Modelling diffusion of energy innovations on a social network and integration of real-world data

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Abstract

Recent developments in complexity science enable the study of the effect of social influences on the diffusion of new innovations, along with the spread of information through the overlapping communities to which people belong. This paper describes work by an interdisciplinary team of engineers, mathematicians and social scientists applying these ideas to modelling the diffusion of domestic energy innovations on a social network at the city level. We ultimately aim to develop tools to inform decision-making by local authorities and others seeking to promote the adoption of such innovations as part of strategies to mitigate climate change.

The model developed in this work represents individual households as nodes on a complex network, whose adoption of an energy innovation is based on a combination of personal and social benefit, where social benefit includes positive feedback from an individual's personal social network and from the wider population. Different types of household will weight these three factors differently according to their preferences.

Numerical simulations have previously been carried out to explore the diffusion of energy innovation on various network topologies, based on a homogeneous population of households in the model. This paper describes an updated version of the model in which households are assigned different parameters, to reflect different preferences, making the population heterogeneous, and thus more like a real social system.

The paper compares this model with existing models that address related questions. We describe the way in which real-world data on household preferences, gathered through a survey and other sources, are incorporated into the simulations, and discuss the incorporation of this data into the model and how this can influence the results.

Finally, we discuss potential applications and extensions of the model, in relation to informing decision-making on the uptake of pro-environmental innovations.

INTRODUCTION

There has been much interest in applying complex systems thinking to real world problems and recently there have been examples of the application of complexity science techniques to understanding and addressing energy challenges[1].

In this paper we describe some results from a project in which the aim was to apply complexity science to enable effective decision-making on energy at the city level by developing the type of tools that a local authority could use to assess the implications of different energy-related interventions. With the UK's heavily urban population, cities have a major impact on energy sustainability. Indeed, cities are responsible for around two-thirds of global CO_2 emissions[2]. Local authorities hold significant indirect influence over the provision and use of energy in cities, and are in a position to influence residents and businesses to reduce energy demand through the services they deliver and their role as social landlords, community leaders and major employers (in addition to their regulator and strategic functions)[3]. Decision-making tools are therefore needed to support local authorities in achieving their potential contribution to national and international energy and climate change targets.

The problem of how to quantify and integrate real-world data into mathematical and simulation models needs to be addressed for them to be seen as reliable, and to encourage take-up and use as tools by strategic planners. The aim of the current work is to assess the dependence of one potential simulation method on available data. This is done by running our model of diffusion of energy innovations and looking at how the results change as the parameters of the model are varied, and, therefore, which parameters strongly affect the model. These model parameters relate to real world factors which could be either quantified using available data, where it is shown to be necessary, or otherwise given approximate values which lead to meaningful results. Additionally, the sensitivity of the model outcomes to various parameters can be used to guide which are the most effective targets for network interventions in the real world, and what additional data need to be gathered.

Interventions implemented by local authorities and targeted at the domestic sector can include both the direct deployment and the indirect promotion of various energy-efficient and renewable technologies, which are usually selected after cost-benefit analyses. These analyses are generally derived from the expected savings (in terms of both cost and greenhouse gas emissions) of these technologies assuming certain user behaviours (e.g. Cheng & Steemers[4] and

Clinch & Healy[5]). However, this type of analysis makes (often implicit) assumptions about the socio-technical aspects of an intervention, without evidence that these assumptions are appropriate to the intervention (for example, that the decision to adopt a certain technology will be based on rational economic decision-making and personal preferences alone). Models based on individual behaviour tend to assume rational choice or reflect psychological motivations[6], whereas approaches that address the social context of decision-making tend to be more qualitative[7], and there is a clear need for approaches that integrate the two concepts.

Both the individual preferences and the social network influence are important factors in the adoption of energy innovations, and that local authorities have the means to potentially harness these influences to their advantage in encouraging increased adoption. Since average uptake of an innovation emerges as a result of adoption behaviour of individuals connected on a social network, in order for us to investigate potentially successful interventions, a complex-systems perspective is needed.

Recent developments in complexity science allow study of the effect of social influences on the diffusion of new innovations[8], as well as the importance of network structure and the role played by the overlapping communities to which people belong[9]. In this work we develop a model to investigate the influence of social networks on the adoption of energy-related innovations. Valente[10] describes the term "network interventions" as 'the process of using social network data to accelerate behaviour change' and suggests four strategies for achieving change. These can be categorised as: (1) directing the intervention at individual nodes on the network; (2) directing the intervention towards groups; (3) introducing new connections into the network; and (4) changing the network structure. However, these approaches assume that network data is available to develop the intervention programme. Valente also highlights the need for research to compare different network interventions.

