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An analysis of UK policies for domestic energy reduction using an agent based tool

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HIGHLIGHTS

- Analyse UK energy policy using a novel agent-based domestic stock model.
- Current policies are insufficient to achieve an 80% CO_2 reduction by 2050.
- The addition of a carbon tax on domestic energy use increases the reductions.
- Behavioural change can increase adoption of energy saving technologies.
- The most favourable conditions achieved a reduction of less than 60% from 2008 to 2050.

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ABSTRACT

This paper introduces a new agent-based model, which incorporates the actions of individual homeowners in a long-term domestic stock model, and details how it was applied in energy policy analysis. The results indicate that current policies are likely to fall significantly short of the 80% target and suggest that current subsidy levels need re-examining. In the model, current subsidy levels appear to offer too much support to some technologies, which in turn leads to the suppression of other technologies that have a greater energy saving potential. The model can be used by policy makers to develop further scenarios to find alternative, more effective, sets of policy measures. The model is currently limited to the owner-occupied stock in England, although it can be expanded, subject to the availability of data.

1. Introduction

In 2008, the UK Climate Change Act established an 80% CO_{2e} reduction target to be achieved by 2050, against a 1990 base level (TSO, 2009). Domestic energy use is responsible for 28% of total demand, with approximately 83% of this coming from space heating and hot water (DECC, 2011b). Significant energy efficiency improvements will be required to the housing stock if the overall 80% target is to be achieved – principally fabric improvements (insulation and air tightness), more efficient heating systems and on-site renewable energy generation.

In order to plan to achieve such targets, and to develop appropriate policies, models are used to provide a projection of the likely impact of potential policies, or sets of policies. When focussing on the housing sector, stock models are typically used to analyse the effects of changes. Stock models operate with a set of archetypal dwellings that, when taken together, aim to represent the range of dwellings in the real world stock of interest; then, by tracing the rate of change to the dwelling stock, emission and energy demand reductions can be predicted. UK housing can be split into three broad categories according to tenure. The largest of these, accounting for over two thirds of households, is the owner-occupier sector. In the private rental sector, individuals and companies own dwellings, which they rent out for financial gain. The final sector is the social rented sector where governmental, or quasi-governmental bodies, rent out dwellings to those unable to buy or rent in the private housing market. Due to this ownership structure, improvements to the existing housing stock only occur when their owners decide to carry out such improvements.

Existing stock models do not consider the micro-economic behaviour of the individual household in carrying out their decision making process for installing energy efficient technologies. The Agent Home Owner Model of Energy (AHOME), described in this paper, aims to address this, concentrating on the owner-occupier (homeowner) sector of the market. This paper provides

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a brief overview of existing stock models; discusses the development and validation of AHOME and then presents results of AHOME's analysis of existing government policies under various scenarios. The effect of an additional carbon tax policy is also investigated.

2. Existing domestic energy stock models

Existing models in the domestic housing sector principally adopt a bottom up approach. Such models build up from a set of representative dwellings that can be scaled up to approximate the entire stock. In stock models, the individual unit of analysis is a dwelling, and a model requires a representative set of reference dwellings with different thermal characteristics (e.g. size, detachment, wall type, heating system, etc.). Using an energy assessment tool, the heating and energy demand for each of these reference dwellings can be estimated, based on an assumed usage pattern. Altering the proportions of the reference dwellings can simulate the demolition of existing dwellings and the construction of new ones. Similarly, improving the properties of the building elements can represent retrofit improvements to the existing stock. Together, these two actions represent real world stock changes and can be used to determine the likely effects from such changes. This is a technology rich approach with the potential to provide high levels of detail, including information about the likely adoption rates of different technological solutions under different scenarios. This general approach has been used for a number of models, in both the UK and the rest of the world, e.g. Shorrock and Dunster (1997), Hinnells et al. (2007), Steemers and Yun (2009), and Swan et al. (2011).

In order to understand the operation of these models, it is worth examining one of them in a little more detail. A significant model for UK analysis is UKDCM2 (Hinnells et al., 2007), which has been used for studies such as Boardman's (2007) Home Truths report. The model includes some 20,000 dwelling types to represent the national stock, each of which is subjected to an assessment of its energy demands. By applying changes, and aggregating, national level estimates can be calculated under different scenarios. This is the approach used by Boardman to generate the outputs required for the Home Truths report.

Whilst current, bottom up, stock models apply a technology rich approach to the dwelling stock, they do not do the same with the dwelling occupants. Therefore, they do not simulate occupants' heterogeneous decision making processes when considering energy efficiency improvements. Without including the individual level buying behaviour, the primary role of such models lies with describing what is technically possible. In order to estimate the likely uptake of any technology, there is a need to consider adoption rates based on the expected actions of individual homeowners. This first requires an understanding of the decision making process of the individual householder.

3. Individual dwelling energy modelling

In order to carry out the energy assessment of the individual dwellings in a stock model, UK based models use either the Standard Assessment Procedure (SAP) (BRE, 2011), or its predecessor BRE Domestic Energy Model (BREDEM) (Anderson et al., 1985). SAP 2009 (introduced in 2011) is the version that has been used for the dwelling modelling in this research.

SAP is the statutory method in the UK for the production of Energy Performance Certificates for dwellings, which are required on the construction, sale or let of a property. Table 1 details the main elements that are required for a SAP calculation for an individual dwelling.

Table 1
Data requirements for a RdSAP calculation.

Size	Area: floor, walls, ceiling, openings Room height, exposed wall length
Construction	Age, exposed walls, exposed floors, roofs, doors, windows
Insulation	Exposed walls, exposed floors, roofs, doors, windows
Heating	Fuel type, efficiency, distribution system
Hot water	Fuel type, efficiency
Lighting	No. of incandescent, fluorescent, LED
Renewable technologies	Power of solar hot water and photovoltaic systems, wind turbine dimensions

SAP carries out a steady state estimation of the energy demand per month to provide heating, hot water and lighting. It does this by estimating heat flows into and out of the building: heat losses through walls, roof, floor and windows; solar gains through windows; and incidental heat gains from cooking, lighting, hot water and metabolic heat gains. Physical data is combined with standardised occupancy patterns and heating demands, together with external weather data. For instance, the surveyor assessing a dwelling will determine the construction type of the walls, based on which SAP will assign a standard U-value, U (W/m^2 K) for that wall type. The surveyor will also supply the total wall area, A, and similar figures will be recorded for the other fabric elements: floor, roof, windows, etc. Combining these will produce the total fabric heat loss, as in Eq. (1)

$$\text{Fabric Heat Loss}\left(\frac{W}{K}\right)=\sum_{j=1}^{n}A_jU_j \quad \text{Total fabric heat loss} \tag{1}$$

SAP assumes standardised indoor temperatures, and includes data for average external temperatures on a monthly basis. In essence, the fabric heat loss is multiplied by the indoor/outdoor temperature differential to calculate the power required to maintain the desired internal temperature. The actual SAP calculation also includes ventilation losses and incidental gains from metabolic sources, lighting, etc. This is therefore a steady state model, calculated on a monthly basis. It also estimates hot water demand based on the standardised number of occupants, which is calculated according to floor area, as well as lighting demand.

