Modelling UK domestic energy and carbon emissions: an agent-based approach

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Abstract

As the debate on policy responses to climate change gathers pace, there has been an increasing focus on tools to model national scale energy use and emission characteristics of UK dwellings. This paper reviews some existing models and highlights limitations of their common underlying methodologies. We argue that a radically different, integrated, approach is required to tackle these challenges and ensure that the modelling remain robust and able to meet future demands. We suggest that Agent Based Modelling (ABM) is a suitable candidate modelling paradigm to achieve an integrated modelling framework. We also present DECarb-ABM (an ABM based implementation of an existing model, DECarb) with many of the desired properties of such an integrated framework. The new model is validated against both the existing model and historical data.

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1. Introduction

It is now widely recognized that climate change is a severe threat with a projected increase in global average surface temperatures between 1.1°C and 6.4°C by the end of this century [1]. The UK government is committed to making deep cuts in carbon emissions to mitigate the impacts of climate change, especially in the light of higher energy prices and reduced availability of oil. Under the Climate Act of 2008, *every household in the UK* will need to contribute to reducing national carbon emissions by 80% by 2050 from 1990 levels of which 34% would have to be met by 2020 [2]. Given the scale of cuts, it is likely that most households will need to get quite close to, or even exceed, this figure as other sectors are unlikely to exceed 80%. This target is a revision of the 60% target previously proposed by the Royal Commission on Environmental pollution [3] and the Energy White Paper of 2003 [4]. The UK domestic sector is a major focus for both mitigation and adaptation strategies because it is currently estimated to emit around 26% of the UK's CO_2.

Meeting the target requires strategic planning, efficient resource management and technological development. An important tool to assess the viability of options are long term demand side scenarios that balance future climate projections, demographic change and user behaviour. For example, Natarajan and Levermore recently demonstrated the technical challenges and opportunities that exist in meeting a 60% emission reduction target by 2050

[5]. This work showed that the potential to decrease emissions to such levels exists under at least three different scenarios, but each requires a major departure from current policy and practice if the required levels of reduction are to be achieved. For instance, the Tyndall Centre funded 40% House approach requires a combination of rapid replacement (i.e. demolition of inefficient stock to be replaced by more efficient buildings) as well as refurbishment of existing dwellings and a good spread of domestic low and zero carbon technologies [6]. The BRE's Step Change 2 scenario relies heavily on prescribing a shift towards heat pumps and biofuel boilers to replace all current and future heating systems [7]. A third scenario suggested by Natarajan and Levermore found that failing the above two strategies, only a heavy uptake of low and zero carbon technologies (particularly solar PV for electricity consumption and export) could deliver the necessary cuts [5]. Clearly, achieving an 80% reduction is likely to pose even greater difficulties.

From the supply side, a major focus of recent work has been the potential impact of distributed generation [8, 9]. This is likely to propel a shift away from the current *demand-led* generation model to a *supply-led* consumption model. An important factor in this will be the emergence of a smart grid that can adapt, smooth and self-heal to account for intermittent generation and time-variable load peaks and troughs. The domestic sector will play an important role in this equation through smart metering and smart appliances. Smart metering works through providing real-time consumption cost (monetary, energetic and environmental) to occupants with the expectation that they will be able to adopt informed cost-reducing behavioural changes. At the same time these data will be fed back to the district network operators for load management. Smart appliances could provide even more fine-grained control (both automated and occupant-mediated) over the operation of individual appliances in the home for load shaping and shifting. As smart meters and appliances effectively close the loop between demand and generation, robust communication between the actors at both ends is essential. Models will be required that can test the combined effectiveness of policy measures (pricing mechanisms, technology uptake subsidies, initiatives for the fuel poor etc) and control systems (smart meters and appliances) on energy efficiency and carbon reductions.

The purpose of this paper is to set an agenda for rethinking bottom-up UK domestic energy and carbon models and present a preliminary version of an agent-based simulation that has the potential to address current challenges. The paper also examines existing approaches to model domestic energy consumption and carbon emissions (DECCE), discusses their limitations and looks forward to future challenges.

2. Current models and methods

Given the contribution of domestic sector emissions, considerable effort has gone into building models that can enable analysis of demand side (generally technology-led, bottom up) or supply side (generally policy-led, top-down) changes. It is not within the scope of this paper to go into the detailed differences between these approaches, especially as these have been covered elsewhere [10] and more recently in a comprehensive review of bottom-up residential models [11]. This paper will focus on three current bottom-up UK models each of which was used to produce one of the three scenarios described in Section 1. The BRE work uses the BREHOMES model [12]; the 40% House work uses the UK Domestic Carbon Model (UKDCM) [6] and Natarajan's work uses the Domestic Energy and Carbon model (DECarb) [13].

A common, and fundamental, feature of all three models is that although they were produced for different studies, they share the same energy model to calculate energy use and carbon emissions: the BRE's BREDEM model [14]. This model has a well-established track record for producing accurate predictions of dwelling energy consumption in the UK. It uses building physics based algorithms coupled with empirical data to arrive at energy consumption disaggregated by four end-use types (space heating, hot water consumption, cooking and lights and appliances). As BREDEM is modular, some elements can be replaced with more detailed sub-models. To date, this has mainly been done to replace the lights and appliances sub-model with the comparatively recent DECADE data [15]. With more work being undertaken to validate other aspects of the domestic energy mix, such as the BRE's analysis of domestic hot water consumption from the 1998 EFUS survey [16], other parts of the model could also be replaced.

All three models have been successful in answering important questions on the feasibility of achieving long term carbon emission reductions. BREHOMES is frequently used to inform and justify government policy, UKDCM was used to produce the 40% House scenario—an important set of policy options to achieve 60% reductions—and DECarb was used to validate these approaches independently. However, there are some common limitations to the capabilities of these models, which we now review.

2.1. Average dwellings

Although each model operates at a different level of disaggregation, they all adopt a common approach by defining an *average* performance for a number of dwelling categories that are then scaled up to build a UK-wide picture of domestic carbon emissions. Natarajan has previously demonstrated that less disaggregated models will produce results with lower confidence whilst higher levels of disaggregation produce more accurate results as the averaging process can skew the individual energy and carbon profiles of dwelling categories unpredictably [13]. For example, in the case of a scenario developed using a model with only two 'notional' dwellings [17] it was shown that the expected carbon savings predicted by the author were significantly overestimated [5]. Although DECarb, UKDCM and to a lesser extent BREHOMES went some way towards lowering such reliance on average performance by producing heterogenous stock, they do not solve this problem. A second aspect of this approach is deciding the granularity of the model. Clearly, a model with only one or two dwelling categories is too coarse—but how many categories is too fine? Evidently, this will depend on the granularity of available data to feed these models. DECarb's base dataset and structure is directly informed by the granularity of house condition survey data: 8,064 possible categories for each of six historic age-bands defined from seven metrics (6 wall construction types, 7 dwelling archetypes, 6 heating systems, 4 climatic regions and binary values for wall, window and roof insulation). Linear transformations are applied to these categories to produce future age-bands with 8,064 categories each on a decadal basis. Where further categories need to be defined (for uptake of newer technologies such as photovoltaic panels or solar hot water heating), they are disaggregated from this basic definition using a weighted average approach. BREHOMES uses 1,000 categories for its base dataset but only one composite dwelling for predicting future emissions and UKDCM produces around 20,000 categories by 2050. Clearly, there needs to be an approach to validate and harmonize these approaches to obtain a unified and consistent method that delivers the best mix of detail and robustness of output. However, matching disaggregation to available data is complicated by the issue of future datasets, discussed below.

2.2. Future datasets

The government is currently undertaking a review of its English Housing Survey (EHS) and Energy Follow Up Survey (EFUS) to collect up-to-date data on energy use in the home [18]. The stated objectives of the new study are:

> "(i) understand, monitor and respond to changing patterns of energy use in households, including appliance use and wastage (ii) understand the impact in real homes of installing energy efficiency measures (iii) understand and improve the actual energy performance of new homes." [19]

The UK government (through the Technology Strategy Board, TSB) also recently awarded funding for 87 exemplar projects through its Retrofit for The Future call [20]. The projects are designed to test the commercial feasibility and replicability of retrofit measures to achieve an 80% reduction in carbon emissions from existing housing. The Energy Saving Trust (EST) has been charged with creating and maintaining a common database of collected physical and environmental monitoring data from all 87 projects to enable unified analysis of results. At the time of writing, the TSB has also called for projects on accelerating the integration of smart meters into 'smart homes'[2] and case studies of 'low-impact' buildings[3].

