Understanding energy behaviours and transitions through the lens of a smart grid Agent Based Model

Author – J. Richard Snape
Institute of Energy and Sustainable Development,
De Montfort University,
Leicester,
LE1 9BH
United Kingdom
Email: jsnape@dmu.ac.uk

Author – Dr. Katherine N. Irvine
Institute of Energy and Sustainable Development,
De Montfort University,
Leicester,
LE1 9BH
United Kingdom
Email: kirvine@dmu.ac.uk

Author – Dr. Christophe Rynikiewicz
Institute of Energy and Sustainable Development,
De Montfort University,
Leicester,
LE1 9BH
United Kingdom
Email: crynikiewicz@dmu.ac.uk

Abstract

Investigating the dynamics of consumption is crucial for understanding the wider socio-technical transitions needed to achieve carbon reduction goals in the energy sector. Such insight is particularly necessary when considering Smart Grids and current debates about potential transition pathways (and contingent benefits) for the electricity system and coupled gas and transport systems.

The electricity grid is a complex adaptive system comprising physical networks, economic markets and multiple, heterogeneous, interacting agents. Fundamental to innovation studies is that social practices and technological artefacts shape and are shaped by one another. Different trajectories of socio-technical systems' transition are intrinsically linked to the behavioural and cognitive norms of individuals, businesses, communities, sectors, and governance institutions. Therefore the transition to smart(er) grids inevitably requires a knowledge transition and behaviour change among such actor groups. To date, these effects have not been modelled.

We present a prototype Agent Based Model (ABM) as a means to examine the effect of individual behaviour and social learning on energy use patterns, from the perspectives of adoption of energy saving behaviours, energy saving technologies and individual or community based energy use practices. We draw on the Energy Cultures framework to understand real-world observations and incorporate representative energy use behaviours into the model and discuss the model's relation to case studies, e.g. energy use in island communities.

Such models enable examination of how far we can learn and scale up lessons from case studies to similar Socio-Technical Systems with bigger scale and greater interconnectivity such as the UK national grid.

Introduction: energy consumption in the environmental context

Despite ambitious and in some cases legally binding targets for greenhouse gas emissions reduction, energy consumption has proved somewhat resistant to change. The reluctance of consumers to change consumption patterns (whether through use of technology or change of behaviour) leads to a growing gap between the targets for emissions reduction and the implementation of systems to achieve them on the ground.

This indicates a failure to meet policy targets. For instance, in the UK, between 2003 and 2008, the Governmental commitment to emissions reduction has gone from 60% of 1990 levels (DTI, 2003) to 80% by 2050 and is now legally binding (UK Parliament, 2008). The published scenarios and pathways to achieve this goal (DECC, 2010a) are an early attempt to bring government targets from the high level into the realm of everyday life. Yet the implementation of specific operationalised plans to achieve the overall goal has already fallen well behind schedule (e.g. targets for introducing domestic renewable energy sources (Bergman et al., 2009)), such that the pathways to achieving the overall target look increasingly ambitious. In fact, to achieve the 80% target, either reduction in demand or change to renewable primary fuel supply needs to be at levels described on the pathways generator tool itself as a "Heroic effort, but does not break any laws of physics".[i]

So far, a great deal of very valuable effort has been expended in making machines and technical processes more energy efficient and this must indeed continue. However, despite this technical effort coupled with wide-ranging incentives, policy and legislation, the desired behaviour has not been achieved to date. To achieve such targets, widely accepted as necessary to avoid anthropogenic climate change, we need to understand the mechanisms by which energy *behaviours* are made more efficient. We firmly believe that only through the holistic consideration of the electricity system in terms of technology, human interaction and policy can the "heroic effort" required to achieve targets be successful.

Within this context, it is clear that radical innovation is necessary; existing technological and policy approaches are not achieving the required change at the required pace. In order to effect a change in consumption of the magnitude required a re-conceptualisation of the way in which electricity is generated and consumed is needed. One such radical innovation is proposed within the electricity sector[ii] - a move from the status quo to a smart grid[iii].

The proposed smart grid is a move away from a centralised, unidirectional, largely static electricity grid where the majority of users are passive consumers and change is at the slow pace associated with large infrastructural investment. Instead, the smart grid vision is one of a de-centralised, bi-directional, dynamic grid, with many active users both consuming and generating, with its technological configuration altering with every new piece of technology any user may acquire. Although many definitions of the smart grid exist, we use that of the European Technology Platform for Electricity Networks of the future:

> "...electricity networks that can intelligently integrate the behaviour and actions of all users connected to it - generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies."

(Source: www.smartgrids.eu, 2006)

This paper focuses on a crucial element of the transition to a smart grid: household behaviour. It is acknowledged (especially within electrical engineering) that the dynamic pattern of electricity consumption is heavily influenced by the behaviour of consumers. Such behaviour displays distinct patterns on a daily, weekly, seasonal and yearly basis – the entire existing electricity grid operation is designed to cope with these patterns utilising traditional generation techniques. However, this behaviourally influenced consumption pattern for electricity has traditionally been taken as a given when considering the electricity Socio-Technical System.

To date, behavioural theory has not been widely applied to consumption in computational energy modelling. Specifically, we examine behaviour in terms of the *adoption* of smart technology and the *adaptation* of electricity consumption via change of energy use practice and adoption of energy saving behaviours. Such adoption and adaptation is imperative to enable active Demand Side Management (DSM), which in turn is needed to realise the full efficiencies promised by the smart grid.

