Harnessing social networks for promoting adoption of energy technologies in the domestic sector

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Abstract

This paper presents results from modelling work investigating the effects of social networks on the adoption of energy technologies in the domestic sector. This work concerns ideas on social network interventions which have been successfully applied in other domains but which have seldom been applied to energy policy questions. We employ a dynamical multi-parameter network model where households are represented as nodes on a network for which the uptake of technologies is influenced by both personal benefit and social influences. This is applied to demonstrate the usefulness of this type of model in assessing the likely success of different roll-out strategies that a local authority could pursue in promoting the uptake of domestic energy technologies. Local authorities can play a key role in the retrofit of energy-efficiency and low-carbon energy-generation technologies in order to realise carbon reductions and alleviate fuel poverty. Scenarios are modelled for different local authority interventions that target network interactions and uptake threshold effects, and the results provide insights for policy. The potential for the use of this type of modelling in understanding the adoption of energy innovations in the domestic sector and designing local-level interventions is demonstrated.

Keywords: Modelling, local authorities, domestic sector retrofit, social networks, residential, energy efficiency

1. Introduction

Much recent work in complex systems theory has highlighted the role of social networks in influencing individual behaviours (Barabási, 2003). However, the implications of these ideas have not been fully exploited in the context of the adoption of domestic energy technologies and energy-demand-reducing behaviours. In a recent review paper, Wilson and Dowlatabadi (2007) call for integrated approaches to modelling domestic energy decision-making that better characterise heterogeneity and can be used to help design interventions aimed at influencing behaviours. Models based on individual behaviour tend to assume rational choice or reflect only individual psychological motivations (Nye et al., 2010), whereas approaches that address the social context of decision-making tend to be more qualitative (Shove, 1998). In response to this need, we have conducted new interdisciplinary modelling work to demonstrate the value of a quantitative approach combining personal and social motivation factors.

We present results from a simulation of energy-innovation diffusion on a social network, employing real-world data. In the model, households are represented as dynamical nodes (connection points) on a network who choose whether or not to adopt an energy technology (or energy-efficiency measure) depending on both personal benefit and social influences. (For simplicity, we treat the household as a single decision maker, though in reality, people within the household may vary according to individual personal and social benefit.) Building on our previous work exploring the general mathematical features of a simpler version of this model (Bale et al., 2013b; McCullen et al., 2013), the present work develops the model to the point where it can be used to compare potential roll-out strategies available to a local authority aiming to increase uptake of energy technologies in the domestic sector. We examine interventions using social networks to promote adoption ('network interventions') and also those reducing barrier(s) to adoption ('threshold interventions'). This provides preliminary insights for policy design and highlights the potential for further work.

The objectives of the paper are to:

1. evaluate the potential for applying social network theories to energy policy using a network model for the adoption of energy technologies in the domestic sector;

2. apply the model to explore different strategies that could be implemented by a local authority;

3. identify those interventions that are likely to lead to the highest uptake, providing insight for policy implementation;

4. inform data gathering to enable refinement of this type of model to make it useful as a decision support tool for local authorities.

In section 2, we discuss the empirical challenges that we aim to address and the theoretical approaches on which we draw. In section 3, we discuss the methodology of the modelling work, including the data used, assumptions, and related limitations. We then, in section 4, discuss the results from modelling different interventions that a local authority could take. In section 5, we discuss the insights for local-level policy based on the outputs from the model and areas for further research.

2. Empirical challenges and theoretical approaches

2.1 Local authority decision-making

Local authorities have a significant role to play in the adoption of technologies that reduce domestic energy consumption. This role can be either direct, through the provision of free installation programmes (e.g. Wrap Up Leeds (Leeds City Council and Yorkshire Energy Services, 2012)), or indirect, through energy advice services (e.g. Actio2n Woking (Woking Borough Council, 2012)). Often, initiatives are tailored in an ad hoc manner to suit a given funding scheme, and are limited by available finance (Bale et al., 2012b). Nonetheless, local authorities still have to make choices as to how best to engage with residents on any given initiative. For a simple intervention such as offering free or reduced-cost insulation, local authorities can choose from a range of roll-out strategies, each of which may deliver different adoption rates. This suggests that local authorities need tools in order to be able to assess which strategies would be most successful.

Local authority initiatives (both in the UK and elsewhere) aimed at installing domestic energy-efficiency measures represent a significant opportunity for achieving carbon reductions in line with national targets (Comodi et al., 2012; Hoppe et al., 2011; Sheldrick, 1985). Large-scale retrofit of energy-efficiency and renewable and low-carbon generation technologies in domestic properties (together termed ‘domestic energy technologies’) will be required in order to meet the UK’s legally-binding target of reducing greenhouse gas emissions of 80% by 2050 (compared with 1990 levels) (Great Britain, 2008). In addition, energy-efficiency measures can provide benefits to local residents by tackling fuel poverty and improving health and wellbeing (Clinch and Healy, 2001).

Insulation levels in domestic properties in Great Britain present one opportunity for improvement; it is estimated that, at the start of January 2012, only 60% of homes with lofts had loft insulation of at least 125mm and 59% of homes with cavity walls had cavity wall insulation, while only 2% of homes with solid walls had solid wall insulation (Department of Energy and Climate Change, 2012). Local authorities have a unique role to play in encouraging adoption of energy-efficient measures in the both the social and private domestic sectors (Committee on Climate Change, 2012) as they are both a trusted source of information (which energy companies tend not to be (Bale et al., 2013a)) and have local knowledge of the needs of their residents and communities (which central government does not). In this paper, we examine how local authorities may be able to maximise this influence by harnessing or enhancing existing social networks to promote adoption of domestic energy technologies such as insulation or photovoltaic (PV) panels.

2.2 Social networks

The importance of social network influences on behaviour is well recognized outside of the energy policy domain, and network interventions can be used to accelerate behaviour change (Valente, 2012). In this paper, we define network interventions as purposeful efforts to use social networks to accelerate the increase of adoption of energy technologies in domestic properties. By ‘social network’, we refer to all inter-household interactions that are relevant to energy either face-to-face or online (although the latter currently account for only a small proportion of actual total interactions (King, 2012; Southwell et al., 2012)).

Network interventions have been used successfully for tackling health-related issues (Valente, 2010), and much theoretical work exists on various diffusion processes on networks (Watts, 2002). Yet the insights from social network theory have so far been under-exploited in the area of energy policy. The role of social networks and network interventions in the spread of information on energy technologies and behaviours, and the subsequent adoption rates of both, is a relatively new area for research. There are some early examples of such ideas in the literature e.g. Coltrane et al. (1986), Darley and Beniger (1981), and, in relation to climate change, Maibach et al. (2008). In addition, there has been some recent empirical work on the role of social networks in the diffusion of energy innovations (Fell et al., 2009; McMichael and Shipworth, 2013; Michelsen and Madlener, 2013).

