants and their behaviour on energy demands [30], likewise local climatic conditions [74]. Statistically biased HSEMs are often more accurate than their physical counterparts, but their predictive capabilities are less flexible [17].

Meanwhile, significant advances have been made in the modelling of occupants' activities and dependent behaviours and their corresponding impacts on thermal and electrical energy demands [48, 92, 93, 94, 95]. But these models do not consistently handle diversity in household characteristics or in housing attributes, both of which can influence activities and behaviours. For example, the preferred living room temperature may be decided individually or following negotiation with other householders [96, 94]. There is also a relatively poor quantitative understanding of the extent to which investment and day-to-day operational (e.g. use of lights and windows) behaviours can be influenced. For example, decisions to invest in new technologies may be the consequence of peer pressure, social incentives, or taxation programmes to encourage the efficient use of energy in homes.

In the absence of comprehensive stochastic models of occupants' diverse behaviours and the factors influencing them, occupants currently tend to be represented simply as average heat sources (e.g. by BREDEM and CHM), undermining their ability to account for strategies that may drive behaviour change.

In order to represent this behaviour in a HSEM, each occupant (or collective of them) may be represented as a unit with adaptive rules and responses, also known as *agency*. This agency enables heterogeneity in occupants' behaviour to be captured. For example, the Agent Home Owner Model of Energy (AHOME) and the improved DeCarb-Agent Based Modelling (ABM) are able to include householder responses at building and neighbourhood scales [97, 98].

These responses of householders can also vary considerably over time because of socio-demographic changes, such as the ageing of the population. For example, by reconciling the energy demand with national consumption figures, the BREHOMES predicts housing stock changes by also considering social factors. This approach is also at the core of BREDEM [99]. More detail is provided by the DECM [52], the (Energy Systems Research Unit) Domestic Energy Model (EDEM) [100] and the Stochastic Urban Scale - Domestic Energy Model (SUSDEM) [17], which all include household employment and occupancy profiles to represent collective responses (decision-making), albeit at a regional scale. Steadman's model [83] focuses on the consequence of decision-making and was built to estimate the impact of retrofitted energy efficiency measures and the applicability of related policies, particularly on loft and cavity insulation, and glazing and boiler replacements.

3.4. Top-Down and Hybrid Modelling

BREDEM and its derivatives are essentially bottom-up approaches to the energy modelling of the housing stock. But, top-down and most of the statistical approaches have also been developed to support strategic decision making. Examples of top-down approaches are the Annual Delivered Energy, Price and Temperature (ADEPT) model and the Seasonal Temperature Energy Price (STEP) model [101], and the Energy Demand Model (EDM) [102]. The EDM is a sophisticated econometric predictor with the ability to reconcile policies with energy demand. The ADEPT and STEP models can efficiently estimate the consequences of changes to these external factors.

Integrating the virtues of both top-down and bottom-up approaches into a coherent whole may have merit: handling housing and household behaviours in a parsimonious way. An example of this reconciliation is found in the Technology Assessment for Radically improving the Built Asset baSE domestic model (TARBASE) [103] which evaluates decarbonisation and refurbishment scenarios using algorithms to represent lighting, appliances, DHW, refrigeration, glazing, insulation and solar technologies. This model also enhances the assumptions applied to Equations 2-3 by including more parameters for each gain, but using deterministic profiles. Similarly [104], the Domestic Energy Model for Scotland (DEMScot) complements the building-physics approach with forecasts related to fuel elasticity and carbon intensities; refurbishment maintenance costs and demolition rates; and direct rebound effects.

HSEMs and their underlying datasets have become progressively more comprehensive in their scope and sophisticated in the methods employed. But there remain some shortcomings when representing the 27 million dwellings as a function of their geometric and physical properties and from the chosen statistical modelling approaches. These can be overcome by allowing open access to datasets and modelling modules of HSEMs, and by documenting the decisions and assumptions made during their development. Section 4 identifies some obvious omissions in the scope of HSEMs to support the formulation of policy measures designed to decarbonise the built environment. It also provides the foundations for a systematic evaluation of HSEMs to highlight key areas that require further work.

4. Evaluation of Housing Stock Energy Models

HSEMs are developed to describe the energy flow pathways in a sample of dwellings, and are extrapolated to represent an entire stock. For reasons of practicality, representations of these pathways (such as heat gains, ventilation and infiltration losses) are simplified. However, it is important that these simplifications are appropriate and that the principle of parsimony is respected so that a model is as simple as possible, but no simpler. If it is too simple, its ability to make reliable estimates of performance and inform decarbonisation policies and strategies is undermined.

In previous reviews of HSEMs [12, 74, 105], a set of performance gaps have been identified. The first set is related to data resolution: *a*) a reliance on isolated historical data to formulate correlations; *b*) assumptions about typology form and fabric homogeneity; *c*) onerous computational requirements. The second set is related to the sophistication of physical and behavioural modelling strategies: *d*) poor representation of social and environmental influences on occupant behaviours; *e*) inaccurate descriptions of energy-related decision-making;

f) inability to represent investments in new technologies; *g*) unlinked methods for the co-simulation of specific modelling algorithms.

