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Incorporating technology buying behaviour into UK-based long term domestic stock energy models to provide improved policy analysis

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HIGHLIGHTS

- ▸ Long term energy models are reviewed with a focus on UK domestic stock models.
- ▸ Existing models are found weak in modelling green technology buying behaviour.
- ▸ Agent models, Markov chains and neural networks are considered as solutions.
- ▸ Agent-based modelling (ABM) is found to be the most promising approach.
- ▸ A prototype ABM is developed and testing indicates a lot of potential.

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ABSTRACT

The UK has a target for an 80% reduction in CO_2 emissions by 2050 from a 1990 base. Domestic energy use accounts for around 30% of total emissions. This paper presents a comprehensive review of existing models and modelling techniques and indicates how they might be improved by considering individual buying behaviour. Macro (top-down) and micro (bottom-up) models have been reviewed and analysed. It is found that bottom-up models can project technology diffusion due to their higher resolution. The weakness of existing bottom-up models at capturing individual green technology buying behaviour has been identified. Consequently, Markov chains, neural networks and agent-based modelling are proposed as possible methods to incorporate buying behaviour within a domestic energy forecast model. Among the three methods, agent-based models are found to be the most promising, although a successful agent approach requires large amounts of input data. A prototype agent-based model has been developed and tested, which demonstrates the feasibility of an agent approach. This model shows that an agent-based approach is promising as a means to predict the effectiveness of various policy measures.

1. Introduction

Energy efficiency first came on to the political agenda in the 1970s as a response to the oil crises. Since then it has been gradually gaining in importance. Today, the two main concerns are energy security – ensuring there will be continuous and sufficient supplies of energy; and climate change – concerns over emissions from energy generation (DECC, 2011a). In the UK, the main focus regarding emissions is on CO_2 and in the 2008 Climate Change Act the UK Government has committed the country to an 80% reduction target by 2050 from a 1990 base level. Approximately 28% of energy use is in the home (DECC, 2011b). This can be further broken down to some 56% for space heating, 26% hot water, 15% lighting and appliances and 3% for cooking (DECC, 2011c). Therefore, if an 80% overall target is to be met, significant reductions will be required in the domestic sector. Modelling can be used to help in planning a suitable pathway to 2050 in order to meet the carbon reduction target; for instance, by considering the impact of projected population changes, or to predict the effectiveness of different policy measures. There are two broad types of models: top-down models that are macro-economics based and typically operate on a whole economy basis; and bottom-up models operating at the micro-level and usually sector specific, e.g. domestic dwellings, transport, industry, etc. This paper therefore provides a comprehensive review of existing models that include domestic dwellings, and their various purposes, together with a discussion of the respective strengths and weaknesses of their different methods. To conclude, recommendations are made for new techniques that could be used to improve on existing methods.

2. Types and methods of modelling

As mentioned in the previous section, there are different types of models that use different methods and have different purposes;

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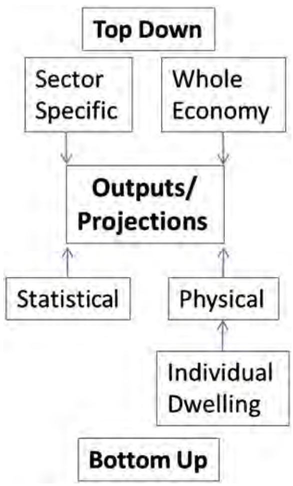

Fig. 1. Top-down and bottom-up model types.

nevertheless there are two broad categories: top-down, and bottom-up models, their constituent families are shown in Fig. 1. The following subsections then discuss each model type in turn.

2.1. Top-down models

Top-down models, as their name suggests, operate at a high level, using macro-level aggregated data, and do not consider the individual and the detail to which the individual is exposed. There are two broad categories of top-down model, whole economy, and sector specific.

2.1.1. Whole economy top-down models

Whole economy models typically operate at the national level, relying on aggregated data that is usually econometric, e.g. GDP, economic growth and inflation rates, population projections, etc. Since these models are looking at the overall picture they are used for large scale and long term planning, typically for energy supply and security. A whole economy model can be used to predict future energy demand, which then allows for planning of the generating mix that is required to satisfy the predicted demand. Therefore, for this sort of usage, high levels of individual data are not useful and disaggregated data is consequently ignored in favour of the macro-level data.

As an example, in Ireland (FitzGerald et al., 2002) an energy demand model has been developed. This was a whole economy top-down model. They found that in the period from 1960 to 2001 electricity demand increased at a rate of 5% pa and non-electricity at 1.2% pa and that the majority of changes to CO_2 emissions were due to changes in the generation mix. Their top-down model essentially considered only the effect of cost on demand – to this end they found that electricity has a very low price elasticity – i.e. large price increases are required to achieve a small reduction in demand. It is possible to suggest two main reasons for this—firstly, except where electricity is being used for heating, there is limited opportunity for substitution, secondly, it would suggest that the price is not yet high enough that excessive use is financially painful and therefore much higher prices would be required to affect behaviour in reducing usage and encouraging adoption of energy efficiency measures.

2.1.2. Sector specific top-down models

Due to their set-up, whole economy top-down models tend to be short on specific details, which can be addressed to some extent with sector specific top-down models.

A domestic sector top-down model will typically predict total energy demand and will track housing demolition and construction rates and similar high level data without a detailed analysis at the individual dwelling level.