2.3 Modelling diffusion of innovations on a network

Diffusion of innovations (Rogers, 1983) is a social communication process that influences individual adoption of a specific innovation. The theory has been applied in the context of domestic energy consumption (Wilson and Dowlatabadi, 2007). The spread of ideas or technologies has been widely studied across different domains as diffusion on networks (Valente, 2005). One of the most commonly studied network diffusion processes is the spread of infection by a single contact where transmission occurs from one individual to another, but, for a consumer product (or behaviour) to spread, empirical studies show that many people wait for a proportion of their social group to precede them in the process (Granovetter and Soong, 1983; Valente, 1996).

Threshold models have been developed to account for this phenomenon (Grönlund and Holme, 2005; Watts, 2002). Diffusion models usually consider only the social aspects of spreading, which is appropriate in many cases. However, the decision to adopt a technology may be based on a combination of factors, including ability to install/use the technology and the willingness to purchase, which will not only include personal considerations but also social influence from peers and the wider population. Modelling therefore needs to take into account these multiple factors: ability to adopt, personal usefulness of the item (as perceived by the householder), and the benefits of aligning with the social norm (Deffuant et al., 2005; Delre et al., 2010; Valente, 1996). In this work we include both personal and social aspects of diffusion in the model.

Mathematical network models can be constructed to reproduce features found on real-world networks (Castellano et al., 2009). Such features include the small-world effect (Watts and Strogatz, 1998) and scale-free degree distributions (Barabási, 2003). In the real-world, people often share common groups of friends, where a friend of a friend is also a friend. This is known as clustering (or *transitivity*) and is found to play a significant role in the dynamics of diffusion on such models (McCullen et al., 2013). However, often the clustering is not uniform across the whole network, with individuals being part of groups or communities within which links are denser between individuals than with the outside world. More realistic network models have been constructed that take this feature into account by linking individuals by associating them through group interactions (Newman, 2003). We use a variation on this type of network model, with added individual links and geographical information (similar to Hamill and Gilbert (2009)). This has the potential to be parameterized using real-world data; the method is described in more detail in the Section 3.

2.4 Network data

Although there has been a considerable amount of research and analysis of social network structures, this has mainly been conducted for networks for which the data is relatively easy to obtain, such as either moderately small systems or online social networks. There is limited empirical data available on the networks that may operate between households in relation to energy technologies or behaviours, and this remains a challenge for modelling the influence of social networks on the adoption of energy innovations. Information is needed on the following aspects of the system:

- The structure of the network — Who do people exchange information with regarding domestic energy technologies?
- The density of the networks — How many others do people communicate with about energy?
- The weight of the links on the networks — What influence do certain links to individuals or groups have on adoption decisions?

In section 3.2.1 we discuss our approach to the inclusion of empirical data, where available, and the assumptions that we have made in the absence of appropriate information. A more detailed discussion of the data requirements for this type of modelling can be found in Bale et al.(2013b).

By its nature, diffusion on networks is intrinsically very sensitive to the structure and properties of the network. In an urban area the true structure of the social network cannot be known exactly (and will ceaselessly change over longer time-scales), and the factors affecting individual decision-making are complex and varied. Given these limitations, methods are required which can assess the most probable outcome of an intervention by means of simulation and scenario analysis over a range of possibilities rather than by means of predictive tools. This is common practice in other disciplines, where models are very sensitive to details and ensembles are used to derive useful insights (Stephens et al., 2012).

2.5 Approach to application of the model in policy-making

Adapting a general complexity policy-making approach proposed by Room (2011), we follow the following process:

- Identify the stakeholders and their relationships: we consider households and those wishing to influence them.
- Use real-world data to map out the connectivity between the various elements of the system (in these cases between households), as well as the options open to policy-makers, and use these to build a conceptual model which will guide the network and dynamical models.
- Modify the system parameters to re-shape the outcomes: we change the parameters of the model in ways that relate to real-world interventions in order to study the resulting variation in uptake.
- Use mathematical and computational models to help to identify the range of possible scenarios and outcomes. This is done not to forecast the future but to guide and inform as to which interventions might provide more leverage.

- Identify areas of the model parameter space which give rise to large sudden changes, as these can indicate instabilities in either the model or the real-world system.

3. Methodology

In previous work we developed the mathematical basis of a model (McCullen et al., 2013) to analyse how the diffusion of innovations depends on personal and social factors. The present paper focuses on developing this model to incorporate the means to explore roll-out strategy scenarios as required for application to local authorities. We first summarise, in section 3.1, our previous work on the main features of the approach and the mathematical basis for the model. Section 3.2 and onwards then describes the novel development and methodology used for the present work.

3.1 Summary of modelling approach — previous work

In the model, households are represented as nodes on a network, with the links between the nodes representing lines of communication between householders, for example between individual households or at workplaces or other group environments. In McCullen et al. (2012) all nodes were homogeneous in their parameters, making the model amenable to mathematical analysis. In Bale et al. (2013b) we discussed how the model could be developed to include empirical data, and reported on the effects of introducing heterogeneous nodes representing different household archetypes into the network.

The nodes on the network are each assigned a binary variable representing the current adoption state of the household they represent, $x_i = 0$ or 1 for non-adoption or adoption, respectively. The number and pattern of adopters changes at each time-step (which for illustrative purposes we take to represent one month) according to the following rules. The total perceived usefulness or *utility* of a product to a household is a combination of factors, broadly divided into personal and social benefit (Delre et al., 2010). Personal benefit p_i is a measure of the perceived benefit of acquiring the technology to the household. This could include factors such as cost savings, comfort gains, alignment with pro-environmental attitudes and interest in new technology. Total social benefit is the utility derived from the perceived benefit of fitting in with others, which can be divided into two parts: the influence from a household's personal social links (peer-group) and the influence from society in general (population) (Valente, 1996). The relative contribution of personal and social benefit for different households is an empirical question. The model we have developed thus has three factors, which can be given relative weightings α_i, β_i and γ_i, (with $\alpha_i + \beta_i + \gamma_i = 1$), to account for different preferences of the household. The parameter α_i is the weighting given to the perceived personal benefit to the household p_i, β_i is the weighting given to the perceived benefit gained from following the influence of adopters within the household's social network neighbourhood s_i, and γ_i is the weighting given to m, the average uptake over the entire population, which represents the perceived benefit of aligning with the mainstream social norm. Different household types will weight these factors differently; we are able to introduce different archetype groups to reflect this. The total utility to each household at any one time is therefore given by the equation:

$$u_i = \alpha_i p_i + \beta_i s_i + \gamma_i m \quad (1)$$

where s_i is the mean average level of uptake amongst the network neighbours of household i (which can be weighted by the strength of communication from each neighbour (the link weight)), and m is the weighted mean uptake for the whole population. Both s_i and m are recalculated at every time-step. The initial state for all households is chosen to represent the proportion of the households who have adopted the technology at the start of the period in question. The decision to adopt a technology is determined at each time-step if the perceived total utility to the household outweighs the barriers to adoption, seen as a combined threshold θ_i, i.e. adoption occurs if $u_i > \theta_i$, and is a one-way process.