These net demands are then converted into gross energy demands according to the efficiency of the appliance satisfying that demand. This calculation will also include energy generated by any renewable technologies installed in the home. Outputs are generated in the form of kWh/month for the different demand types – heating, hot water and lighting (as well as a calculation of a theoretical cooling demand, even if there is no cooling system present). For an Energy Performance Certificate, these elements are combined and converted into a SAP rating from 1 to 100 based on cost per square metre. SAP provides an estimate based on standardised occupancy patterns and so may not exactly match the energy demand of any individual household, but aims instead to represent a theoretical average household.

As previously mentioned, with this level of analysis of the individual dwelling, bottom up stock models can provide a technology rich environment that provides a lot of detail on the penetration of many different energy efficiency technologies. However, they do not couple this with a similar level of analysis of the decision makers who decide when and whether to install these technologies. Existing modelling techniques can be enhanced by including details of the homeowner level decision making process, with regard to the installation of energy saving measures. AHOME aims to incorporate a simulation of the individual decision making process into a technology rich stock model, in order to provide a novel and more comprehensive model of this type.

Table 2
Dwelling physical characteristics.

Age	Detachment	Glazing	Wall	Roof (W/m^2 K)	Heating	SHW	PV
1 Pre-1945	1 Detached	1 Full DG	1 Solid	0 None	1 Condensing boiler	1 Yes	1 Yes
2 1945–1964	2 Semi/mid terraced	2 Part DG	2 Cavity	1 $U=0.16$	2 Combi-boiler	2 No	2 No
3 1965–1990	3 Flat		3 Retro-fit CWI	2 $U=0.29$	3 Regular boiler		
4 1990+				3 $U=0.68$	4 Oil boiler		
					5 Electric		
					6 Solid fuel		
					7 Community heating		
					8 GSHP		
					9 ASHP		

4. Model development

4.1. Agent based modelling

AHOME aims to incorporate the one off technology buying decision making of individual householders with the technology rich environment of a highly disaggregated stock model and, therefore, a suitable method needs to be chosen that will facilitate this new approach. In previous work, agent based modelling (ABM) has been identified as the most appropriate technique to use (Lee and Yao, 2013).

Agent based modelling is ‘a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment’ (Gilbert, 2008). As such, the focus of an ABM is on the individual constituents of a system, rather than the system as a whole. The particular strength, and uniqueness, of an agent based approach is that by simulating actions at the individual level, emergent properties can be observed that could not be predicted by a system level analysis. By way of illustration, Schelling's segregation model (1969, 1971) operated with a spatial grid, and two types of agent. These agents would decide if they were ‘happy’ by counting the number of neighbours of each type and then either stay put or move based on whether they were happy in their current location. This simple rule was sufficient to lead to segregation patterns in the population recognisable by city planners. The observed system level segregation was a property that emerged from the actions of individuals acting to satisfy their own needs.

The housing market can be readily mapped into an ABM with the dwelling stock providing the environment. The individual homeowners, with their individual decision making processes, become the heterogeneous agents interacting with each other and with their environment. Some environmentally focussed ABMs have already been developed, e.g. water saving showers (Schwarz and Ernst, 2009); personal carbon trading (Kempener, 2009); micro-Combined Heat and Power (Faber et al., 2010); short term occupant behaviour (Kashif et al., 2010).

These models have typically been short on real world data and have largely been proof of concept models, relying on assumed behaviour for the agents; therefore such models have limited value for real world predictions. More fully developed models can benefit from a credible empirical base in order that their results have validity and applicability in representing the real world. Empirically based ABMs are only recently beginning to be developed, for example Tran (2012a,b) developed an ABM for new car purchases. Whilst Tran's model was empirically based, with a database for car types and a consumer survey for the purchasers, significant simplifications were carried out that greatly reduced the heterogeneity in both the car types and the consumer types. Therefore, for AHOME to be useable it must be based as much as possible on real data sources and empirically driven. It needs to balance complexity in the model against maintaining a sufficient level of empirical data to be capable of providing worthwhile outputs.

In order to develop AHOME, a suitable programming platform was required. Out of the many available options, Netlogo (Railsback et al., 2006; Wilensky, 1999) was chosen as it is a mature, well known and high level platform, that is ideal for providing a spatial platform for its agents. This ties in well with a spatially distributed housing market. AHOME has been developed in Netlogo version 4.1.3, released in 2011.

4.2. Stock modelling

In the UK, dwellings are either owner-occupied or tenanted. The vast majority of residential tenancies are assured shorthold tenancies, which, after an initial period, usually of 6 months, can be brought to an end by the landlord with 2 months' notice. This brings limited security of tenure for tenants, who have little say on carrying out energy efficiency improvements, beyond asking their landlords for improvements to be carried out. Consequently, AHOME concentrates solely on the owner-occupied sector of the market, which accounts for approximately 67% of dwellings in England (CLG, 2011b).

To apply SAP 2009 in modelling the thermal properties of individual dwellings, AHOME was populated with initial stock data from the English Housing Survey (EHS) (CLG, 2010). EHS carries out an annual physical survey of thousands of dwellings, with 7790 owner-occupied dwellings in the 2008 data set. The following different building elements have been identified from the EHS data and used to describe the dwelling stock: age (4 options), detachment (2 options), glazing (2 options), wall type (3 options), roof insulation (4 options), heating system (9 options) and renewable energy generation (presence or absence of solar hot water and solar PV). Some restrictions have been placed on the available combinations (e.g. a flat with another dwelling above is assumed not to be able to have solar hot water or PV, as it has no direct roof access). This leads to a total of 7992 different combinations, represented as 7992 different dwelling types available in the model. The available options are detailed in Table 2.

Not all of these combinations are present in the EHS stock (e.g. dwellings with ground and air source heat pumps) and therefore the initial model stock of 7790 (to match the number of dwellings in the EHS) consists of 781 different dwelling types, with several instances of dwellings with the most common set of characteristics. Each of the different dwelling types has been modelled in SAP 2009 to estimate their energy demand in kWh/year. This can be combined with the carbon intensity of the different fuels being used to provide annual emissions for each dwelling in the model.

As with the stock models previously described, summing the emissions from each dwelling can provide an overall figure that represents the entire dwelling stock.

4.3. Decision making theory

The agents in an agent based model require heuristics, or a rule set, to dictate their decision making process. In this case, the agents represent households making one off buying decisions. The types of products being considered have a range of features, or attributes, that need to be considered during the decision making process.

A range of appropriate tools, collectively referred to as multiple attribute decision making methods, could be applied which offer different approaches to selecting from a set of complex options (Yoon and Hwang, 1995). Broadly, there are two approaches – compensatory and non-compensatory. Non-compensatory methods are generally simpler in that features are considered individually; a strength in one feature cannot be used in the assessment of a product to make up for a weakness in another feature. In contrast, compensatory methods aim to combine the different features together in a range of ways; the benefits of each feature of an option are combined to create an overall perceived value, which can then be used to compare the different options. Having evaluated each option, the one that provides the most perceived value is then chosen. The challenge is therefore to determine the value of the perceived benefits of each feature of the various options available.