Apart from these government-led initiatives, independent research has also been carried out to investigate changes and new patterns in: electricity use through appliances [21], hot water use [16], space heating settings [22] and energy use in low energy housing [23]. Recent modelling work has focussed on generating domestic load signatures through innovative simulation techniques. Richardson et al have developed high resolution time use (i.e. occupancy profile) data using Markov-Chain Monte Carlo simulations [24]. A slightly different approach for deriving domestic load signatures has been proposed by Jardine [25]. In addition, approaches from the social sciences have contributed new understanding on the interaction between occupants, dwellings, energy saving measures and technologies. For example, it was recently suggested that householders may not adopt Compact Fluorescent Lamps (CFLs) as ready replacements for incandescent lamps because they do not meet the quality of light and design expectations of occupants [26]. As CFL replacements are an important policy tool to achieve energy savings

[2] `http://www.innovateuk.org/content/competition-announcements/accelerating-progress-towards-integrating-smart-me.ashx`, announced 20 May 2010

[3] `http://www.innovateuk.org/content/competition-announcements/innovating-to-reduce-the-energy-cost-and-carbon-fo.ashx`, announced 20 May 2010

and emission reductions — the government has planned a complete phase out of all incandescent lamps by January 2011 [4] — reluctance to adopt the technology can significantly dent speed of uptake and potentially create residual demand for incandescent lamps or other more energy hungry options.

All of these developments are signposts towards new data on, and understanding of, domestic energy use that will supersede our current datasets and understanding. In addition, there will be other studies—either already planned or not yet conceived—that could significantly impact our understanding of domestic energy use. They could be significant because there are areas where empirical evidence simply does not meet modelled expectations. For example, in a study of 3,000 dwellings for the Warm Front project, it was shown that installed energy saving measures (new heating systems and extra insulation/draught proofing) did not deliver expected energy efficiency savings [27, 28]. Significantly, the study could not isolate the cause of the shortfall [29]. As these energy saving measures are a central plank of all future scenarios, a robust study to tease out the underlying causes is quite likely to be undertaken. It is therefore *essential* that any model built today to investigate future carbon emissions is flexible and adaptable to the data demands of tomorrow.

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[4] `http://www.energysavingtrust.org.uk/Resources/Features/Features-archive/Energy-saving-light-bulbs-take-over`. Note however that this does nto include halogens.

2.3. Deterministic versus probabilistic modelling

A recent study that undertook sensitivity analysis of model inputs to large scale domestic models rightly criticises existing models for not estimating the effect of uncertainty in model inputs on predictions [30]. This is because deterministic models, such as those used in the three studies quoted above, do not capture such uncertainty due to the use of what are essentially deterministic (fixed *a priori*) inputs. In modelling future emissions both the inputs and outputs are exploratory and therefore inherently uncertain—the objective being to develop a robust assessment of future options rather than any precise computation of a given scenario. Deterministic models are therefore clearly unsuitable for such a task, although they are very useful in identifying a baseline technical potential[5] for future emission reductions, as the three studies quoted above have done. The shift from baseline deterministic models to more sophisticated probabilistic models is reflected in the current UK Climate Impacts Programme (UKCIP) climate scenarios (UKCIP-09) and current EPSRC funded projects based on these probabilistic climate scenarios[6]. Another limitation of current models is the short to medium term timeframe in which they operate (i.e. up to 2050). Given that the majority of projected increases in temperatures are likely to be after 2050 [1] and the

[5]'Technical potential' may be defined as a model or scenario that does not explicitly take into account performance degradations or the likelihood of non-occurrence of events in an envisioned scenario that might occur due to either technical, operational, economic or social constraints in the real world. In such scenarios, the probability of a specified event occurring is always 1.

[6]`www.epsrc.ac.uk/CMSWeb/Downloads/Calls/ClimateChangeCall07.doc`

current slow pace of change in emissions reductions, the extended time frame to 2100 cannot be ignored. Such an extension increases the uncertainty of projections and is therefore better addressed by probabilistic modelling.

2.4. Human↔building interaction

None of the scenarios described in Section 1 explicitly consider the impact of human-building interaction on energy use. The behavioural aspect of building performance is often recognized as a major factor in energy consumption although hitherto largely unquantified [31, 32]. For example, the fourth assessment report of the Inter-governmental Panel on Climate Change (IPCC) on mitigation states that "occupant behaviour, culture and consumer choice and use of technologies are also major determinants of energy use in buildings and play a fundamental role in determining CO_2 emissions". However, the IPCC report also recognizes that there is limited evidence to support this [32, p.389]. We have already hinted at the the fact that purely sectoral approaches to analysis and modelling of domestic energy consumption can be limited in their capacity to explain the disjunction between modelled and actual energy use (Section 2.2). While it is widely believed that these discrepancies are due to inadequate characterization of occupant operation of buildings and systems, there is very little understanding of this phenomenon.

All the models described earlier model energy use behaviour[7] through

[7]It has been suggested that the notion of an 'energy behaviour' is a misnomer since the occupant or user does not use energy, but rather a service (microwave to cook, washing machine to wash etc.) that results in energy use [33]. In this paper we use the terms 'energy behaviour' and 'energy use behaviour' interchangeably to mean the use of energy resulting from the demand for a service.

defining "normal" behaviour. For example, although BREDEM is able to model different switching behaviour for heating system operation, the main document defines standard occupant operation profiles for weekdays and weekends [14, p.8] which are adopted *de-facto* by the stock models. Much of the data underpinning these "normal" building occupant behaviours relates to studies conducted in the wake of the energy crisis of the late 1970s—three decades ago—raising the question of their continued relevance. As the number of households in a given modelling category increases, the impact of different occupant energy usage profiles can significantly affect the model outputs. For example, in DECarb's base dataset, the average number of dwellings per dwelling category was around 4500, and 70% of dwellings fell into categories with more than 10,000 dwellings in them. Ignoring the variance in occupant behaviour within each category could result in an erroneous estimate of future domestic carbon emissions just like the averaging errors discussed previously.

The idea of an occupant-centred approach to energy use has primarily been examined by researchers in the social sciences. The most robust and important such study was that conducted by van Raaij and Verhallen in the Netherlands which established a novel model of household energy behaviour incorporating both the *physical* aspects of the dwelling and the *behavioural* aspects of the occupant showing a 30% variation between least and most energy efficient household groups [34]. Unfortunately, although this paper continues to be cited in studies on consumer behaviour and economic psychology, the model has not been developed further by researchers and practitioners in building science. Nearly a decade after van Raaij and Verhallen's study, Lutzenhiser proposed a ‘cultural model of household energy consumption’ through a survey of existing approaches in engineering, economics, psychology, sociology and anthropology [35]. In this model, individual actors (“consumers”) make choices that are ‘culturally-sensible’ and ‘collectively-sanctioned’ and the engineering (i.e., the building fabric, technologies, etc.) and economic (i.e., monetary aspects of culture) aspects are subsets of the overall cultural framework. The model was an outcome of previous research indicating significant variations in the consumption of individual households’ energy consumption “even when controlling for weather, system efficiencies, family size, and [...] identically-equipped dwellings” [36, 37, 38]. However, this model does not appear to have moved beyond a purely theoretical construct.

More recently, efforts have been made to quantify the impact of occupant effects on specific elements of domestic energy consumption—although in most cases it is difficult to extrapolate these to national levels due to their limited scope. For example, Yohanis et al found that though domestic electricity consumption correlates well with total floor area (a well established metric in BREDEM), households with higher incomes consumed 100% more than those with lower incomes [39]. However, the study comprised only 27 dwellings in Northern Ireland, whose entire stock represents only around 2.5% of UK stock [40, p.108]. Firth et al also report wide variations in domestic electricity use in a monitored sample of 72 UK dwellings, though the study does not attempt to correlate occupant characteristics to these variations [21]. Similarly, Gram-Hanssen suggests that heating energy consumption in Danish households living in identical dwellings may vary by 300%, though this appears to be a conclusion based on a small sample of 5 households [41][8].