The aim of this mainly conceptual paper is to address two questions:

1. How might we conceptualise and model smart grid policies to evaluate their likely impact (in light of the impact of existing policies in related areas)?
2. How can Agent Based Modelling (ABM) be used to this end, in particular how can more sophisticated behavioural representation be added to existing work to enhance model capability?

The paper is structured as follows:

In the first section, we briefly summarise Socio-Technical Systems and Transition theories which we use to conceptualise the electricity grid system as a whole and shed light on the potential transitions to a smart grid.

The second section outlines behavioural theories and the Energy Cultures framework as a theoretical basis to understand how actors within the system behave and learn.

The third section outlines the use of Agent Based Modelling (ABM) as a modelling framework and how the summarised theories above may be integrated. We highlight prior ABM work as related to Socio-Technical Systems, behavioural representation and smart grids and where the current work adds to these.

The final section is a discussion of prototype results, further work and potential implications.

Socio-Technical Systems and transitions in practice and everyday life

In order to understand the behavioural influences on the system as a whole, we must consider the many elements and relationships within the system, how they interact and what changes are possible (both within the elements and in their relationships). Such a study is fundamentally inter-disciplinary and hence a framework is needed which can incorporate insight from a wide range of literature, from economics to engineering and psychology to policy. Socio-Technical Transition theories offer a framework in which to study the system as a whole, incorporating change in system actors, relationships and technology.

The current line of research of the Sustainability Transitions Research Network (STRN, 2010) asks how individuals can be encouraged to 'accept' or co-construct major sustainability innovations, for example by consuming greener and more efficient products. It continues to explore the motivations and drivers of everyday consumption behaviours, considering how individuals consume in pursuit of status, meaning, and happiness. The aspects of dynamics of consumption, social learning and user innovation are then central.

We define a Socio-Technical System as

> "At the level of societal functions, a range of elements are linked together to achieve functionality, for example technology, regulation, user practices and markets, cultural meaning, infrastructure...This cluster of elements is called a Socio-technical system"

(Source: Geels, 2005, p.1)

It is easy to see that the electricity system constitutes such a system, with a strong technical and infrastructural component; influences of user practices on its operation; socially determined patterns of consumption; and large amounts of regulation. In addition to the fact that there are a large number of interacting elements to consider, none of these elements are static - for instance the UK is currently consulting on large infrastructure installation and changes to regulation and market structure (DECC, 2010b). It is therefore appropriate to consider the transition of the electricity network (e.g. to a smart grid) as a Socio-Technical Transition (Verbong & Geels, 2010; Verbong & Geels, 2007; Bergman, 2009; Zegers, 2009)

The Multi-Level Perspective (MLP) (Rip & Kemp, 1998; Geels, 2002; Geels, 2005) offers a framework in which to study Socio-Technical Transition – how innovation (in technology, behaviour or practice) appears and changes the system. The relationship of the MLP to other theories within Socio-Technical Transition has been explored by Geels (2010a). The framework describes transition in terms of a socio-technical *regime*, which is the dominant mode of operation of the system within its socio-technical *landscape*. Many *niches* operate below the regime with different modes of operation. These niches have the potential under certain circumstances (where developments in all three levels reinforce) to usurp the regime, which describes a transition in the Socio-Technical System. This is illustrated in **Figure 1**:

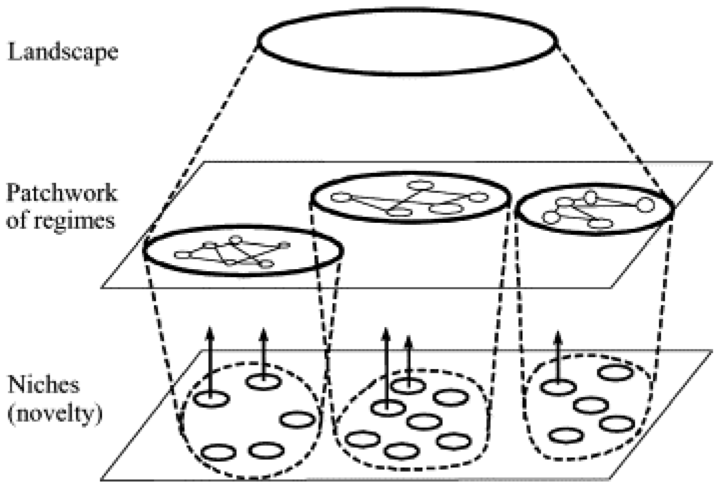


Figure 1: Multi-Level Perspective nested hierarchy. *Source: F. W Geels, 2002*

The MLP has been expanded by Haxeltine et al. (2008) into a conceptual framework adding to the concepts of niche, regime and landscape to add empowered niche (a niche which is capable of replacing the regime) and changing practice which is suited to analysis of the electricity network. This expanded conceptual framework has been successfully realised in an Agent-Based Model (Bergman et al., 2008).

Social learning is fundamental to analysis of Socio-Technical Transition – it captures the means by which Socio-Technical Systems are produced or re-produced by their actors – through imitation or exchange of experience (Geels, 2005, pp.19-20). Such learning will heavily influence the growth or otherwise of niches, in some cases to become the dominant regime. A study of the mechanisms by which this occurs will enhance the potential for policy makers to encourage certain socially desirable niches – such a policy approach has been described as Strategic Niche Management (SNM) (Kemp et al., 1998).

Whilst the influence of behaviour was *implicit* in much of the early discussion surrounding Socio-Technical Transition, this paper aims to contribute to understanding and modelling that influence *explicitly*.