These gaps have since been partially addressed by augmenting existing algorithms and techniques. For example, societal effects have been improved in models that include agency, such as DeCarb and AHOME. They account for human interactions with a dwelling, its systems, and appliances, although these relationships are based on a modest amount of empirical evidence. Furthermore, models such as AHOME, SUSDEM, EDEM and DDM have improved our ability to assess building fabric by adopting GIS to better represent building form, and by including investment scenarios.

In addition to these assumptions and considerations of modelling scope and rigour, it is important that an HSEM be modular. Kavgic et al. [74] find that BREDEM is modular but its links are not always transparent. All algorithms should be editable and thoroughly documented, if their scope of applicability is to be well understood.

4.1. Evaluation of Functionality

Some concerns about data resolution and modelling abstractions were identified in Sections 2 and 3, respectively, highlighting a need to evaluate existing HSEMs to determine their fitness for purpose. To this end we evaluate the functionality and accessibility of some twenty-nine UK HSEMs. We use ASHRAE's general framework [106] for selecting, or determining the appropriateness of a modelling strategy, using six criteria:

1) *Accuracy:* Has the model been tested and validated and is it capable of estimating prediction uncertainties?

2) *Sensitivity:* How sensitive is the model to the design options under consideration?

3) *Versatility:* Does the modelling method allow for the analysis of all design options under consideration?

4) *Computability:* How appropriate is the computational time when compared to the resolution of predictions?

5) *Reproducibility:* Is it likely that different users aiming to solve the same problem will make the same input choices and how reproducible are the predictions?
6) *Usability:* How easy is it for a user to make their input choices and to analyse predictions?

Although these criteria are helpful in guiding our review of the principal modules that comprise HSEMs; in particular to determine the ability of an HSEM to successfully model energy flows and the socio-economic drivers that influence them; it is worth noting that they were developed to evaluate energy models of individual buildings rather than of stocks of buildings, and so they do not explicitly address the characterisation of the housing stock that is being modelled. To do this, databases should be evaluated considering their resolution (sample), completeness (scope), coherence (compatibility between datasets), regularity of updates, and the integrity of any underlying databases that have been unified. Nevertheless, the ASHRAE criteria, augmented by an analysis of transparency, are a valuable starting point. They are used here to support our evaluation of both data resolution and modelling sophistication, which is summarised in Table 3. In this, transparency or accessibility is evaluated by assigning scores according to whether each of the modules are restricted or absent (black box: 0), open and editable (white box: 1), or somewhere in-between (grey box: $\frac{1}{2}$). We also consider accessibility to the HSEMs' documentation, the operating system(s) used and software license restrictions. The evaluation also aims to identify the components of HSEMs that could be augmented by the consideration of diverse disciplines that have historically been unrelated to energy models, such as health and socio-demographic studies that explore responses to indoor stimuli.

Some of these models cannot strictly speaking be considered HSEMs, but they have been included because they share common data sources (e.g. DDM and MDM) or computational engines (e.g. RdSAP). The SAP is included in this analysis because some HSEMs directly use elements of it to make predictions (e.g. EDEM, DEMScot, DECoRuM, CHM, DDM and RdSAP), or apply it indirectly via its reduced format RdSAP (e.g. CHM and TARBASE). Furthermore, given the fact that BREDEM is at the core of many HSEMs to perform their energy balance [53, 52], we adopt its structure to define the evaluation categories (rows in Table 3), which correspond to the description given in Sections 3.1, 3.2 and 3.3. Likewise, we differentiate among the three categories: fabric, systems and occupancy. The evaluated HSEM are grouped by their modelling approach, and we use their latest version in our evaluation (see Figure 3).

By way of demonstration of our evaluation, as set out in Table 3, let us consider BREDEM's geometry module. Firstly, its sensitivity, adaptability, usability, and accuracy can be assessed as limited, because it does not explicitly consider the dwelling volume and only retains A_T, a derivative of building geometry. However, this module could in principle be replaced by a more detailed model to improve the accuracy of energy demand predictions. The outputs of this module are inputs to other modules and so its usability is restricted. Hence, four of the criteria are considered to be grey boxes (i.e. $4 \cdot \frac{1}{2}$). Further, this module is highly compatible with other algorithms and data, and so its predictions are reproducible (i.e. $1 \cdot \frac{1}{6}$). In the same vein, its adaptability depends on the purpose of the model because it can easily be included in isolated algorithms or in stock models (i.e. $1 \cdot \frac{1}{6}$). Overall, the geometry module scores 4 of 6 and is considered to be a white-box module because of the likelihood of future editing and the consequent improvement of its attributes.