The ADEPT (Summerfield et al., 2010) model provides a suitable example of the way a domestic sector top-down model can operate. In developing this model it is argued that an analysis of the overall energy demand does not require an understanding of the mechanisms driving individual changes, and instead aims to rely on the minimum possible level of data to provide an energy demand model. Therefore the model concentrates on the delivered energy of the average household, Q_d. The main data source used for the model is the Digest of UK Energy Statistics (DUKES) (DECC, 2011d). DUKES provides total domestic sector energy use (from which average energy use per household can readily be derived) together with temperature data. Combining this with price, ADEPT was defined as a simple regression equation as follows:

$$Q_d = B_0 + B_1\theta_e + B_2 P_q \tag{1}$$

Where $B_{0,1,2}$ are the regression coefficients, θ_e is the heating season's average external temperature and P_q is the energy price index (baseline set in 2005 where $P_q = 1$). This model therefore predicts the average energy demand based solely on energy cost and external winter temperature. As would be expected θ_e and P_q are negatively correlated with Q_d – i.e. as the external temperature increases energy demand decreases, and as energy prices increase energy demand decreases.

Therefore, such a model can be used for overall annual demand predictions; however, it is not appropriate for short term overall predictions, e.g. for continuous grid management. Nor does it consider the underlying changes that will take place to achieve the reductions predicted. So, depending on the aim of the model this is a significant short-coming of top-down models in that they can make projections of overall demand and predict future demand reduction without any consideration of the technologies that might be used for those reductions.

2.2. Bottom-up models

There are essentially two bottom-up approaches, statistical or physical. Statistical models rely on a sample of dwellings and typically look for relationships between appliance use and energy demand, typically via some form of regression with common regression factors such as appliance ownership and weather data (Swan and Ugursal, 2008). The predicted response for the sample is then extrapolated upwards for the wider population under consideration, whether that be local, regional or national. Therefore such models tend to be restricted to considering the relatively short term as they concentrate on day to day usage as opposed to long term stock transformation.

By way of contrast, physical models consider the physical characteristics of the dwelling stock. Using some form of thermodynamic assessment or heat balance, the energy use of an individual dwelling can be predicted, then by scaling up a suitable representative sample the entire dwelling stock can be modelled. This is therefore an explicit consideration of long term changes to the dwelling stock, which is consequently ideal for providing long term modelling and predicting the effect of different uptake rates for the various energy efficiency technologies available.

Physically based models rely on modelling some representative sample (either real or simulated) of the housing stock, which can then be aggregated to provide a simplified approximation to the entire dwelling stock being considered. Therefore, before considering the various physically based models, it is first necessary to consider the methods used for modelling an individual dwelling.

2.2.1. Individual dwelling models

In the domestic sector individual dwelling models will typically be physically based and their primary use will be for regulatory purposes—in the UK and the EU this will principally be to satisfy the requirements of the Energy Performance of Buildings Directive (EPBD) (EU, 2002). In the UK there are two versions for regulatory purposes for dwellings, the Standard Assessment Procedure (SAP) (BRE, 2011a) for new dwellings and the Reduced data Standard Assessment Procedure (RdSAP) for existing dwellings. RdSAP is a special version of SAP that makes assumptions, typically based on the age of the dwelling, for certain details that cannot easily be measured for an existing dwelling (e.g. wall U-values). SAP is therefore primarily designed as a regulatory assessment tool, as opposed to a prediction model. The full version of SAP is used for new dwellings where more detail will be available from the plans for the dwelling. These are the statutorily approved methods for carrying out a domestic energy assessment, and a SAP-based certificate, providing an efficiency rating on a scale from 1 (poor) to 100 (excellent), is required whenever a dwelling is constructed, sold or let. SAP is a physical based individual dwelling model largely based on the older BRE Domestic Energy Model (BREDEM) (Anderson et al., 1985, 2002). By considering the fabric of the dwelling, fixed heating and cooling appliances, and renewable energy technologies, SAP (and RdSAP) estimate the energy demand from space heating and cooling, hot water and lighting. But it excludes appliances and cooking (although it does include heat gains from these energy uses). Therefore SAP analyses over 80% of current domestic energy use; however, as the thermal properties of dwellings are improved and the efficiency of heating appliances improves and more renewable technologies are installed it can be anticipated that this proportion will reduce therefore making appliance use more significant. An important feature of SAP is that it makes standard assumptions as to usage for its calculations and makes no allowance for different types of occupants. For instance it assumes that living rooms will be heated to 21 °C for 9 h a day during the week and for 16 h a day at the weekend, with other rooms heated to 18 °C at the same times. These sorts of assumptions therefore make no allowance for variations in individual use. Whilst this decision may reduce the true accuracy of the model it potentially makes it more useful for comparison purposes as it allows an easy comparison of the energy demand of two different dwellings. Indeed this is one of the main aims of the European Energy Performance of Buildings Directive (EPBD) which requires an energy assessment on the construction, sale or lease of a property, with the intention that the assessment could be used as extra information for a prospective owner or tenant when deciding which dwelling to take.

In a similar vein to SAP, which is primarily for regulatory purposes, there are individual dwelling models intended for use as design tools. One of the main such tools is the Passive House Planning Package (PHPP) (Passive House Institute, 2007). PassivHaus was originally a German standard for recognising energy efficient new buildings and is now being exported to other countries, and also now has an option for dwelling refurbishment. PHPP is the UK tool for demonstrating compliance. In order for a dwelling to achieve the PassivHaus standard the modelling tool needs to predict energy demand below certain limits, e.g. specific heating demand $\leq 15\,\mathrm{kWh/m^2\,yr}$ and specific primary energy demand $\leq 120\,\mathrm{kWh/m^2\,yr}$. The primary energy demand includes appliances and so therefore PassivHaus makes an attempt at including appliance use, although this is primarily to ensure there is not overheating due to incidental gains from inefficient appliances, as opposed to a detailed modelling of appliance use. There are other tools for analysing dwellings that attempt to be more comprehensive, e.g. BREEAM—the BRE Environmental Assessment Method (BRE, 2011b), which, as well as energy use, considers other environmental impacts, e.g. water, waste, transport, etc. However, the energy component is typically SAP based.

