Synergies and conflicts on the landscape of domestic energy consumption: beyond metaphor

Dr David Shipworth
School of Construction Management and Engineering
The University of Reading, Whiteknights
P.O. Box 219, Reading, Berkshire, RG6 6AW
England
d.t.shipworth@reading.ac.uk

Keywords

socio-technical systems, complex systems, Bayesian belief networks, barriers, energy policy, research design, transdisciplinary

Abstract

A transdisciplinary research and modelling process is presented. This goes beyond the metaphor of a 'landscape' of influences on domestic energy consumption, to construct a Bayesian Belief Network model of such a landscape.

Bayesian Belief Networks are of both academic and practical interest. They are applied in many areas governed by complex sets of socio-technical drivers including management of water catchments, ecosystems and fisheries. Such models allow better understanding of the range of social, economic and environmental impacts of a given management strategy and how benefits in one part of the system may be offset in another. These interactions between influences generate the 'landscape' of the system.

The research design for development of a Bayesian Belief Network model of the socio-technical influences on home energy use is presented. A realist synthesis of the literature identifies factors influencing domestic energy use, their strength, and the direction of their interrelationships. These are represented as a network diagram. This initial network is presented to experts for elaboration and verification. Data is used to estimate probabilistic relationships between the factors. Primary qualitative social research methods identify new, and contextualise known factors for the UK. Data from primary or secondary quantitative analysis is integrated to refine estimates of the influence of key factors. This process is iterated to build and refine the model.

This research design will be presented, and the policy implications of this modelling approach explored. This research forms part of the UK's recently launched 'Carbon Vision' programme on carbon reductions in buildings.

Introduction

The literature on energy use in homes has had a consistent socio-technical stream since Princeton University's 'Twin Rivers Project' in the 1970's showed that energy use in technically similar dwellings, occupied by demographically similar families, can vary by 200 to 300% (Lutzenhiser 1993). The inclusion of demographic variables increases this variability still further (Gellings 1994). Costanzo notes that *'Achieving energy conservation is a twofold challenge, partly technical and partly human. The development of energy-conserving technologies is a necessary but insufficient step toward reduced energy consumption. Unless adopted by a significant segment of consumers, the impact of technical innovations will be negligible.'* (1986, p 521). These are key reasons why estimates of theoretical technical potential for carbon reduction from buildings have not been realised, and why the IPCC Third Assessment Report finds that the building sector is the sector with the largest unrealised technical potential for emissions reductions (IPCC 2001 p 7).

This paper details the research design to be used for constructing a Bayesian Belief Network model of the socio-technical influences on domestic energy consumption in the UK under the Carbon Vision programme. The Carbon Vision programme is a major UK research programme addressing carbon mitigation. The programme focuses on two areas - the built environment and process industries. The built environment stream, entitled 'Building Low Carbon Communities' (BLOCC) is receiving approx. 7 Million Euro over 4 years (2005-2008). This funding is divided between three consortia: Carbon Reduction in Buildings 'CaRB' (approx. 4.1 Million Euro), Technology Assessment for Radically Improving the Built Asset Base 'TARBASE' (approx. 1.8 Million Euro) and Building Market Transformation 'BMT' (approx. 1.3 Million Euro). The work described here is one of four primary work packages taking place within the CaRB consortia. It is designated CaRB Socio-Technical (CaRB-ST) and constitutes approximately 30% of that programme of work.

In overview, CaRB Socio-Technical uses *qualitative* social research methods to understand the socio-technical influences on household carbon emissions, uses *quantitative* methods to measure statistical relationships between these influences, then uses Bayesian Belief Networks to *model* the relationships between the influences. The network grows iteratively through firstly *understanding*, then *measuring*, the direct and progressively more indirect socio-technical influences on household carbon emissions. The research design is explicitly transdisciplinary with qualitative Bayesian statistical methods providing a common epistemology acceptable to the technical energy modelling community, policy makers and the social and psychological sciences.

Socio-technical Systems

The Socio-Technical Systems (STS) view of energy use in buildings envisages society (from personal practices through to institutional structures) and technology as forming co-evolving 'socio-technical' systems. This socio-technical systems perspective provides a broad theoretical framework for understanding how technology is produced, diffused and ultimately changes society (Bijker and Law 1992). STS ideas have informed the application of specific research methods such as Actor Network Theory (ANT) (Callon 1986) and the Social Network Analysis (SNA) of the diffusion of innovations (Valente 1995). STS as a theoretical framework is well suited to the analysis of the complex social, economic and technical changes necessary to reduce energy use in buildings (Rohracher 2001). Early STS theory as developed by the Tavistock Institute has been strengthened through interaction with both ANT and the wider field of Social Shaping of Technology studies (Williams and Edge 1996).

In addition to finding application through methods like ANT and SNA, these theories can be applied using 'technology assessment' methods from the fields of Constructive Technology Assessment, Environmental Technology Assessment and Real Time Technology Assessment. Such technology assessment (TA) tools are well established and are used by environmental organizations (e.g. UNEP's International Environmental Technology Centre) to assess the likely impact of a technology within a socio-technical system (IETC 1996). Such tools are also used proactively in innovation and market transformation studies (Guston and Sarewitz 2000; Blumstein, Goldstone et al. 1998) to tailor technologies to the needs of their recipient socio-technical systems. These applied technology assessment fields share common methods and tools applicable to both historical analysis of successful innovation strategies, and the development of research and development strategies for new technologies.