Behaviour change in the transition to smart grid

Smart grid: concepts and required changes

The smart grid concept involves using enhanced system information to match consumption with generation in a situation with increased variability of generation over time (due to a larger fraction of renewables in the supply mix). In order to achieve this, smart devices will make use of enhanced system information about demand and generation (e.g. cost, emissions per unit of consumption) at a fine timescale. The 'smart' label relates to using this information to make informed decisions about when a consumer should generate, store or consume electricity. To date, much effort has been concentrated on the research and development of technology - to acquire fine-grained consumption data; to present cost (in terms of money or emissions) to the consumer; and to use the acquired data to schedule consumption and generation automatically. However, an equally important area of development must be how such information is assimilated into knowledge (or rejected) by the various actors within the system and, further, how this knowledge, mediated by other influences, translates into behaviour change.

In order for the smart grid to provide the expected benefits, people must engage to some extent with at least three[iv] behavioural changes:

1. Adaptation of demand (by means of energy saving behaviours or changes in consumption practice) in response to a signal to do so;
2. Adoption of a smart control device to automatically optimise (some elements of) consumption;
3. Adoption of a micro-generation device.

It is essential in considering these dynamic behaviour changes to treat the system as a whole – to acknowledge that once the complex interactions of humans with each other and energy networks are under consideration, the system is not reducible. To understand the dynamic consumption patterns we see on the grid and the range of behavioural response to different policy initiatives, we must have a model which incorporates the reciprocal influence between behaviour and technology. Understanding what influences the behaviours that cause these energy consumption patterns, and how they may be modified, is vital.

In considering behaviour as related to energy consumption, the consumption has been characterised as being 'doubly invisible' (Burgess & Nye, 2008), in that people are both unaware of the amount and impact of a given quantity of energy use and unaware of how their daily practices contribute to that energy use. This is especially relevant to electricity consumption, which at the point of use (i.e. the socket) has a time-variant relationship to the amount of primary fuel energy used (depending on the fuel mix of generation at that time).

One of the 'soft' benefits of installing smart technologies in the home or community is that it can 'lift the veil' by allowing the user to see the effects of their behaviour(s) on energy consumption and therefore efficiency and emissions. As argued by Bergman (2009), micro-generation in the home can give the user a far closer relationship with their energy consumption, thereby revealing the effects of their behaviours on electricity consumption and the primary fuel required to produce that electricity. This example illustrates the reciprocal way in which "social practices and technological artefacts shape and are shaped by one another" (Smith & Stirling, 2007).

Behaviour in context

For some time, academics from a number of disciplines have attempted to address the duality of behaviour and context. In psychology, Kurt Lewin proposed the idea that behaviour was the product of both the person and the environment (Lewin, 1951). Sociology offers similar integrative concepts such as *habitus* (Bourdieu, 1977), which has been incorporated into the idea of *lock-in* (e.g. Shove, 2003; Maréchal, 2010) to account for people's unwillingness to change in the face of what appear to be rational reasons to do so, as well as changes in cultural norms which can lead to a change in expectations and consumption patterns[v].

In order to characterise the infinite variety of individual consumption behaviours in a fashion compatible with modelling separate yet mutually dependant internal and external influences, we can turn to the Energy Cultures framework (Stephenson et al, 2010). This framework is specifically concerned with energy behaviours as inextricably embedded within a social context, taking account of cognitive norms (e.g. beliefs, understandings), material culture (e.g. technologies, building form) and energy practices (e.g. activities, processes) as influences on behaviour[vi]. Figure 2 shows the building blocks of the framework – illustrating the use of the framework in the case of heating behaviours. An example of how a computational model might utilise categorisation of influencers toward smart grid adoption and adaptation using the Energy Cultures framework is given later in Table 3.

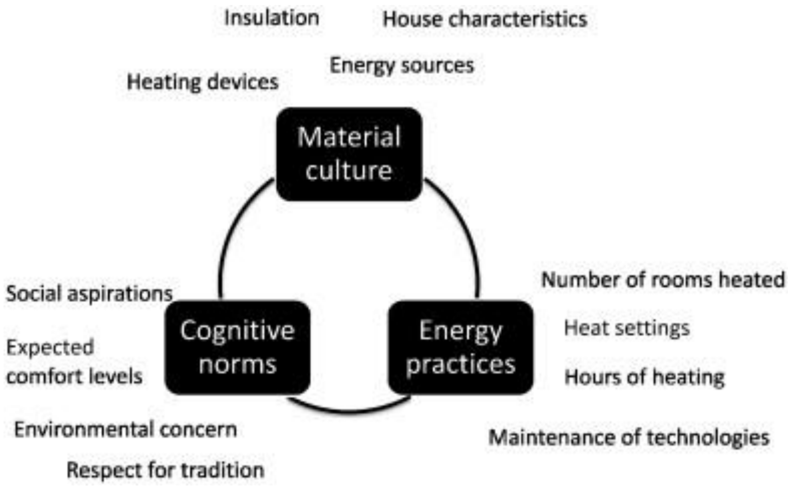


Figure 2: Using the Energy Cultures framework to characterise some home heating behaviours. *Source, Stephenson et al, 2010*

Behavioural theory: the influence of the individual

To successfully model a change in behaviour in response to smart grid initiatives, we need an understanding of how a change in available information leads to a knowledge transition and combines with multiple influencers to affect a change in behaviour in the individual actor. Existing theories of how people behave or take action seek to relate potential influencers including their personal norms and predispositions, social influence, habits and emotions. A number of these are outlined in Table 1; see e.g. Jackson (2005) for a comprehensive review of behaviour theories with respect to pro-environmental behaviour. The selections in Table 1 are chosen to highlight the variety of approaches available, their similarities and differences and the implications which each may have if their constructs are used to represent behaviour change in a computational model.