Therefore there are a range of individual dwelling models, but they are primarily concerned with the fabric and heating and cooling systems, and do not provide detailed analysis of varying occupant numbers and behaviour. As can be seen, they have been primarily created for use in the design or regulatory processes, and are therefore predominantly assessment tools rather than predictive models, but as such can provide a useful under-pinning for stock-based models. These individual models tend to use standardised occupancy patterns that may not exactly match any individual household, but aim to be similar to a theoretical 'average' family, and therefore, if aggregated across the entire dwelling stock, should provide a reasonable estimate of total emissions.

2.2.2. Physical stock-based bottom-up modelling

Physically based models (also known as engineering models) operate by preparing a sample set of dwellings, applying changes to those dwellings and then calculating the effect of those changes. A number of these models have been developed for both the UK and other countries, a representative sample of which is discussed below.

2.2.3. Johnston

Johnston's model (2003) serves as a good introduction to stock-based bottom-up modelling in the domestic energy sector. As a stock-based bottom-up model it relies on having different types of dwelling in the model to represent the real world housing stock. In this case, the stock is disaggregated into just two types, based on construction date—pre-1996 and post-1996; the two types are then intended to be representative of the overall stock. The emissions of the individual dwelling types are calculated using an adapted form of BREDEM.

From this base, assumptions are made about the uptake of new technologies, population trends and changes in energy usage. By varying the input assumptions different scenarios can be analysed so that different future pathways can be explored.

Johnston produced three main scenarios to represent three different approaches to future energy demand, with the model providing projections from a start date of 1996 to an end date of 2050. The first scenario is Business as Usual (BAU)—the aim of this scenario is to simply continue the current trends to project the position in 2050 without any further government intervention. The BAU scenario therefore acts as a base point against which other scenarios can be measured, this scenario predicted a 33% reduction in CO_2 by 2050 from its 1996 starting point. The two other scenarios were Demand and Integrated. The Demand scenario focussed on demand reduction and predicted a 58% reduction in emissions, whilst the Integrated scenario added improvements to the grid electricity supply to the demand side changes to achieve a 74% reduction.

Whilst this simple model demonstrates the basic working of a bottom-up model, with the use of scenarios to consider various different situations, it has obvious limitations—in particular as it only uses two dwelling types the resolution of detail available is significantly curtailed.

2.2.4. BREHOMES

In contrast to Johnston's model, the BREHOMES (Shorrock and Dunster, 1997) model was a highly disaggregated model, which used an annual survey of around 18,000 homes to build up its stock profile into 1000 dwelling types. This greater resolution of detail in the housing stock allows for much finer analysis of changes and the installation of new technologies. As with Johnston's model the emissions of the individual dwelling types are calculated using a form of BREDEM. In the same way as Johnston's model, BREHOMES produced a default scenario, Reference, as a base point against which to compare other scenarios, and the main alternative scenario was Efficiency. This was an earlier model than Johnston's and as such the scenarios were not looking for particularly high savings nor over the very long term, instead the Efficiency scenario predicted a 13% reduction by 2020 from a 1995 base.[1]

This illustrates a potential problem with models. As they are projecting into the future it can be difficult to gauge their likely accuracy, and one potential method of comparing different models is to compare their outputs. However, it is difficult to do this accurately because different models tend to start from different positions, and analyse different scenarios. In addition, as many models are either difficult to use, proprietary, or do not publish all their assumptions it is frequently impossible to run the same scenario in two different models for comparison purposes. One of these problems – the end date – is usually addressed in newer models since many targets, both nationally and internationally, focus on 2050, so most newer models are typically aiming at the 2050 date, although they can often be used for in between dates too, usually 2020 and 2030, for which there are various subsidiary targets.

2.2.5. UKDCM2

The UK Domestic Carbon Model (UKDCM2) (Hinnells et al., 2007) is a newer model, with 2050 as its main target, and this is again a large scale model and is further disaggregated with some 20,000 dwelling types available. Again, these dwellings have their emissions calculated using BREDEM. UKDCM2 was used to produce the Home Truths report (Boardman, 2007) which analysed a number of future scenario pathways aiming for an 80% reduction by 2050. With the level of detail included in UKDCM2 it was possible to follow the installation rates of different technologies and the impact of different policy measures on the installation rates. As such it can be seen that a detailed stock-based model can be used for policy analysis. However, the policies analysed with UKDCM2 were largely prescriptive as the model lacks the requisite behavioural data for analysing policies that do not mandate a change but might instead alter the economics of a choice.

This highlights a further shortcoming of traditional bottom-up modelling; whilst a stock model can be used for analysing the effectiveness of policies that mandate a change (e.g. a ban on the sale of non-condensing boilers) they are poor at being able to model behaviour changing policies (e.g. a technology subsidy) as that requires further data sets to be able to understand and simulate the decision making process at the individual level.

2.3. MARKAL

The previous sub-sections concentrated on describe building sector stock models. There is a wide range of MARKAL (MARKet ALlocation) models used in many different countries (Zonooz et al., 2009). The UK implementation of MARKAL has been used for policy analysis for projections to 2050 (Skea et al., 2010). MARKAL models are bottom-up, energy service driven and whole economy. As service driven models they search for a least-cost optimisation between supply and demand. The residential sector is therefore modelled as a set of demands, appliances satisfying those demands, and energy sources driving those appliances (Kannan, 2007a), therefore MARKAL models are less explicit than the dedicated stock models previously described (Kannan and Strachan, 2008). In order to try and address this limitation some inputs are taken from other models; in particular, in the domestic sector UKDCM is used to enhance the inputs (Anandarajah et al., 2009). As MARKAL relies on inputs from other models it necessarily imports some of the limitations of those other models, in particular MARKAL is limited in modelling individual behaviour (Kannan et al., 2007b). Therefore it demonstrates the possibility of integrating different models to create a comprehensive model, but to improve the comprehensive model the constituent parts need to overcome their respective limitations.