These approaches differ markedly from past models of research, development, demonstration, dissemination and diffusion. The traditional approach has tended to see these as sequential and largely independent. The socio-technical approach and the more recent diffusion of innovations literature see these as iterative, integrated and of equal importance (Rogers 1995; Blumstein, Goldstone et al. 1998). While both approaches are equally technically demanding, the latter is far more socially demanding, and greatly increases likely uptake of the innovation. It is this process of engagement with end-users as co-designers in the development of the solution that greatly enhances its acceptance and diffusion. These engaged and iterative approaches to diffusion of innovations within socio-technical systems are paralleled by recent approaches to the study of policy formulation. Sabatier (1999) has analysed the policy formulation process and developed a theory of Policy Advocacy Coalitions (PAC). The PAC model of policy formation argues that policies emerge from negotiations between coalitions of actors. These coalitions of actors coalesce around common sets of normative beliefs and values. They adopt and advocate policy ideas concomitant with their shared beliefs. Acting through, and with, 'policy entrepreneurs' ('change agents' in SNA terminology) these PACs seek to shape government policy formation in ways which reinforce and promote their interests, normative beliefs and values. The PAC model of policy formation reflects lessons from the wider SST literature onto the policy formation process to envisage it as contingent, socially embedded, evolutionary and systemic. Understanding policy formation processes is of more than just academic interest in the context of large-scale government research projects. Those seeking to affect real change in domestic energy use cannot do so without at least tacit, or preferably explicit and active support from government policy and programmes. If one accepts the PAC policy model, and the STS diffusion of innovations and market transformation models, then reflexive application of these requires adopting knowledge construction and representation methods for research projects which are themselves similarly contingent, socially embedded, evolutionary and systemic. This is one of the open challenges in the energy research field.

This is reflected in Elizabeth Shove's conclusions from her ESRC funded review of building energy research as reported in papers to ECEEE 1995 and Energy Policy (1998). She noted that:

'An alternative or at least additional strategy might therefore start by describing and perhaps modelling portions of the sociotechnical world in all their complexity. Working from this base forward, it might be possible to identify socially as well as technically viable opportunities for energy conservation.' (p.1110)

This call is echoed by Ekins (Johnson & Ekins 2003) in his capacity as Academic Co-ordinator of the ESRC Environment and Human Behaviour Programme. In this broader context Ekins concludes that:

'Understanding human behaviour towards the environment and how this might change/can be changed is a complex task indeed. As with most complex realities, seeking an explanation requires this complexity to be simplified through the use of frameworks, models

and theories. Nowhere is this more evident than in the multi-causal domains of human behaviour and public policy.' (p.2)

The CaRB-ST research design has been developed to be consistent with Socio-Technical Systems theories of energy us in homes as well as the Policy Advocacy Collation model of policy development. It explicitly attempts to model 'socio-technical landscapes' by subjective statistical modelling of the multi-causal domain of energy use in homes using Bayesian Belief Networks. The research design through which such models are built is itself informed by the need to engage with the stakeholder communities for which the model is being developed.

INTERDEPENDENT INFLUENCES AND LOCAL CONTEXTS

Two additional characteristics of socio-technical systems are their complex multi-causal structure, and the role of context and contingency in determining the efficacy of different change strategies. Models of the factors influencing consumption generally (Jackson 2005); environment and human behaviour (Johnson & Ekins 2003) and the socio-technical influences on domestic energy consumption (Rohracher 2003) are consistently complex and multi-causal. Complexity arises because the causes, or influences, on home energy use are interdependent. Factors, such as household head education level, simultaneously increase the likely uptake of messages from energy efficiency information campaigns thus acting to lower energy use, while being correlated with increased household income which is itself correlated with increased energy use. Such interdependencies between variables create conflicts within the interdependent and multi-causal network of influences on home energy use. A consequence of such conflicting interdependences is that programmes targeting change through one set of influences frequently fail to affect the anticipated change because of countervailing effects arising through other parts of the network.

Modelling such complex interactions between influences, particularly where the role of influences is uncertain and hence statistical modelling is required, has traditionally presented difficulties. Consequently, influences have been modelled as being independent rather than interdependent, and the ability to capture important properties of the complex, interdependent, multi-causal correlation structure of the network of influences has been lost.

Another expression of socio-technical systems' interdependent multi-causality is the particular role of context in determining the efficacy of different change strategies. Much of the sociological literature on energy use in homes draws particular attention to this issue. Wilhite and Nakagami (1996) review the implications of cultural contexts and find them central to domestic energy consumption practices in Japan and Norway. Evans *et al* (1999) have highlighted the role of contingency in urban energy policy while Guy and Shove (2000) have stressed the importance of understanding how energy consumption practices in buildings are embedded in specific social contexts. From an energy policy programme perspective, this embeddeding of practices within local contexts necessitates being able to understand the role of context, and the tailoring of programmes to fit. Models and other forms of knowledge representation on which energy efficiency programmes are based need to be able to take such contingencies into account if they are to support effective programme design.

Collectively, this socio-technical view of energy use in homes is well captured by Shove's metaphorical image of the socio-technical 'landscape'.

'It is enormously helpful to see the world out there as a bumpy and uneven terrain in which new and not so new technological strategies 'make sense' in different ways and at different moments in time. ... But there is more to come for if we are to take full account of the diverse contexts of action, and the variety of sociotechnical landscapes, we must also recognise the multiple contexts in which expertise and experience is formed.' (Shove 1998 p.1109)

While Shove's use of the term 'landscape' is a metaphorical one, there are academic disciplines in which this term has a carefully defined meaning. Perhaps not coincidentally, these same disciplines are ones characterised by the study of complex, interdependent, multi-causal systems. The use of methods developed in such fields, which are now starting to be applied more widely, offers the opportunity to step from landscape as metaphor - to landscape as model.

Complex systems

Complex Adaptive Systems (CAS) theory studies the behaviour of systems consisting of large numbers of interdependent variables. Such systems arise in many fields including medical diagnosis, genetics, economics, ecology and sociology. They are characterised by non-linear behaviour where changes in input are neither proportional to changes in output, nor is the input to output relationship fixed over time. The presence of nonlinearities in CAS is a direct result of interdependencies between components of the system (Coveney and Highfield 1995). As Goerner (1994) notes, it is only through the study and incorporation of interdependencies that we can understand the behaviour of, and develop meaningful management strategies for, complex adaptive systems.

In such systems, finding the 'optimal' solution for the system as a whole cannot be achieved by simply incrementally changing each of the components in turn. The positive and negative interdependencies between components means that optimising one, frequently leads to a sub-optimal solution for another. In such situations, the system is said to be 'frustrated' as the optimal solution for the system cannot be achieved by optimising each of its components independently. The consequence of this is that the set of all possible states of the system (called its 'state-space'), is neither convex nor concave, but has a complex topography with ridges, plateaus, troughs and peaks. It is this complex topographical surface representing all possible states of a system which in the Complex Adaptive Systems literature is referred to as a 'landscape'. Finding the optimal solution on such complex landscapes is difficult. In the field of Complex Adaptive Systems research, graphical models are the dominant underlying mathematical structure for studying such landscapes. (The term 'graph' here is taken in its formal mathematical meaning as a set of points (called 'vertices') connected by lines (called 'edges') – essentially a mathematical version of 'join the dots').