Theory	**Constructs**	**Author**	**Generic / Specific behaviours**	**Linear / recursive**	**Notes on use in ABM behavioural representation and pro-environmental context**
Theory of Planned Behaviour	- Attitude - Subjective Norm - Perceived Behavioural Control - Intention	Ajzen (1991)	Specific	Linear	Well supported applicability and relative influence of constructs in various contexts via extensive meta-analyses. Extensively used in the pro-environmental behaviour context. Theory of Reasoned Action is the antecedent.
Theory of Interpersonal Behaviour	- Attitude - Social Factors - Affect - Intention - Habit - Facilitating Conditions	Triandis (1977)	Specific	Linear	Explicit consideration of habit important in describing repetitive behaviours. Greater complexity of the model – increases difficulty of encoding and potential to introduce hidden assumptions when coding.
Belief-Desire-Intention	- Beliefs - Desires - Intentions	Bratman (1987)	Specific	Linear	Well suited to programmatic representation and well used in computational agent based systems. Foundations in philosophy with folk psychology terminology and justification.
Value-Belief-Norm	- Values - Beliefs - Personal Norms	Stern (2000)	Generic	Linear	Integrative theory drawing on New Environmental Paradigm and Schwartz's Norm Activation Theory. The constructed personal norm may be used as a basis on which a range of pro-environmental behaviours are enacted. This is attractive in terms of reduction of programmatic complexity.
Social Cognitive	- Expectation - Perception of	Bandura (1986)	Specific	Recursive	Able to incorporate social influence, feedback from historical experience and internal

Theory	others - Self efficacy - Goals - Outcomes - Socio-structural factors				influencers. Has been applied to the diffusion of technology innovations. Habit not explicitly accounted for.

Table 1: Comparison of behaviour change theories

One of the major selection criteria for which theory to use in order to model an agent's behaviour is which has been empirically shown to have the most explanatory power in empirical studies of pro-environmental behaviour. With this in mind, it is clear that the Value-Belief-Norm theory and the Theory of Planned Behaviour have received widespread usage in the environmental field and therefore carry a considerable weight of empirical evidence to inform the selection of appropriate weighting factors for each construct in a computational model.

It is noted that the theories compared in Table 1 are related specifically to the behaviour of an individual. This presents a problem when applying them to a model of domestic electricity consumption, where data are monitored at a household level. Work has been conducted in Denmark (Thøgersen & Grønhøj, 2010) which has explicitly considered this issue and analysed electricity saving behaviours under the Social Cognitive Theory with the unit of analysis being the household whilst gaining empirical evidence of the influence of intra-household factors on the behaviour.

Behavioural Theory: Influence of social learning and community

Social learning is a term which describes the process of adapting behaviour in response to influence from social contacts. It intrinsically links learning of new ideas or behaviours (or knowledge and actions) to the social context in which they exist. It has been used to describe both Social Cognitive Theory (Bandura, 1986) and the related but discrete concepts of situated learning and communities of practice (Lave & Wenger, 1991). These theories describe knowledge and learning itself as part of the social context and the thoughts and actions of the individual as inseparable from it. In their investigation into the sociopsychological drivers of energy-use patterns, Nye et al. (2010) conclude that "...'social' factors are central to explaining patterns of aggregate electricity demand" and highlight the need for further exploration of this.

We can relate the conceptual tool of communities of practice to the Energy Cultures framework. The example quoted by Stephenson et al. (2010) to illustrate the use of the Energy Cultures framework (a Transition Town community) describes the initiation and subsequent growth of what could easily be termed a 'community of practice'. Such a "well-functioning community of practice is a good context to explore radically new insights without becoming fools or getting stuck in some dead end" (Wenger, 1998, p.214).

There are some indications that momentum is beginning to gather for community-based action to accelerate 'green' initiatives. The growth in Transition Town groups (Transition Network, 2011), the funding of community-based academic research projects (Grassroots Innovation, 2010) and the emergence of community energy generation projects (e.g. WOCR, 2010) all indicate both a growing recognition of the importance of community-based initiatives amongst community leaders and a willingness to participate within communities. Such community-based initiatives, or niches, are groups bound together by common practice. As the niche grows and gains membership, it will undoubtedly influence members' behaviour. Thus, niches may not be geographically based (as one may intuitively assume), but may be based on group membership, common ownership or some other binding factor.

Agent Based Modelling: Characterising behaviour in a Complex Adaptive System computational model

Agent Based Modelling (ABM) of Complex Adaptive Systems

A Complex Adaptive System is one in which the relationships between elements is fundamental (complex) and which changes over time (adaptive) (c.f. Miller & Page, 2007). The electricity grid to date has mainly been characterised as a CAS in economics when studying the wholesale electricity market (Li & Tesfatsion, 2009; North et al., 2002). However, such a treatment is of interest to a wider range of disciplines. There is a growing recognition that in order to understand the collective behaviour of large CAS, models which explicitly account for the behaviour of individuals and groups are needed.

To date, computational models in the energy field have not included representations of actors' behaviour and learning beyond those which are rational (or boundedly rational only in the sense that actors operate based on incomplete information). Models of technology in idealised circumstances used by perfectly rational actors are no longer sufficient – models incorporating behaviour and learning are required if we are to gain full benefit from technological advances. This focus implies a corresponding move in the modelling fraternity from a focus of modelling supply side interventions such as technology, industry, universities and governance institutions (Geels, 2010b) to a framework where models explicitly address the need to understand what is interacting and co-evolving with what and how those interactions occur. This paper outlines a model which can elucidate these interactions and the system evolution.