The model was written in *Python* using *NetworkX* for the construction of the networks and *Scientific Python (SciPy)* for the dynamical time-stepping. Codes are available at http://sourceforge.net/projects/netdifmodel/.

3.2 Development of the model — the present research

For the scenario analysis presented here, we base our model on the City of Leeds, where we conducted a survey to gather some of the data needed for the model. However, the insights are more broadly applicable to urban areas and could easily be modified to represent other areas.

In these model runs, the average properties of the network are largely fixed (except for the exact locations of the links, which are randomized), in order to investigate a dense set of possible realities covered by the uncertainty in the network structure. We also investigate the effect of weighting all links to either 1 or 0.5 in order to represent different innovations (more details given in section 3.2.6).

We first summarise the main data collection process, and then discuss the approach to integrating data for the structure and properties of the network, the archetypes (parameter distributions for α, β and γ) and the threshold (θ)

3.2.1. Data

We have taken primary data from a survey we conducted of domestic households in the City of Leeds, and these data are intended to be sufficient to inform and illustrate the operation of the model rather than a definitive work on attitudes to energy use in the City of Leeds.

To collect empirical data with which to populate the model, a survey of Leeds residents was undertaken in May–June 2011. Two convenience sampling methods were used to reach different segments of the population: 1) through an online collection method whereby participants were recruited by email and social media advertising via large organisations in Leeds (e.g. the university, council and other large employers) and 2) attending a twice-weekly drop-in centre for residents in the east Leeds area of Burmantofts to encourage participation in the survey by low-income households without access to the internet. Burmantofts is an area with a large proportion (> 50%) of council-owned homes and has a high score on a number of socio-economic deprivation indices (Office for National Statistics, 2011). The questionnaire sought information on attitude and behaviours with regard to energy use in the home as well as demographic information (including income level, employment status, and geographic area). A series of questions was also asked about the respondent's social network, current sources of information about energy, and likely organisations that they would trust to provide energy advice. In total, 1068 valid responses were received, which represents 0.34% of the total number of households in the metropolitan district of Leeds. The sample was found to be broadly representative of the population in terms of tenancy, house type and pro-environmental behaviour (as benchmarked to the Defra Survey of pro-environmental behaviours (Thornton, 2009)). However, the difficulties in reaching certain sectors of the population resulted in under-sampling of the unemployed, the retired and those on lower incomes. SPSS was used to analyse the questionnaire data.

Figure 1 shows the key data that were used to develop the network representation.

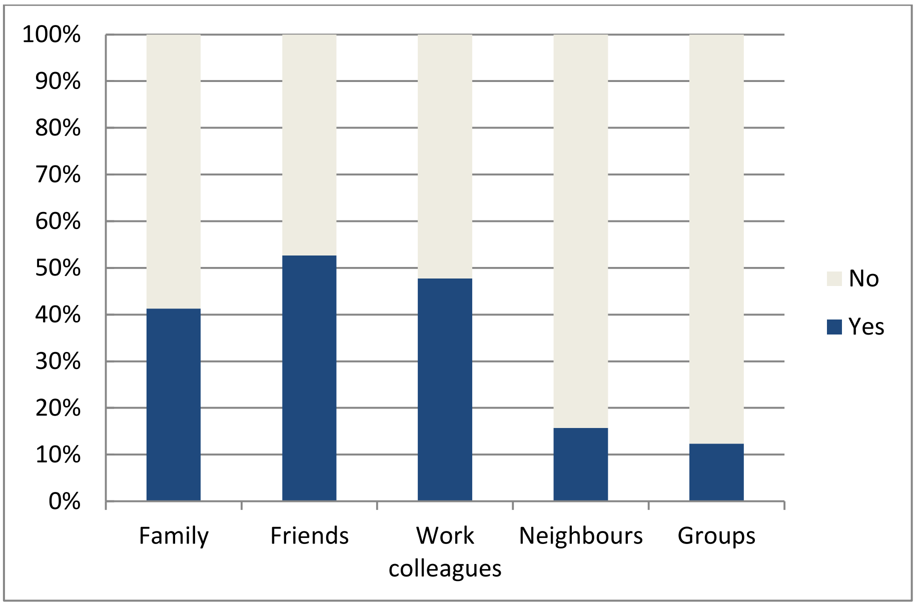

Figure 1: Responses (valid percentage, excluding missing values 3–7 %) to the question 'Do you currently talk to any of the following people about energy use and/or saving money on energy?' from 1068 households in Leeds.

Our survey showed that around 40–50% of people discuss energy use issues with family, friends or work colleagues, whereas only 10–20% talk about energy use to neighbours or members of other social groups to which they belong. These results are comparable with those reported by Southwell et al., (2012) who found that one third of a sample of people in the US reported sharing information about energy use. Importantly, they also found that, of those households, 85% shared information verbally and only 3% reported sharing through online social networking sites. These findings suggest that, although sharing energy information is not nearly ubiquitous, there is a significant proportion of the population that can be targeted by the local authority and their existing social networks utilised.

It was not possible to ascertain the relative weight that people assigned to the views of others in their social network or the wider population, without undertaking a more in-depth survey. For all model runs, p_i, the personal benefit of the innovation to the household, is set to 0.5 for all nodes. Through the modelling, we investigate how the decision to adopt depends on the relative weighting of this personal benefit and the social benefits derived from others adopting, relative to that household's uptake threshold value.

3.2.2 Network

We gathered information on the network links related to energy information that exist in the City of Leeds. Using information from questions in the survey of 1068 respondents, we developed a social network relating to the sharing of information on energy between households. In the network, each node representing a household shares information with other nodes in the network with which it has individual, group or workplace links, as shown in table 1. Suggested types of group were given in the questionnaire to aid understanding (although the type is not important for the modelling): community/volunteer groups, religious meeting places, social groups, sports groups, groups related to children's activities or other. The option of 'none' was also available.

If respondents reported talking to friends, family and/or neighbours about energy they were assigned 5, 3 and 2 (or combinations thereof, up to a maximum of 10) links to other nodes, respectively. It was not feasible in a questionnaire format to ask respondents to keep track of and report the number of these links, so these are arbitrary values for each category. If the respondent reported talking to groups about energy, then that household was associated with their reported number of groups. Workplace links were assigned if the respondent was employed and reported talking to colleagues about energy. From 1068 responses it was found that 756 households reported talking about energy-related issues to at least one other individual household, group (local) or workplace (long distance). The remaining 312 households are represented as nodes that are unconnected to the network but are able to adopt if seeded, or if their combination of personal benefit and the influence of the total population exceeds their threshold value.

Table 1 – Number of households with various links on the network.

Active Individual Links			*Active* Group Links			*Active* Workplace Links		
# of Links	# of Nodes	% of Nodes	# of Links	# of Nodes	% of Nodes	# of Links	# of Nodes	% of Nodes
0	394	37	0	948	89	0	588	55
1	0	0	1	50	5	1	480	45
2	24	2	2	40	4			
3	90	8	3	25	2			
4	0	0	4	3	0			
5	192	18	5	2	0			
7	42	4						
8	247	23						
10	79	7						

The construction of a model network based on association with groups (as well as individually) is shown in figure 2.