As Jordon (1999 p.1) notes in the introduction to 'Learning in Graphical Models':

'Graphical models are a marriage between probability theory and graph theory. ... Probability theory provides the glue whereby the parts are combined, ensuring that the system as a whole is consistent, and providing ways to interface models to data. The graph theoretic side of graphical models provides both an intuitively appealing interface by which humans can model highly-interacting sets of variables as well as a data structure that lends itself naturally to the design of efficient general-purpose algorithms.' (Jordon 1999 p.1)

A Bayesian Belief Network (BBN) is one form of graphical model.

Cooper (1990 p.403) showed that '…probabilistic inference using multiply connected belief networks with uninstantiated variables is NP-hard'. This means that virtually all substantive management applications of BBN decision support systems will have multiple optima. Multiple optima means (potentially) large numbers of 'better' management strategies which can be found by changing one variable at a time and observing whether this makes things better or worse. A better strategy (local optima) is reached when any further incremental change to the variables under management control makes the system worse. These better management strategies may, however, be very far from the 'best' management strategy (the global optimum) for the system and it also means that finding the 'best' management strategy (the global optimum) can be exceedingly difficult. Moving from a better management strategy (a local optima) to the best management strategy (the global optimum) usually involves making the system worse (over coming a barrier on the system landscape) before the management dividend can be realised. Without a model which can capture the interdependencies which create these multiple optima, it is not possible to explore the landscape of alternate management strategies in search for more optimal ways to manage the system. Without such a model, finding the best management strategy is akin trying to find the highest peak in the Himalaya - without a map and in thick fog with only an altimeter to guide you. There is no option but to simply walk up hill until you can go no higher, take a reading, and then head back down to try again in some other random location. This is a rather inefficient way to get to the top of Mt. Everest!

Recently, with the development of new inference engines and sufficient computational power BBNs have become sufficiently powerful to be applied to large scale practical applications. In the case of policy driven BBNs, the joint probability distribution usually reflects a property of policy interest which needs to be 'optimised' in some sense. In the case of BBN's built in the area of integrated water resource management (e.g. Cain 2001), the joint probability distribution of the network can represent catchment water demand, and management of this means balancing the needs of multiple user communities while minimising water use, and variations in that use, over time. Changing the states of variables in the interdependent network of variables governing water use in a catchment, changes total water demand. It follows that some sets of states of the variables are 'better' (as measured by total water demand) than others. Applied BBN models therefore provide a decision support system for managers of such complex systems involving interdependencies between social, economic and environmental variables. Managers can explore the implications of changing the states of variables and see the likely impact on the parameter of the system they wish to manage. As discussed, incremental change may simply lead to local optima, but there is no guarantee that this is the global optimum, i.e. best management solution for the system as a whole. Moving from local optima, to the global optimum, may involve climbing up over a ridge or 'barrier' in the landscape. In effect, affecting significant cuts in the parameter of interest, in this case energy use in homes, may require rather more radical programmes of change which involve fundamentally changing the structure of the system or altering several variables at once. Modelling the complex, interdependent network of variables influencing energy use in homes using Bayesian Belief Networks, and understanding the topography of the landscape of such a network, can therefore lead us to a more concrete, empirically grounded, discussion around questions of interdependence, context, barriers and management strategies for change.

Bayesian Belief Networks

Bayesian Belief Networks (BBNs) are an intuitive method for reasoning under uncertainty, combining different datatypes, and learning from new observations as they become available (Jensen 1999). Developed in the late 1980's, theoretical understanding of such networks grew through the 1990's seeing major advances in the applicability of BBN modelling with a number of public domain, well validated numerical methods and modelling environments becoming available. The development of these modelling environments has reinvigorated applied Bayesian analysis (Carlin and Louis 1996). Post 2000 has seen applied work expanding rapidly (O'Hagan 1998) particularly in the fields of epidemiology, econometrics and environmental management (Dorfman 1997; Congdon 2003).

Bayesian Belief Networks are a specialisation within the wider field of Bayesian statistical modelling and share their methodological advantages. In *Bayesian Methods: A social and behavioural science approach* Gill (2002) lists advantages of Bayesian methods as including: the ability to learn as new information is received or population variables change; the capacity to systematically integrate a wide variety of data types and any prior available knowledge; overt and clear model assumptions and straightforward sensitivity testing.

Bayesian statistical modelling allows you to progressively integrate new data into existing probability distributions and see how this changes the shape of the resulting distribution over time. As Congdon (2001 p.1) notes: '[Bayesian statistical modelling]…provides a way of formalising the process of learning from data to update belief in accord with recent notions of knowledge synthesis.' In addition BBNs allow predictions about the likely future state of the system based on what is currently known about the system and assumptions about future data. Heckerman (1999 p.301) notes: '…a Bayesian network can be used to learn causal relationships, and hence can be used to gain understanding about a problem domain and to predict the consequences of intervention.' BBNs also offer modularity. The structure of the network can be changed, or the network extended, as the understanding of the relevant variables and their interdependencies changes improves. This permits growth and rearranging of the structure of the network without entailing the reassessment of all conditional probabilities in the network.

Bayesian Belief Networks also support:

- The construction of consensus based, transparent, decision support systems;
- the clear and intuitive display of relationships between variables;
- use of categorical and continuous variables;
- the integration of qualitative and quantitative data from experts, case studies, data-sets and models;
- highlighting the conflicts or synergies between variables.

BBNs can be used, and their outputs presented, in a number of ways. The probability of the states of the dependent variables of interest can be given as the joint probability distribution over their influencing variables. Conversely, and more powerfully from a management perspective, it is possible to calculate the states of the influencing factors that would be required to achieve the desired state of a dependent variable of interest. (Marcot et al 2001).

BBNs are used to represent a complex set of interacting variables (called nodes) in a domain of substantive interest. There are two aspects to the network, a graphical part that describes the relationships between the variables (termed network structure or architecture), and a probabilistic part that encodes the correlations between the variables (termed conditional probabilities). The probabilistic part defines a joint probability distribution across the set of variables (the correlation structure). (Jensen 1999)

Construction of a BBN involves three broad steps:

1. Identification of the domain variables;
2. Identification of the relationships between these variables and;
3. Identification of the probabilities describing these relationships (Druzdzel & van der Gaag 2000).