Let us similarly consider CHM and DECM, which are bottom-up physically biased models, both of which use BREDEM [54]; although DECM does not fully document the algorithms it applies. DECM's focus is on the assessment of uncertainties, which is valuable but limited by its lack of model transparency. Neither model explicitly accounts for dynamic responses to indoor conditions or detailed household representations. The assessment of energy performance and carbon intensity is limited to their sample units, which are SOA and LA, respectively. If we compare these two HSEMs, the CHM ranks higher because it is more transparent, despite the fact that DECM supports scenario projections and uses an index of carbon intensity. However, its limited transparency undermines its functionality.

The Domestic Equipment and Carbon Dioxide Emissions (DECADE) model and DECoRuM are both statistical biased models. DECADE relies heavily on historical tendencies to create a set of scenarios using some fixed conditions [43, 107]. DECoRuM uses BREDEM and SAP to calibrate its estimations, although their application is restricted spatially to a district scale analysis. DECoRuM is essentially a visualisation tool, and so its dependence on physical models provides an easy opportunity to expand its scope [108, 80]. The approaches of both models render them unable to represent geometrical- and contextual-related values. Changes to these values are embedded into their models, which are assessed as partially or fully restricted. Nevertheless, their ability to represent trends and changes in the properties of the elements (i.e. ageing) is highly beneficial and may complement the outcomes from physical-biased approaches. Some of the other statistically-biased models are ranked lower than DECADE and DECoRuM because of their limited scope or focus, and not because they are less fit-for-purpose.

Table 3 systematically rates all HSEMs that are currently available (distributed and/or published) in the UK using a range of core underlying functions (see Section 3) to rate and rank them. The rankings are based on the assumption that individual functions (rows in the table) are equally weighted, and so they should be used with caution. Table 3 shows that statistically biased and top-down models, which lack fidelity in the handling of physical phenomena, are nevertheless able to consider societal parameters reasonably well. The bottom row of Table 3 suggests that CHM can be considered the best performing model. Its relative functionality and transparency may explain why it is used to provide a statistical evaluation of the UK housing stock for the *Energy in the UK* documents [54]. However, CHM and other similar models could be improved considerably by substituting modelling algorithms, for example to support dynamic simulation, by substituting the calibration data with more up-to-date or sophisticated alternatives, and by accounting for household attributes that affect decision-making and the way energy is used in the stock of dwellings.

[Table 3 about here.]

4.1.1. Anomalies and Omissions

The inclusion of detailed household information is essential for assessing the effects of changes in energy demand when occupants adopt reduction measures, either by investing on new technologies or by modifying patterns of use. Mitton et al. [109] identify two advantages of including this type of household information: the ability to represent ageing elements, and the ability to describe the—typically complex—interactions between them. To date, their inclusion is still problematic and can create gaps in an HSEM. It is easier to insert a replacement module and validate it if it is directly linked to a single open source platform rather than persisting with the current practice of developing and maintaining a plethora of closed-source HSEMs.

Therefore, it is important to consider the representation of occupants' behaviours in response to underlying environmental stimuli or the demand of energy-related services. Behavioural responses can result from the interplay between the building, its systems, and the interactions between them. Currently, the parameters that affect behaviour are blurred in HSEMs (see Table 3). The indoor environment of a building may be affected by available fuel sources and geometric shape constraints that are a function of its location. A building can define an occupant's needs, but an occupant may also define the building's environment. For example, larger spaces may demand more energy to keep them warm, but occupants may invest in insulation technology so heat losses are minimised. Conversely, they may alter their utilisation of space and, with time, reduce the volume used and heated during the heating season. A modelling approach that considers householder behaviours as a function of occupancy and environmental stimuli would signify a transition from a simplified energy balance modelling approach to dynamic simulation. An inability to accurately represent these dynamic processes, and the socio-economic processes that influence household decisions, seriously undermines the functionality of HSEMs. Required information could be obtained from socio-economical surveys and used to inform either top-down or bottom-up models.

The representation of domestic appliances in a HSEM requires data related to household ownership, efficiencies or rated powers, and associated usage patterns. To date, there is no HSEM that comprehensively represents these parameters. Current representations of appliance use and its dependency on household characteristics is often reduced to a scalar correlation factor using national stock averages. Any departure from this simplified function (whose theoretical basis is unclear) would negatively impact on its predictive accuracy. For example, Equation 7 is incapable of encapsulating factors that affect appliance use. As a result, its associated energy demand is insufficiently granular.

Societal factors could be incorporated from AHOME or Steadman's model, or even substituted with more rigorous alternatives. Improving the modularity of the CHM, and other similar models, would also allow modelling algorithms and calibration data to be substituted with more sophisticated and up-to-date alternatives. For instance, descriptions of dwelling geometry could be improved, perhaps using a similar volumetric method to that used by DOMVENT, yet focussed on ventilation and infiltration rates. Incidentally, several studies have identified that dwelling heating demand is most sensitive to fluctuations in these rates [110, 79]. It has also been suggested [79] that existing algorithms, such as those used by SAP [111] and BREDEM [75], may be overly simplistic and based on limited empirical evidence. This suggests that there is a need for a more rigorous representation of infiltration rates in homes, requiring a combination of rigorous fieldwork and improved modelling. This would then lead to more refined predictions of health risks in homes.