Agent based modelling is a technique which is well suited to modelling Complex Adaptive Systems. Gilbert describes some criteria which apply to systems in which ABM is a suitable modelling technique (Gilbert, 2008), of which the modelling of the smart grid fulfils many, including:

- Need to model heterogeneous agents;
- Interactions between agents is important;
- Agents are *boundedly* rational;
- Learning will occur

The suitability of the ABM technique for modelling socio-technical transitions has been described in (Schilperoord et al., 2008). ABM offers the opportunity to model heterogeneous agents within an environment and to scale up such a model far beyond the practical and ethical limits of a real-world trial. In the context of this paper, agent is defined to be "any entity which can affect electricity consumption" and therefore includes individuals, automata, firms, communities and regulators. The environment includes physical, policy and economic environments (e.g. weather, regulation, incentives, market design).

ABM has previously been used in the electricity sector to model electricity wholesale markets from the Agent Based Computational Economists' (ACE) point of view. Two of the most significant models in this regard are EMCAS (North et al., 2002) and AMES (Sun & Tesfatsion, 2007). Whilst EMCAS has the facility to incorporate large scale renewable plants in its generation model, neither model has addressed either the integration of distributed micro-generation in large amounts or the active management of consumption behaviour.

Thus far, there have been few attempts to model social learning in the context of the transition to a smart grid, although we are aware of one study into smart meter adoption which characterised the agents adopting meters as subject to social influence from a network of contacts (Zhang & Nuttall, 2008). This study uses constructs from the Theory of Planned Behaviour (TPB) to model each agent's decision to adopt a smart meter, with social contacts providing a positive influence for the supplier they have selected with or without a smart meter. The sum of such influence over all contacts is characterised in the model as the agent's subjective norm toward a particular supplier / smart meter combination. Attitude is modelled by a single value of price sensitivity. The limitations of this approach are that the behaviour under consideration is not entirely specific – the "behaviour" appears to encompass both the obtaining of a smart meter and the switching of electricity supplier. In addition, the quantification of the TPB constructs appears overly simplistic, for instance the attitude toward obtaining a smart meter being represented only by price sensitivity and the weighting of the subjective norm being pre-conditioned from a random distribution rather than calibrated from previous empirical studies in related areas. Nonetheless, this model represents an initial study into the social effects on behaviour with regard to smart technology adoption under different policy contexts.

In other sectors, some work has been done in applying social learning to an ABM. In the context of understanding the success of a lottery, Chen and Chie (2008) apply a social learning framework to a population of potential lottery players in order to analyse the effect of different lottery designs on the revenue they generate. Lamberson (2010) models social learning in the context of generic technology adoption. However, he makes the assumption that actors can perfectly observe the payoffs from the decisions of their social contacts – something which is unlikely in reality.