Steps one and two generate the network architecture, while step three generates the correlation structure. In theory, these steps are done in turn. In practice however, the relationship between network architecture and correlation structure is such that these steps must be performed iteratively if the best possible network is to be built within given time and cost constraints.

As Cain (2001 p 10) notes: *Tests have shown that Bayesian networks are usually able to represent the most important factors in the system effectively. Since the networks are diagrammatically based, it is relatively easy for users to understand how those factors interact and, as a result, how the DSS produces its outputs. For the same reason, it is also fairly easy to communicate the information on which you have based your decision.*

CURRENT USES IN ENVIRONMENTAL MANAGEMENT

The use of Bayesian models is expanding rapidly in the field of environmental management. Uses range from the application of Bayesian statistics to the management of fisheries (Fernandez et al 2002), wildlife (Cohen 1988), and forests (Crome et al 1996). Dixon and Ellison (1996) and Ellison (1996) provide good overviews of the application of such models in ecological research and decision making.

Bayesian Belief Network models have found wide application in environmental management because, as Marcot et al (2002 p.30) note, they '...provide a means of modelling the likelihoods of management effects'. BBNs have been used to model land manager decisions with respect to options for land use change (Bacon et al 2002); the performance of bird conservation programmes in the Columbia Basin (Wisdom et al 2002); the management of fisheries resources (Lee and Rieman 1997); for participatory agricultural land management (Cain et al 2003); for participatory resource management (Cain et al 1999); for integrated water resource management (Bromley et al 2004; Cain et al 2001).

The interest in applied Bayesian Belief Networks lies principally in their use as decision support systems. They are offer the opportunity to capture expert knowledge in the field as well as structure this in a way supports programme development and implementation. Their capacity to integrate data of varying quality and type, as well as synthesising relevant factors in social, economic, ecological and technical fields, makes them particularly useful in the complex socio-economic/socio-technical environments of sustainable development.

BAYESIAN EPISTEMOLOGY

The development of BBN models in substantiate applications almost always involves combining quantitative conditional probabilities derived from analysis of existing datasets, with qualitative assessments of conditional probabilities derived from expert elicitation. Bayesian statistical modelling allows the integration of qualitative, semi-qualitative (ordinal level) and quantitative data. The basis of the distinction between the Bayesian and frequentist statistical approaches lies in their treatment of existing knowledge. By definition, the classical or 'frequentist' approach to statistics is based on observed long run frequencies of an event's occurrence. This creates problems where no such data exists. In the Bayesian approach, '…probability is interpreted as a numerical measure of the degree of consistent belief in a proposition, consistency being with the data at hand.' (Jordan 1999 p.9) The Bayesian approach does not, therefore, depend on observed long-run frequencies, and is free to use other sources of knowledge such as expert opinion as an initial basis for modelling uncertainties. Use of expert opinion, gathered through a range of sociological and psychological research methods, is frequently used as the basis of prior knowledge. This prior knowledge is then updated using semi-qualitative or quantitative data as the situation changes or more accurate data is gathered. This capacity to integrate and weight expert opinion with quantitative data within modular, extensible statistical models provides a framework within which energy reductions from a suite of policies and programmes can be assessed. This is particularly relevant for modelling the likely effect of 'softer' mitigation measures such as economic incentives and behavioural change campaigns the effects of which are real, but often difficult to quantify. In such cases predicted savings based on expert opinion or non-representative data can be used as a basis for initial savings projections.

NETWORK TERMINOLOGY

As noted by Jordon (1999), Bayesian Belief Networks combine two areas of mathematics: graph theory and probability theory. They take their structure from graph theory and adopt its nomenclature. In Bayesian Belief Network literature variables are termed *nodes*, and the interdependence relationships between variables are termed *edges* (or links). There can be three types of nodes: *constants* are fixed and specified in a data file; *stochastic* nodes are variables that are given a distribution (stochastic nodes may be observed in which case they are data, or may be unobserved and hence be parameters and can be either continuous or discrete); *deterministic* nodes are logical functions of other nodes. There can be two types of edges: *probabilistic* relationships specified by a probability of occurrence; and *logical* relationships specified by a mathematical expression. Bayesian Belief Networks also adopt nomenclature from the structure of family trees. Variables on which a variable is dependent are termed its *parent nodes* (or *parents*), and variables which are dependent on a variable are termed its *child nodes* (or *children*).

Like conventional Bayesian analysis, BBNs allow for the continual integration of new observations or data with prior distributions representing best available current knowledge. In cases where no other data is available, these prior distributions are frequently constructed using expert elicitation methods. BBNs usually model such prior knowledge using discrete Dirichlet distributions which are conjugate to the multinomial distributions used to represent data.

In Bayesian Network the 'architecture' of the network refers to the nodes and the links between the nodes. For CaRB-ST, this architecture is the graphical component of the model and captures the relationships between the underlying influencing factors (nodes) which cumulatively give rise to the observed variability of energy use in technically similar dwellings. Linking nodes allows us to model and understand why changing one variable does not necessarily lead to a proportionate change in overall energy use, as that variable may be both positively and negatively correlated with energy use through different pathways through the network. Within each discrete stochastic node is a Conditional Probability Table (CPT). This encodes the correlation between nodes through the probability of the variable being in any given state, given the states of its parents. An important consequence of this is that BBNs are 'factorizable', in that the contribution of each node is limited to the interaction of that node with its parents. This is what makes networks easily extensible and modifiable as only the CPT's of nodes directly linked to any changes are affected.

ARCHITECTURE

While the bulk of resources invested in constructing a BBN lies in identifying probabilities, Druzdzel and van der Gaag (2000) note that 'Experience with constructing probabilistic networks for various domains of application has established a consensus that the graphical structure of a network is its most important part...' p.483. This importance arises for two reasons. Firstly, the output of the network (its correlation structure over the domain of variables) is more sensitive to changes in the architecture than to changes in conditional probabilities. Secondly, the time required to construct a network is heavily dependant on the number of probabilities required which is in turn heavily dependent on the architecture (Laskey & Mahoney 2000).