Some other parameters that are required to model the complex energy interplay within dwellings are neglected in many existing HSEMs. These include lighting level, air quality, and noise. Different ratios of artificial and natural light affect the indoor light quality and activities that depend on it. Similarly, airflow between a dwelling and its external environment is considered via a range of different strategies, and so the pollutant content of that air should be considered. Some activities, such as cooking, will affect indoor air quality and occupants' use of windows and fans to regulate it. Noise is also related to the energy demand of a dwelling. For example, occupants may attempt to moderate external noises by closing windows, or attempt to mitigate internal noise by switching off, or avoiding the use of, fans. It is clear that the consideration of noise and air quality should not be decoupled.

One final factor that is often overlooked is householder health, which a dwelling can both improve and harm. The main purpose of a dwelling is to provide shelter from the weather, but it also provides security, comfort, and privacy. However, these benefits may cause a building to limit flows of daylight, air, noise, moisture, and heat (affecting temperature and thermal comfort). Accordingly, poor indoor environment quality may adversely affect the physical and mental health of occupants. This highlights the relevance and importance of health as an HSEM module.

It is clear that the underlying drivers that affect householder behaviour (i.e. investments and energy using practices) and their interaction with their dwellings are limited in some HSEMs and ignored by most. A consideration of these drivers could lead to real changes in the energy demand of houses, and their omission from HSEMs significantly limits their ability to estimate the varying conditions of housing and households at stock level [98, 26]. Multi-agent simulation techniques would appear to have much to offer in this endeavour [112, 113].

Finally, the ability of HSEMs to predict indoor comfort, and the impacts of associated heating system set-point temperature choices, is limited by the granularity of the underlying energy model. Predicting comfort and the impacts of the allocation of the energy and comfort co-benefits from energy-related renovation investments, meaning that potential energy savings may be offset by improved comfort and health arising form high set-point temperatures, requires dynamic simulation.

4.2. Future Functionality

A transparent model clearly describes its underlying algorithms so that its users can comprehend its rationale and either confirm or discard them to adapt the model to meet specific needs. A preliminary open framework rationale is presented in [63], whose processes can only be accomplished under an open-source philosophy. This philosophy requires a significant reinterpretation of the way data is handled, collected, processed, and shared. Hence, emphasis should be placed on the usability of data, so that it can enhance the communication between models and users. For instance, the National Statistics Harmonisation Programme whose rationale is to standardise classifications, definitions, and standards among datasets [114], and the pool of energy-related building data developed by European countries to improve the analysis of regional and local stocks [14]. By improving data collection intervals and the way data is calibrated, the likelihood of its adoption can be increased. Instead of relying on historical data, models can use more up-to-date and more comprehensive housing and household data. Lorimer [53] finds that the calibration of data can also be used to help implement measures designed to reduce non-heating end-use energy demand as part of national programmes.

Improvements in the transparency of HSEM data and modelling algorithms should be complemented with improvements to modularity. Modularity prolongs the life of a model by allowing it to be improved and delays obsolescence. Such modularity should also facilitate the execution of sensitivity analysis methods that can be used to identify the most important inputs to a model, to highlight areas where further data gathering should be focussed, and where models should be refined to more faithfully represent phenomena addressed by them [107, 18, 115, 79]. These analyses should be complemented by a quantification of the uncertainties in a model's predictions. It should account for both deterministic (building physics) and stochastic (behavioural) phenomena, and the data that underpin their representation. The reporting of errors and omissions enhances the understanding of the accuracy of different modelling strategies and their descriptions of the energy flow pathways at stock level.

5. Conclusions

This paper evaluates some twenty-nine Housing Stock Energy Models (HSEMs) that have been used to investigate the consequences of energy demand reduction policies and interventions in UK housing, and the data that are used to provide inputs to them. Our evaluation of these HSEMs and their functionality shows that very few are completely transparent, which makes it difficult to understand all of the methods and algorithms that have been used to make predictions of energy demand and thus to judge their fitness for purpose. This is compounded by the limited scope and simplicity of many HSEMs, which are generally based on simplified steady-state energy balance models augmented with statistical models relating to lighting, system and appliance usage extrapolated to the stock of like typologies. Here, it is important to understand how physical phenomena have been (over-)simplified, or where and on what basis statistical relationships have been incorporated, so that they can be improved in the future, as necessary. Failing to do so undermines the utility of HSEMs and their ability to faithfully predict performance at the stock level, or for the stocks of individual building typologies.