2.4. Model summaries and international models

The previous sub-sections concentrated on describing some prominent UK-based bottom-up models. As short-comings have been identified, for completeness it is necessary to provide a brief summary of models used in other countries; therefore, the following table details the key characteristics of a more extensive range of UK models together with a representative sample of non-UK models (Table 1).

As can be seen from the table, whilst a number of models attempt to consider household variation in modelling the day to day energy demand from a dwelling only one, Yucel and Pruyt (2011) attempt to consider household variation when it comes to renovation driven improvements to the existing dwelling stock. There are a number of studies that try to consider the effect of different household types and behaviour (Yao and Steemers, 2005; Streimikiene and Volochovic, 2011; Yu et al., 2011). However, such research tends to concentrate on day to day usage and habitual type behaviour, as opposed to the one off behaviour when installing insulation or buying energy efficient equipment. Various pieces of research (e.g. Wilhite and Ling, 1995; Wood and Newborough, 2003; Abrahamse et al., 2007; Ouyang and Hokao, 2009) suggest that savings from such day to day behavioural change will only be of the order of 5–10%, thus showing the importance of physical improvements, and demonstrating a need to understand the influence of behaviour on the installation rates of the different technologies available.

3. Types of individuals in the UK housing sector

If the behaviour of individuals is to be modelled it is necessary to consider the different types of actors in the domestic sector. In the UK, there are essentially three different types of actors that are relevant. The first is the traditional owner-occupier: as the name suggests these people own their home (frequently with the aid of a mortgage) and live in it, as such they have the greatest flexibility over what improvements (if any) are carried out to their homes. The next category is tenants: in the UK most tenancies since the late 1990s are Assured Shorthold Tenancies, after an initial term of six months the tenancy can usually be terminated by the landlord giving two months' notice, or by the tenant giving one months' notice; therefore, tenants have much less surety of long term occupancy, and will only be able to request improvements to their home, it will then be up to their landlord to decide whether to carry out any improvements. If there are tenants there must be landlords, which is the third category of actors. The landlord category really needs to be further split into two sub-categories: the first is the private landlord—private landlords range from commercial organisations that have large portfolios of dwellings down to individuals who may only own a handful of properties and even the so-called 'accidental' landlord, who, due to the current economic climate

[1] Later work with BREHOMES produced scenarios to 2050 and indicated that a 60% carbon dioxide emission reduction was feasible (ShorrockL D., et al., 2005. Reducing carbon emissions from the UK housing stock. BRE Report BR480.).

Table 1
Summary of a representative sample of models.

Model name/authors, country	Summary	Disadvantages
BREHOMES (Shorrock and Dunster, 1997), UK	BREDEM based, 1000 dwelling types, weighted stock transformation, scenario analysis to 2020 (later extended to 2050)	No modelling of buying decision making
Johnston (2003) UK	BREDEM based, 2 dwelling types, weighted stock transformation, scenario analysis to 2050, highest possible saving 82%	Disaggregation too low for analysis of technology diffusion, no modelling of buying decision making
UKDCM2 (Hinnells et al., 2007) UK	BREDEM based, 20000 potential dwelling types, weighted stock transformation, scenario analysis to 2050 including 80% reduction	No modelling of buying decision making
DECarb (Natarajan and Levermore, 2007a, 2007b) UK	BREDEM based, 8064 dwelling types per age class with an initial 6 age classes	No modelling of buying decision making
CDEM (Firth et al., 2010) UK	BREDEM based, 47 dwelling archetypes as averages of dwelling stock	Lack of scenario outputs, no modelling of buying decision making
DECM (Cheng and Steemers, 2011) UK	BREDEM/SAP2005 based, 50 initial dwelling types, allows for regional analysis, includes an element of social modelling in predicting energy demand	No modelling of buying decision making
CREEM (Farahbaksh et al., 1998), CREEEM (Fung et al., 2000), CHREM (Swan et al., 2011), Canada	Several versions produced. Latest – CHREM: c: 17000 unique house descriptions. Latest version incorporates artificial neural network (ANN) to predict demand	Deals with houses only, not flats. No modelling of buying decision making
Chen et al. (2008), China	Statistical sample led collection of energy use and building characteristic data	Early stages, predictions and policy implications not yet available
Georgopoulou et al. (2006), Greece	Combined residential and commercial buildings 72 categories and 17 reduction measures. Scenarios based on technically feasible and economically feasible measures	No modelling of buying decision making
Steemers and Yun (2009), USA	3358 dwelling stock—reduced to 2718 for cooling, includes socio-economic factors when considering heating and appliance use	No modelling of buying decision making
Yucel and Pruyt (2011) Holland	3 dwelling archetypes, 9 household types. Attempts to model typical buying decisions based on economic viability	Real technologies not used, decision making purely economic, limited stock disaggregation

Table 2
Dwelling stock: by tenure United Kingdom 2009 (CLG, 2011a).
Source: CLG, 2011a: "Dwelling Stock: by tenure United Kingdom 2009, Live tables on dwelling stock" "http://www.communities.gov.uk/housing/housingresearch/housingstatistics/housingstatisticsby/stockincludingvacants/livetables/.

Owner occupied	Private tenancy	Registered social landlord tenancy	Local authority tenancy	Total
17,991,000	4,231,000	2,531,000	2,356,000	27,109,000
66.4%	15.6%	9.3%	8.7%	100%

has been forced to let out their own home and become a tenant elsewhere. The other type of landlord is the social landlord—these are governmental, or quasi-governmental organisations that will typically have a portfolio of several thousand dwellings which they own and manage. Table 2 shows figures for the housing distribution between these different sectors. As can be seen, owner occupiers account for two-thirds of dwellings, with governmental type landlords providing 18% of housing and the remainder being provided by private landlords.