An important factor in respect of this kind of variation could be ‘habitual’ behaviour (defined as frequent and automatic behaviour) which underpins most daily decisions. For example, Pierce et al found that much of everyday consumption behaviour was not the result of conscious or motivated action on the part of occupants [42]. Instead, they discovered that engagement with micro-level (e.g. local thermostat settings) and macro-level (e.g. HVAC standards and infrastructures) systems shaped everyday user experience. For example, two participants in their study, when asked about why they never altered the pattern in which they used their washer, replied *“...I keep doing it because it is working”* and *“I’ve never needed different results. I’ve never had any reason to change what I do”*. Interestingly, the reason for the adoption for many patterns of use were themselves not the result of a reasoned choice and in one case, the reason provided was simply that their mother had told them to do it that way. Habitual behaviour can also be quite powerful. For example, one participant reported that despite learning that warmer temperatures on the washer were not required for better cleaning and could save money and energy, they preferred and continued to use the warmer settings. This demonstrates both the resilience of habitual behaviours, once set, and also their relatively arbitrary origins. This suggests that while habitual behaviours may be hard to change towards more conserving practices, once set they might be relied upon to continue without change.

[8] The 5 selected households were a subset, ultimately, of 500 households part of a larger quantitative survey, so this conclusion may be representative of the full set, however this is not clear in the paper.

In addition to the impact of individual household decision making on DECCE savings, it is also important to consider what, if any, impact the household's neighbourhood may have on these decisions. van Raiij and Verhallen have explicitly stated this as a critical factor in determining household energy behaviour [43, 34]. More recent research such as that by Weenig and Midden [44] has suggested that the level of social cohesion and density of the social network are important indicators in determining the impact of the neighbourhood. Although the presence or absence of immediate neighbours is to some extent determined by dwelling typology, the impact of neighbourhood patterns on energy use is currently not explicitly considered in any of the existing models. This could be an important factor where future policy depends on self-regulation through peer feedback. For example, in a socially cohesive neighbourhood, a powerful motivation for DECCE reductions could be provided by smart meters that ranked individual household consumption against others in the same neighbourhood. Another potential benefit of such information could be the capacity for the modelling of local scale scenarios for a city or a region of the UK. Therefore, the absence of physical neighbourhood information is a weakness of contemporary models that requires investigation and evaluation.

Since achieving DECCE reduction centres on users adopting lifestyles, technologies and behaviours that can result in savings, modelling these behaviours to quantify both the opportunities and risks in putative strategies will be essential.

2.5. Summary of limitations

This section has argued that though current national-scale UK domestic sector models have been successful in answering important questions, the approaches they adopt are not inherently sustainable. We highlighted some limitations common to all these models that will need rethinking if they are to continue to be useful. These include (i) the use of average dwellings and the granularity of the model, (ii) the difficulty of including emerging and future datasets, (iii) the use of deterministic modelling for uncertain futures and (iv) the difficulty of modelling the impact of building occupants through their interaction with both the building and the wider socio-economic environment. The next section discusses some alternative approaches to solving these issues.

3. Planning for the future

Section 2 concluded that existing modelling approaches will need to be reconsidered in order to meet future modelling challenges. Clearly, some of these issues can be solved by modifying current approaches. For example, the problem of probabilistic modelling can be attacked by adopting well established methods such as Monte Carlo simulations. New datasets can be incorporated by making piecemeal changes to existing code. Human↔building interaction can be accounted for through implicit assumptions or through scenario specification. An example of this would be the current practice to account for changing thermal comfort expectations by specifying assumed demand temperatures. Conversely, other issues—such as the use of average dwellings or the impact of the neighbourhood—are not tractable through traditional (equation based modelling) methods. In fact, the use of average dwelling categories would have to be an inherent feature of any resource-effective equational model.

As highlighted in Section 2.4, sectorally defined models can only answer a part of the problem. When framing national policy, it is crucial to understand where outcomes from one sector are being supported or defeated by outcomes from another sector. We therefore need a single unified modelling framework that is capable of meeting all of these challenges with a computational cost that is not greater than those available in typical research facilities. Whilst doing so, we need to remember that a model is only an idealised representation of the features considered significant from the real world and is not meant to represent every complexity of the real world.

Before we discuss possible alternative approaches, it is worth noting that the issues we have raised are neither exhaustive nor selected for the greatest impact on domestic energy use and carbon emissions modelling. Rather, they have been selected to demonstrate the range of current and foreseeable problems with existing approaches. Indeed, the real impact of some of these issues (e.g. neighbourhood impact) is not known at present. What we are proposing is that the research community needs a unified and agreed upon approach that allows us to quantify the impact of these questions without requiring expensive or exhaustive methods to test them in the real world.

3.1. An alternative modelling paradigm

In reviewing current approaches used to undertake analysis of Domestic Energy Consumption (DEC), Keirstead defines two broad frameworks: 'disciplinary frameworks' and 'integrated frameworks' [45]. The disciplinary frameworks he identifies are essentially the same as those identified by Lutzenhiser (engineering, economics, psychology, sociology and anthropology), as described in Section 2.4. However, Keirstead recognises Lutzenhiser's proposed 'cultural model of household energy consumption' as a different kind of approach which he terms an integrated framework. He defines this as "a conceptualisation of DEC that acknowledges the expertise of disciplinary approaches but seeks to situate this knowledge within the broader context of energy consumption including social and behavioural factors". Clearly, the issues we have identified in Section 2 are inter-disciplinary and any effort to model them as part of the same system must necessarily fall under the definition of an integrated framework. This position (cited by Keirstead) was also identified as far back as 1983 by Yates and Aronson [46, p.435], saying that DEC "can no longer be viewed as a purely technical or economic problem but as a people problem as well".

Before moving on to describe the agent-based implementation of DECarb it is useful, from a modeller's point of view, to reflect upon the macro-level requirements that an integrated framework imposes on the modelling tools that are going to support it. The two essential characteristics of an integrated model are that:

(i) It comprises multiple discipline-specific models, some of which may be pre-existing; each of these needs independent *and* integrated verification and validation to ensure that isolated and embedded behaviour match; furthermore, each needs to be independently controllable for fidelity of modelling both for alignment with other components and for providing a means for the user to zoom in on particular aspects of the integrated model.

(ii) It provides adequate means to specify and control—both at design time and during run-time—the linkage between the discipline-specific components.

It is exactly this flexibility, as Keirstead argues, that is provided by agent-based modelling, encouraging as it does bottom-up thinking, focussing on the details of interactions between individuals. Such an approach also enables both the independent testing of small populations in isolation, the encapsulation of existing models by individual agents, as needed, and the integration of multiple models through individual agent interactions.

Equational- and agent-based modelling are often seen as opposing poles with no real connection between them, but this is not necessarily the case. Indeed, we argue there is clear progression from one to the other that is characterised by the degree of autonomy accorded to each individual:

- at the equational end, the individuals are totally regimented, being represented at their simplest as a single datum, but perhaps more likely as a data tuple, and each undergoing a globally defined transformation that is the equation determining the evolution of the individuals.
- at the opposite end, the individuals are completely autonomous, being represented at their most complicated as multiple planning systems with databases of information about their environment, other individuals and themselves. Transformation comes about through communication with other individuals and consequent updates to the databases, but at all times, under the control of the individual.

In between, there is a discrete spectrum of recognised modelling approaches that go by various names, depending on discipline and characteristics. For example: the transformation can be determined by a combination of the global rules and the current state—that is using elements of the current state to navigate conditional transformations, so that individuals are processed by the same rules, but which subset of those rules apply is a function of local state. There are a number of ways this can be achieved, but in general such systems are called "marionettes" [47] and have the attraction of being operationally very close to Equation Based Modelling (EBM), but through the random individual value, exhibit some variation in behaviour. We have used this technique to validate the ABM implementation of DECarb described in the next section. Other variations on the spectrum between EBM and ABM are recognisable in cellular automata, the classical Game of Life and swarm intelligence.

In programming terms, the differences between the variations outlined above are not that significant; as with programming languages, it is a matter of choosing the right approach for the domain. What matters is that individual behaviour is determined by using some combination of global rules and individual data to determine the next state of an individual. However, a simple reorganization of this model enables the progression to full autonomy: the first step is for each individual to have its own copy of the global rules; clearly the consequent behaviour would be equivalent to the previous model. Then, we may allow individuals to have their own distinct rules, leading to individual behaviours and subsequently to full autonomy as outlined earlier.

4. An ABM implementation of DECarb

As a first step to realising the desired properties of a domestic stock modelling system, we briefly present an implementation of DECarb as an ABM system. This implementation does not yet contain many of the requisite features for a fully fledged model, but does provide a robust framework for building up to a complete feature-set. To differentiate between the two implementations, we refer to the equation-based model as DECarb-EBM and the agent-based model as DECarb-ABM.