Future HSEMs should have a modular architecture and be freely available so that they can be edited and updated continuously. This could encourage cross-disciplinary collaboration and increase the rate of improvement to the modelling of phenomena within HSEMs where there is significant prediction uncertainty, such as householder behaviour. Furthermore, whilst some HSEMs specialise in the prediction of a specific aspect of dwelling energy demand, both their utility and longevity could be improved by incorporating them within a larger modular HSEM architecture.

The analysis of data sources shows that it is easy for significant errors to be incorporated into a database. These can occur from a wide number of processes, such as sampling biases, the imputation of missing data, or the aggregation of information to make it more manageable. One process that is currently unavoidable is the identification of properties shared by a large number of dwellings so that they can be clustered together. Whatever the process, it is clearly important to track the origins of data to avoid error propagation at each stage of aggregation. Finally, most sources of data are updated periodically, but most housing stocks evolve more or less continuously. Accordingly, there is a need to continually update databases to maintain their validity and to share them freely.

Essentially, all models are wrong, but some are useful [116]. It is important that HSEMs are made less wrong and more useful by improving their transparency and modularity, by using better data, and by sharing both the model and the data freely. Only then can one reasonably hope to provide HSEMs that are useful and informative tools used to support policies makers who seek to reduce the energy demand and carbon emissions of housing stocks.

Abbreviations

ABM Agent Based Modelling

ADEPT Annual Delivered Energy, Price and Temperature

AHOME Agent Home Owner Model of Energy

APS Annual Population Survey

ASHRAE American Society of Heating, Refrigerating, and Air-Conditioning Engineers

BREDEM Building Research Establishment Domestic Energy Model

BREHOMES Building Research Establishment's Housing Model for Energy Studies

CHM Cambridge Housing Model

DDM Domestic Dwelling Model

DECADE Domestic Equipment and Carbon Dioxide Emissions

DeCarb Domestic Energy and Carbon Model

DECC Department of Energy and Climate Change

DECM Domestic Energy and Carbon Model

DECoRuM Domestic Energy, Carbon Counting and Carbon Reduction model

DEFRA Department for Environment, Food and Rural Affairs

DEMScot Domestic Energy Model for Scotland

DHW Domestic Hot Water

DOMVENT Domestic Ventilation Model

DUKES Digest of UK Energy Statistics

EDEM (Energy Systems Research Unit) Domestic Energy Model

EDM Energy Demand Model

EEP Energy and Environment Predictions

EFUS Energy Follow Up Survey

EHS English Housing Survey

EST Energy Saving Trust

GHG Greenhouse Gas

GIS Geographical Information System

GOR Government Office Regions

HEED Homes Energy Efficiency Database

HIDEEM Health Impact of Domestic Energy Efficiency Measures

HSEM Housing Stock Energy Model

LA Local Authority

LARA Local Area Resource Analysis

MDM Cambridge Multisectoral Dynamic Model of the British Economy

MTP Market Transformation Programme

NEED National Energy Efficiency Data-framework

NSW National Survey for Wales

NIHCS Northern Ireland House Condition Survey

NISRA Northern Ireland Statistics and Research Agency

NRS National Records of Scotland

NSW National Survey for Wales

NUTS Nomenclature of Territorial Units for Statistics

ONS Office for National Statistics

RdSAP Reduced Standard Assessment Procedure

SAP Standard Assessment Procedure

SHCS Scottish House Condition Survey

SOA Super Output Area

STEP Seasonal Temperature Energy Price

SUSDEM Stochastic Urban Scale - Domestic Energy Model

SW Statistics for Wales

TARBASE Technology Assessment for Radically improving the Built Asset baSE domestic model