We reported on the development of a multi-parameter dynamical model of innovation diffusion on a social network in a recent paper[11]. In this previous work this model was restricted to a set of homogeneous nodes (representing households) with uniform parameters, in order to derive some analytical insight into the underlying behaviour of the system. This provided a great deal of theoretical understanding of the model, but these simplifications made the model less representative of the real world. In order to make the model useful for informing specific decision-making, in this paper we discuss the process for developing this model fur-

ther by making the nodes represent heterogeneous households and integrating real-world data. Our aim is to enhance and assess the usefulness of these types of models in understanding adoption of energy innovations and identifying interventions that could lead to their increased uptake. In subsequent work we have investigated this idea in more detail and present the development of the model for use to investigate different interventions a local government agency could take to try to increase uptake of energy-technologies in the domestic sector [12].

BACKGROUND AND OBJECTIVES

The spread of ideas or technologies has been studied by many people as diffusion on networks and the importance of social networks in the diffusion of innovations is well established (e.g. Choi, Kim, & Lee[13]; Delre et al.[8], and references therein). Network diffusion models are widely used to study the spread of diseases, but these typically require only a single contact for a transmission to occur from one individual to another. However, 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[14]. Threshold models have been developed to account for this phenomenon.

There have been some recent developments in understanding and modelling network influences on the diffusion of energy innovations. Multi-parameter models similar in principle to this work have previously been investigated, such as the model of Choi, Kim and Lee[13], who numerically investigated individual realisations on a model balancing intrinsic value with network influences. A three-parameter model that includes influence from the wider population (as well as peer-group) was simulated by Lee, Lee and Lee[17], who investigated complementary effects of competing products. The effect of feedback from the wider network and external drivers were considered in addition to the feed-back from other nodes by Basset et al[18]. A closely related model to ours was developed by Tran[19], using the same three influence factors as the ones we describe below, using an agent-based model (ABM) to simulate and investigate competing technologies. It was found in these investigations that network influence can play an important role in accelerating energy-innovation diffusion. Our approach differs from an agent-based model in that the rules governing a transition from a non-adopter to an adopter are deterministic and equation-based, rather than defined by a probability, but our model could be easily adapted to run in this way.

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The objectives of this paper are twofold:

1. To present a method for modelling diffusion of energy-efficiency innovations on a social network of *heterogeneous* households in order to aid decision-making in local authorities;

2. To describe the systematic approach to integration and use of empirical data in this type of social simulation and identify the gaps where more data are required.

In the next section we outline our approach to the model development. We then present the systematic integration of empirical data. We conclude with comments on the methodology developed so far and its suitability in addressing the original aim, as well as areas for further research.

APPROACH

For a full description of the basic model that this work builds on see McCullen et al.[11], which also includes a description of some of the features exhibited by the simulation results and mathematical analysis of the model. We include brief details of the main approaches and basis for the model here.

The model represents individual households as nodes on a complex network, each with a binary variable representing their current state, $x_i = (0, 1)$, for non-adopters or adopters, respectively. The initial state for all households is chosen to represent the proportion of the households who have adopted the technology at the start time.

The basic idea behind the model is that a household will decide to adopt the energy innovation if the perceived usefulness or *utility* exceeds a threshold (which encompasses their ability to adopt). The total perceived utility of an innovation (either technological or behavioural) can be attributed to a number of factors; for this model we divide these broadly into personal and social benefit[8]. Personal benefit p_i is a measure of the perceived practical use of implementing the innovation to the ith household. The total social benefit is the utility derived from agreeing with peer groups and mainstream social norms. The social benefit can thus be divided into two parts: the influence from an individual's personal peer-group network and the influence from society in general (the total larger population in the network; that is, the social norm)[20].

The total utility therefore has three factors: personal benefit, social benefit from the peer-group of one's network neighbour connections and a benefit derived from following the wider population. In the work of Tran[19], this third factor was derived from the interaction with a subset of the whole population, representing an individual's wider contact network, whereas we look at the influence of the whole population (for example from both the wider contact network and via the media as a reflection of the mainstream social norm).

In the model we have developed we assign these three factors to each household with the relative weightings α_i, β_i and γ_i (with $\alpha_i + \beta_i + \gamma_i = 1$), to account for different behavioural *archetypes*. The parameter α_i is the weighting given to the personal benefit of adoption to the individual p_i, β_i is the weighting given to the average value of x_i within the individual's social network neighbourhood s_i, and γ_i is the weighting given to m, the average of x over the entire population.