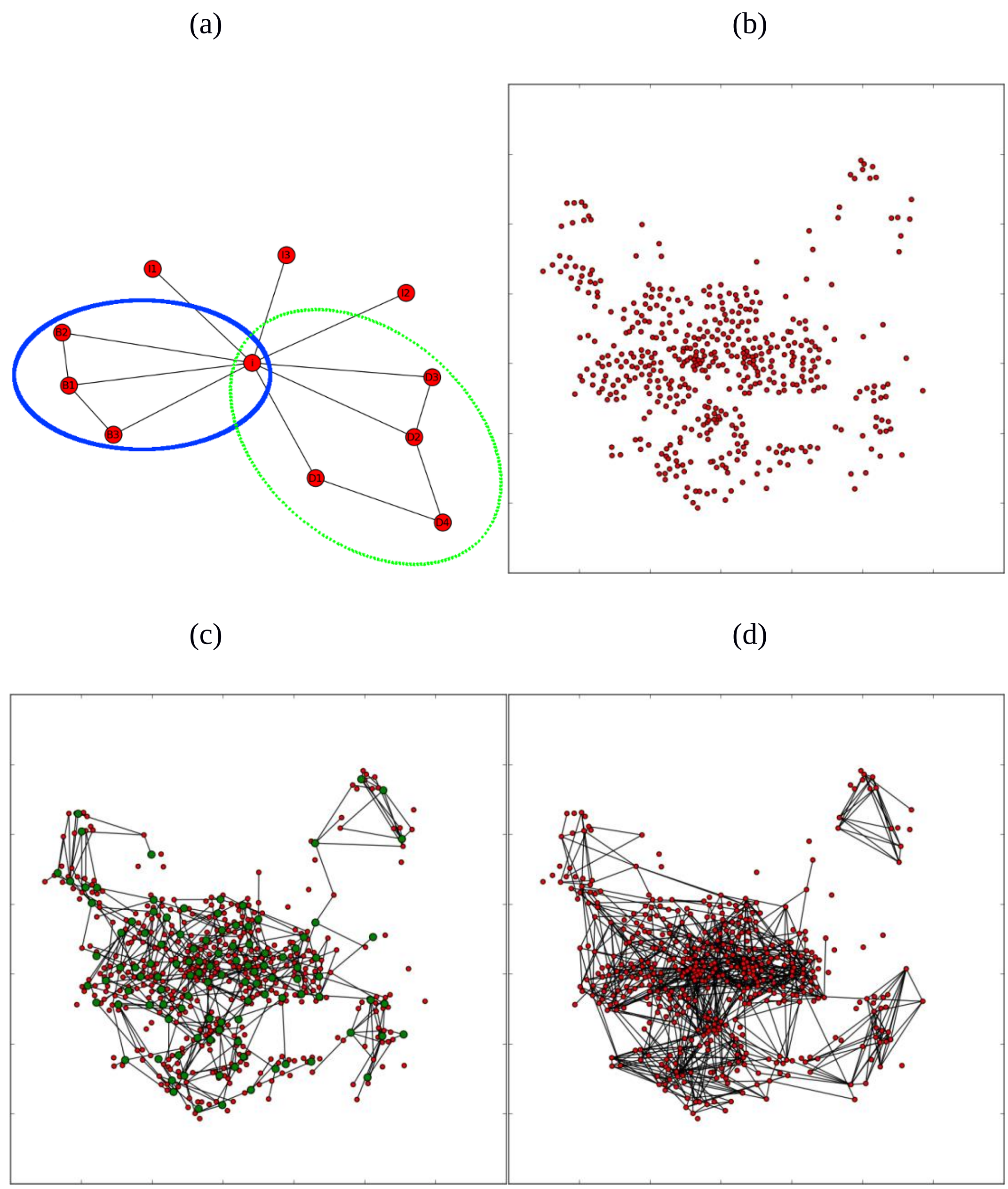

Figure 2: Building a network to include groups association (a) each node is associated with others as part of association with various groups or individually, (b) the red dots show locations (based on the 476 lower level super output areas (LLSOA) in Leeds) for households and the larger green dots for theoretical group locations (based on the 108 middle layer super output areas (MLSOA), (c) household nodes are associated with local groups, (d) links are formed to five of the other households with whom they share group membership. Further stages in the process involve forming links through workplaces (in a similar manner to local groups) and individual links. Some nodes are present but remain unconnected on the network, representing those households that do not talk to any other household or group about energy.

3.2.3 Archetypes

The archetypes in the model refer to the segments of the population with different preferences with regard to the weighting of factors *p*, *s* and *m*; that is, we define a particular (*j*) archetype $A_j=(\alpha_j, \beta_j, \gamma_j)$. None of the interventions we investigate in the present work change the number and/or types of archetypes; instead the interventions are aimed at altering the network, threshold, or both. This translates to the interpretation that in the real world it would be very difficult for a local authority to alter individual household preferences as to whether decisions are led by personal or social (peer or population norm) benefit. We do, however, set the archetypes to include heterogeneity in the population, as would be seen in the real world. Every run presented in this paper is set with three different archetypes: A_1 = (0.7, 0.3, 0.0), A_2=(0.4, 0.3, 0.3), A_3=(0.1, 0.1, 0.8), with proportions P(A_1, A_2, A_3) = (0.3, 0.5, 0.2). This implies that, for half the population, personal, social and societal factors are all significant, whereas other parts of the population are more strongly personally oriented or strongly influenced by society. The values, for both the relative weighting in each archetype and the proportion of that archetype in the population, were chosen on the basis of where meaningful results arose in previous analytical work and in order to reflect what is known about the proportions of people who exhibit different behaviour in diffusion theory, e.g. early or late adopters (Rogers, 1983). From previous work (Bale et al., 2013b), we know that the proportion of different archetypes will make a significant change to the simulations. However, here we maintain the archetype groups in these proportions, as the aim of this work is to compare intervention scenarios for a set population.

3.2.4 Threshold

In the model we introduce further heterogeneity by allocating different thresholds across the nodes, relating to households' ability to adopt. The threshold categories and values are estimated as shown in table 2. The percentage of households (nodes) assigned to each category are based on household income, house type and tenancy using empirical data collected from the survey. We grouped households into threshold categories. Those living in flats, halls of residence, or in shared or rented accommodation are deemed unable to adopt, as they will typically not be able to change the physical fixtures and fittings.

Table 2 – Threshold rules and number of nodes assigned to each value for N=1068 (1% missing values). The percentage of our sample with a threshold of θ=1 compares with 41% in this category using data from the 2001 Census for the Leeds area (Office for National Statistics, 2001).