Constructing the network architecture can be done in two primary ways:

1. Learning the architecture from the data (possible in very data-rich domains) and;
2. Generating the architecture from literature and expert elicitation. (Druzdzel and van der Gaag 2000).

In the domain of socio-technical influences on domestic energy consumption, the data is incomplete and highly variable and so and so literature and expert elicitation are used.

RELATIONSHIP BETWEEN ARCHITECTURE AND PROBABILITIES

For nodes with a given number of discrete states, the number of probabilities required is exponential with the number of edges between nodes (Druzdzel & van der Gaag 2000). As noted above however, the number of probabilities is a function of the architecture of the network. This, in turn, determines the size of the Conditional Probability Tables within the nodes. The CPT within any node contains the Cartesian product of the number of states of the variable and its parents. A three-state variable, with two three-state parents, would have a CPT with 3^3 (27) probabilities. Adding one additional three-state parent means the probability of each of these 27 states needs to be assessed for each of the 3 states of the new parent node. This increases the required probabilities to 81 illustrating the exponential relationship between variable interdependence and data requirements. The number of probabilities can be reduced buy altering the architecture of the network.

Druzdzel and van der Gaag (2000 p.483) note however that

> *Changes to the graphical structure of a probabilistic network and the use of parametric distributions are likely to come at the price of accuracy. There currently is little insight in whether or not a fully detailed network with separately specified assessments has a better performance than a network that is carefully reduced using the approached outlined above. There is no doubt, however, that the reduced network will have required considerably less time on the part of the experts involved. The time thus saved can be exploited for verifying the refining the network.*

This point is important and applies to all areas of network development. Overall network utility is always best served by directing inevitability limited resources to those aspects of network development which will yield greatest effect.

PROBABILITIES

Determining the probabilities for the correlation structure is the majority of the effort in constructing a working BBN model.

There are three broad approaches to this:

1. Statistical analysis of primary or secondary datasets;
2. Probabilities reported in the literature and;
3. Expert elicitation.

The method used depends on the quality of the data available.

Primary and secondary data analysis

Ideally, large empirical datasets in the direct context of the study are used to determine the correlations between variables. More frequently, secondary data provides estimates of correlations with low statistical power in a close, but not matching context to that of the study. All the usual problems of the meta-analysis and synthesis of data from different times and places arise, and frequently experts are asked to make judgements as how best to adjust the statistical data to the current context.

Literature

Data from literature present similar challenges. Findings from studies seldom report the characteristics of the studies' population in sufficient detail to determine how closely these match those of the target population. Probabilistic findings in literature are also frequently expressed in the reverse direction of causation, i.e. the frequency with which a possible cause is observed in the target population. By way of example, knowing that 30% of the people who turn off lights in unoccupied rooms are school aged children does not tell you the probability that a school aged child will turn off lights in an unoccupied room. Again, considerable domain specific knowledge from experts is required if such data are to be correctly interpreted and used.

Elicitation

There is a long history of elicitation of experts' estimates of uncertainty across many disciplines. Early work in the statistical community stems back to Hogarth (1975). Much of this work has focused on eliciting full probability distributions, either for direct use in models where no other data is available, or for conventional Bayesian analysis (O'Hagan 1998). While Bayesian Belief Networks only require point estimates of conditional probabilities rather than full distributions, useful understandings of the underlying psychology of uncertainty estimating can be found from in the broader Bayesian literature as well as direct contributions from psychologists (Anderson 1998).

O'Hagan (1998), in his work with engineers on estimating costs of maintaining water treatment works, found that distinguishing between sources of uncertainty, and having experts consider these explicitly, aided the elicitation process. O'Hagan notes that experts estimates of uncertainty are (frequently unconsciously) conditioned by the sources of uncertainty they are considering in making their judgements. One of the aims of collective elicitation methods, such as modifications of the Delphi technique, is to expand the pool of factors experts should consider in arriving at their estimates of uncertainty.

O'Hagan also concludes that 'It is essential to ask about quantities that the experts understand best, and in a language that is as simple and familiar as possible' This is supported by other authors (Kandane and Wolfson 1998 p.4) who note that 'experts should be asked to assess only observable quantities, conditioning only on covariates which are also observable or other observable quantities'.

Kandane and Wolfson also note that consensus has been reached on the need for frequent feedback to be given to experts during the elicitation process and for both conditional and unconditional probabilities to be elicited on hypothetical observed data.

The Bayesian Belief Network development process

Network development progresses through two broad phases. Phase one involves a realist synthesis of the literature, initial construction of the BBN architecture, and population of the network with preliminary estimates of conditional probabilities. Phase two proceeds iteratively through network sensitivity analysis; uncertainty analysis; validation; verification; expansion; and contextualisation. This creates a process of network development intended to focus resources on those areas to which the output of the network is most sensitive.

PHASE 1: REALIST SYNTHESIS OF LITERATURE

A 'realist synthesis' or 'realist review' of literature is an approach to literature analysis recently developed by Pawson and Greenhalgh (2004) under the auspices of the UK Economic and Social Research Council (ESRC). It is intended to produce policy guidance decision support rather than explicit policy prescriptions. It is therefore complementary to the aims of BBN decision support systems. This focus on guidance, rather than policy prescription, arises from the explicit recognition of the importance of context and contingency in assessing programme success. In addition, a realist synthesis is distinguished by its strong emphasis on stakeholder participation, its focus on understanding and illuminating the theories underlying policy makers' approach to programme development, its emphasis on testing these theories against empirical evidence, and its iterative nature. These are discussed in turn.

The realist review is intended to provide decision support to policy makers in the policy formulation process. As the authors express it, it gives policy makers' the 'highway code' - rather than explicit instructions on how to get from A to B. This emphasis on decision support, rather than decision making, stems from an overt recognition of the importance of context and contingency in programme implementation - something which the proponents say more prescriptive systems fail to take into account. The success of any given policy strategy is contingent on the social, cultural and economic context in which it is implemented. Programmes which are effective in one region can have minimal effect another. Realist reviewers contend that through providing policy makers with an understanding of the context of programme success, empowers them to tailor programmes to their specific environment, thus improving their effectiveness.