UK United Kingdom

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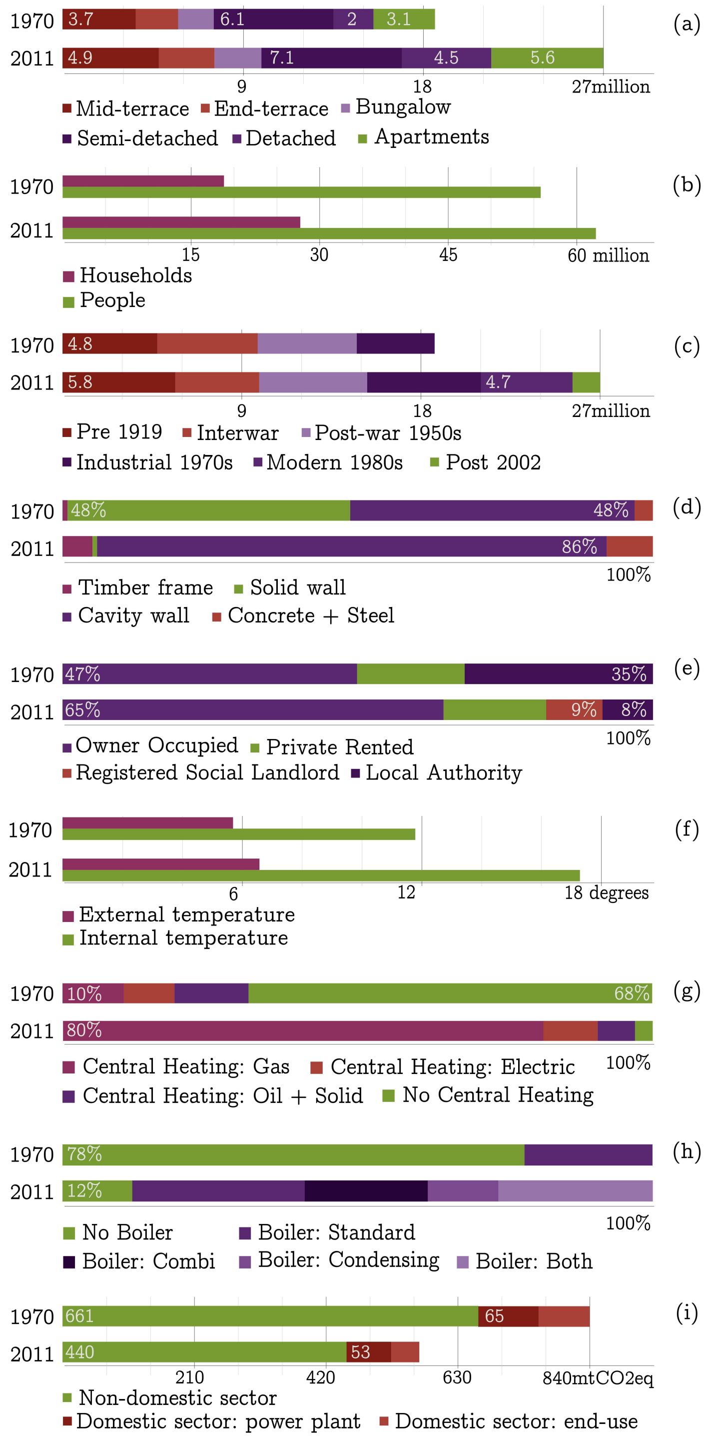

Figure 1: Housing stock growth comparison
Source: [9, 40]

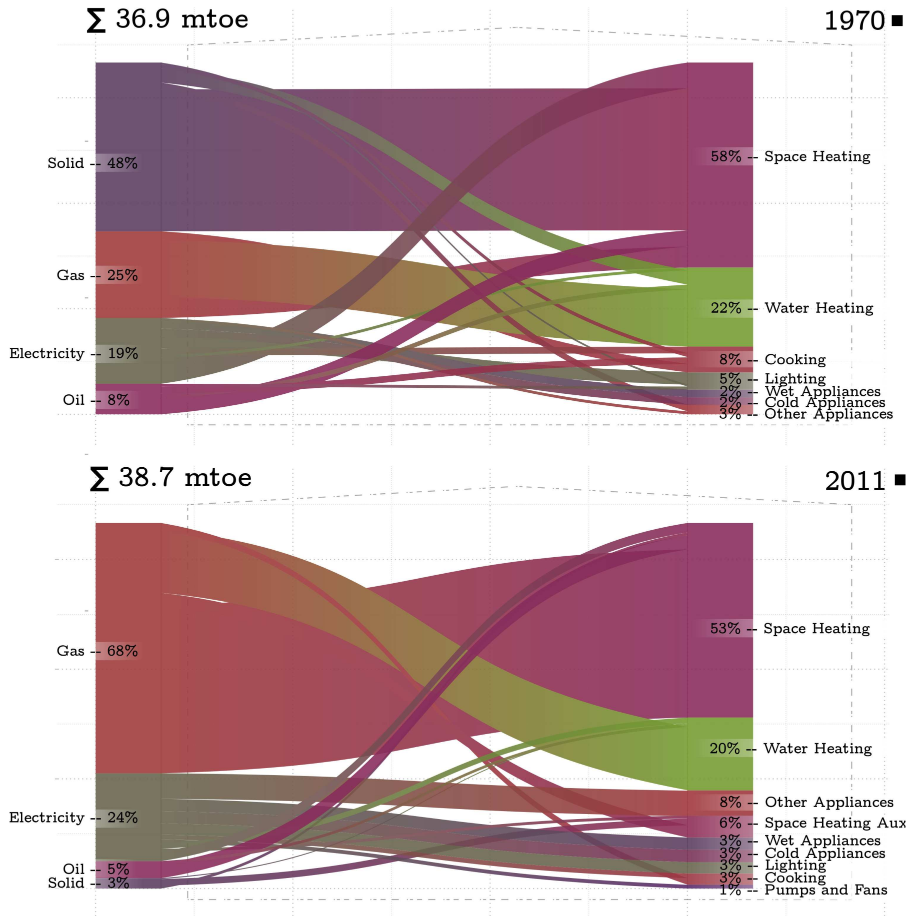

Figure 2: Change in domestic final energy consumption by fuel supply and demand services
Source: [9]