Threshold Value (θ)	**Rules for type and tenancy of household with threshold(θ)**	**Banding threshold level for those households that are able to adopt**	**Percentage of population in model with threshold (θ)**
0.25 (Low)	***Able to adopt*** House types: Detached; Semi-detached; Terrace. Tenancy: Owned outright; Buying with mortgage.	High income band (> £40,000 pa)	25
0.45 (Mid)		Middle income band (£40,000 < £20,000 pa)	16
0.75 (High)		Low income band (< £20,000 pa)	4
1	***Not able to adopt*** House types: Flat; Halls of residence; Other. Tenancy: Shared; Rented (Privately or from Council, HA etc.); Other.		52

Given the personal utility value, p_i = 0.5, that we adopt (see section 3.2.1), this implies that the adoption of the energy technologies will be personally beneficial to high- and middle-income households, but not to low-income households or those unable to adopt (because, for example, they are in rented accommodation). Whether those households that are able to adopt actually do so will depend on the relative weighting of their personal, social and societal benefits.

3.2.5 Estimates

In the absence of complete data, we have had to make estimates in the model, as follows. For the network representation we assume that households have 5 friends, 3 family links and 2 neighbours. If a household has a group or workplace link then we assume that the household has five *active* group contacts within that group. This gives the numbers shown in table 1. We assume values for p and the archetype groups. Once a household's perceived utility exceeds the threshold they immediately become adopters at the next time-step. In reality, the time taken for making the decision and then completing the contracting and installation process could be considerably longer, but this would not change the basic operation of the model. We also assume that all decisions are made synchronously and at regular (monthly) intervals, which is computationally convenient but unrealistic in the real world. Although the proportions of households assigned to each threshold level are those defined by the survey data, the threshold values are assigned only to give meaningful results in the simulation, as there are no existing data to enable us to easily quantify these values.

3.2.6 Simulation of policy scenarios

For each simulation, a social network is created based on the above rules and assumptions, and an initial seeding chosen. The model is run for 36 time-steps. This was found to be enough to give a stable final configuration. For each initial network configuration this is repeated for 100 random realisations to give an average final uptake.

Having developed a network representation of the city based on empirical evidence (table 1 and figure 2), we simulated the different roll-out strategies that could be implemented by the local authority. We largely follow the framework of network interventions outlined by Valente (2012), informed by strategies that have been proposed, such as the Committee on Climate Change's proposal that energy-efficiency measures be rolled-out in a street-by-street/neighbourhood approach (Committee on Climate Change, 2009). However, we also propose interventions that are aimed at the threshold (barrier to adoption) as opposed to altering the network itself. The different strategies are simulated by altering different parameters in the model and can have effects in the following ways: seeding different initial conditions for the households that already have the technology at the outset, or have it imposed on them at time-step 1; strengthening or adding the weights of the links on the network; or lowering the threshold value. The first two strategies are closely related to Valente's categories *segmentation* and *induction*. The *incentive* and *snowball* strategies are informed by ideas from interventions that local authorities have implemented (Bale et al., 2013a)

In addition to the baseline case (*Do Nothing* scenario), we investigated four different roll-out strategies:

- **Seeded**: Free installation of the technology directly to a percentage of households (that are able to adopt (θ<1)) randomly chosen on the network – modelled by increasing the initial seed to a range of 5 to 20% of households.

- **Communities:** Free installation of the technology directly to households that are connected via a number of (work or local) groups on the network – modelled by seeding all nodes (who are able to adopt (θ <1)) of a given number of groups from 0 to 20, an attempt to induce a 'critical mass' for propagation by clustering effects (see McCullen et al.(2013)).

- **Incentive**: A voucher is made available to all households on the network which lowers their threshold to adoption (if they are able to adopt) – modelled by decreasing the threshold for all households that are able to adopt (θ<1).

- **Snowball:** A recommend-a-friend voucher is given to each household that becomes an adopter (which gives them a reward for spreading the word). Each new adopter is assigned one extra link to another node on the network (at random) and the threshold to one, two or all of their linked households is lowered to represent the voucher incentive they can pass on to other households.

In addition, this is implemented for two specific technology examples: (a) photo-voltaic (PV) panels and (b) loft insulation, which would have different social diffusion mechanisms representative of the different characteristics of the technologies. Strong peer effects have recently been identified in the diffusion of PV panels; Bollinger and Gillingham (2012) show that additional installation of PV panels increased the probability of adoption for homes in the same geographic area by a significant and observable degree. Bollinger and Gillingham propose that increasing the visibility of adoptions would be expected to increase the rate of adoption. In this modelling work the set of archetypes remain the same (as do all other parameters in the given scenario) but in case (a) the technology is visible and therefore likely to have a higher social diffusion element compared to case (b), where the technology, once installed, is hidden from view. In case (b) the network links are weighted to 0.5, whereas in case (a) weighting remains at 1. The parameter values for all scenarios and both cases can be seen in Table 3. Weighting all links by 0.5 is represented in the model by altering equation (1) to:

$$u_i = \alpha_i\, p_i + 0.5\beta_i\, s_i + 0.5\gamma_i\, m \qquad (2)$$

for case (b).

Table 3 — Intervention scenarios and parameter values. The value for $p = 0.5$ is set the same for all runs. Each scenario is run for a set of archetypes $A_1 = (0.7,0.3,0.0)$, A_2=(0.4,0.3,0.3), A_3=(0.1,0.1,0.8), with proportions P(A_1, A_2, A_3) = (0.3, 0.5, 0.2). For technology case (a), where innovation is more easily socially diffused (such as solar panels, as people tend to see and discuss these more), all links are weighted to 1; for technology case (b), for those that are not (e.g. insulation, where the intrinsic benefits are considered by potential adopters but the technology, once installed, is hidden from view), links are weighted to 0.5.

Scenario	Type of Intervention	Example of possible action taken by LA to affect intervention	Parameters
Do Nothing (Fig 3 & 4)	None.	None.	θ = values assigned in table 2 Initial seed = 0 Network = Baseline
Seeded (Fig 5)	***Network***: Target individual households on network.	Free installation of the technology to a proportion of randomly selected households in the city.	θ = values assigned in table 2 Initial seed (m_0) = 0.05–0.20, randomly assigned Network = Baseline
Communities (Fig 6)	***Network***: Target households connected by a	Free installation of the technology to a proportion of	θ = values assigned in table 2 Initial seeding (m_0) for 0–

	group or community hub.	households in the city who are connected to selected groups.	20 groups, assigned via groups Network = Baseline
Incentive (Fig 7)	***Threshold:*** Reduce threshold for random selection of households.	Voucher to refund part of the cost of installation for all households in the city.	θ = values reduced by 0–0.20 Network = Baseline
Snowball (Fig 8)	***Threshold and Network:*** One new link to another random node on the network is added to each new adopter. In addition the threshold is reduced for 1 (single voucher scheme), 2 (two vouchers) or all (unlimited vouchers), of the adopters' network neighbours.	Money-back voucher(s) for new adopters which they pass to other households whose threshold is lowered.	θ reduced by 0–0.20 for households that receive a voucher from a new adopter on the network. Network = Baseline + increased number of links on the network at each time-step.