Firstly, to provide some context, we outline the equational model from which we started (DECarb-EBM: Figure 1) and briefly describe the main components. The model consists of an Interface into which a given scenario can be fed. The Interface is supported by Core Data consisting of: (i) physical dwelling data, separated into six historical age-classes, derived from house condition survey and national statistics, (ii) spatial data for dwelling archetypes, (iii) UKCIP climate data (UKCIP02 at present) and (iv) other supporting data. We group the interface and the core data, as DECarb Core in the diagram. Information flows from DECarb Core to the EBM-Engine which uses the Age-Class Builder object to produce new age class data. These data are then fed into the DECarb Energy Calculator object which implements a version of BREDEM to undertake energy and carbon emissions calculations. This last component is particularly important, since we are able to re-use it in the ABM simulation to compute changes for individual households (see section 4.2.1)

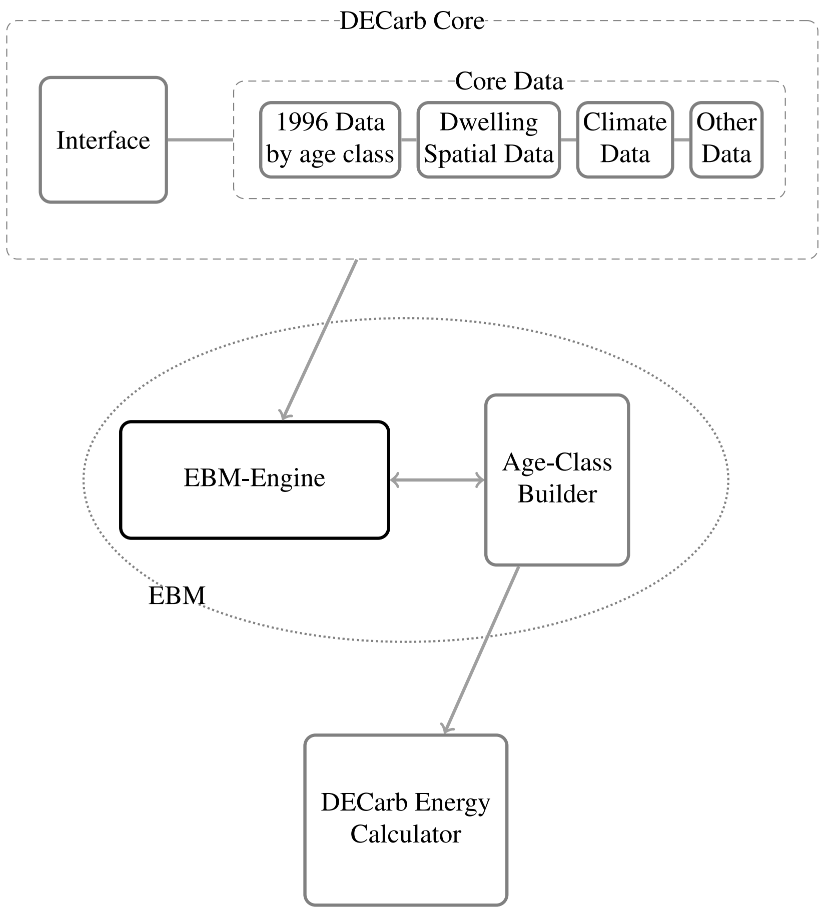

Figure 1: DECarb-EBM architecture

4.1. Model setup

When modelling a problem domain, a critical early part of the process is the identification of individuals and of observables. Observables are measurable characteristics of interest that change over time; they can be associated with either an individual or a collection of individuals [48]. In DECarb-EBM, the individuals are the 8,064 *dwelling categories* (for each age class) and the observables are the *attributes* of these categories (dwelling type, construction type etc.). The essence of the computational model is then one of transforming a dataset by applying the same set of mathematical operations to each individual at each time step[9] to obtain a new dataset. Thus, the individuals are passive and the modelling approach is typically called "top-down". Using the same observables, but modelling *homes*[10] as individuals, it is possible to take a micro, or bottom-up, view of the problem, where the individuals are active and the behaviour of the model is characterised by observation of individual interactions, making it a kind of complex system.

A complex system is typically defined as one with emergent properties that arise from non-linear interactions between its multiple, usually large in number, interacting constituents. Jennings defines a complex system as many subsystems related hierarchically, these subsystems work together to achieve

[9]'Time step' here is used to mean an arbitrarily long period that is determined by the requirements of the domain being modelled. We have chosen a time step of one decade, starting from 2000, because this is appropriate for the phenomena under consideration and a finer resolution results in unnecessary computation, but this can be adjusted for other intervals, such as annually, as required.

[10]Here, by home, we mean both the physical dwelling and the occupying household.

the functionality of their parent systems [49]. The separate subsystems can interact with their environment and are able to respond to changes by altering their internal structure. If a home is to be the finest grain constituent of the system, it is necessary to decide exactly how one home is represented.

4.1.1. Dwellings as individuals

The immediately intuitive idea is to model a dwelling as an individual. After all, it is the dwelling to which all these measurable attributes belong; it is the dwelling that has the insulated walls, double glazing etc. It is also to the dwelling that any energy consumption related changes will be made. But there are also problems with this approach: what happens if the dwelling is demolished? Estimations have placed an upper bound on the annual demolition rate as being 130,000 by 2030 [6], which would create a massive turnover every year and affect the continuity of the simulation. Additionally, a dwelling is a passive object for humans and cannot interact or exchange stimuli with another dwelling. The argument to model houses as individuals unravels rapidly from that point onwards. While it is necessary to model the physical characteristics of a dwelling, we also need to take account of behavioural properties, leading the discussion on to the concept of modelling households as individuals.

4.1.2. Households as individuals

A household can be defined as the inhabitants of a dwelling: they are not physically tied to their residence and they can move freely from one house to the next. Modelling households as individuals addresses the limitations that modelling dwellings as individuals posed. If a dwelling is demolished, the household will just move to another property. From this perspective, the physical dwelling simply becomes an attribute of the household. Crucially, households can have other attributes such as different behavioural characteristics and traits, facilitating the creation of a heterogeneous model. Households, as actors in a wider environment, can react to changes in the physical (environmental), political, regulatory and economic climate whilst simultaneously responding to changes in other households. For example, a two-person household with young occupants would have a different occupancy and heating pattern to a two-person household with Old Age Pensioners (OAPs). Obviously, these households will exhibit varying energy use for the same heating set-point. This complexity is manageable with more traditional EBM methods. However, with a fully autonomous ABM, one could model the same young two-person household changing at some future time step to a three-person household with a different requirement for heating set-points and patterns. The ABM implementation explicitly allows for such traits to be associated with the household, though this has not been implemented yet. While BREDEM is somewhat simplistic in its treatment of these variables, it carries the capability for modelling these variations provided new data on household energy behaviour becomes available.

4.1.3. RePast

DECarb-ABM uses RePast which is a software framework for agent-based simulation created by Social Science Research Computing at the University of Chicago, for ABM in the social sciences[11]. It provides an integrated li-

[11] `http://repast.sourceforge.net/index.html`

brary of classes for creating, running, displaying, and collecting data from an agent-based simulation. RePast has an unconstrained approach—allowing any type of agent-based model, and also offers explicit support for several common ABM tasks [47]. In addition to this, RePast was designed to have a short learning curve and offers comparable performance to similar frameworks when weighed against its other benefits [50]. It provides a wide range of library packages which allow the modeller to access features such as QuickTime movies and snapshots and uses Java which is largely free of the memory leaks (found in C, C++ and Objective-C) that are often problematic for large-scale, long-running simulations.

4.2. DECarb-ABM architecture

A RePast model consists of three kinds of components: (i) a model, describing the essential elements of the simulation (ii) a space, which controls the environment (iii) at least one agent, being the entities that co-exist and interact in the space. Although the model is the most complicated part of the simulation, most of the details can be hidden from the developer, because they are the same for many kinds of simulation. Consequently, the developer typically just inherits this packaged behaviour by creating a subclass of the standard RePast model class `SimModelImpl`. A similar situation occurs with the space object which can just be a standard RePast container for the agents. DECarb-ABM's space is a spatial grid rather than an abstract space and every agent has a location within this space defined by a pair of coordinates. Modelling the landscape spatially conveniently reflects a physical aspect of the real world, by giving households actual locations, which provides the means to model the influence of geographical neighbour's actions. Although we do not address it in the current implementation, we are also aware of the need to capture social structure, which can also be a strong influential factor on agent (in the economic sense) actions. RePast also provides the abstract spaces in the form of networks and these could readily be used to realize social connections and hence incorporate their influence on agent actions. Following the conclusion of the discussion in sections 4.1.1 and 4.1.2, the basic agent (individual) in DECarb-ABM is the household and encapsulates the seven metrics that define dwelling categories in DECarb-EBM (see Section 2.1)—that is, the dwelling attributes are *part* of the household object, as argued above—which are then processed by the stock transformation method. Figure 2 shows the basic setup for DECarb-ABM and the individual elements are described below.