The social landlord sector is the easiest for the government to intervene in, and encourage energy efficiency improvements. In recent years the prime policy mover for social landlords has been the Decent Homes standard. This set a target that all social housing should meet a minimum quality standard (including thermal performance) by the end of 2010; however, that date has progressively slipped and it was estimated that 92% of the social housing stock met the target on date, leaving 305,000 'non-decent' and a revised 100% target for 2018–2019 (CLG, 2010). Nevertheless, that is a fairly high compliance rate and suggests that minimum standards are a significant driver in this sector without the need for detailed analysis of the individual social landlord and their individual tenants. The rate of change can be seen in Table 3

The table shows that there has been improvement in the private dwelling stock too, but suggests that the private sectors are essentially about 10 years behind the social sectors. This therefore demonstrates that the greatest need is for improvements in the owner-occupied sector, which not only has the bulk of available improvements but also the bulk of the housing stock.

Having identified the owner-occupier sector as potentially the most fruitful, it is necessary to consider the data that needs to be compiled to understand the individual household and their decision making process. Essentially there are two questions that need to be considered: what triggers the decision making process; and once that process has been triggered, what are the factors that influence the final outcome? The answers to those questions are going to be unique in each situation, therefore a successful model will need to simulate a number of different responses with the aim of being representative of the entire population. Therefore consideration needs to be given to a suitable approach for incorporating such information into a model.

4. New methodologies

As discussed above, a new method needs to be found to incorporate individual (in particular home-owner) buying decision making into traditional bottom-up domestic energy modelling. Lee and Yao (2010) suggested an agent-based approach to incorporate this element, but before work progresses on an agent-based model it is first necessary to consider whether any other methods may be useful. Three potential methods were identified, as candidate methods requiring further consideration of their applicability at the individual level. These three possible ways forward are Markov chains, artificial neural networks, and, as mentioned above, agent-based modelling.

4.1. *Markov chains*

Markov chains describe state transition based on the probability of moving from one state to another. A traditional Markov chain has a set of available states and assumes a constant probability of change from one state to another, a simple example

Table 3
SAP energy rating by tenure for England (CLG, 2011b).
Source: CLG, 2011b "English Housing Survey Stock Report 2009" http://www.communities.gov.uk/publications/corporate/statistics/ehs2009stockreport.

Year	1996	2001	2003	2004	2005	2006	2007	2008	2009
Owner occupied	41.1	44.4	45.0	45.6	46.1	46.9	48.1	49.6	51.3
Private landlord	37.9	41.9	44.4	45.7	46.0	46.6	48.1	50.2	51.9
Local authority	45.7	49.6	52.0	53.9	55.3	55.8	56.2	58.0	59.6
Registered social landlord	50.9	56.4	56.7	57.3	58.9	59.3	59.3	60.3	62.4
Average	42.1	45.7	46.6	47.4	48.1	48.7	49.8	51.4	53.1

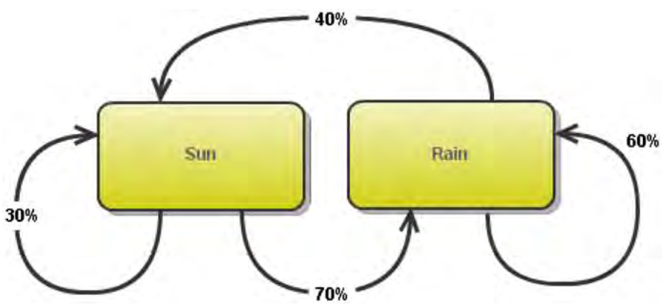

Fig. 2. Weather Markov chain.

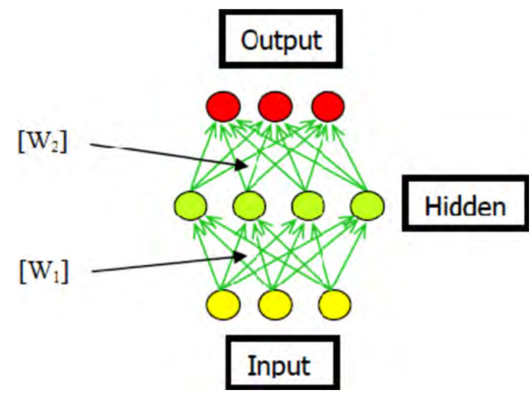

Fig. 3. An artificial neural network (Bhatikar et al., 1999).

is shown in Fig. 2 with the probability of tomorrow's weather based on today's, assuming only two available weather states—sun or rain.

As can be seen in this simple example the only information needed is the current state and the probabilities of changes from that current state to the available new states (which may include the current state). Therefore, in a typical Markov chain the state at time $t+1$ is only dependent on the state at time t (Elaydi, 2005). In addition it can be seen that a Markov chain can return to an earlier state. When considering householder buying decisions this level of certainty and independence from historic states is unlikely to apply; for instance, the probability of the installation of a new technology can be expected to increase with time (primarily due to expected rises in fuel bills and reductions in new technology costs). In addition, a return to previous states may not be possible, e.g. the probability of the removal of cavity wall insulation will be virtually zero. In using a Markov chain to run a simulation the output would be a set of probabilities of different states, and attempting to apply that at the individual level would not be intuitive, since it would suggest each household would install a non-sensible quantity of each technology. Markov chains have been used in energy modelling (e.g. Richardson et al., 2008; Widen et al., 2009; Richardson et al., 2010; Ardakanian et al., 2011) although this has primarily been short term load modelling, typically based on occupancy patterns. Therefore, Markov does not look like the right method for considering one-off buying behaviour in the long term, but is of use in short term load profiling.