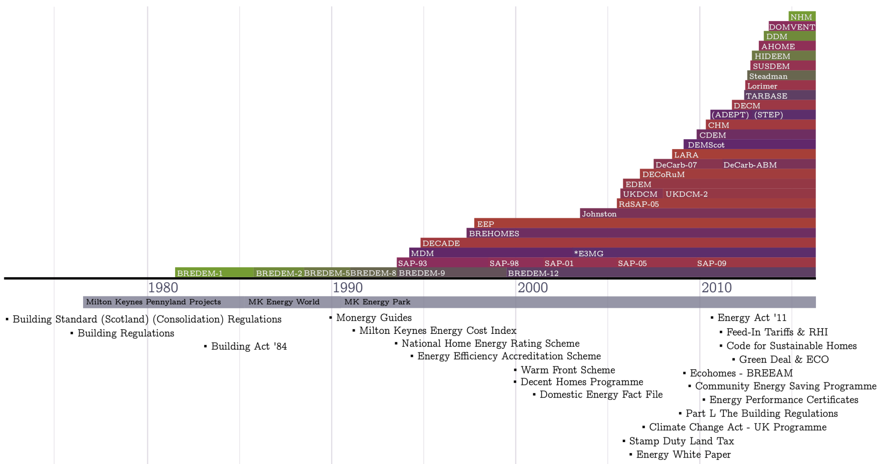

Figure 3: Development of HSEM and energy related policies in the UK (adapted from [16])

	Census			LA	NUTS*			SOA°	
	People	**Households**	**Dwellings**	**LA**	**1st**	**2nd**	**3rd**	**Middle**	**Lower**
United Kingdom	62,055,838	27,651,734	27,580,884	406	12	37	140	8,429	41,773
Great Britain	60,267,499	26,903,499	26,832,836	380	11	36	135	8,429	40,883
England and Wales	55,071,113	24,429,618	24,359,880	348	10	32	112	7,194	34,378
England	52,059,931	23,044,097	22,976,066	326†	9	30	100	6,781	32,482
Wales	3,011,182	1,385,521	1,383,814	22	1	2	12	413	1,896
Scotland	5,196,386	2,473,881	2,472,956	32	1	4	23	1,235	6,505
Northern Ireland	1,788,339	748,235	748,048	26	1	1	5	NA	890

Notes: † Local Authorities (LAs) include non-metropolitan districts, metropolitan districts, unitary authorities and London boroughs.

* These values correspond to the NUTS-2010 nomenclature, regulated by the European Union.

° The output areas define synthetic polygons around an average of 125 households. Lower-SOAs are made of output areas and typically enclose about 1500 households. Middle-SOAs contain an average of about 7200 households.

Table 1: UK regional classification in 2011
Source: Office for National Statistics (ONS)

Source	Size	Sampling Units	Building Fabric	Heating Systems	Energy Bills	Meter Readings	Household Composition	Socio-demographics	Household Attitudes	Measured Temperature	Retrofit Measures	Specific Metrics °	Historical Metrics †	Coverage	Support
			Scope and Properties												
EHS	∼ 14 k	sample of Postcodes and LSOA	✓	✓	✓		✓	✓						Eng	DCLG
EFUS	∼ 2.5 k	extract from EHS physical surveys	✓	✓	✓	✓	✓	✓		✓				Eng	BRE, DECC
NSW	∼ 1.2 k	sample of LSOA	✓	✓	✓		✓	✓						Wal	UK Data & Wal Gov
NIHCS	∼ 10 k	sample of Postcodes	✓	✓		✓	✓	✓			✓			NI	UK Data & NI Gov
SHCS	∼ 18 k	sample of LA	✓	✓	✓		✓	✓	✓	✓				Sct	UK Data & Sct Gov
DUKES	∼ 27 M	readings from Postcodes and LA						✓				✓	✓	UK	DECC
Census	∼ 27 M	UK household population	✓	✓			✓	✓						UK	ONS
NEED	∼ 25 M	sample from Experian (HEED and EPC)				✓	✓	✓			✓			Eng,Wal	DECC
HEED	∼ 15 M	EST	✓	✓							✓			UK	EST

Notes: † Include retrofits on insulation, boiler, heaters and windows

° Include metrics from coal, petroleum, gas, electricity, renewables and combined heat and power

Table 2: Summary of Surveys and Datasets

Table 3: Evaluation of models according to the level of transparency as a function of accuracy, computability, reproducibility, sensitivity, adaptability and usability. Models are sorted by year and type of approach Notation: ■: black-box models, ⊠: grey-box models, □: white-box models