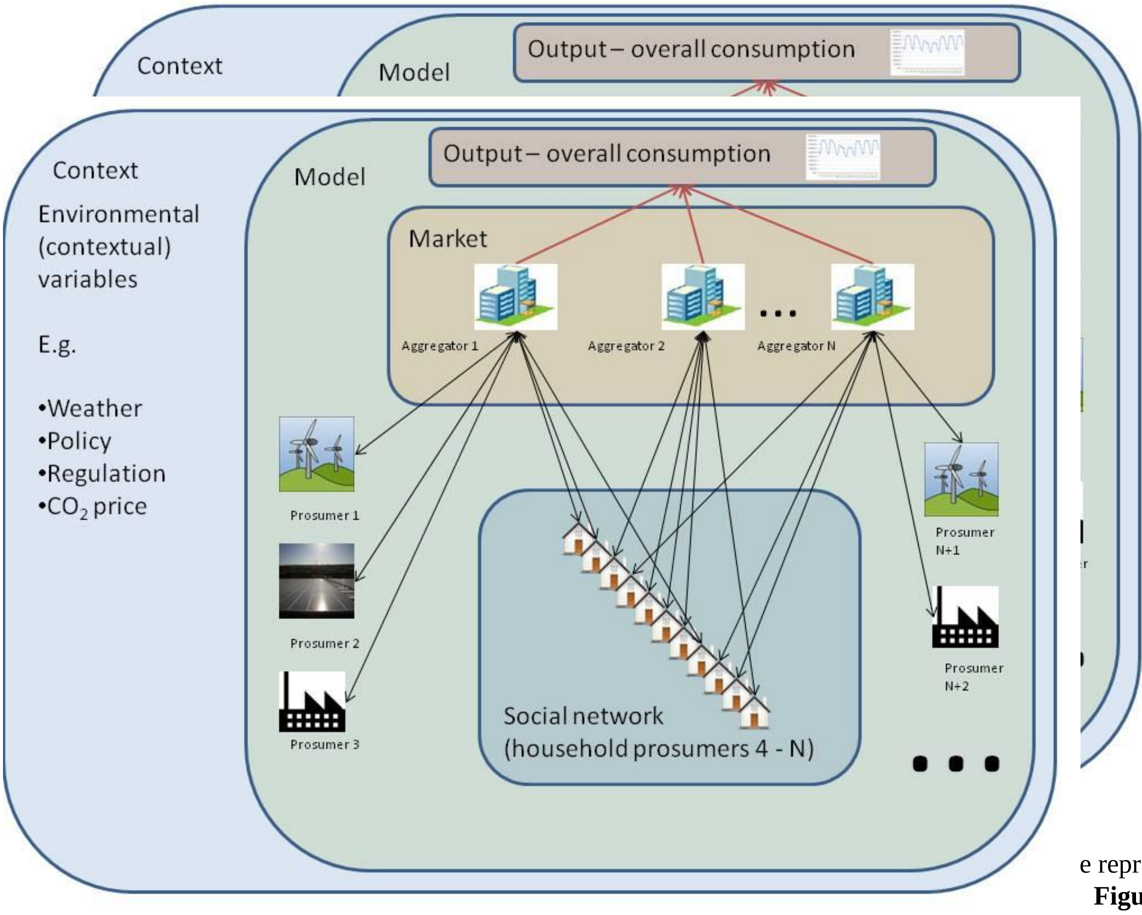
Model description

The Agent based model will abstract the key players in the electricity network by modelling "prosumers", "aggregators" and the environment. A "prosumer" is an agent who may *pro*duce or con*sume* electricity – it should be noted that this is a somewhat narrower sense than that used in some other discussions of a prosumer (e.g. Toffler, 1981), however the term remains apt for our discussion of an agent who can both produce and consume electricity. At either end of the spectrum, a prosumer may be a pure generator (for instance today's power stations), or a pure consumer (such as most households today). However, the prosumer abstraction allows for a rich heterogeneity of agents (like a household with microgeneration, or a community level storage facility) who may produce, consume and store electricity at various scales.

The aggregator will co-ordinate the prosumers' behaviour and will represent the interests of a group of prosumers (their customers) on the wholesale market. Thus, the main roles of an aggregator will be:

- deciding what signals to send to the prosumers in order to actively manage their demand
- deciding what strategy to employ on the wholesale market

The model is represented below in **Figure 3**. Whilst output is simply shown as the overall system consumption, one of the benefits of an ABM is that outputs may be captured at several levels, so net consumption by individual prosumers, particular groupings of consumers (niches) and aggregators of groups of aggregators is possible. It is also possible (and desirable) to understand the proportion of renewable generation which is supplying that consumption.



e represented in **Figure 3** as the household prosumers within the social network box. Agents with the ability to socially interact are connected together in a social network. The precise interconnection of this social network (i.e. which prosumer interacts with which other consumer) is one of the model initial conditions. In initial trial, a small world network was selected to be representative of the social contacts of a household and this network will remain throughout a simulation run (i.e. households do not make or break social contacts). Each prosumer within the social network is given a series of sensitivities to various factors and a series of outputs relating to the same factors (or influences).

Each agent moderates the influence which it transmits regarding the adoption of various technologies or behavioural practices according to the novelty of those technologies or practices and the success they bring.

Within the model, certain niches pre-exist – for instance a representative number of prosumers who have micro-generation technologies installed and a representative number of renewable generation prosumers (e.g. wind farms). However, the regime is the existing paradigm of large central generation prosumers (i.e. power stations) supplying household prosumers who are essentially pure consumers. The growth or elimination of niches over many simulation runs under different policy conditions is one of the outputs of the model.

The model is implemented in Java using the RePast ABM toolkit. The design outlined above is described in detail in (Snape et al., forthcoming).

Behavioural representation

Encoding behaviour

As mentioned in the introduction, the realisation of smart grid benefits requires (at least) three behaviour changes. Of these, we characterise the adoption of micro-generation plant and/or a smart demand management device as two separate, specific pro-environmental behaviours. As these are in effect adoption decisions – such decisions have been characterised in the literature as "one-shot" or investment efforts.

The other behaviour change – active engagement with energy saving behaviours – is not a specific behaviour change, but an agglomeration of various behaviours to a common end. The behaviours involved in this area are repetitive in nature (switching lights off when leaving a room, setting the dishwasher to come on at night, filling the kettle half full) that have been characterised as repetitive or operational efforts. In order to model these, a richer behavioural model is required, accounting for social and personal norms, habits and influences.

In using a behavioural theory as the representation of electricity consumption behaviour within a computational model, it is important to consider three factors in addition to the fundamental consideration of which theory appears to most nearly model the situation under consideration:

- What empirical data is available to pre-calibrate the model for the context? E.g. which constructs are present in any given agent, to what degree (a numerical level) and to what extent they influence the agents behaviour?
- How will the theoretical constructs be encoded?
- How will the resultant behaviour be validated against empirical study?

When considering the first issue, as Jackson (2005, p.116) notes, "as the conceptual complexity of the models rise, however, their empirical applicability diminishes." Thus, the more integrative theories described above have, in general, fewer empirical studies from which to draw inferences as to the relative importance of their constructs in the decision to perform a given behaviour.

Similarly, with increasing complexity comes increased difficulty in encoding a particular behavioural model into a computational framework. In addition, where a theory has been developed for its power to elaborate a narrative rather than to provide a statistical analysis of observations, the encoding of the theory becomes more difficult and in some cases more than likely invalid.

Finally, when considering validation, behaviour may be validated in two ways. Firstly, individual behaviour evolution through a simulation run may be observed and compared to empirical studies of household behaviour under smart grid initiatives. Secondly, as more trials of smart grid installations and incentive schemes at scale are initiated, aggregated results of the behaviour representation in the model may be compared with aggregate results from these trials[vii].

The final selection of the appropriate theoretical basis to encode household agent behaviour within our model remains an open topic of research.