4.2. Neural networks

The second potential method identified is an artificial neural network (ANN). An ANN has a number of layers of interconnected neurons, there are two visible layers—the input and output layers, and at least one hidden layer of perceptrons, as illustrated in Fig. 3.

In the figure, W1 and W2 refer to the weights applied to the different connections in the network. Neural networks typically run by being given an initial set of training data, which the computer uses to determine the most likely output for each input. During the training process the weights applied to the different connections inside the network are progressively altered with the aim of providing as close a match to the training data as possible. Once a network has been established it can receive some validation by inputting further data where the outcomes are known and in that way some indication can be achieved of the likely accuracy of the network when exposed to new data for which the outcomes are not known (i.e. the situations that the network is being used to model). In applying this to domestic energy technology buying decisions it can be seen that the inputs would be the individual householder's current state, information about the technology being considered, and information about external factors influencing the buying decision (previous experience, taxation, advertising, disruption, etc.); and the outputs would be predictions of whether or not an individual would buy the technology, given their unique set of circumstances. ANNs therefore appear to be quite a promising avenue, subject to being able to obtain sufficient training data for a model. ANNs are already being used in energy research, one of the earliest was Park et al. (1991) working on load profiling, which was similar to the Markov work previously described, following them there have been many more (e.g. Khotanzad et al., 1997; Pino et al., 2008; Bakker et al., 2008). As mentioned in Table 1, CHREM (Swan et al., 2011) uses an ANN in a longer term model, which is a development of Aydinalp et al.'s (2002) ANN work, but again, the ANN is being used for demand modelling, rather than explicitly modelling the technology buying decisions. Therefore, even though ANNs are beginning to be incorporated into long term bottom-up models they are only being used for a short term element of such models. There has also been research using ANNs in top-down research (Ekonomou, 2010; Kankul et al., 2011) which clearly lacks the detail of the bottom-up models. There is a also a major limitation with ANNs, in that they operate in a black box manner such that it is not normally possible to examine and understand the internal processes in the hidden perceptron layers of the network (Johannet et al., 2007). It may be the case that the network has identified some relationship between input and output data that was not anticipated and that only happens to work for the training data; indeed, with a complex decision making process where not all real world data will be able to be captured and quantified there would appear to be a greater chance of a network identifying some false relationship and relying on that.

4.3. Agent-based modelling (ABM)

Gilbert (2008) describes agent-based modelling as '*a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment*.' It can be seen that this can be applied to long term domestic energy stock modelling, whereby households will be the interacting agents and their environment is the housing stock, and indeed other households. In the period from now until 2050 it can be anticipated that most people will move home. This therefore adds a spatial dimension to long term domestic stock modelling, as householders will make decisions on improvements in more than one dwelling. In an ABM it is possible to include a spatial element, indeed, Schelling's seminal segregation model (1969, 1971), one of the foundations of ABMs, had autonomous agents which moved around a spatial grid in response to who their neighbours were. In this model Schelling had two types of agent and each turn the agents would decide whether they were 'happy' where they were based on the mix of neighbouring agent types. Just by operating this simple rule the model produced segregation patterns of the two populations that would be familiar to town planners looking at population distributions across a city. This is one of the strengths of ABMs, in that by setting simple rules at the micro-level, macro-level observations can be made that could not be determined simply by observing the system as a whole. These (often unexpected) observations are frequently referred to as emergent properties. Indeed, Grimm and Railsback (2005) describe ABMs as '*Models of individual behaviour that are useful for explaining population level phenomena in specific context, with contexts being characterized by the biotic and abiotic environment, sometimes including the individual's own state*.' Therefore the aim of a domestic stock ABM will be to predict the outcomes at the population level (principally finding a pathway to a 80% CO_2 reduction by 2050) by varying the specific contexts (e.g. changing the taxes and subsidies, altering the rate of construction, etc.). With an ABM it is not only possible to have the agents in the model being autonomous, but each can have its own rule set making them genuinely heterogeneous, and thus more able to replicate a real world system.

4.3.1. Existing domestic energy related ABMs

Therefore an ABM looks like the most promising route for producing a long term domestic stock model that considers buying decisions at the individual household level. There have been a number of largely exploratory energy or environment ABMs (e.g. Ma, 2006; Schwarz, 2007; Kashif et al., 2011). This review has also identified some existing research in the domestic energy field using ABMs.

Kempener's (2009) model is designed to analyse the impact of personal carbon trading (PCT). In order to run the model he laid down five initial requirements: individuals know the marginal abatement cost of any reductions and their current emissions; they can assign economic value to their emitting activities; through economic value they can compare the relative advantages of not doing an activity and selling their carbon allowance; there is a large market of buyers and sellers; and finally, price is determined by the intersection of supply and demand curves. As can be seen this framework broadly describes a perfect market and thus provides a simplified virtual world for the model's agents to inhabit. Agents in the model were differentiated by wealth and by attitude: some wanting to maximise profit; some aiming to maximise holidays; and a third group trying to be as environmentally friendly as possible. Different mixes of agent types were used and it was found that even though the agents operated in a more or less perfect market they still appeared to make their decisions opportunistically and as a result not all carbon credits were used, which meant that they did not fully diffuse through the market, but also meant that emissions were always less than the cap. This model therefore demonstrated that it was possible to test whether this one policy would have an effect, although the agents' rules were set arbitrarily meaning that no real world conclusions could be made on the basis of this model.