Two main data gathering approaches can be applied in determining the value of perceived benefits: revealed preference or stated preference (Adamowicz et al., 1994). Revealed preference relies on data from real world decisions, i.e. actual purchases. This brings the distinct advantage of reflecting a genuine decision, where the decision maker's own money has been used for the purchase. However, this only provides one decision per decision maker and it is therefore difficult to identify the underlying components that lead to that decision. In contrast, stated preference relies on discrete choice surveys. A discrete choice survey is typically arranged to provide respondents with a choice between two products, and by providing repeated questions with different features for each product, estimations can be made as to the impact from the different underlying factors. In the case of a technology such as a heating system, households do not buy a system purely so that they have one, but to satisfy underlying demands (heating to provide thermal comfort, hot water for washing, etc.). Although stated preference is not based on real transactions, it allows for multiple responses from each individual. This makes it easier to identify the different sub-components that are considered in the decision making process, and therefore the underlying demands that are being satisfied by a particular technology. In this way, it becomes possible to compare different options, by weighing the effect they have in satisfying the underlying demands.

A common method when using discrete choice survey data is to use a willingness to pay approach, whereby the values ascribed to the different features of a product impact on the willingness to pay for that particular product (Carlsson and Martinsson, 2001). This method therefore puts a monetary value on the individual components that make up a product, typically via a discrete choice survey. This is essentially the same as a multiple criteria decision making process using simple additive weighting (Zhou et al., 2006). There are several similar approaches that are dependent upon the results from a discrete choice survey that allow for an estimation of the value ascribed to sub-components of a product. By doing this, a total utility value for a product can be obtained and this can be compared with the utility of competing products to determine an individual's preferred option.

4.4. Modelling householder decision making

The previous section indicates that discrete choice surveys are a preferable method for estimating the weights to be applied here to the factors influencing a buying decision. There is a need to identify suitable data sets that will allow for a simulation of the decision making process of individual households as they consider making energy efficiency improvements to their homes. The most suitable data sets identifiable for this were from discrete choice surveys carried out in 2008, one by the Energy Saving Trust (EST) (EST, 2009) for the Department of Energy and Climate Change (DECC) and one by Element Energy (EE) (Element Energy, 2008) for the Department of Business, Enterprise and Regulatory Reform (BERR). EST canvassed 2019 owner-occupiers in England and EE included 1171 English homeowners. Both surveys provided respondents with a number of scenarios. Based on the responses, the impact of different factors can be estimated. These factors include cost, savings, maintenance costs, disruption, incentives and subsidies, and the effect of recommendations.

By combining the two data sets, it has been possible to produce a simple additive weighting algorithm to estimate the utility value of different options, as shown in Eq. (2) (Zhou et al., 2006):

$$V(A_i) = \sum_{j=1}^{n} w_j v_j(x_{ij}) \quad i = 1, 2, 3, \ldots, m \quad \text{Utility algorithm} \tag{2}$$

In this equation, the utility of alternative A is the sum of the weight applied to the various attributes of that particular alternative, w is the weight applied to each attribute, and $v(x)$ is the value (or performance) for each attribute. For each respondent, EST provided a utility value for maintaining the status quo and not installing a technology. For a particular alternative to be selected it needs to have a higher utility value than any alternative option and to have a higher utility than the status quo option.

The EST data separated the respondents into seven groups corresponding to the seven clusters identified by DEFRA (2008) according to their environmental willingness. DEFRA's most pro-environmental cluster were the ‘Positive Greens’, the people most likely to engage with a green agenda; whilst at the other end were the ‘Honestly Disengaged’ who were least inclined to engage in energy efficient or pro-environmental behaviours. In order to provide a heterogeneous population, the values were clustered into seven groups corresponding to these seven clusters. Individual agents' values were distributed around the centre point for their respective clusters. In this way, each individual agent, whilst using the same decision making process, has its own unique weightings to apply; for instance, one agent may value a £1 saving on energy bills as worth an upfront cost of £3, whereas the next agent may value such a saving as worth £3.25 up front. These individual differences mean that each decision making process will be unique as both the housing stock and the individual household agents have distinct properties.

Having set up the householder agents' decision making algorithm, it is necessary to determine the trigger points that will lead to a decision taking place. EST research (2011) indicates the likely trigger points for an energy efficiency improvement decision. To approximate this in the model, moving home and boiler breakdown are used as the triggers for decision making. Based on the EST research, in each model year 7% of agents are randomly chosen to move home, and heating systems have been given a randomly distributed life cycle with an average 15 year lifetime. House moving triggers a consideration of all available improvements, whilst heating system failure simply triggers a search for a replacement heating and hot water system, without looking at the other measures that may be possible in that particular dwelling.

4.5. Model validation

At this stage, the model was based solely on stated preference data from the two surveys, as opposed to revealed preference from real world decision making. It can be anticipated that there will be differences between the stated preferences given in a discrete choice experiment and the true revealed preferences when a decision maker faces the decision in the real world.

With prediction models, validation is often an issue as there is no real world data available against which to compare a model's outputs. This is then clearly an issue for any model aiming to predict energy and emissions forward to 2050. Windrum et al. (2007) discuss possible validation and calibration methods that are available, with an emphasis on calibration by comparison with empirical data. They identify a limitation with empirical validation, in that reliable empirical data is frequently not available, or is only available for a limited number of a model's outputs. Nevertheless, empirical calibration is required in order to provide the model with more credibility.

In order to calibrate AHOME, it was run backwards from 2008 to 1996 to compare with historic installation rates for loft insulation and cavity wall insulation (only these items were used as they had the most reliable historical data). This allowed for a comparison between the stated preferences from the survey data and the revealed preferences according to the penetration of the different technologies over that 12 year period. At this stage, a relatively good fit was observed with R^2 values of 0.9563 for loft insulation and 0.7801 for cavity wall insulation, indicating that the stated preferences were relatively close to the real world decisions.

By altering the weighting in the agents' algorithm, it is possible to adjust the likelihood of the adoption of a technology. The simplest ways to do this were by adding a constant to the utility and by applying a scaling factor to the EST status quo utility value. Repeated runs with different values for these two calibration factors improved the goodness of the fit and achieved R^2 values of 0.9584 and 0.9068 for cavity wall insulation and loft insulation respectively when comparing model data with data from the English House Condition Survey for the available years back to 1996. This demonstrated that the model was providing a good simulation of historic outcomes and could start to be used for future projections and scenario and policy analysis.

4.6. User controls and outputs

AHOME is designed to analyse policy effectiveness to 2050 (or any other year of interest) and has a number of controls for end-user input. These controls allow for the setting of inflation rates, subsidies, taxation, population growth, demolition, etc. By adjusting these inputs, it is possible to analyse an almost limitless number of different scenarios. Having designed a scenario, it can be run in the model to generate output files.

The main output from the model is raw data detailing many items including annual CO_2 emissions and energy demand. It also records the annual installations of the various technologies, together with the costs to the government of any subsidies, and the income from any carbon tax being levied.

4.7. Model summary

Fig. 1 provides a graphical framework of the model's operation. As Fig. 1 shows, the central component of the model is the decision making process, which happens at the level of the individual agent. The model will trigger this process each year, as a number of agents will move home, and a number of heating systems will break down. The agent then refers to the Dwelling Stock Database and the Improvements Database for details on the technology in their dwelling and the options available for improvements. The decision making process is then further impacted by recommendations from neighbours and the impact of any policy measures. The output of the decision making process is the selection (if any) of new technologies to install in the home. These installations then lead to altered energy demand and related CO_2 emissions. This process is repeated thousands of times during a model run, as each year 7% of agents move home and 1 in 15 heating systems fail.

4.8. Model capabilities and limitations

As previously mentioned, the model is currently limited to the English homeowner stock. This is in order to concentrate on simulating the energy investment decision making of the homeowners, which is not captured in existing models. Broadly comparable changes could be made to the non-owner occupied stock, but the decision making processes in those cases will be different.