A primary aim of the realist review is to improve policy formulation through understanding and informing policy makers. The method places engagement with, and understanding of, policy makers' understandings of the world centrally. Through working with policy makers, understanding the theories implicit in their policy making actions, and assessing the evidence base for such theories, realist reviewers are able to engage with policy makers on their own epistemological ground. This engagement gives the policy makers themselves a sense of ownership of the review and the resulting epistemological familiarity makes accepting the review's findings easier.

The focus on understanding the theories implicit in policy makers' actions makes realist review particularly useful to construction of Bayesian Belief Networks. The term 'theories' here is meant with a lower-case 't'. These are not 'Theories' as would be recognisable within academic communities, but more the entailed assumptions underpinning policy makers' beliefs as to which factors influence each other and why. For example, policy makers advocating use of subsidies for instillation of loft insulation are implicitly assuming that economic rational action model of occupant behaviour. A realist reviewer having observed this in stakeholder participation meetings would then assess the evidence base for such a theory.

Realist reviews are iterative to permit ongoing stakeholder engagement, to permit focusing of the review around emerging theories, and to provide an environment for the learning of both stakeholders and reviewers.

In the context of a realist synthesis conducted for the purposes of generating a Bayesian Belief Network, some additional and more specific information is required. This is primarily focused on identifying the factors influencing home energy use and their relationships for construction of the architecture of the BBN. These are as follows:

1. The estimated strength of the relationships between factors identified in the realist synthesis.
   a) In the context of the research which gave rise to the finding of an effect.
   b) In a manner which can be explained to an expert community in context of a probability elicitation exercise.
   This informs the merits of including the variable in the BBN, and assists in focusing resources on estimating probability data for the most important correlations.
2. The direction of the effect (which variable is independent and which is dependent).
   a) For each variable, identify those variables on which it is dependent (it's 'parents' in BBN terms).
   b) For each variable, identify those variables which are dependent on it (it's 'children' in BBN terms).
   BBN architecture has directionality with edges going from independent to dependent variables. This allows us to link the variables to form the architecture of the BBN
3. The type of evidence supporting the claim of an effect. It is necessary to know the strength of the evidence supporting the correlation between variables (in addition to the strength of the correlation covered in point 1). This informs the confidence placed on the existence and strength of estimates of correlation in the BBN.
4. Options for the representation of each variable in discrete form.
   This indirectly impacts on the architecture of the BBN through its iterative relationship with data gathering as it is one of the primary determinants of the number of probabilities needed to operationalise BBN model. For this reason it is strongly preferable to have the minimum number of states which will capture the correlation between the variables meaningfully.

This tailored realist synthesis allows the first two steps of Bayesian Belief Network model construction to be completed:

1. The initial architecture of the network is determined from the realist synthesis of literature.
2. Initial estimates of conditional probabilities are established from data and literature.

PHASE 2: ITERATIVE NETWORK DEVELOPMENT

Phase two proceeds iteratively through network sensitivity analysis; uncertainty analysis; validation; verification; expansion; and contextualisation again with the intention of focusing resources on those areas to which the output of the network is most sensitive.

1. Sensitivity analysis is used to uncover to which probabilities network output is most sensitive.
2. Uncertainty analysis is used to ensure the joint probability distribution of the network as a whole remains within expected bounds.
3. Primary quantitative data analysis, secondary data analysis or additional elicitation methods are used to identify better estimates of key probabilities.
4. Nodes and links to which the output of the network is insensitive are pruned.
5. Primary qualitative research is conducted to extend the network though expanding our current knowledge.
6. Primary quantitative research is conducted to contextualise which variables are influential under which conditions.

Once the first two stages are complete development proceeds in two parallel streams, one qualitative, one quantitative. Primary qualitative research is used to both extend our understanding of the influences on domestic energy consumption (extend the network), and clarify our understanding of the contexts in which different influences predominate (constrain the network). Primary and secondary quantitative research is used to refine estimates of those probabilities to which the network is most sensitive.

Steps one to six are iterated to refine the architecture and conditional probability structure of the network and rely on repeated application of sensitivity analysis and uncertainty analysis.

Sensitivity analysis tests the extent to which the output of the network is sensitive to changes in the estimates of probabilities describing the relationships between the variables. Sensitivity analysis proceeds by systematically altering each variable through each of its states while holding all independent variables constant. Changes in the joint probability distribution are observed against changes in each variable, with greatest changes indicating greatest sensitivity. This is a mainstay of BBN assessment and development and is automated with most commercial BBN packages.

Uncertainty analysis explores the range of possible outputs of a network by changing all probabilities in the network simultaneously. Each probability is drawn from an underlying distribution and the effect on network output is recorded, this is repeated until a large proportion of the probability space has been sampled. This effectively amounts to performing a Monte Carlo style sampling of the model space. The intention is to see if the network as a whole returns estimates of the variable of interest which are implausible to domain experts. Where this happens, the network can be reanalysed to assess why this has occurred. In this sense uncertainty analysis is a form of network verification. Uncertainty analysis also reveals the extent to which the network is sensitive to changes in its probability estimates.

This iterative procedure allows network builders to focus resources on those areas which will provide the greatest benefit.

Model development and application

COSTS

The costs of constructing Bayesian Belief Network models can be considerable. The costs are primarily associated with the staff time required for stakeholder consultation, synthesising the literature, secondary data analysis and any primary data collection. These costs are associated with the initial construction of a BBN model at the national level in a new field. Potentially the single largest expense is primary data collection. Social survey work is expensive with collection of data for the conditional probability tables of even a small number of nodes at statistically significant sample sizes at around 100 000 Euro. It is partly for this reason that expert elicitation methods (while more subjective) are frequently used. This also underlies the need to use secondary analysis of existing data, and credible literature sources where ever possible.

SCALE OF IMPLEMENTATION

The model can be applied at national, regional, community or individual home scales. The stochastic nodes that model the variables influencing home energy consumption have some number of discrete states. Normally, each stochastic node will be a multinomial probability distribution. This is effectively a normalised histogram showing the relative proportion of the population who are in each state. By way of example, a variable 'household size' may have four states {1; 2; 3 or 4; 5 or more}. At the national level, this variable would be a distribution reflecting the distribution of these household sizes in the national population. At the regional and community levels it would likewise be a distribution, but one based on these populations respectively. At the individual household level however that variable would be 'instantiated' to the household size in question. Some variables may be instantiated at other levels. For example if the presence of a community energy programme was found to be influential, then a variable 'community energy programme' may have two states {yes; no} and may be instantiated at the community level as well as the household level. It is anticipated that the CaRB-ST model will be built to include nodes applicable to national, community and technology levels. The technology level is include as it is known that different technologies engender very different use patterns and it is this socio-technical interaction that is of particular interest.