It is noteworthy that while this paper primarily ascribes agent-behaviour to households, almost any entity that interacts with households can be an agent in the model space. For example, one could seed a Local Authority agent that set special renewable energy targets, a Central Government agent that sets time-varying tariffs for exported renewable energy and an Installer agent that provides free PV installation and recovers cost through a fixed repayment from the household. Indeed, the model is capable of handling an almost arbitrary number of (and types of) agents that can be customised to examine the impact of specific policy or technical measures on the housing stock. This type of seemingly arbitrary extensibility is extremely difficult to reproduce with other approaches, such as stochastic or Monte Carlo modelling.

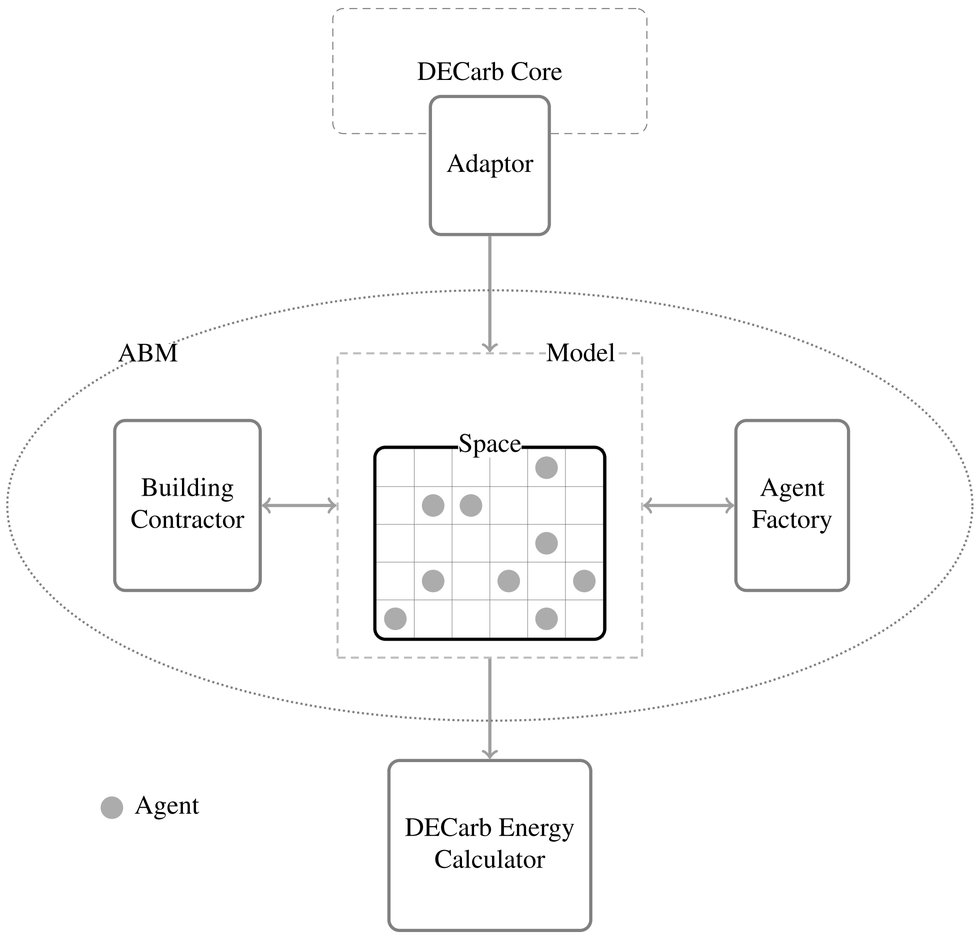

Figure 2: DECarb-ABM architecture

4.2.1. Adapter

The adaptor class acts as an interpreter between the re-usable elements of DECarb-EBM and DECarb-ABM. The make-up of each static age class for the 1996 housing stock (the base year in DECarb-EBM) is defined in separate Microsoft Excel files. For each age class, the proportion of the population that each dwelling category represents is recorded. DECarb-EBM reads in these files and creates six objects, one for each age class. In DECarb-ABM, the Adapter passes each such object to the model and using these figures, agents are generated in a deterministic order and each one is placed at a randomly determined location on the grid. The effect of populating the grid in a deterministic order has, at present, not been explored as agent location does not affect output. In a situation where the location of an agent had a bearing on the output of the model and the results of the model were being used to prove a hypothesis, it would be necessary to examine the effect of placing the agents in a deterministic order versus the effect of placing the agents in a nondeterministic order.

4.2.2. Model and Space

DECarb-EBM models four different regions, representing different areas of the UK, whose outputs are added to form a national figure. There are currently no dependencies between these regions and they can therefore be modelled separately in DECarb-ABM.

Library functions for 2D-spaces in RePast return all of the agents within a certain distance of a grid point. There are two common techniques for determining the neighbours of an agent: Moore and von Neumann (Figure 3) [51]. DECarb-ABM adopts the Moore neighbourhood pattern as it was

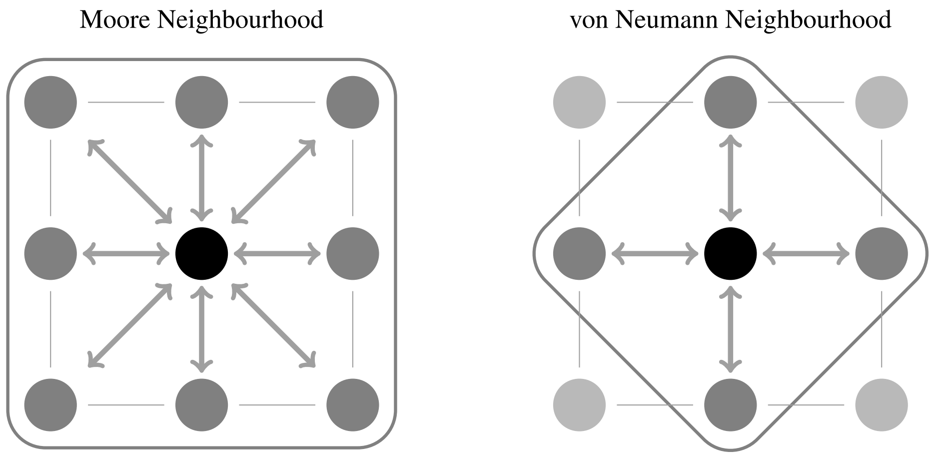

Figure 3: Moore and von Neumann neighbourhoods

felt to capture better the realworld situation. There is no data to test this against and so this is simply an assumption made in the model.

4.2.3. Agent Factory

Agent generation is encapsulated using the "factory" design pattern [52]. A static method in the factory returns an agent with a base set of attributes and the age class to which the agent belongs. Implementing in this fashion ensured that agent creation was kept separate from the computation in the model, and as such any changes to the creation of the agents was entirely hidden from the model. Every agent returned by the factory represents one UK household. However, as this implementation was developed on a small laptop machine, a scaling factor was introduced to reduce the number of agents to take account of the memory available at the time. The scale factor is defined as:

$$scale factor = \frac{total\ households}{agents\ created}$$

The scale factor in this case was 200, but is calculated by the model at the start of the simulation to ensure that categories with dwellings less than 200 can be accounted for. Total households refers to all households in every dwelling category in the age class—even those that are not represented in the ABM (i.e. those for which the dwelling category contained fewer households than the scale factor). This ensures that the correct number of total households is represented. At any point in the simulation, multiplying the agent population of an age class by the scale factor provides the total number of households in that age class.

4.2.4. Building Contractor

The Building Contractor class was designed to allow greater fidelity in modelling dwelling demolition in DECarb-ABM compared to the demolition model in DECarb-EBM. In DECarb-EBM, the number of dwellings to be demolished are calculated from user-supplied data for total population, persons per household and demolition rate per annum. From these data, the model demolishes dwellings starting from the oldest age class (with the assumption that older dwellings would be more inefficient compared to newer ones). DECarb-ABM implements the Building Contractor class, initially for the purpose of replicating this behaviour, and thereby validating the ABM implementation, but also to allow for the evaluation of other demolition policies.