As a stock model, the focus is on the fabric, heating and hot water systems, and micro-renewable generation, and changes to these building elements. The model is therefore limited to the SAP estimates of energy demand (and supply) due to these items. As such, it is not considering appliance usage. Since the model is SAP based it is not capturing potential changes in behaviour that might reduce demand (e.g. reducing thermostat settings), and conversely, it is not modelling uptake of technologies that might increase demand (e.g. new appliances, air conditioning).

In an attempt to balance complexity and realism, a number of assumptions and limitations have been made. A flat with another dwelling above is assumed not to be able to have solar hot water or PV (i.e. only one flat – the top floor one – can benefit from such measures). After 2016, heating systems for new dwellings are restricted to heat pumps, community and bio-fuel systems. Retrofitting insulation to solid walls improves them to the same level as retrofitting an equivalent cavity wall. It is also not possible to predict what new technologies may become available, or how the efficiency of current technologies may change over time; instead, the highest efficiencies currently available in SAP have been used to provide generic technology data.

The model is capable of providing estimates of future energy demand and associated emissions. It can also provide lower level data concerning the uptake of different technologies, as well as the cost effectiveness of different economic policy measures intended to influence the decision making process. The model is also designed so that different scenarios and different sets of policy measures can be analysed in order that effective solutions can be identified.

5. Scenario design

The model has around 40 variables, each of which can take one of a range of values that can be changed for each year of a model run (with a typical run being 42 years (2008–2050)). This high dimensionality leads to an unmanageable number of potential scenarios that is in excess of 10^{30}. It is wholly impractical to run all of these potential scenarios, or even a very small percentage. Instead, a method is required to determine which scenarios should be analysed. There are two related approaches to doing this, the first being simply to lay out all the potential scenarios graphically (a mathematical multi-dimensional space is required with one dimension for each variable), impose a grid over the scenarios and then select one scenario from each grid square (Flood and

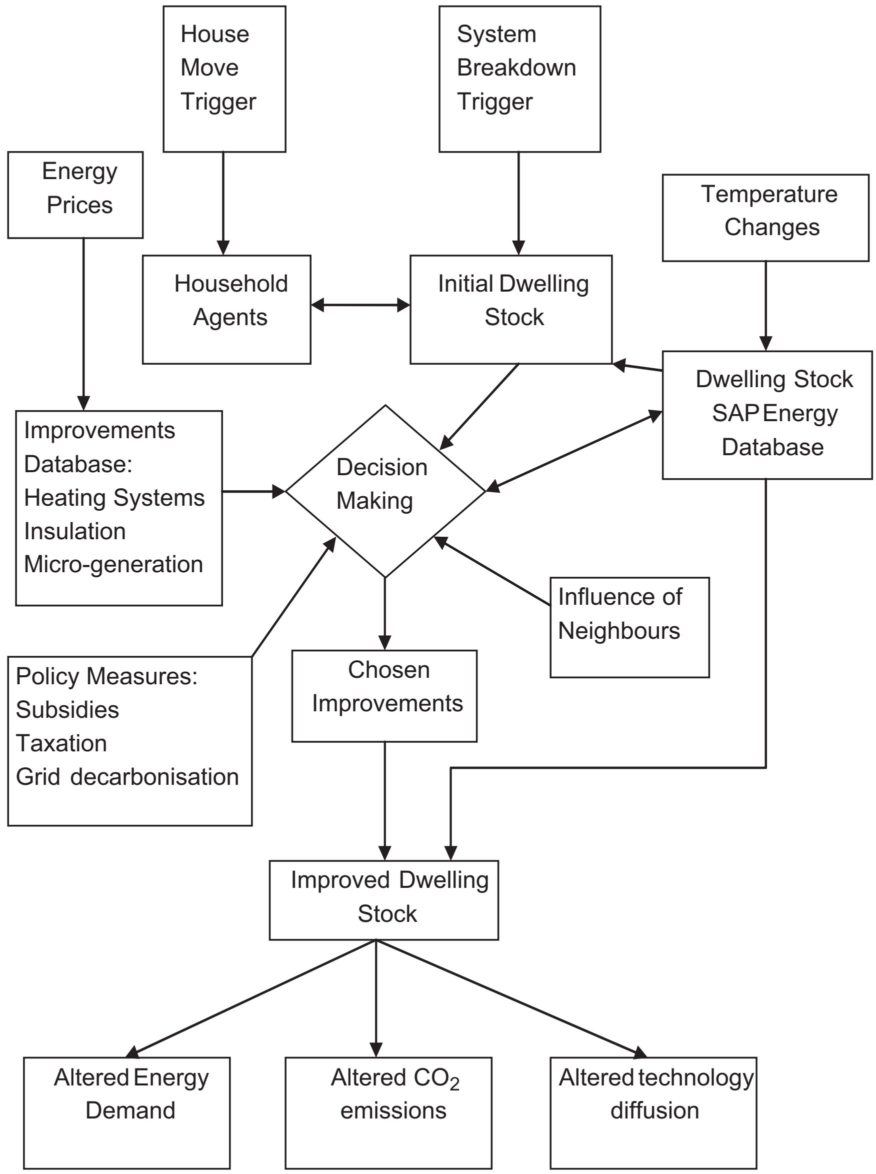

Fig. 1. The framework of the model.

Korenko, 2010). Whilst this approach is understandable and would achieve a representative selection, with the sheer number of potential scenarios available such a selection could quite easily miss plausible scenarios that should be considered. A related method is to use Delphi – this is a system designed to canvas and refine expert opinion (Linstone and Turoff, 1975; Yang et al., 2010) and to carry out cluster analyses of the suggested pathways to generate aggregate scenarios suitable for study (Tapio, 2003). For this research, the approach taken is closer to the Delphi approach. An initial scenario has been developed as a Business as Usual (BAU) case that aims to represent current government policy and projections, based on a number of available data sources (ONS, 2011; CLG, 2011a; DECC, 2012; EST, 2012; Friends of the Earth, 2010; Committee on Climate Change, 2011; Jenkins et al., 2009). Table 3 summarises the main settings used for the initial BAU simulation run.

As well as this basic scenario, additional scenarios were produced and simulated with slight variations from the original BAU. Since it is not possible to consider all the potential scenarios, just three variables are changed to produce the alternative scenarios. The first variable to be changed is grid decarbonisation. The Renewable Energy Review (CCC, 2011) recommends 90% grid decarbonisation by 2030, which has been set as the base line assumption in the BAU scenario. However, there are political disagreements over this target (Economist, 2012), therefore an alternative with no grid decarbonisation is provided; whilst this may seem an extreme variation it gives an indication of the extent to which grid decarbonisation can contribute to domestic emissions reductions. The second option included in this paper is a carbon tax, which has been set at an initial level that approximates to a 20–25% increase in electricity prices. The final option is to withdraw all the subsidies – again, this may seem extreme – but it can give a useful indication of the cost effectiveness of current subsidy levels. Even just using two options for these three variables give eight potential scenarios, as detailed in Table 4.

6. Results

Each of the eight scenarios detailed in the previous table was run in AHOME 12 times, so that runs could be averaged out to allow for random variations and the potential for an outlier

Table 3
Business as usual scenario assumptions.