EXPECTED USERS

The model is primarily intended for policy formulation (national level) and programme design and implementation (local level). It is expected, however, that valuable lesions will also be learnt regarding the design and installation of technologies in homes. This is of use not only in formulating policy such as building regulations, but also to technology designers, building designers and installers regarding the impact of their design/installation decisions on likely use patterns.

Conclusion

Bayesian Belief Networks appear to offer considerable potential as a transdisciplinary method for knowledge synthesis across the social, economic and behavioural sciences. They allow for construction of consensus based, transparent, decision support systems for use in energy policy and programme development. The process of their construction fits well with the iterative and engaged models current in fields such as socio-technical systems theory and diffusion of innovations, as well as with current theories of policy advocacy and formation.

Bayesian Belief Networks permit synthesis of qualitative and quantitative data from a variety of sources, modelling continuous and discrete variables, and the progressive integration of new data over time. They therefore create 'live' models which can be continually refined and updates as more empirical data is collected or new theoretical light is shed on a problem.

Bayesian Belief Networks are built on the subjective Bayesian statistical epistemology that views probability as a numerical expression of the degree of consistent belief given the evidence at hand. From a social theory perspective, this makes them congruent with a social realist perspective and complementary to current best practice in knowledge synthesis for policy from literature such as Realist Synthesis.

The construction of a BBN over a domain of variables, such as the socio-technical influences on domestic energy consumption in the UK, generates a 'landscape' (in the mathematical sense of this term) with a specific topography of peaks, ridges, valleys. This topography allows us to define terms like 'barriers' as ridges on the landscape separating optimal solutions. Such barriers and optimal solutions can be identified as specific combinations of states of the variables defined in the Bayesian Belief Network. The topography of this landscape therefore has direct implications for the development of policy and programme strategies.

Alternative models of home energy use are conventionally based on deterministic building thermodynamic modelling and target-lead scenario projections of market penetration rates of alternate building technologies and consumer appliances. Such models mask the known large variability in energy use across even technically similar households. This variability tells us that some householders are already living considerably lower energy lifestyles than average. Understanding the causes and extent of this variability is important for policy makers for two reasons. Firstly, such low energy lifestyles provide valuable case study material on domestic practices which use less energy. Secondly, modelling and explaining this diversity allows us to understand what factors, or combination of factors, make this possible. To use a genetic analogy, in any system trying to evolve in a given direction diversity is essential. Diversity creates a 'gene-pool' of traits which should be favoured for selection. Knowledge of this diversity, and the detailed factors which create it, allows us to create policy environments which favour these desirable traits. Returning to energy policy, if for example it is known that operant ambient conditioning (giving more control over their immediate environment building occupants) decreases net energy use, then this can be encouraged through building regulations, building standards and practices.

In addition to being deterministic, alternative models of home energy use assume the influences on household energy use are independent and linearly related (or first order non-linear in the case of partial equilibrium economic models). Such models fail to capture the complex, interdependent and contextual nature of the socio-technical realm. Understanding and modelling interdependence is important for policy makers. Interdependence gives rise to systems in which finding a 'better' management strategy is easy – but in which finding the 'best' management strategy can be particularly difficult. Finding the 'best' strategy will probably involve policies targeting a combination of factors simultaneously. The possible combinations of factors that could be targeted are immense. Without a model which maps the 'landscape' of socio-technical possibilities, the chances of finding the right combination of factors to manage is small and the process of finding them amounts to a blind search.

The research design for the CaRB-ST research programme will marry the methodological advantages of Bayesian Belief Networks with those of the Realist Synthesis in an attempt to generate a stakeholder engaged, evidence based model of the interdependent socio-technical influences on home energy consumption.

Acknowledgements

This work forms part of Carbon Reduction in Buildings (CaRB) Consortium, which has 5 UK partners: De Montfort University, University College London, The University of Reading, University of Newcastle upon Tyne and The University of Sheffield. They are supported by the Carbon Vision initiative which is jointly funded by the Carbon Trust and Engineering and Physical Sciences Research Council, with additional support from the Economic and Social Research Council and Natural Environment Research Council. The partners are assisted by a steering panel of representatives from UK industry and government.

References

Anderson, J. (1998). "Embracing uncertainty: The interface of Bayesian statistics and cognitive psychology." *Conservation Ecology* 2(1).

Bacon, P. J., J. D. Cain, et al. (2002). "Belief network models of land manager decisions and land use change." *Journal of Environmental Management* 65(1): 1-23.

Bijker, W. and J. Law (1992). *Shaping Technology / Building Society: Studies in sociotechnical change*. Cambridge, MIT Press.

Blumstein, C., S. Goldstone, et al. (1998). "A theory-based approach to market transformation." *Energy Policy* 28: 137-144.

Bromley, J., N. Jackson, et al. (2004). *The use of Hugin to develop Bayesian networks as an aid to integrated water resource planning: A report on the MERIT (Management of the Environment and Resources using Integrated Techniques) EU Framework V funded project* http://www.merit-eu.net. Wallingford, Centre for Ecology and Hydrology.

Cain, J. (2001). *Guidelines for using Bayesian Networks to support the planning and management of development programmes in the water sector and beyond*. Wallingford, Centre for Ecology and Hydrology.

Cain, J. D., K. Jinapala, et al. (2003). "Participatory decision support for agricultural management. A case study from Sri Lanka." *Agricultural Systems* 76(2): 457-482.

Cain, J., C. Batchelor, et al. (1999). Belief Networks: A Framework for the Participatory Development of Natural Resource Management Strategies. *Environment, Development and Sustainability* 1, no. 2: 123 (11 pages).

Callon, M. (1986). *The sociology of an actor network: The case of the electric vehicle. Texts and their Powers: Mapping the dynamics of texts and their powers*. M. Callon, J. Law and A. Rip. London, Macmillan.