The data used to populate the model show that a significant portion of the social interactions important to domestic energy-use behaviour are between households that are not physically adjacent, due to social interactions in other venues (e.g. the workplace) that affect behaviour at home (Thøgersen and Ölander, 2003). This was a typical feature of all of the strategies investigated. Hence, the "communities" strategy, for example, focuses on communities that are not necessarily geographic, but rather those that are work-based or social in nature.

4. Results

In this section we discuss the results from the intervention scenarios modelled (table 3).

4.2.1 Scenario analysis

Model results are shown in Figure 3 for the baseline case where the local authority has taken no intervention. Note that maximum uptake is limited by the high proportion (50%) of households in this case who are unable to adopt (threshold value, $\theta = 1$).

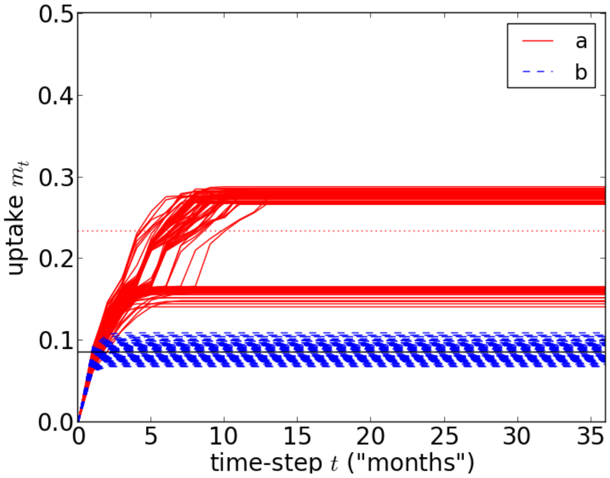

Figure 3: Uptake over 36 time-steps on the baseline model with no initial seeding for cases (a, red) and (b, blue). The dashed lines give the average of all the runs. In case (a) links on the network are weighted to 1.0 and in (b) are 0.5. 100 runs are shown to assess the effect of the initial conditions.

The uptake curves exhibited in figure 3 can be explained as follows. In the first month, uptake is entirely a consequence of adoption for those households for whom the weighted personal benefit to them exceeds their personal threshold ($\alpha p > \theta$). In the following months, those who are initially below the threshold begin to adopt as the social benefit from peer-group (βs) and the wider population (γm) come into effect. The higher level of uptake for case (a) compared to case (b) is a result of the social effect being greater as the connection weighting is stronger (1.0 versus 0.5). This shows the effect of the greater visibility of the technology inducing social network propagation.

There are two steady states found in case (a): one where the uptake ‘stagnates’ at around 15% and one where uptake of nearly 30% is achieved. This is a particular feature of the sensitivity of networks, where cascading dynamics can depend strongly on the precise network structure. For these reasons we look at ensemble averages over 100 different realizations for the following results.

‘Seeded’ and ‘communities’ scenarios

Figure 4 shows the results from the ‘seeded’ scenario, where we represent the local authority giving the technology free of charge to a certain number of households. Nodes in the model are randomly seeded and are therefore assigned to the adopted state at the start of the model run. The model reveals that there is a certain range in the level of initial seeding, in which the total rate of adoption is greater than one-to-one with the level of investment. This level is seen at a lower level of seeding (m_0) in case (a) than case (b). This effect gives rise to more adoption by propagation on the network than could be achieved by the seeding alone. This demonstrates how such network models can reveal non-intuitive results that would give the local authority a better return on investment (‘more bang for their buck’) and could be explored in more detail when designing interventions of this type.

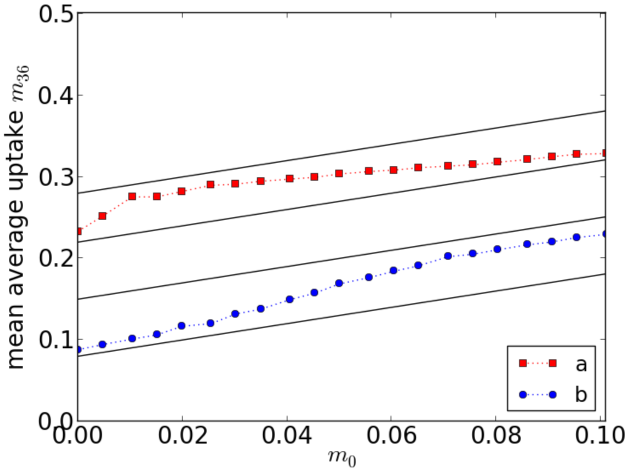

Figure 4: *Seeded* scenario: Increasing the initial level of seeding (m_0) randomly across the network. The average final uptake after 36 time-steps, over 100 realizations, is shown for case (a; red squares) and case (b; blue dots); the lines show the 1:1 ratio in rates of increase of seed level to final uptake.

In figure 4, segments of the graph with a slope greater than the 1:1 line indicate levels where more adoption is induced through the network effects over and above the increase in seeding level alone.

In figures 5 and 6, the '*communities'* results are shown, where the seeded nodes are linked to a certain number of groups, either workplace groups (figure 5) or social groups (figure 6), instead of being assigned randomly across the network.

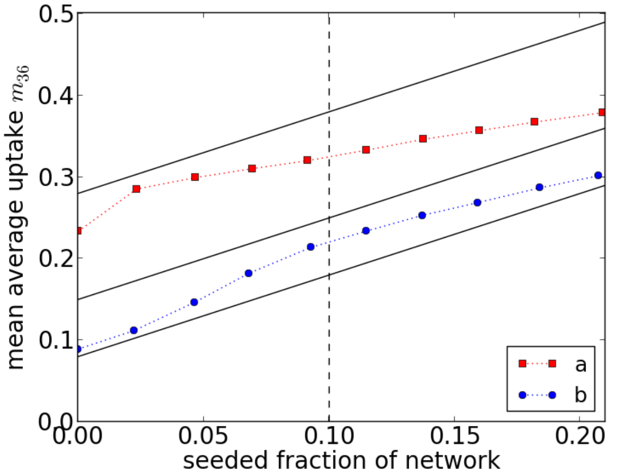

Figure 5: *Communities* scenario – workplace group case: Results are shown for case (a; red squares) and case (b; blue dots); the lines show the 1:1 (seed level:final uptake) ratio in the increase of seeding. A line is drawn in at 10% to allow comparison with the results in figure 4 and 6. There are 24 households assigned to each workplace and 0–10 workplaces are seeded.