	2008–2009	2010–2011	2012	2013	2014–2015	2016–2020	2021–2025	2026–2030	2031–2035	2036–2040	2041–2045	2046–2050
Upfront subsidies (£)												
PV-grant	2500	2500										
Solar-grant	300	300	300									
Heatpump-grant (GSHP)	1250	1250	1250									
ASHP-grant	850	850	850									
Solid wall grant	1500	1500	1500	1500	1500	1370	1175	1010	870	745	640	550
Loft grant	250	250	250	250	250	250	250	250	250	250	250	250
Cavity grant	250	250	250	250	250	250	250	250	250	250	250	250
Boiler grant		400										
Biofuel-grant	950	950	950									
Generating subsidies (p/kWh)												
PV-FIT		43	21	13	10	6	4	4	4	4	4	4
RHI-solar				8.5	8.5	8	7	6	5	4	3	3
RHI-heatpump (GSHP)				4.3	4.3	4	3.4	2.9	2.5	2.1	1.8	1.8
RHI-ASHP				3	3	2.6	2.2	1.9	1.6	1.4	1.2	1.2
RHI-biomass boiler				7.6	7.6	7	6	5.2	4.5	3.9	3.4	3.4
Annual population growth												
Construction rate (%)	0.9	0.9	0.9	0.9	0.9	0.8	0.8	0.7	0.7	0.6	0.6	0.6
Demolition rate (%)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Fuel Inflation (%)												
Oil	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3
Gas	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
Solid fuel	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Grid electricity	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9
Annual grid decarbonisation (%)			11	11	11	11	11	11				
5 Yearly average temperature rise (°C)						0.1	0.1	0.1	0.1	0.1	0.1	0.1

simulation. The headline results, in terms of CO_2 reduction, are shown in Figs. 2 and 3.

To complement Figs. 2 and 3, Table 5 provides the average reductions for each scenario.

None of these scenarios gets close to achieving an 80% reduction. It should be noted that these reductions are from 2008 to 2050, whereas the target is from a 1990 base. However, this does not significantly reduce the outcomes as the historic reduction achieved from 1990 to 2008 was approximately 5.5% (DECC, 2011a).

It can also be seen that grid decarbonisation has an important role to play, as the non-decarbonised scenarios achieve reductions at least ten percentage points less than the equivalent decarbonised scenarios. Furthermore, it can be seen that grid decarbonisation has a significant impact on the effectiveness of a carbon tax: BAU-Tax achieves around ten percentage points more than BAU, but BAU-NoDecarb-Tax only achieves around two percentage points more than BAU-NoDecarb. These differences are due to the impact on heat pump costs: when carbon is taxed and grid electricity is decarbonised heat pumps become a more attractive technology. However, without grid decarbonisation, their carbon tax is of the same order of magnitude as condensing boilers, so there is less incentive to adopt the lower carbon technology.

Arguably, the most surprising headline results concern the presence or absence of subsidies. In the graphs, the effect is most clear with BAU and BAU-NoSub in Fig. 2, in that the scenario runs without any subsidies achieved greater CO_2 reductions than the scenarios with subsidies intended to encourage uptake of energy saving technologies. For three out of the four pairs of scenarios, the subsidy free scenario achieves a greater reduction by 2050 than the equivalent subsidised scenario. As the standard deviation of each set of runs is quite small, these are statistically significant results ($p < 0.0001$, in each case). Only for BAU-Tax and BAU-Tax-NoSub does the subsidised scenario achieve a larger reduction, although this result does not quite achieve statistical significance ($p = 0.055$), and even a statistically significant difference of 0.4% would not be an endorsement of the current subsidy regime. Clearly, this is a very counter-intuitive result, which needs further investigation to determine the cause.

Table 4
Summary of selected scenarios.

Scenario	Subsidies	Grid decarbonisation by 2030	CO_2 tax (p/kg CO_2)
BAU	Normal	90%	0
BAU-Tax	Normal	90%	5 (+5% pa indexation applied 5 yearly)
BAU-NoDecarb	Normal	0	0
BAU-Tax-NoDecarb	Normal	0	5 (+5% pa indexation applied 5 yearly)
BAU-NoSub	None	90%	0
BAU-Tax-NoSub	None	90%	5 (+5% pa indexation applied 5 yearly)
BAU-NoDecarb-NoSub	None	0	0
BAU-Tax-NoDecarb-NoSub	None	0	5 (+5% pa indexation applied 5 yearly)

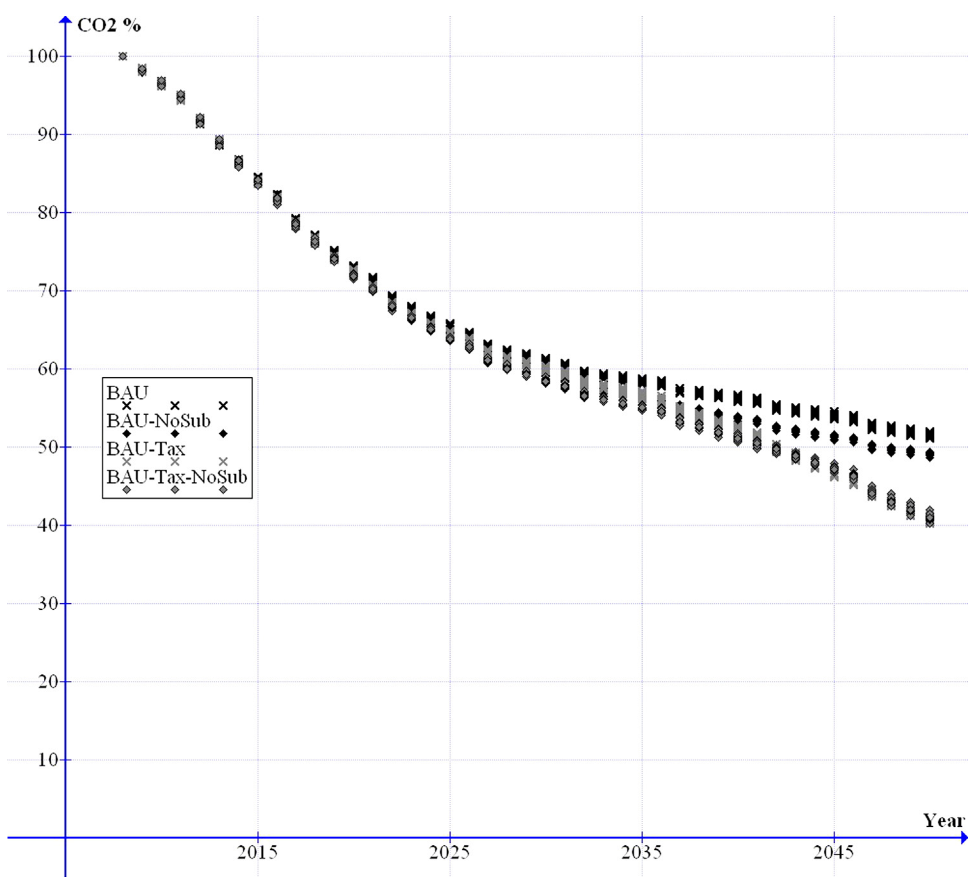

Fig. 2. CO_2 BAU, BAU-NoSub, BAU-NoDecarb, and BAU-NoDecarb-NoSub.