4.2.5. DECarb energy calculator

In the current implementation, the agent attributes produced in the previous steps are passed to DECarb-EBM, which implements a version of BREDEM to calculate energy consumption and carbon emissions (see Figure 2). In principle, this can be any model that can undertake such calculations. Apart from further technical improvements in model physics, future functionality could include modelling of impact on space heating, hot water or lights and appliance use by accounting for household characteristics (age, income etc.) supported by empirical data.

4.3. Validation and verification

One of the important tasks for a simulation study is determining how accurate a simulation model is with respect to the real system [53]. Effective validation[12] and verification[13] can increase confidence in the model, which in turn makes the outputs more informative and valuable. Kennedy and Xiang have separated these methods into subjective (face validation, tracing, Turing test and parameter sweep) and quantitative (docking and historical data validation) approaches [53, 54].

As part of our approach to validating the new model, DECarb-ABM currently employs marionette agents [47, See also]. As described in Section 3.1,

[12] Validation involves making sure that the correct abstract model was chosen to accurately represent the realworld phenomenon, best captured through a qustion of the form "Did I produce the right simulation?"

[13] Verification involves making sure that the code generating the phenomenon has been written correctly to match the abstract model, best captured through a question of the form "Did I produce the simulation right?"

these agents do not possess autonomous behaviour and are guided by system level aggregate properties. Agents are assigned probabilites for adopting various traits (such as adding insulation characteristics) at a global level and they adopt these traits at each model time-step as a function of their individual assigned probability for that particular trait. Parunak et al promote this technique as a middle-ground between ABM and EBM in relation to how the behavioural decisions of an agent can be determined by evaluating equations [48]. Agents have no local or global knowledge—they are simply marionettes acting as they have been instructed. Taken with the case made by Parunak, we conclude that using marionettes in itself is a means to build confidence in the abilities of the ABM stock transformation method, and paves the way for further exploration of using ABM for this purpose, whilst opening the way to using agents with greater degrees of autonomy.

DECarb-EBM was validated using back-casting from the base year, 1996, to 1970 and comparing output to known energy use (from the Digest of UK Energy Statistics, DUKES) and modelled carbon emissions (from the Domestic Energy Fact File, DEFF)[14]. DECarb-ABM uses the same approach [13]. This allows the output to be docked[15] with DECarb-EBM and validated against known data.

Figures 4 and 5 show the result of docking DECarb-ABM with DECarb-EBM disaggregated by age-class, of which there are six, from pre-1900 to

[14]Back-casting is just like forecasting in that it starts from a fixed time point, but the model is run *backwards* in time to test the capability of the model to reproduce observed data. See [13] for a detailed explanation of back-casting.

[15]Docking is a process of validation through model-to-model comparison

1980–1996. Every point (p) on the plots is derived from the difference between the ABM and EBM value (in Peta Joules, PJ or Million tonnes of Carbon, MtC) for a given age-class (i) in a given year (y) divided by the corresponding sum (PJ or MtC) of all age-classes in the EBM for that year[16]. Thus:

$$p_{i,y} = \frac{ABM_{i,y} - EBM_{i,y}}{\sum_{i=Pre-1900}^{1980-1996} EBM_{i,y}}\%$$

The results for the ABM are the mean averages of twenty runs of the ABM[17]. The figures show that the differences are very small in comparison with the total figure for any given year. In both figures, the 1980-1996 age-class for the year 1990 shows the greatest difference between the two models: -2% (equivalent to 40.4 PJ) in Figure 4 and -1.5% (equivalent to 0.7 MtC) in Figure 5, respectively, of total predicted energy consumption and carbon emissions by the EBM in 1990. It is therefore evident that, whilst there are small differences, the ABM successfully replicates the behaviour of the EBM.

Figures 6 and 7 compare aggregated DECarb-ABM outputs against DUKES and DEFF data with DECarb-EBM outputs for reference. Here again, the results are a mean of 20 runs of the ABM. The differences evident in the 1990 time-point calculation have been documented and discussed for DECarb-EBM [13], and are due to 1990 being a much warmer year than the 30-year

[16] By measuring the deviation against the aggregate EBM for each year, we get a better picture of the ABM's performance compared to measuring directly against the EBM age-class.

[17] The EBM is run only once as, being deterministic, it always produces the same result.

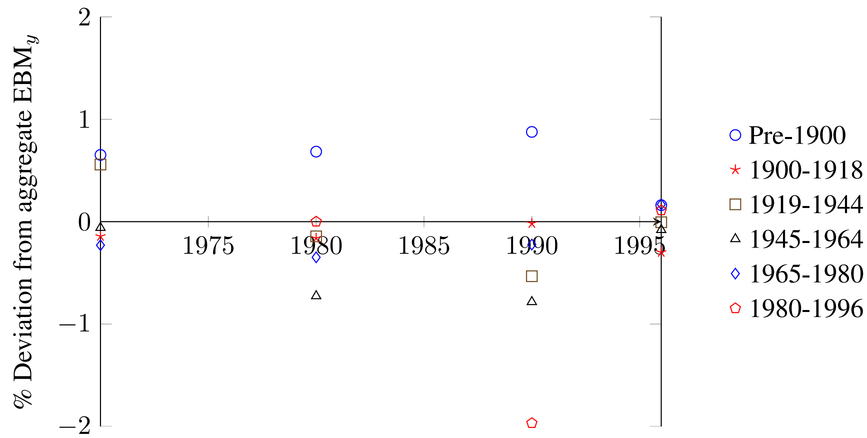

Figure 4: Deviation in modelled energy consumption of each age-class (DECarb-ABM_i − DECarb-EBM_i) compared to DECarb-EBM's aggregate for all age-classes, in each year.

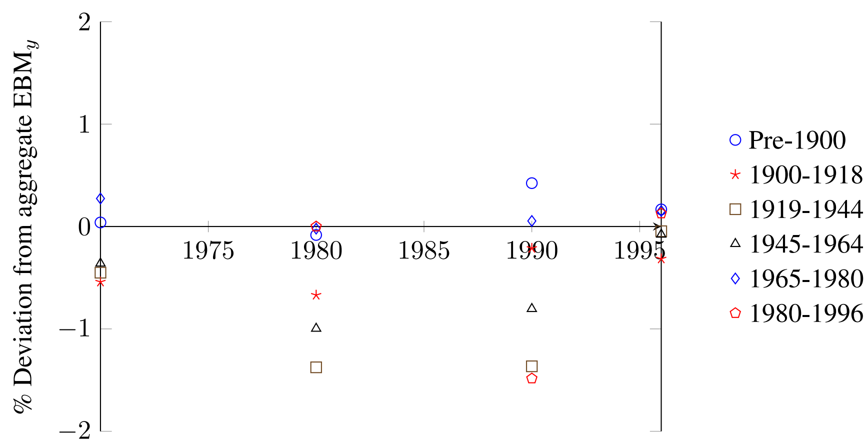

Figure 5: Deviation in modelled carbon emissions of each age-class (DECarb-ABM_i − DECarb-EBM_i) compared to DECarb-EBM's aggregate for all age-classes, in each year.

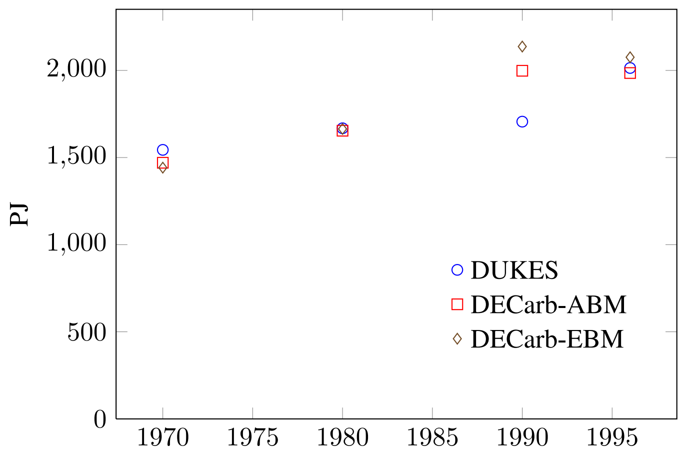

Figure 6: DECarb-ABM and DECarb-EBM modelled energy consumption compared to actual energy consumption from DUKES [55] data (PJ).