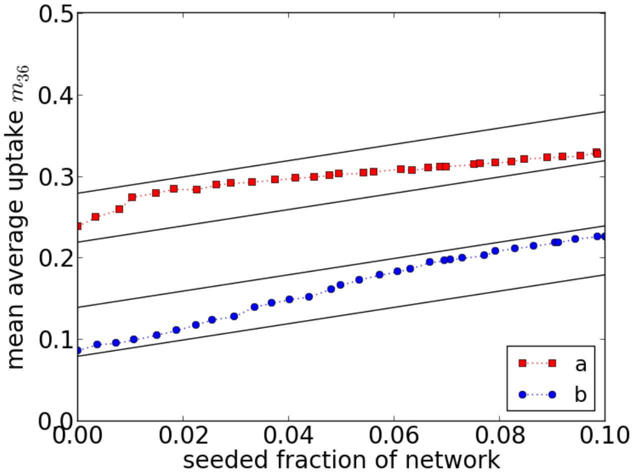

Figure 6: *Communities* scenario – social group case: Results are shown for case (a; red squares) and case (b; blue dots); the lines show the 1:1 (seed level:final uptake) ratio in the increase of seeding.

This is a scenario which, in theory, as a result of propagation via clusters, was expected to show a significant increase in uptake versus the randomly seeded scenario. However, as can be seen in figure 5, the model does not support this assumption. The results for the *'communities'* scenario for seeding up to 10% are no better than in the 'seeded' scenario, and higher levels of seeding do not result in any significant increase in final uptake. On closer consideration, we conclude that this is because there is no significant overlap between communities (seeded clusters), and thus even once each cluster is seeded there is no mechanism for adoption to propagate socially across the whole network and the results are therefore similar to those in the randomly seeded case.

For the social group 'communities' case shown in figure 6, the uptake is much the same as in the workplace case, however more people are connected to, and talk with colleagues at, workplace, so there is potentially scope for increased peer reinforcement towards adoption.

'Incentives' scenario

Figure 7 shows the results from the intervention which aims to reduce the threshold to adoption rather than altering anything related to network properties.

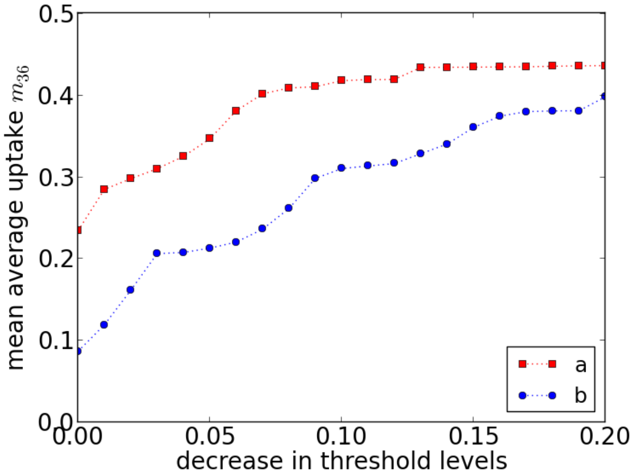

Figure 7: *Incentives* scenario: Results are shown for case (a; red squares) and case (b; blue dots). The thresholds are lowered by increasing amounts (except those with a threshold of 1, who cannot adopt, and remain unable to do so).

In case 7(a), where there is a higher social spreading component (reflected by the connection weightings), a small decrease in threshold level significantly increases the uptake of the technology at a critical value. This is the point at which the thresholds of members of one of the archetypes are reduced below the level of their utility required to induce social spreading, bringing final adoption up to the theoretical maximum. A larger decrease in the threshold levels is needed in case 7(b), as their utility is lower due to the reduced weighting on social aspects. In this latter case, several steps can be seen as increasingly more subgroups are enabled by their threshold crossing below their utility.

'Snowball' scenario

Results are shown in figure 8 for the snowball scenario intervention, where a link is added to nodes that have just adopted and thresholds reduced for their new network neighbour, two neighbours, or all of their neighbours. This is a simple model of a voucher scheme, which would encourage interaction by giving cash-back for the giver, and make the receiver more likely to listen by giving them an incentive (reducing their threshold). This can be seen to have a positive effect on uptake. For full comparison with the other scenarios, more data would be required on the effect on individual behaviour of such a voucher scheme. However, these results are a first attempt to model roll-out strategies based on network-based interventions, and can be seen to show potential gains in levels of adoption.

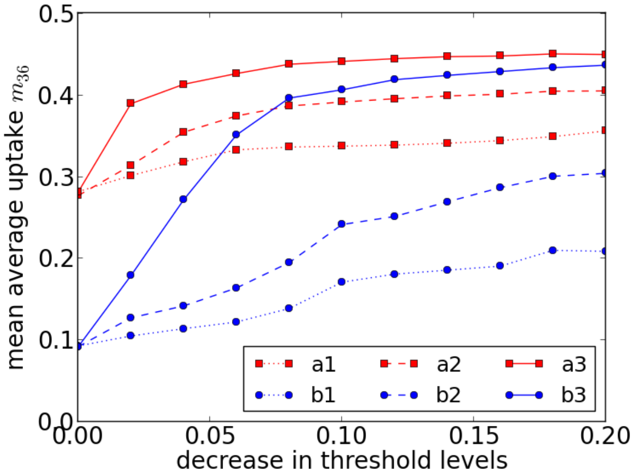

Figure 8: *Snowball* scenario**:** Results are shown for case (a; red squares) and case (b; blue dots). A new link is added to every adopting node to another node randomly selected in the network. In 1 (dotted lines) the newly connected node has the threshold parameter reduced by a set amount (single voucher scheme), in 2 (dashed lines) this happens for two network neighbours (two vouchers) of the adopting node, and in 3 (solid lines) all network neighbours have their thresholds reduced (unlimited vouchers). Results are plotted over a range of this fixed reduction.

4.2.2 Evaluation of scenarios

The aim of modelling the different roll-out interventions is to determine the potential for employing network models to compare and identify those interventions that will most likely lead to increased uptake of the technology.

The most easily comparable results are the two seeded scenarios, seeded (where households are randomly seeded) and communities (where groups are seeded). Here we can compare directly, as costs for either intervention would be roughly the same (because they are proportional to the number of people to whom we seed the innovation). The only difference will be the logistic costs of delivery, as it would likely be cheaper to install technologies if the seeded households were located close to each other. In this case we see, unexpectedly, that there is no appreciable difference between the effectiveness of the two scenarios. This is at first surprising, as we might have expected to induce a ‘critical mass’ of adopters from which the innovation would spread via the clustering effects given in McCullen et al. (2013). Here the model reveals the possibility that the system does not meet intuitive expectations and we are driven to ask why, and whether this could arise in the real world. The network topology we use in these simulations has very little overlap between communities; this is seen as the primary reason for the lack of enhanced spreading. If many members of one (seeded) community were also members of another, the cluster-based spreading would take over as a diffusion mechanism, but this is not the case here. This highlights two findings: firstly, that these models can reveal possible diffusion dynamics that it would be difficult to anticipate without a model, which could have a negative or positive effect on the outcome, and, secondly, that we need to be careful that the essential features revealed by the model are accurately programmed using real-world data to ensure that we are seeing the correct behaviour. In general, to quantify and fully compare the different strategies would need two things: i) better understanding of individual-level behaviour in response to various incentives and information, in order to quantify the relative level of modification of the network parameters; and ii) costing of the various options, so that a cost-benefit analysis could be carried out by a local authority.