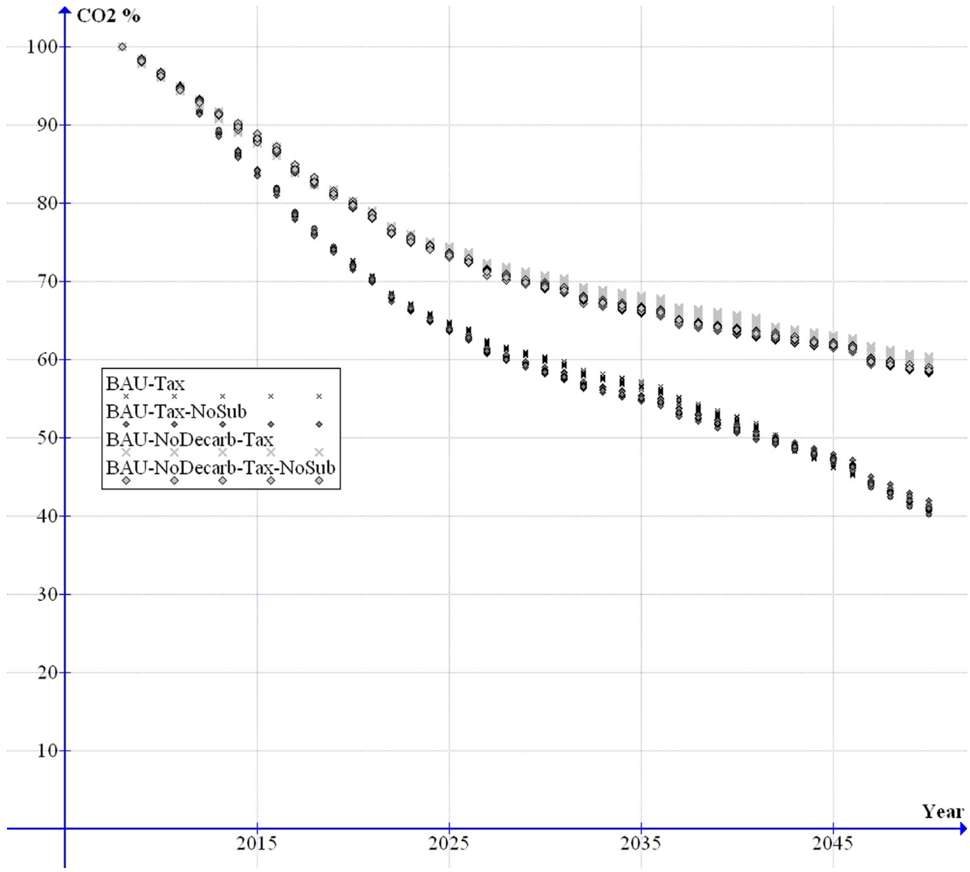

Fig. 3. CO_2 BAU-Tax, BAU-Tax-NoSub, BAU-NoDecarb-Tax, and BAU-NoDecarb-Tax-NoSub.

Table 5
Scenario average CO_2 reductions by 2050.

Scenario	% CO_2 reduction	Standard deviation
BAU	48.5	0.2
BAU-NoSub	50.9	0.2
BAU-NoDecarb	38.2	0.3
BAU-NoDecarb-NoSub	39.7	0.3
BAU-Tax	59.4	0.3
BAU-Tax-NoSub	59.0	0.4
BAU-NoDecarb-Tax	40.0	0.3
BAU-NoDecarb-Tax-NoSub	41.4	0.2

In order to do this it is necessary to look at the underlying changes in the stock that lead to the headline reductions. Amongst the other data that the model records are the technology penetration levels and the CO_2 savings achieved by each technology. Fig. 4 provides the heating system penetration levels for condensing boilers (Cond), ground source and air source heat pumps combined (HP), solid/bio-fuel systems (Solid/Bio) and insulation measures combined (Insulation) for the BAU and BAU-NoSub scenarios:

The model starts with an initial population of 7790 so the number of installations detailed here refers to the actual numbers of installations in the model. Initially, in 2008, the majority of heating systems (5496) are non-condensing gas boilers, thus the initial uptake of condensing boilers is the replacement of the non-condensing systems.

The BAU scenario includes subsidies designed to encourage the uptake of biomass and both ground and air source heat pumps. However, the results presented above suggest that those technologies are better able to compete for market share in the subsidy-free scenario, where there is more of a decline in condensing boiler numbers. This is not an outcome that would be expected (that a technology is less successful when subsidised); nevertheless it can be explained by looking at the combined insulation figures. Without subsidies, the total number of insulation measures is reduced, and with a less well insulated fabric a heating system needs to work harder to satisfy the subsequently larger heating demand. Therefore, when there is a larger heating demand, the savings possible from a more efficient heating system are greater and this consequently favours heat pumps and biomass over gas. Alternatively, when a dwelling is well insulated, the heating demand is less and therefore the potential savings from an innovative heating system are less, such that more individuals choose to remain with gas heating. This result is similar to Faber et al.'s (2010), where they found that the adoption of micro-CHP was suppressed when they improved the fabric of the dwellings. However, the findings in this research are with a heterogeneous stock of both dwellings and occupants, and are empirically based, as far as possible.

To complement the data presenting the number of installations, the model also records the CO_2 saving per installation (this is just the saving in the year of installation, as opposed to the saving over the expected lifetime of the technology). Fig. 5 presents the savings per technology type for the BAU scenario (the renewables being solar PV and solar hot water).

This further confirms that the majority of the savings come from the initial move to condensing gas boilers, and it is not until the late 2020s that the other technologies begin to provide the majority of the CO_2 savings. It can also be seen that the contribution from insulation measures is gradually falling over time – this is because the number of poorly insulated houses is steadily decreasing and so the available savings are reducing.