The total utility is therefore given by:

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

where s_i is the mean average of x over the k_i neighbours of individual i and m is the mean value of x for the whole system.

Adoption at each time-step occurs if perceived total utility to the household outweighs the barriers to adoption, the threshold:

$$u_i > \theta_i. \qquad (2)$$

This is a one-way process and the state at the next time-step remains 1 (i.e. the node remains an adopter).

Modelling the Social Network

The individual nodes (here representing households) interact with others in their peer group (their *network neighbours*) via a fixed set of connections, or *edges,* on the network. Several common models of network topology were investigated in our previous work[11], including

random [21] and *small-world* [22] models. The most important factors influencing take-up by households in the network were found to be the *node degree*, i.e. the number of connections belonging to each node, and the clustering coefficient (or *transitivity*) i.e. the proportion of second-degree neighbours who are also directly linked (the so called "friend-of-a-friend is a friend" effect).

Whilst the total number of contacts may vary greatly between individuals, it is clear that most individuals maintain a relatively small number of close associations who influence adoption decisions more strongly than the whole peer-network [23]. In the real-world social interactions often occur via communities, which can be either social groups or workplaces, where individuals meet each other and form connections with a limited number of other members. A model containing these features is the *random-clustered network* model of Newman[24]. In these models the degree of clustering can be varied in a natural way by linking individuals via their mutual association with groups. The following work uses this type of model for the structure of the social network, assigning N nodes each to a number G_i of groups out of a total of W. This number G_i can be either homogeneous, such as each node being associated with $G = 2$ groups, or varying from node-to-node in a more realistic manner. The number of members per group (in the homogeneous case) is then given by $M = GN/W$, and this, along with the number of links per group L, determines the average degree of clustering within groups. Additionally we can assign a number of individual connections across the network, representing links that are not associated through groups. This increases the number of connections for a node (its degree) without the clustering property derived from both being part of the same group. In all other respects, group based and individually assigned connections are identical and perform the same function. In the results below there are no individual connections unless otherwise stated. It is possible to give the nodes and groups geographic locations and associate them with each other preferentially based on proximity. However, the outcomes of such simulations (not shown here) are not found to differ significantly, so in the following results nodes and groups are assigned to each other at random, as in the original scheme of Newman[24]. A simple version of this model for a small number of nodes is shown in Figure 1.
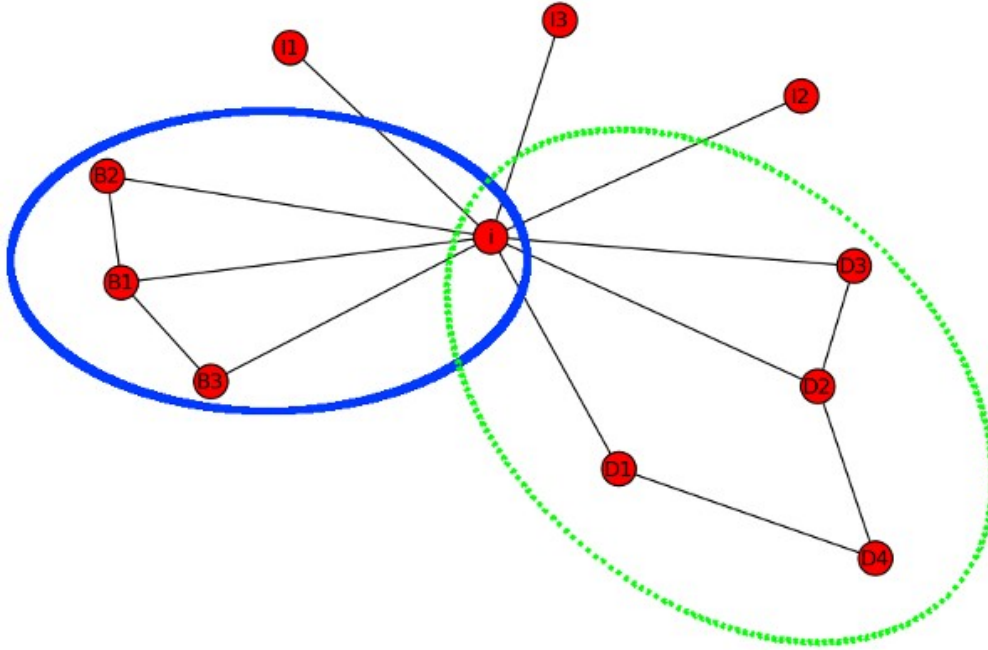
Figure 1. Network features: A simple network consisting of N=12 nodes and W=2 groups (circled). Node *i* has L = 3 links for each type of association, giving connections assigned both individually (to nodes I1, I2 and I3) and via the two groups that of which it is a member (to B1, B2 and B3 in the "blue" group and D1, D2 and D3 in the "green" group). Groups have a higher level of common connections between members than to the rest of the network and, therefore, higher clustering.