	BREDEM-12	SAP-09	BREHOMES	Johnston	RdSAP-05	CDEM	DEMScot-2	CHM	DeCarb-ABM	DECM	SUSDEM	HIDEEM	AHOME	DOMVENT	NHM	DECADE	EEP	*E3MG	EDEM	DECoRuM	UKDCM2	LARA	TARBASE	Lorimer	Steadman	DDM	MDM	(ADEPT)	(STEP)	
Layout Geometry	□	□	□	⊠	□	□	□	□	□	□	□	⊠	⊠	⊠	□	⊠	⊠	■	□	□	□	⊠	⊠	■	□	□	■	⊠	■	Fabric
Construction Materials	□	□	□	■	□	□	□	□	□	□	□	⊠	⊠	⊠	□	□	□	■	□	□	□	□	⊠	■	□	□	■	⊠	■	Fabric
Ventilation Rates	⊠	⊠	⊠	⊠	⊠	⊠	⊠	□	⊠	⊠	⊠	□	⊠	□	⊠	⊠	■	■	⊠	⊠	⊠	■	⊠	■	⊠	⊠	■	⊠	■	Fabric
Infiltration Parameters	⊠	⊠	⊠	⊠	⊠	□	⊠	□	⊠	⊠	⊠	□	⊠	□	⊠	⊠	■	■	⊠	⊠	⊠	■	⊠	■	⊠	⊠	■	⊠	■	Fabric
Context & Orientation	⊠	⊠	⊠	⊠	⊠	⊠	⊠	□	⊠	⊠	□	⊠	⊠	□	⊠	■	□	■	⊠	⊠	⊠	□	⊠	■	⊠	⊠	■	■	■	Fabric
Solar Gains	□	□	□	■	□	□	□	□	□	□	□	⊠	⊠	□	□	■	⊠	■	□	□	□	⊠	⊠	■	⊠	□	■	■	■	Systems
Infiltration Gains	⊠	⊠	⊠	⊠	⊠	⊠	⊠	□	⊠	⊠	⊠	□	⊠	□	⊠	⊠	■	■	⊠	⊠	⊠	■	⊠	■	⊠	⊠	■	⊠	■	Systems
Thermal Mass Gains	□	⊠	□	■	⊠	□	⊠	□	□	□	⊠	⊠	⊠	⊠	□	■	■	■	□	□	□	■	⊠	■	⊠	□	■	⊠	■	Systems
Appliances Gains	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	■	⊠	■	⊠	⊠	□	⊠	⊠	⊠	⊠	□	⊠	□	⊠	⊠	⊠	⊠	⊠	Systems
Lighting Gains	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	■	⊠	■	⊠	⊠	□	⊠	⊠	⊠	⊠	□	⊠	□	⊠	⊠	⊠	⊠	⊠	Systems
Occupants Gains	⊠	⊠	⊠	⊠	⊠	⊠	□	⊠	⊠	⊠	■	⊠	□	⊠	⊠	■	⊠	■	⊠	⊠	⊠	⊠	■	■	■	⊠	■	⊠	■	Systems
Cooking Gains	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	⊠	□	⊠	⊠	⊠	⊠	□	⊠	□	⊠	⊠	⊠	⊠	⊠	Systems
Water Flows	⊠	⊠	⊠	■	⊠	⊠	⊠	□	⊠	⊠	■	■	■	■	⊠	⊠	⊠	■	⊠	⊠	⊠	■	■	■	■	⊠	■	■	■	Systems
Light & Noise Quality	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	Occupancy
Air Pollutants	■	■	■	■	■	□	■	■	■	■	■	□	■	□	⊠	■	⊠	■	■	■	⊠	⊠	⊠	■	■	■	⊠	■	■	Occupancy
Draught Risk	■	⊠	■	■	■	■	⊠	⊠	■	■	■	□	■	□	■	■	⊠	■	■	■	■	■	■	■	■	■	⊠	■	■	Occupancy
Comfort Responses	■	■	■	⊠	■	■	■	■	⊠	■	■	■	⊠	■	■	■	■	⊠	⊠	■	■	■	⊠	⊠	⊠	■	⊠	⊠	⊠	Occupancy
Peer Pressure	■	■	■	⊠	■	■	■	■	⊠	■	⊠	■	□	■	⊠	□	⊠	□	⊠	⊠	■	□	⊠	⊠	⊠	■	⊠	□	⊠	Occupancy
Budget Effects	⊠	⊠	⊠	⊠	⊠	⊠	□	⊠	⊠	□	⊠	■	□	■	⊠	□	⊠	□	⊠	⊠	⊠	□	□	□	□	⊠	⊠	□	⊠	Occupancy
Awareness	■	■	■	⊠	■	■	⊠	■	⊠	■	⊠	■	□	■	⊠	□	⊠	□	⊠	⊠	■	□	⊠	⊠	⊠	■	⊠	⊠	⊠	Occupancy
			bottom-up *physical* biased													bottom-up *statistical* biased											top-down			
rank	-	-	15	23	17	7	3	1	6	9	13	11	20	4	2	18	14	26	7	5	10	19	22	24	21	12	25	16	27	