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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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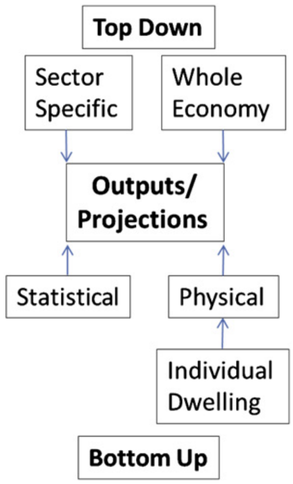

Fig. 1. Top-down and bottom-up model types.

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.