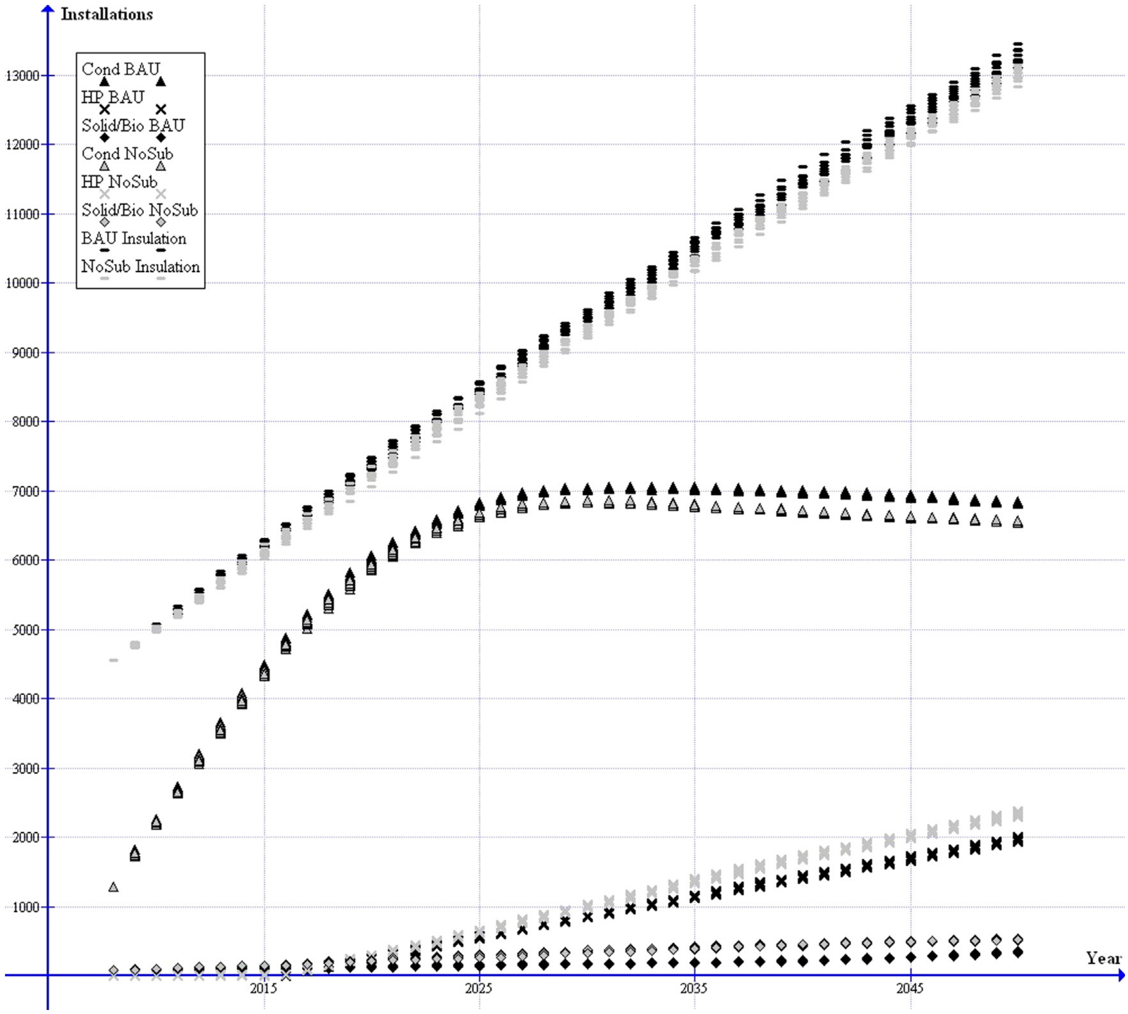

Fig. 4. BAU and BAU-NoSub technology installations.

As well as the CO_2 savings provided by the different technologies, the model also records cost effectiveness of subsidies per technology in terms of £/kgCO_2. Some of the subsidies are generation subsidies, which provide a subsidy in pence per kilowatt-hour of energy produced; these future costs are simply converted into a current cost using a net present value calculation and a discount rate of 3.5% (HM Treasury, 2003). In the same way as the CO_2 savings per technology previously presented, the cost effectiveness has been based on just a single year's CO_2 saving, as opposed to the entire expected lifetime of the technology. Figs. 6 and 7 detail subsidy cost effectiveness for the BAU scenario.

It can be seen that there is essentially an order of magnitude difference between the two sets of subsidies; there is therefore a wide variety of cost effectiveness in the current subsidies for the different measures available. There are also significant changes over time, not only due to changes in the subsidy levels, but also due to changes in the dwelling stock. For example, the cost effectiveness of cavity wall and loft insulation reduces over time, as the most cost effective improvements have generally already been installed in the earlier years, so the remaining dwellings have less to gain from the insulation measures.

7. Conclusions

Current government domestic energy efficiency policy has been analysed using the AHOME model, together with alternative scenarios varying the taxes, subsidies and grid decarbonisation. The results of this analysis suggest that current policies will fall well short of the domestic sector being able to achieve the 80% reduction target by 2050. The most favourable conditions achieved a reduction of less than 60% from 2008 to 2050. Whilst it is not essential for every sector to achieve 80%, as long as the overall target is achieved, any sector that does fall short would have implications for other sectors. Here, industry and transport would be required to achieve greater reductions to make up the short fall. It should also be noticed that AHOME found potential for much greater improvements based on the spare capacity for further improvements. This is in line with existing bottom up models that can identify the theoretically and technically possible. However, the model suggests that current policies are not sufficient to encourage such wide scale adoption of technologies.

The scenarios presented have illustrated the advantages of an agent based approach and the resultant emergent properties that would not be predicted by a traditional model. In particular, the finding that current subsidy levels could act as a disincentive is an unexpected, but important finding. This has implications for policy makers that suggest a need to reconsider the setting of subsidy levels and consider the knock-on effects and the interactions between technologies.

Care needs to be taken to ensure that a policy favouring one technology does not have a knock-on effect of subsequently reducing the take up of another technology with the potential to provide greater savings. As the model can provide detail rich

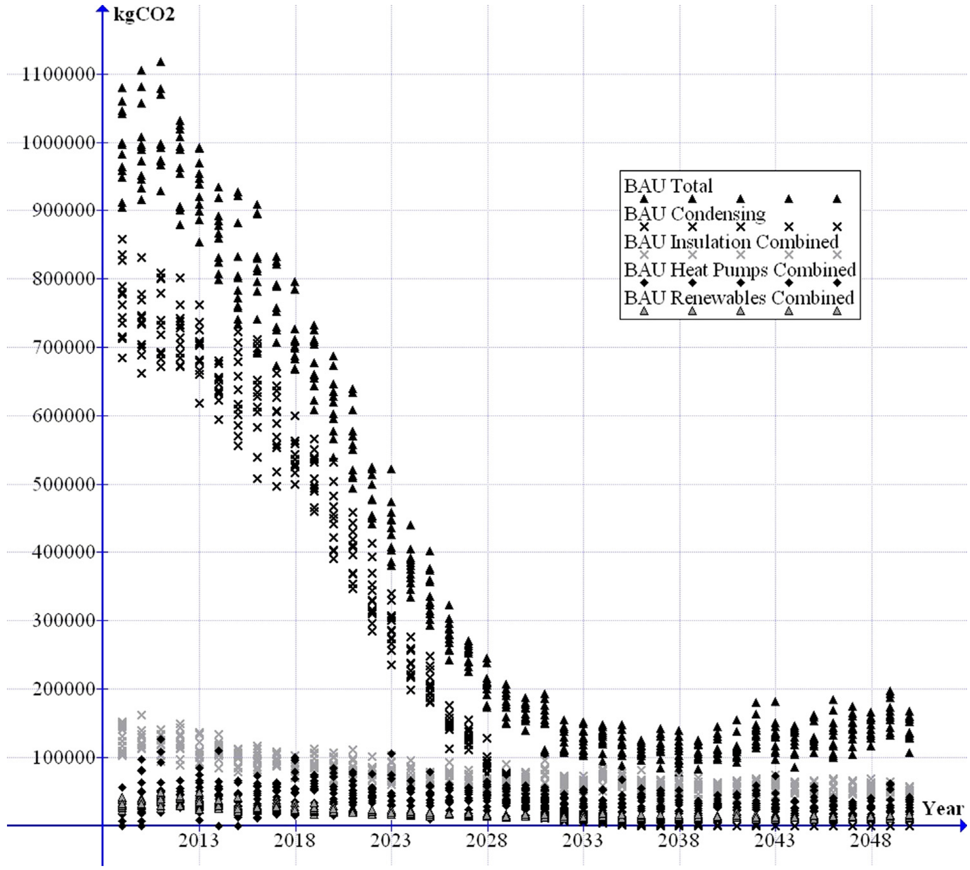

Fig. 5. CO_2 savings per technology type.