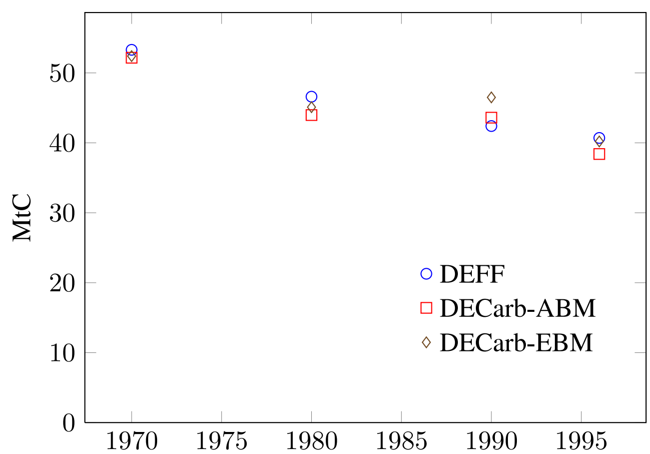

Figure 7: DECarb-ABM and DECarb-EBM modelled carbon emissions compared to DEFF [56] modelled data (MtC).

	Deviation from DUKES	Deviation from DEFF
DECarb-ABM	+2.5% (−2.4%)	−2.7% (−4.5%)
DECarb-EBM	−5.4% (−1.3%)	−0.9% (+2.0%)

Table 1: Average deviation from historical domestic energy consumption data (DUKES) and modelled carbon emissions (DEFF). Figures in brackets show the deviation if data for 1990 is suppressed.

average climate data used in DECarb[18]. Table 1 shows the difference between DUKES and DEFF data compared to outputs from both DECarb-ABM and DECarb-EBM, with and without 1990 outputs.

5. Exploration of non-deterministic issues and agent autonomy

This paper has thus far concentrated on the replication of previous, equation based, results to demonstrate the validity and robustness of an ABM approach to domestic sector stock modelling. Work is currently in progress to explore the modelling of non-deterministic issues and agent autnomy. We discuss some preliminary results below to demonstrate the potential of ABM in terms of its easy extensibility.

[18] As DECarb was built in the first instance to develop long term scenarios using the UKCIP climate data, it was necessary to use modelled 1960-1990 average UKCIP data so that changes resulting from climate change could be consistently compared. Since DECarb-ABM inherits legacy code from DECarb-EBM, it is not possible at present to use real weather data. We do not see anything to prevent its incorporation in the future if required, nor would we expect this to have any significant impact the validation results.

5.1. Demolition Policy

We carried out a preliminary evaluation of three demolition policies[19]: (i) oldest properties are demolished first (ii) random properties are demolished and (iii) least energy-efficient properties are demolished first. The simulation revealed differences between the three policies that were consistent with the expectation that demolishing oldest and least efficient properties would be better options than random demolition. However, the tests also showed that the magnitude of differences between the three scenarios is very small—scenarios (ii) and (iii) differed from (i) by only between 0.4% and 2.8%—in terms of eventual overall stock energy characteristics. If true—and it is worth stressing again that these results are preliminary—this result could have important policy implications, as it suggests that aggressive replacement of inefficient stock may not have a significant net benefit compared to random (which we take as representative of market-driven) replacement. The only aspect of demolition that appears to count is the total number of demolished dwellings replaced with more efficient stock. Under such a scenario, resources would be better chanelled towards increasing demolition rates without regard for the nature of stock being replaced.

5.2. Household Behaviour

We designed a simple theoretical behavioural framework to test the capability of the model to simulate behavioural responses of households to changing conditions. Using van Raaij and Verhallen's behavioural model, we posited that a household's uptake of double glazing was influenced by three

[19] That is, demolition of dwellings with the intention to replace with more efficient stock.

factors: (i) household income (ii) installation by neighbours and (iii) government policy. Preliminary evaluation suggests that the model captures expected behaviour under variations of all three variables: higher household income allowed households to adopt double glazing at a faster rate, the more neighbours with double glazing the greater the rate of adoption and fiscal incentives from the government stimulate uptake. Here, useful inferences for policy can be made by replacing the theoretical assumptions of the framework (both the assumptions themselves and the starting conditions) with empirical data collected, say, from surveys.

5.3. Emergent Properties

What both these examples demonstrate is the value of an ABM approach for exploring emergent behaviour. In an equational environment, adding such functionality, if even feasible, would require significant re-coding. We were able to implement these tests—preliminary as they are—with very little coding and computational overhead. In both cases, the agents themselves were no longer marionettes responding to global level instructions. Each household agent had independent ability to make decisions within the boundaries specified by the simulation (i.e. they were bounded-rational agents). These two cases help underline what we see as the prime potential benefit of adopting ABM: the capacity to explore new issues with relatively small technical and computational overhead, while keeping the research focussed on the problem and not diverted by the complication of the tools.

6. Conclusions

This paper presents a number of arguments for a step change in the methodology for modelling national scale domestic energy consumption and carbon emissions. In summary, the paper argues that:

(i) The current use of average dwelling categories to represent dwelling stock requires validation and testing to achieve an efficient balance between modelling power and granularity of available empirical data.

(ii) Future datasets from a range of current studies will need to be incorporated in stock models which will impact the granularity of dwelling categories.

(iii) Methods using deterministic modelling are inappropriate for exploratory analysis of inherently uncertain scenario-based futures.

(iv) The real-world impact of technological options on energy use and carbon emissions can only be achieved through incorporating household adoption, purchasing and maintenance behaviours.

We also argue that these issues can be tackled through the use of an integrated Agent Based Modelling approach. A preliminary model using Agent Based Modelling, DECarb-ABM, based on an earlier equational model, DECarb-EBM, is presented. The ABM model was successfully docked with the EBM and validated through comparison with historical data. There are two noteworthy aspects to the results from the validation through docking:

(i) DECarb-ABM tracks the results from DECarb-EBM quite closely over the entire backcast period (1970-1996) using the same input data. However, enough differences in the data are evident, particularly between 1980 and 1996, to demonstrate that though these results are functionally equivalent they arise from methodologically diverse processes. This is important as it demonstrates that the ABM is not simply mimicking the EBM, even though the initial conditions for both simulations are the same.

(ii) The back-cast is within $\pm 5\%$ of both actual measured domestic energy consumption obtained from DUKES and modelled carbon emissions from the well established DEFF data. This suggests that the model is robust and is able to replicate real-world conditions sufficiently, giving confidence in future simulations.

Future work will expand the ability and scope of DECarb-ABM as indicated in Section 5 to investigate the effect of different household behaviours and demographic and technical scenarios, through both increasing the autonomy of individual agents—combined with regression testing to build and maintain confidence—and scaling simulations up to benefit from the greater computational power now available.

References

[1] IPCC, Climate Change 2007 - Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri,

R.K and Reisinger, A. (eds.)], Technical Report, IPCC, Geneva, Switzerland, 2007.

[2] Lord Turner of Ecchinswell, D. Kennedy, S. Fankhauser, M. Grubb, Building a low-carbon economy - the UK's contribution to tackling climate change, Technical Report, Committee on Climate Change, 2008.

[3] RCEP, Twenty Second Report. Energy - The Changing Climate, Technical Report, Royal Commission on Environmental Pollution, London, HMSO, 2000.

[4] DTI, Energy White Paper: Our energy future - creating a low carbon economy, Technical Report, Department for Trade and Industry, The Stationery Office, London, 2003.

[5] S. Natarajan, Levermore GJ, Domestic futures - Which way to a low-carbon housing stock?, Energy Policy 35 (2007) 5728–5736.

[6] B. Boardman, S. Darby, G. Killip, M. Hinnells, C. Jardine, J. Palmer, G. Sinden, K. Lane, R. Layberry, A. Wright, M. Newborough, S. Natarajan, A. Peacock, 40% House, Technical Report, Environmental Change Institute, University of Oxford, Oxford, 2005.

[7] L. Shorrock, J. Henderson, J. Utley, Reducing carbon emissions from the UK housing stock, Technical Report BR 480, Building Research Establishment, Garston, Watford., 2005.

[8] P. Dondi, D. Bayoumi, C. Haederli, D. Julian, M. Suter, Network integration of distributed power generation, Journal of Power Sources 106 (2002) 1 – 9.