Learning

Many learning mechanisms have been suggested for agents within an ABM, see, for instance, Brenner (2006) for a review. Largely, these have been mechanisms based on the learning of individuals based on their own prior experiences, decisions, outcomes and predicted futures. Although the algorithms by which individuals evaluate past experience and therefore decide future action vary, these models can be broadly described as 'trial and error' in nature – predicated on individual action and learning and consisting of the individual determining the trade off between *experimenting* with a new and potentially beneficial action and *exploiting* a previously tried beneficial action. As Brenner suggests, a useful consideration when selecting the learning representation in an ABM is the degree to which the action under consideration is due to cognitive deliberation versus sub-conscious or routine processes. This is not dissimilar to the concept of mindfulness in the psychological literature (Langer, 1989). In general, however, ABM work to date has concentrated on learning representations which are based either in well-trodden psychology (e.g. various forms of reinforcement based learning) or have no psychological basis but tend to some optimal behaviour over time (e.g. Bayesian learning, least squares learning).

Empirical studies show that a simplistic representation is not sufficient when considering real-world learning and behaviour change as models relying on such a representation are unlikely to capture the effects of policy interventions and observe transitions in a modelled system where such behaviour is integral. We can see in the real world that behaviour does not progress in an ordered way to optimality, even under a policy environment explicitly designed to encourage a certain outcome; we must be able to see the same in our modelled environment.

In this model, we explicitly choose to model learning as a belief-based social process. We compare the outcome of such a mechanism with that expected from purely individual based learning and zero learning in agents.

Example factors used in modelling social learning of behaviour change are shown in Table 2. These constitute the external factors affecting an agent's behaviour.

Factor	**Value range**
Susceptibility to influence in adopting micro-generation technology	0-1
Susceptibility to influence in adopting automated demand management	0-1
Susceptibility to influence in reducing consumption	0-1
Propensity to transmit effects of adopting micro-generation technology	0-1
Propensity to transmit effects of adopting automated demand management	0-1
Propensity to transmit effects of reducing consumption	0-1

Table 2: Example social learning factors

In addition to the explicitly social factors, an agent's behaviour is also mediated by internal factors such as habit, predisposition, perceived ability to act and many others, which we may describe in terms of their energy culture. These factors may change over time based on both social / observational learning factors and internal learning from prior experience and projection of future success. Here, we consider some of the factors which are likely to influence electricity consumption behaviour and how they relate to the Energy Cultures framework. Again, some examples from our initial model design are given in Table 3.

Factor	**Energy Culture category**
Sensitivity to increased cost	Cognitive Norm
Attractivity of lowered cost	Cognitive Norm
Belief in impending climate change problem	Cognitive Norm
Belief in human responsibility for above	Cognitive Norm
Perceived ability to action	Cognitive Norm
Perceived effect of personal change on climate change globally	Cognitive Norm
House construction type	Material culture
Existing appliances	Material culture
Income	Material culture
Age bracket	Material culture
Existing pro-environmental consumption behaviours	Practice
Travel attitude (proxy for EV adoption likelihood?)	Practice

Table 3: example energy culture factors for household consumption

Each agent calculates their intention to perform a behaviour based on a weighted sum of factors. Each factor, in turn is changed from its value at the start of the simulation (the agents' predispositions) by the influence which an agent receives from their social contacts in the model.

In modelling learning as having a social component, however, it is important that we do not make the visibility and influence of one agent's actions on another too significant. For instance, whilst the installation of a solar panel on the road-facing roof of a house may be very visible and therefore may be construed to have some effect on our peers, the installation of the same panel on the other side of the street will not face the road and therefore may have less influence. In an even more extreme case, installing a smart meter (whilst it may be a pro-environmental behaviour) may well be completely invisible to an agent's peers.

Thus, a major area of further study concerns which factors are crucial in a model of consumption and the relative importance (or weight) of each factor in an agent's decision to change behaviour.

Case study

The scenario studied at this time represents a small community similar in nature to the isolated communities described in (Rynikiewicz & Snape, 2010), with 1000 prosumers representing households and 1 prosumer representing a community scale wind generation facility. One aggregator is incorporated to generate the signal to the prosumers and collate the total net demand of the community. The aggregators' objective is to present zero net demand to the grid. Analogies may be drawn between this simple test case and a Virtual Power Plant (VPP) as proposed in the literature (e.g. Pudjianto et al., 2007).

Behavioural cultures are seeded at the start of each model run according to parameters inferred from the UK Department for Environment, Farming and Rural Affairs framework for pro-environmental behaviours (DEFRA, 2008). This framework segmented the UK population into seven groups based on their pro-environmental behaviour type. The segmentation was based on extensive surveying of lifestyle and attitude towards environmental issues and groups the population into groups of like *ability* and *willingness* to act on a number of specific pro-environmental behaviours. Among the behaviours researched were behaviours in the home and habitual behaviours including energy efficiency measures (installation of insulation, turning off appliances on standby) and pro-environmental purchases (energy efficient appliances, micro-generation, smart meters). Whilst not all of the behaviours could be directly related to the study of electricity consumption and the smart grid, the study is the best starting point available to "pre-seed" a UK based population with representative behaviours with regard to sustainable consumption.

We then employ a social learning treatment to this population in order to adapt the energy practices present. This social learning will take account of the existing energy culture as well as dynamically changing information provided by observation of others (within and without the agents own energy culture), financial reward / cost and consumption information to make decisions about future energy practices.

Discussion

At the time of writing, the ABM described in this conceptual paper has been implemented at small, prototype scale within the CASCADE project (CASCADE, 2010). Within this small scale trial, the ability of the model to simulate a dynamically managed demand in response to a signal has been demonstrated. The impact of the behaviour and learning of agents on the dynamics of consumption over day and week long time scales has been observed.