Carlin, B. and T. Louis (1996). *Bayes and Empirical Bayes Methods for Data Analysis*. London, Chapman & Hall.

Cohen, Y. 1988 Bayesian estimation of clutch size for scientific and management purposes, *Journal of Wildlife Management*, Vol. 52, No. 4, pp.787-793.

Congdon, P. (2001). *Bayesian Statistical Modelling*, John Wiley and Sons.

Congdon, P. (2003). *Applied Bayesian Modelling*, Wiley.

Cooper, G. F. (1990). "The computational complexity of probabilistic inference using Bayesian belief networks." *Artificial Intelligence* Vol.42, No.2-3, pp. 393 - 405.

Costanzo, M.; Archer, D.; Aronson, E. & Pettigrew, T. (1986), 'Energy Conservation Behaviour: The Difficult Path From Information to Action', *American Psychologist*, May, Vol. 41, No. 5, pp. 521-528.

Coveney, P. and R. Highfield (1995). *Frontiers of Complexity: The search for order in a chaotic world*. London, Faber and Faber.

Crome, F., M. Thomas, et al. (1996). "A novel Bayesian approach to assessing impacts of rainforest logging." *Ecological Applications* 6(4): 1104-1123.

Dixon, P. and A. Ellison (1996). "Introduction to Ecological Applications of Bayesian Inference." *Ecological Applications* 6(4): 1034-1035.

Dorfman, J. (1997). *Bayesian Economics Through Numerical Methods: A guide to econometrics and decision-making with prior information*. New York, Springer.

Druzdzel, M. and L. van der Gaag (2000). "Building Probabilistic Networks: 'Where Do the Numbers Come From?'" *IEEE Transactions on Knowledge and Data Engineering* 12(4): 481-486.

Ellison, A. (1996). "An Introduction to Bayesian Inference for Ecological Research and Environmental Decision Making." *Ecological Applications* 6(4): 1036-1046.

Evans, R., S. Guy, et al. (1999). "Making a Difference: Sociology of scientific knowledge and urban energy policies." *Science, Technology, & Human Values* 24(1): 105-131.

Fernández, C., E. Ley, et al. (2002). "Bayesian modelling of catch in a north-west Atlantic fishery." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 51(3): 257-280.

Gellings, C. (1994), *Utility Marketing Strategies: Competition and the Economy*, The Fairmont Press Inc., Lilburn, GA, USA.

Gill, J. (2002). *Bayesian Methods: A Social and Behavioral Sciences Approach*, CRC Press.

Goerner, S. (1994). *Chaos and the Evolving Ecological Universe*. Langhorne, Pennsylvania, Gordon and Breach Publishers.

Guston, D. and D. Sarewitz (2000). "Real-Time Technology Assessment." *Technology in Society* 23(4).

Guy, G. and E. Shove (2000). *A Sociology of Energy, Buildings and the Environment: Constructing knowledge, designing practice*. London, Routledge.

Heckerman, D. (1999). A tutorial on learning with Bayesian networks, In *Learning in Graphical Models*. M. Jordan. Cambridge, MIT Press: 301-354.

Hogarth, R. (1975). Cognitive processes and the assessment of subjective probability distributions (with discussion), *Journal of the American Statistical Association*, Vol 70, pp.271-294.

IETC (1996). *Workbook for Training in Environmental Technology Assessment for Decision Makers*. Kuala Lumpur, United Nations Environment Programme.

IPCC (2001). *Third Assessment Report - Climate Change 2001: Working Group III on Mitigation - Synthesis Report - Summary for Policymakers*, IPCC.

Jackson, T. (2005). *Motivating Sustainable Consumption: a review of evidence on consumer behaviour and behavioural change*. London, Sustainable Development Research Network: 170.

Johnson, C. and P. Ekins (2003). *Theoretical approaches to policy change and human behaviour*, ESRC New Opportunities Programme: Environment and Human Behaviour: 19.

Jordan, M., Ed. (1999). *Learning in Graphical Models*. Adaptive Computation and Machine Learning series, MIT Press.

Kadane, J. and L. Wolfson (1998). "Experiences in elicitation." *The Statistician* 47(1): 3-19.

Laskey, K. and S. Mahoney (2000). "Network engineering for agile belief network models." *IEEE Transactions on Knowledge and Data Engineering* 12(4): 487-497.

Lee, D. and B. Rieman (1997). "Population viability assessment of salmonids by using probabilistic networks." *National American Journal of Fish Management* 17: 1144-1157.

Lutzenhiser, L. 1993, 'Social and behavioural aspects of energy use' *Annual Review of Energy and the Environment*, Vol. 18 pp.247-89

Marcot, B. G., R. S. Holthausen, et al. (2002). Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. *Forest ecology and management*. 153: 29 (14 pages).

O'Hagan, A. (1998). "Eliciting Expert Beliefs in Substantial Practical Applications." *The Statistician* 47(1): 21-35.

Pawson, R. and T. Greenhalgh (2004). *Realist synthesis: an introduction*. ESRC Research Methods Programme. Manchester, University of Manchester.

Rogers, E. (1995). *Diffusion of Innovations*. New York, The Free Press.

Rohracher, H. (2003). "The Role of Users in the Social Shaping of Environmental Technologies." *Innovation* 16(2).

Rohracher, H. (2001). "Managing the Technological Transition to Sustainable Construction of Buildings: A Socio-Technical Perspective." *Technology Analysis & Strategic Management* 13(1): 137-150.

Sabatier, P., Ed. (1999). *Theories of the policy process*. Boulder Colorado, Westview Press.

Shove, E. (1998). "Gaps, barriers and conceptual chasms: theories of technology transfer and energy in buildings." *Energy Policy* 26(15): 1105-1112.

Valente, T. (1995). *Network Models of the Diffusion of Innovations*. Crsskill, Hampton Press.

Wilhite, H. and H. Nakagami (1996). "A cross-cultural analysis of household energy use behaviour in Japan and Norway." *Energy Policy* 24(9): 795-803.

Williams, R. and D. Edge (1996). "The social shaping of technology." *Research Policy* 25(1996): 865-899.

Wisdom, M., B. Wales, et al. (2002). "Performance of Greater Sage-Grouse Models for Conservation Assessment in the Interior Columbia Basin, U.S.A." *Conservation Biology* 16(5): 1232.