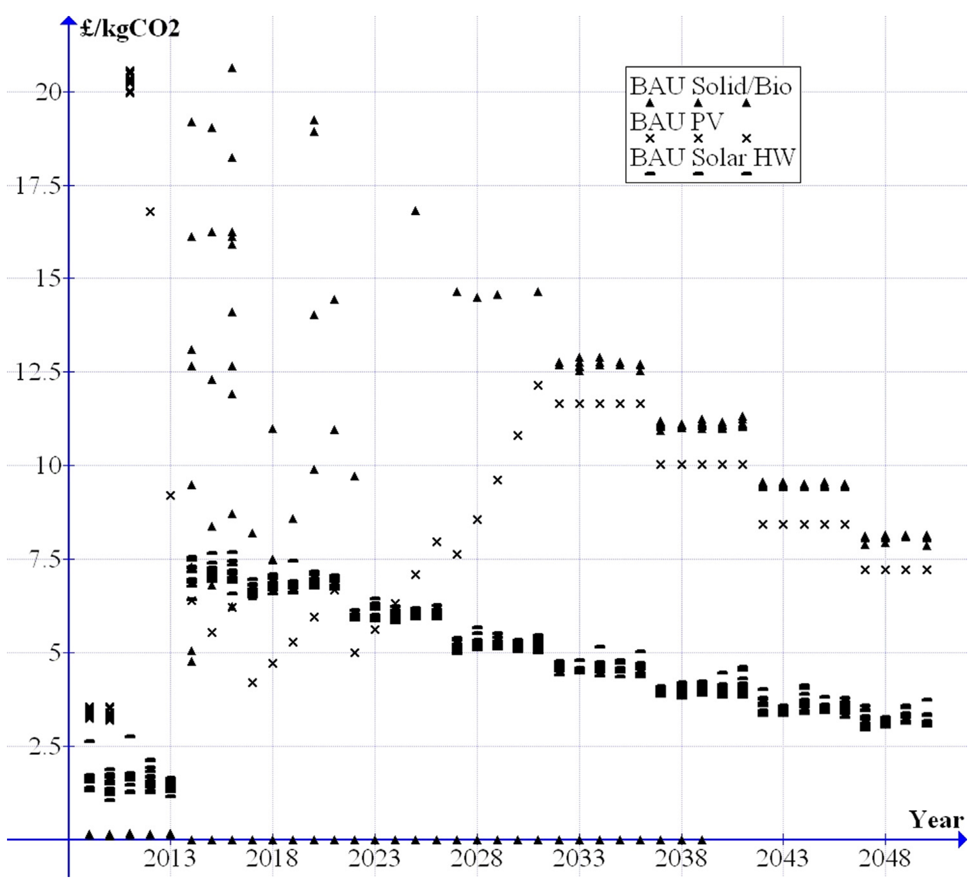

Fig. 6. BAU Subsidy cost effectiveness – high cost measures.

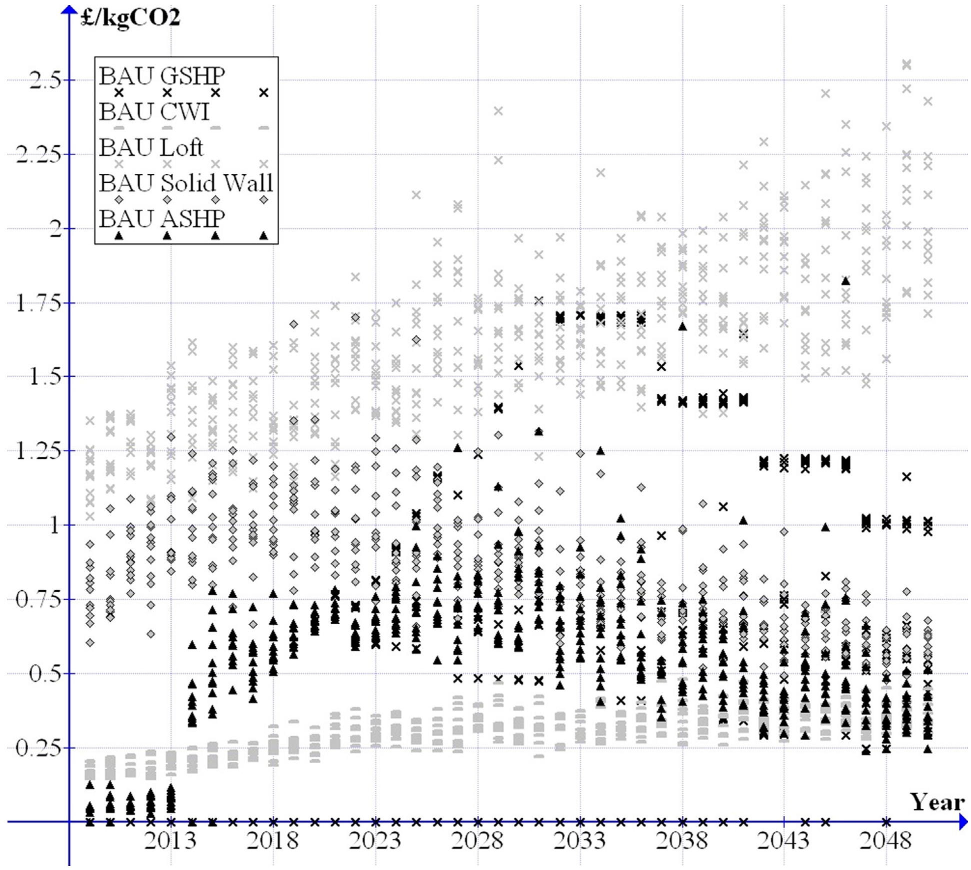

Fig. 7. BAU Subsidy cost effectiveness – low cost measures.

outputs, it offers potential for policy makers to re-examine subsidy setting; by adjusting current subsidy levels, a more effective solution can be sought.

One new policy that has been briefly explored in this paper is the addition of a carbon tax, which, at the level tested here has a noticeable impact in reducing energy demand towards the later years of the scenario runs. However, the use of such a policy may be hard to achieve politically for a number of reasons. Firstly, there is a concern in the UK over fuel poverty – which is defined as any household spending 10% or more of its income on heating and hot water. The imposition of a tax will artificially increase energy prices and therefore may take more people into fuel poverty. Conversely, as a tax, this is a revenue raising policy, and there would therefore be the opportunity to target some of the money raised into improving the energy efficiency of the stock occupied by those in fuel poverty. In addition, as a tax, politicians would need to consider the best way to be able to market the policy so that it would be accepted by voters, as raising taxes is typically an unpopular political move. As well as targeting the revenues raised on the fuel poor, it would also be possible to use them to enhance the subsidy levels provided more generally in a further effort to encourage greater adoption of energy saving technologies across the entire housing stock. Frank (2011) suggests that such an approach – of using the tax in a redistributive manner – may be an appropriate approach, and a similar suggestion was made by Green Fiscal Commission (2009). Should a policy maker decide to explore such options in more detail, AHOME would be an appropriate tool, as it records details of both subsidy cost and tax. Therefore, a policy maker could run many scenarios and apply small changes to arrive at a cost neutral solution, or to estimate the revenue generating capacity of different scenarios.

Finally, it needs to be remembered that whilst AHOME has been validated as much as possible against available data, it can be updated and recalibrated as more real world data becomes available. This will ensure it successfully projects the expected trends under different scenarios. Such updating will therefore be able to make it a useful tool for policy makers.

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