Differing theoretical foundations for behaviour have been implemented in the prototype and the comparison of their effects is under way. Calibration of the model utilising secondary data from studies of behaviour in relation to smart grid implementation will be an ongoing process which will be recursively refined as more studies become available.

The advantage of the modelling approach is that, once calibrated and validated, findings may be scaled up to systems far bigger than those with which it is possible to conduct real-world trials. Thereby a range of smart grid implementation strategies and policies may be tested – something which would be probably impossible and almost certainly unethical to do with the system itself.

This approach to modelling could yield interesting data for policy makers, regulators and funders alike when considering where to target incentives and financing in order to seed the changes which will yield most benefit.

Conclusion

This paper has described the necessity of including behaviour and learning of agents in a model of changing energy consumption. We have outlined a novel framework in which to model behaviours and learning pertaining to energy consumption adaptation and adoption of smart devices and renewable generation.

We present an Agent Based Model to incorporate behavioural and learning capabilities in a simulation to describe the transition of the electricity network to a Smart Grid and its effect on consumption. The model has the flexibility to incorporate heterogeneous Energy Cultures and social learning of consumption patterns and measure their impact on the dynamics of the consumption. Initial prototypes indicate that individual and social behaviour is significant in the overall consumption and therefore system efficiency.

Extensive further work is required to develop both the richness of the model in order to usefully model the full complexity of behaviour described in the framework above. From this, the scale of the model will be enhanced and further tested.

The model presented allows different technologies and policy incentives to be tested free from the usual practical and ethical constraints of real world experimentation. It allows the incorporation of different assumptions about how actors behave and learn and the sensitivity of the modelled scenario to these assumptions.

Use of the model will aid understanding of observed patterns of consumption and micro-generation adoption and help to refine our understanding of how consumption patterns are learnt and changed at an individual, community and system level. It may also highlight where and in what form green financing initiatives are needed at national, individual or community level in order to provide funds to catalyse this change. In turn, this understanding may help to facilitate policy directives, regulation and incentives employed to encourage and accelerate the move toward a lower emission, more energy efficient society.

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Endnotes

[i] See http://2050-calculator-tool.decc.gov.uk/pathways/1/primary_energy_chart - to achieve 80% reduction by 2050, at least one of the input measures must be set to level '4' which bears the quote: "Heroic effort, but does not break any laws of physics"

[ii] Electricity consumption is a significant contributor to emissions as a whole (e.g. in the UK, domestic electricity consumption contributes 13% of total emissions (DECC, 2008). The total emissions from domestic electricity use may be reduced by a combination of two factors. Firstly, overall reduction of consumption – however energy used (million tonnes of oil equivalent) to provide domestic *electricity* shows a rising trend (DECC, 2008). Secondly, a shift in electricity generation from non-renewable to renewable sources; again there is an adverse trend for this method in the UK domestic sector (Bergman et al., 2009). In 2004, the UK government intended that 400,000 micro combined heat and power (µCHP) units (DEFRA, 2004) and 200,000 photovoltaic (PV) installations (DTI, 2004) would be installed by 2010. Yet, a review of actual installations in 2009 reveals 100,000 micro-generation installations across *all* technologies – indicating that the level of µCHP and PV installations within this are vastly behind targets set only 5 years previously. In the same period, the governmental commitment to emissions reduction has gone from 60% of 1990 levels (DTI, 2003) to 80% by 2050 and is now legally binding (UK Parliament, 2008).

[iii] We acknowledge that environmental benefits are not the sole driver toward the implementation of a smart grid. There are various co-benefits including enhanced energy security, reduced infrastructural investment and increased liberalisation. However, for the purposes of this paper, we consider the environmental benefits.

[iv] In addition to these, other changes ***may*** be necessary to realise some smart grid benefits. For instance, the acquisition and use of an Electric Vehicle to enable the smart grid to reduce emissions due to mobility as well as to provide 'smoothing' of the overall demand on the grid (Inage, 2010); or the move of space heating demand from the coupled gas network to the electricity network.

[v] Shove gives the example of air conditioning to demonstrate such a change in norm and its associated lock-in effects. Air-conditioning is incorporated initially into what individuals consider a normal level of comfort. The habitual expectation of individuals leads to incorporation of air conditioning into the cultural norm in climates where air conditioning has previously been considered unnecessary. Such a behaviour becomes 'locked-in' as building standards and practices design and build with the incorporation of air-conditioning as a given. Such a lock-in also locks in the associated consumption of electricity.

[vi] The framework was inspired by an example of seemingly counter-intuitive behaviour where the adoption of a lower-cost, more energy-efficient industrial process was resisted apparently due to factors which could not be accounted for economically.

[vii] The modelled effects will be compared with observed behaviour change in small scale tests. From a behavioural point of view, the PowerCents DC study is one of the most interesting studies completed so far in the smart grid context, (eMeter Strategic Consulting, 2010; Wolak, 2010). It measured consumption behaviour change in 900 voluntary participants in response to three different pricing schemes based on smart metering – often seen as one of the predicates of smart grid benefits. The schemes were designed to be revenue neutral (i.e. the same usage would give the same bill), however the study found that one scheme achieved far greater peak demand reduction than either of the other schemes, whilst another was reported as most popular amongst study participants. This is explicable only if behaviour and perception of participants is taken into account – the design of the experiment was such that rational choice would indicate the schemes were equivalent.

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