Faber et al. (2010) also produced an interesting agent-based domestic energy model. In this case the model looked at the uptake of micro-Combined Heat and Power (mCHP), as an innovative heating solution, which would need to compete for market share against an existing installed base of gas fired condensing boilers. When the model was run S-curves were produced for diffusion of the new technology, which is the expected pattern, showing a slow initial take up before widespread adoption amongst the majority of the population, followed by a tailing off of the adoption rate as saturation is achieved. Furthermore, by repeated runs with different subsidy levels it was theoretically possible to search for an optimal cost-effective solution that would provide a cost efficient subsidy to CO_2 savings ratio. Therefore the model demonstrated that it was possible to make predictions about the adoption of one new technology against an installed base of an existing technology. However, the model was short on disaggregation of different house types; the savings available – both monetary and carbon – will depend on the details of the dwelling in which the technology is to be installed, and without differentiation of dwelling types it would not be possible to discern real world technology diffusion. To partially address this issue the model was re-run with an adjusted dwelling type; in the re-runs the dwellings were more thermally efficient. As a result of the increased thermal efficiency the boilers would be used less leading to reduced savings from using mCHP with the end result that the mCHP did not diffuse successfully into the market and widescale adoption did not take place. This adaptation therefore essentially showed that the diffusion of one technology (insulation) prevented the diffusion of another (mCHP) and subsequently indicates that such a model needs a high degree of disaggregation in both the dwelling stock and the householders if it is going to be able to be a reasonably life-like model such that its output will be usable.

5. Prototype agent model

Having established the feasibility of an ABM as a potential way forward to incorporate micro-economic behaviour into a bottom-up model it becomes necessary to test whether it will be possible in practice to construct such a model. In order to do this a test model has been constructed using a mixture of real world data and assumed data for simplification.

There are several agent platforms and programming languages available, so before construction of the model could begin a suitable modelling platform needed to be chosen. Railsback et al. (2006) provide a useful review of many different programming languages and environments that are suitable for building ABMs and they recommend NetLogo (Wilensky, 1999) as an ideal platform for concept testing, as it allows very simple models to be built quickly, yet is sufficiently flexible to allow further development to produce very complex models.

Having chosen a programming environment, the level of detail in the model had to be specified. One of the problems with any forecasting type of model is that it is difficult to verify the accuracy of its output as the outputs cannot be compared with real world data, therefore validation is needed. To allow for validation the starting state of the model was set to approximate the UK dwelling stock as it was in 1996. This would allow for comparison with Johnston's model, a well known existing model—as previously discussed, which provides outputs for 1996–2050, and would also allow a comparison with real world data for technology diffusion for the period of the model representing the past. To create the dwelling stock a semi-detached house was approximated and then RdSAP was used to calculate emissions and running costs with varying insulation and technology arrangements: cavity wall (CWI) or solid wall insulation (SWI) (yes or no); loft insulation (yes or no); condensing boiler (yes or no); solar PV (yes or no), this made a total theoretical stock of 32 dwelling types. However, the initial state of the model used only four of those types; out of a total population of 800 houses 100 had CWI and loft insulation, 100 had loft insulation but no CWI, 350 had neither, and the remaining 250 had uninsulated solid walls, these proportions approximate to the Domestic Energy Fact File data for 1996 (Utley and Shorrock, 2008).

The next item required was the trigger points for decision making. The Energy Saving Trust (EST, 2011 estimates that 22% of homeowners are considering refurbishment in the next three years. To provide an approximate simulation of that level of change, each year in the model 7% of agents were randomly chosen to move home, and then considered carrying out improvements on their new home. In addition, each dwelling's boiler was given a randomly distributed initial age and a randomly distributed lifetime with an average expected lifetime of 15 years, with the breakdown triggering a decision making process. An important feature to test with the prototype was that different attitudes of different homeowners could be modelled. To this end the agents were arbitrarily split into three groups, 12.5% 'environmentals' 12.5% 'economicals' and the 75% bulk 'indifferents'. Each of these three groups had an average acceptable payback period for a technology—indifferents 3 years; environmentals 6 years; economicals 9 years. The individual agents in each group were then given a normalised random acceptable payback period based around their group average. NetLogo provides a spatial representation via a grid so that each square has 8 neighbours; this was used to simulate the effect of homeowners talking to their friends and neighbours. Therefore, as part of the decision making process an agent counts the number of its 8 immediate neighbours with a technology—the higher that number the greater the adjustment allowed to the acceptable payback time. The payback periods and the effect of neighbours were set arbitrarily, as illustrative values only. The following piece of pseudo-code illustrates the algorithm running inside the agents for deciding whether or not to adopt a technology:

```
Saving=Current_running_cost – Improved_running_cost
Install_cost=Technology_cost – Subsidy
Payback_period=Install_cost/Saving
Payback_adjustment=3*Count_neighbour_tech/8
Acceptable_payback=Present_payback+Payback_adjustment
If Payback_period < Acceptable_payback Adopt new tech
```

As can be seen from the pseudo-code there was also a subsidy element, the model provided four variable up-front subsidies: for boilers, wall insulation, loft insulation, and PV. In addition there was a Feed in Tariff (FIT) subsidy available – FIT provides an extra income for electricity generation from PV panels – and this was used to calculate the improved running costs, thus increasing the annual saving, rather than reducing the installation costs.

6. Results

The initial test was to run the model without any subsidies in place and examine its output predictions for the year 2050. With no subsidies in place – Business and Usual (BAU) scenario – 10 runs provided an average CO_2 reduction of 32.3% with a standard deviation of 0.8%. Johnston's BAU scenario predicts a 33.2% saving over the same period. Considering the acceptable payback periods were set arbitrarily this is a very close result, and suggests that the model is, albeit perhaps coincidentally, producing expected results in its initial state.

As discussed earlier this can be further checked by comparing the installation rates of cavity wall insulation and condensing boilers in the early years of the model. To test whether the uptake is broadly as expected results from the years 1996–2006 can be compared with real-world data from the English House Condition Survey (CLG, 2009), as shown in Fig. 4.