[9] F. Blaabjerg, R. Teodorescu, M. Liserre, A. Timbus, Overview of control and grid synchronization for distributed power generation systems, Industrial Electronics, IEEE Transactions on 53 (2006) 1398 –1409.

[10] IEA, Mapping the energy future - energy modelling and climate change policy, Technical Report, International Energy Agency / Organisation for Economic Cooperation and Development, 1998.

[11] M. Kavgic, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, M. Djurovic-Petrovic, A review of bottom-up building stock models for energy consumption in the residential sector, Building and Environment 45 (2010) 1683–1697.

[12] L. Shorrock, J. Dunster, 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 25 (1997) 1027–1037.

[13] S. Natarajan, Levermore GJ, Predicting future UK housing stock and carbon emissions, Energy Policy 35 (2007) 5719–5727.

[14] B. Anderson, P. Chapman, N. Cutland, C. Dickson, S. Doran, G. Henderson, J. Henderson, P. Iles, L. Kosminat, L. Shorrock, Bredem-8 - model description: 2001 update, 2002.

[15] ECI, 2MtC (DECADE), Technical Report, Environmental Change Institute, Oxford, 1997.

[16] Building Research Establishment, Estimates of hot water consumption from the 1998 EFUS. Implications for the modelling of fuel poverty

in England., Technical Report, Department for Environment Food and Rural Affairs and Department for Trade and Industry, 2005. A summary report presenting data from the 1998 EFUS produced by the BRE Housing Centre on behalf of DTI and DEFRA.

[17] D. Johnston, R. Lowe, M. Bell, 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 33 (2005) 1643–1659.

[18] DECC, Invitation to Tender for Research Project: English Housing Survey Energy Analysis & Household Energy Model Development, 2009.

[19] DECC, BRH 120, Annex 4, EFUS 2011 Summary for Tender 20Nov09 Final, 2009. Invitation to Tender for Research Project: English Housing Survey Energy Analysis & Household Energy Model Development.

[20] Technology Strategy Board, Retrofit for the future, `www.innovateuk.org/competitions.ashx`, 2009.

[21] S. Firth, K. Lomas, A. Wright, R. Wall, Identifying trends in the use of domestic appliances from household electricity consumption measurements, Energy and Buildings 40 (2008) 926–936.

[22] M. Shipworth, S. K. Firth, M. I. Gentry, A. J. Wright, D. T. Shipworth, K. J. Lomas, Central heating thermostat settings and timing: building demographics, Building Research & Information 38 (2010) 50–69.

[23] A. J. Summerfield, A. Pathan, R. J. Lowe, T. Oreszczyn, Changes in energy demand from low-energy homes, Building Research & Information 38 (2010) 42–49.

[24] I. Richardson, M. Thomson, D. Infield, A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (2008) 1560–1566.

[25] C. Jardine, Synthesis of high resolution domestic electricity load profiles, in: First International Conference and Workshop on Micro-Cogeneration Technologies and Applications, National Arts Centre, Ottawa, April 29 - May 1, 2008.

[26] T. Crosbie, K. Baker, Energy-efficiency interventions in housing: learning from the inhabitants, Building Research & Information 38 (2010) 70–79.

[27] R. Critchley, J. Gilbertson, M. Grimsley, G. Green, Living in cold homes after heating improvements: Evidence from Warm-Front, England's Home Energy Efficiency Scheme, Applied Energy 84 (2007) 147–158.

[28] J. Gilbertson, M. Stevens, B. Stiell, N. Thorogood, Home is where the hearth is: Grant recipients' views of England's Home Energy Efficiency Scheme (Warm Front), Social Science & Medicine 63 (2006) 946–956.

[29] T. Oreszczyn, R. Lowe, Challenges for energy and buildings research: objectives, methods and funding mechanisms, Building Research & Information 38 (2010) 107–122.

[30] S. Firth, K. Lomas, A. Wright, Targeting household energy-efficiency measures using sensitivity analysis, Building Research & Information 38 (2010) 25–41.

[31] N. Baker, K. Steemers, Energy and Environment in Architecture. A Technical Design Guide, Taylor and Francis, 2005.

[32] IPCC, Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer L. (eds.)], Technical Report, IPCC, 2007.

[33] H. Wilhite, E. Shove, L. Lutzenhiser, W. Kempton, Society, Behaviour, and Climate Change Mitigation, volume 8 of *Advances in Global Change Research*, Springer Netherlands, pp. 109–126.

[34] W. F. van Raaij, T. M. Verhallen, Patterns of residential energy behaviour, Journal of Economic Psychology 4 (1983) 85–106.

[35] L. Lutzenhiser, A cultural model of household energy consumption, Energy 17 (1992) 47–60.

[36] L. Lutzenhiser, B. Hackett, H. Schutz, Social Variation and Electricity Consumption in San Diego, California: Exploratory Data Analysis and the California Energy Commission's Electricity Demand Forecast Model, Technical Report UER-196, University of California Energy Research Group, Berkeley, CA, 1987.

[37] B. Hackett, Energy consumption and energy billing in apartments, in: W. Kempton, M. Neiman (Eds.), Energy Efficiency: Perspectives on Individual Behavior, American Council for an Energy Efficient Economy, Washington, DC and Berkeley, CA, 1987.

[38] B. Hackett, L. Lutzenhiser, Energy billing, cultural variation and residential energy consumption, in: Summer Study on Energy Efficiency in Buildings, American Council for an Energy-Efficient Economy,, Washington, DC.

[39] Y. G. Yohanis, J. D. Mondol, A. Wright, B. Norton, Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use, Energy and Buildings 40 (2008) 1053–1059.

[40] S. Natarajan, Modelling Energy Use and Carbon Emissions from the UK Domestic Sector, Ph.D. thesis, University of Manchester, 2006.

[41] K. Gram-Hanssen, Residential heat comfort practices: understanding users, Building Research & Information 38 (2010) 175–186.

[42] J. Pierce, D. J. Schiano, E. Paulos, Home, habits and energy: Examining domestic interactions and energy consumption, in: CHI (ACM Conference on Human Factors in Computing Systems): Home Eco Behavior, pp. 1985–1994.

[43] W. F. van Raaij, T. M. Verhallen, A behavioral model of residential energy use, Journal of Economic Psychology 3 (1983) 39–63.

[44] M. W. Weenig, C. J. Midden, Communication Network Influences on Information Diffusion and Persuasion, Journal of Personality and Social Psychology 61 (1991) 734–742.

[45] J. Keirstead, Evaluating the applicability of integrated domestic energy consumption frameworks in the UK, Energy Policy 34 (2006) 3065–3077.

[46] S. Yates, E. Aronson, A social psychological perspective on energy conservation in residential buildings., American Psychologist 38 (1983) 435–444.

[47] L. Gulyas, Understanding Emergent Social Phenomena, Ph.D. thesis, Computer and Automation Research Institute, Hungarian Academy of Sciences, Budapest, 2005.

[48] H. V. D. Parunak, R. Savit, R. L. Riolo, Agent-based modeling vs. equation-based modeling: A case study and users' guide, in: Proceedings of the First International Workshop on Multi-Agent Systems and Agent-Based Simulation, Springer-Verlag, London, UK, 1998, pp. 10–25.

[49] N. R. Jennings, An agent-based approach for building complex software systems, Communications of the ACM 44 (2001) 35–41.

[50] N. Collier, Repast: An extensible framework for agent simulation, Chicago: Social Science Research Computing, University of Chicago, 2002.

[51] N. Gilbert, K. G. Troitzsch, Simulation for the Social Scientist, Open University Press, 1999.

[52] E. Gamma, R. Helm, R. Johnson, J. Vlissides, Design patterns: elements of reusable object-oriented software, Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1995.

[53] R. C. Kennedy, X. Xiang, G. R. Madey, T. F. Cosimano, Verification and validation of scientific and economic models, in: Proceedings of Agent

2005: Generative Social Processes, Models, and Mechanisms, Chicago. Argonne National Laboratory.

[54] X. Xiang, R. Kennedy, G. Madey, Cabaniss, Verification and validation of agent-based scientific simulation models, in: Proceedings of the 2005 Agent-Directed Simulation Symposium, April 2005. The Society for Modeling and Simulation International, pp. 47–55.

[55] DTI, Digest of UK Energy Statistics, Technical Report, Department of Trade and Industry, The Stationery Office, London, 2005.

[56] L. Shorrock, J. Utley, Domestic energy fact file 2003, Technical Report BR 457, Building Research Establishment, Garston, Watford., 2003.