In all the modelled scenarios, it is important to note that the results show non-trivial emergent behaviour that would not have been revealed through conventional analysis. In this respect, there is a clear case for using this type of complexity modelling to support the design of local-level policy interventions.

5. Discussion

We have shown the importance of this type of dynamical network modelling to understand the role of network interactions in the diffusion of technologies by using complexity modelling to assess the emergent behaviour of the system. This method provides several advantages for studying the diffusion of energy technologies, and assessing interventions, that other methods may not provide. These include the ability to:

- include the effects of both personal preferences and social influences in the diffusion process.
- model a heterogeneous population of households with different network connections, thresholds to adoption, and preferences towards the balance between personal and social benefits.
- include nodes on the network that, while they may not be ‘active’ in terms of talking to others about energy, are still important to include, as they may mediate the spread of technologies by their adoption state being visible to others and may still be able to be seeded (if they are able to adopt $\theta < 1$)).
- include nodes that are ‘active’ on the network, cannot (under our rules) themselves become adopters, but may still have a role in the diffusion process. For example, they could either block diffusion by being non-adopting neighbours of a potential adopter, or be a potential route to higher rates of adoption if the barriers to their adoption are specifically targeted.

- model a population without the need to understand the exact motivation of each individual household for adopting a certain technology (e.g. pro-environmental behaviour, saving money, enthusiasm for the technology). With further insight into the types of household that fall into different archetype groups and different threshold categories (alongside information on the social network), it is envisaged that larger datasets of socio-economic information could be used in future to define a population and assist modelling at the city level.

This work, therefore, provides the basis for decision-making tools that could be used by a local authority to inform the design of roll-out strategies for initiatives aimed at encouraging uptake of energy technologies in the domestic sector. Informal feedback we received from local authority representatives suggested that this type of quantitative modelling and scenario analysis would be useful in supporting internal business case development for energy-efficiency retrofit programmes. There are many variations that could be made to the scenarios as implemented in the model and to the parameters of the model (thresholds, network properties, archetypes). However, we have chosen illustrative strategies guided by the literature of technology uptake – see section 2.1. In the absence of specific data, examining further strategies would not at this stage provide further insights. Nevertheless, the investigation and development of the model we have undertaken to date could, with appropriate inputs, form the basis of a decision-making or assessment tool for specific local-level interventions. Suggestions for future investigation include:

- Different policy scenarios where those with barriers to adoption are targeted, e.g. private rented sector where tenants do not have the power to install technologies that alter the building.

- The uptake of different energy technologies that each exhibit different social diffusion properties.

- Uptake of the Green Deal (Department of Energy and Climate Change, 2011) in the UK. Local authorities are likely to play a significant role in encouraging uptake (Bale et al., 2012a) and network effects could be used to leverage the social benefits.

As we consider in detail elsewhere, the issue of availability of data is key, and it is worth emphasising that more data and experiments in this area, as well as evidence (as to the success or otherwise) of real-world network interventions for promoting uptake, are warranted.

Although it would be important to investigate in more detail using data appropriate to each specific intervention and target population before using models such as ours to support specific decisions, we are able to draw some useful generic policy implications for local authorities seeking to influence the likely uptake of an energy technology. As we have explained above, our model scenarios were parameterized using generalized, rather than policy-specific, input data (section 3.2.1).

As can be seen from the numbers presented in table 2, we estimate that 50% of our sample is not able to adopt either insulation or PV panels because they are either in flats (with limited roof area per resident and where concerted action is needed) and/or rented properties (where the decision would be out of residents' hands). Enabling such households to adopt specific energy technologies would have an enhanced effect, over and above simply their own level of adoption, by making them active influences on the network, 'unblocking' obstacles in the whole-system network and allowing spreading to occur more widely. The return on investment in such cases has the potential to be greater than that expected when not accounting for network effects.

Initial adopters who adopt because the technology is considered personally beneficial to their household are needed to trigger spreading on the network. Increasing the perceived value of the innovation (p) or its average relative weighting in the decision process (α) would increase this activation. It would be difficult for a local authority to change the intrinsic preferences of a household, and thereby influence the weighting factor α. A potentially easier route to the same outcome would be to make the personal benefits of the technology clearer to different groups across the city (including those that are on low incomes and/or those who are landlords of privately tenanted properties).

An important finding is that network effects can play a significant role in increasing uptake, as is particularly seen in the *Snowball* scenario. Potentially beneficial social network effects can be enhanced by increasing the communication of energy information between peers on the network. Encouraging communication of energy-related issues increases the weighting of the links, which in turn can lead to a wider uptake.

Prior to the application of modelling results in policy decision support, it would be important to investigate in more detail using data appropriate to each specific case, where necessary.

6. Conclusions

In this paper we have highlighted the value of incorporating complex-systems thinking on social networks into models of energy decision-making and policy interventions. This is based on consideration of the existing evidence for the success of network interventions in other domains and the development of a model that enables exploration of different roll-out strategies for local authority interventions. In this model we have incorporated both personal benefits (and therefore intrinsic properties of the technology, e.g. cost) and social influences in order to draw together both sides of the decision-making process. For a case for which the social influence is reduced, corresponding to a less visible technology, there are lower levels of technology uptake in the model, showing the importance of social network effects. Whilst our work does not go all the way to addressing the problems identified by Wilson and Dowlatabadi (2007), this type of modelling could be useful in bridging the gap identified between adoption models based only on individual behavioural motivations and more qualitative approaches based on the social context of decision-making (Nye et al., 2010). We have shown the potential for use of these modelling methods in the assessment of local authority interventions. The results of the simulations have revealed the qualitative dynamics of the uptake in response to various alternative strategies and provided a strong motivation for using this type of network model-based thinking to inform policy decisions. Further work is certainly needed in this area, including more data, experimental evidence for the success (or otherwise) of different strategies, and a better understanding of household decision-making related to different energy technologies. Nonetheless, the results presented here suggest ways in which a dynamical network approach could be used as the conceptual basis of a decision-support tool for local authority interventions in domestic energy demand.

We propose that local authorities could use this type of modelling to their advantage for maximizing adoption of retrofit domestic energy technologies at a time of limited resources and great imperative for action in the face of rising fuel bills and climate change.

Acknowledgements

The authors would like to thank the Engineering and Physical Sciences Research Council for supporting this work under grant EP/G059780/1 '*Future Energy Decision-Making for Cities — Can Complexity Science Rise to the Challenge?'*. We would like to thank colleagues Tao Zhang, Peer-Olaf Siebers and Uwe Aicklen of the University of Nottingham, who also worked on the wider EPSRC project, for helpful discussions. We would also like to acknowledge, with thanks, input and active collaboration from Leeds City Council. We are grateful in particular for detailed discussions with Dr Tom Knowland (Head of Sustainable Development) and colleagues. Finally, we thank the anonymous reviewer for detailed and helpful comments on our manuscript.

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