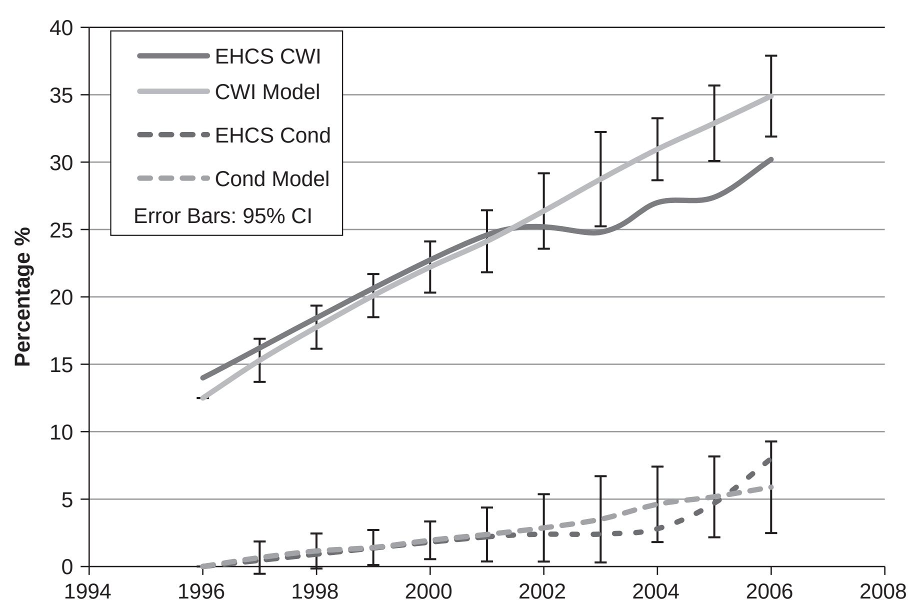

Fig. 4. Percentage technology diffusion in the housing stock (CWI and condensing boiler diffusion for the period 1996–2006 model outputs compared with English House Condition Survey).

Table 4
Ten run average CO_2 reductions under different policy assumptions for model runs from 1996–2050.

Scenario	BAU	Halfmaxsub	Maxsub
10 run average CO_2 reduction	32.3%	57.6%	63.5%
Standard deviation	0.8%	0.65%	0.85%

As can be seen, the general upward trend is observed in the model, and the majority of the model outputs are reasonably close to the EHCS figures considering the simplifications and assumptions made for this test model.

The final test that could be carried out with this prototype was to check that the addition of subsidies would increase the CO_2 savings predicted. In this case, due to the restricted number of dwelling types and technologies available it is not possible to compare this test with real world projections or projections from other models; instead, its prime aim is to check that increased subsidy levels lead to increased technology adoption. To do this two scenarios were produced to be added to the BAU scenario. The first of these – Maxsub – applies arbitrarily set high subsidy levels to check that adoption rates increase. These subsidy levels were as follows: an up-front PV subsidy of £4000; an up-front boiler subsidy of £3000; a generating subsidy for the PV of 50p per kWh; an up front wall insulation subsidy of £5000; and a loft insulation subsidy of £300. The second scenario – Halfmaxsub – simply halved these subsidy levels. The 10 run average results are shown in Table 4.

As can be seen, and as expected, when the subsidy levels were increased the CO_2 reductions increased due to the greater uptake of the available measures (wall and loft insulation, condensing boilers, and solar photovoltaics), since the householder agents reacted to the extra incentives available. It can also be seen that there are cost effectiveness implications for policy makers. Whilst the Maxsub scenario achieves an extra 31.2% saving over the BAU scenario, the Halfmaxsub scenario still manages to achieve an extra 25.3% when the available subsidies were halved. As would be expected there is a diminishing return from ever increasing subsidy levels and there is therefore a need for policy makers to find the appropriate balance between cost and reward.

In the world of this prototype it would be possible to keep testing different scenarios with different subsidy levels to find the optimal balance between cost and benefit, and this would facilitate the policy maker in reaching their preferred compromise between the reduction target and the costs of achieving that target.

7. Recommendations and conclusions

This research has shown that bottom-up modelling is the most appropriate method for predicting dwelling stock emissions to 2050. However, approximately two-thirds of homes belong to owner-occupiers and energy efficiency improvements will only happen when those individuals decide to invest in green technologies. Therefore models need to be able to incorporate heterogeneous individual buying decisions. Agent-based modelling has been identified as the most promising method to include such micro-level behaviour, a feasibility study including a prototype model indicated that this will be possible.

The challenge for future research will be to understand the individual's decision making process. There should be two parts to this: firstly, to determine the trigger points that cause a decision to be made; secondly to identify the different factors affecting the decision making process and the weighting that should be applied to each factor. A number of technologies still have very small installed numbers – less than 1% of the housing stock – in those cases the installations will typically have been from environmentally aware early adopters or from new builds where the owner-occupier will have had no input in the technology buying process. Therefore it will be difficult to predict the responses of the bulk of the population based on the actions of the early adopters. This suggests that, initially at least, a substantial amount of data will need to be collected via simulated buying experiments, with the obvious caveat that stated preferences will not be identical to real world decisions. This therefore further suggests the need for longitudinal studies and calibration against real world data as it becomes available.

Therefore, if suitable data can be collated, agent-based modelling has a lot of promise for the analysis of pathways to 2050 and considering the cost effectiveness of both individual policies and packages of policy measures. Scenarios can be constructed with different sets of policies, e.g. subsidies, taxation, grants, loans, etc., and the diffusion rates of different technologies can then be tracked over the lifetime of the model to find cost effective pathways to 2050. Therefore a full agent-based model, with a comprehensive dwelling stock and suitable decision making data, will be usable by policy makers to simulate the effectiveness of different sets of policy interventions; this will enable policy makers to test current policies and compare them with alternative options in an effort to maximise emissions reductions, whilst simultaneously minimising the associated costs. The detailed information of how to operate this model and comprehensive scenario-based case studies relating to the UK energy policies will be presented in a forthcoming paper.

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