In this work we wish to systematically investigate the parameter space of the model and the effect that including real, heterogeneous data could have on the expected level of uptake of an energy innovation. We have applied this to a case study for the city of Leeds, but this could easily have been applied to other geographic areas, and also for other types of innovation.

In order to populate the model with some empirical data a survey of Leeds residents was undertaken in May–June 2011. Additional details of the survey can be found elsewhere[12].

SIMULATION AND EVALUATION

A major aspect of our research is determining whether the insights and tools of complexity science can be useful for understanding energy interventions at the city level. It is, therefore, useful to understand the degree of complexity to which we need to represent the system in our models, and the degree of accuracy that is required for the model parameters. To do this we have systematically investigated the influence of the network structure, the threshold parameter and the archetypes (weightings for α, β, and γ). Determining the degree to which a correct representation of the statistical properties of the model parameters is critical to the

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outcome of any intervention will give us an understanding of the data requirements needed to produce useful simulations.

We indicate where empirical data from the survey has been used in the model in the details covered in the next section regarding the systematic analysis of the parameter space. Table 1 shows an overview of this.

Table 1 – Data sources used to parameterise the model.

|	Parameters	Data source (if used)
Network structure	*N, G, M	W, L*	Survey	Assumption
Individual connections	*I	L*	Survey	Assumption
Group connections	*G	L*	Survey	Assumption
Archetypes	$A_{j=}(\alpha_j, \beta_j, and \gamma_j)$, $P(A_j)$	Simulation
Threshold	θ, $P(\theta)$	Survey	Assumption

The model was written in the multi-platform, open-source *Python* programming language, using freely available modules *NetworkX* for the construction of the networks and *Scientific Python (SciPy)* for the dynamical time-stepping. Plotting was done using *Gnuplot*. Codes and compiled versions of the model will be available at https://wiki.bath.ac.uk/display/~nm268.

In the modelling described below we assume that the network of contacts remains fixed for the duration of a simulation, as do the parameters of the individual nodes. In some cases we assume that all individuals take the same values of some or all parameters as each other (the homogeneous cases). The uptake rules are here deterministic, but could easily be modified so that there is a probability of uptake derived from the dynamical equations (1) and (2), making the approach closer to an agent-based model.

For the following investigations we want to understand the isolated effect of varying one of the network or parameters of the dynamical model, by keeping all other factors fixed. In all cases the personal utility p is set to 0.5 and the initial seed proportion m_0 is set to 5% of nodes. We define an *archetype, A_j,* in the model to be a specific set of (α_j, β_j, γ_j) parameter values which describe the decision-making behaviour of a subset of individual nodes in relation to the adoption of a particular innovation. In the simplest manifestation of the model we use a homogeneous population, by setting all nodes to be of the same archetype. This was done in our previous work [11] to enable us to derive analytical expressions to explain the ob-

served simulation results. Here, the results allow us to observe the individual responses of the different archetypes and guide us in choosing which archetypes to use in more realistic versions of the model simulations. At each set of (α_j, β_j, γ_j) archetype values we perform 20 individual realisations of the system, simulating the uptake of the innovation on the network from a different initial seed, with the same model and network parameters but different precise details, such as individual links.

The results for the simplest case are shown in Figure 2, with colours plotted to represent the mean average uptake of the population after a fixed number of time-steps, which is here 36 (months), chosen to be after the level settles to a constant value. This shows the same behaviour as that seen and analysed in detail in McCullen et al.[11], which can be summarised as follows. The parameter space can be seen to be divided into distinct regions, each with different expected values for the likelihood of success. When the weighting to personal preference, α, is large and the other parameters small (bottom left corner) then universal uptake is a certainty, as personal utility p is greater than the threshold θ ($\theta = 0.25$ in this case). Close to $\gamma = 1$ (bottom right) everyone waits for everyone else to take the lead, so this never occurs (with only the initial seed ending up adopting the innovation). The situation is less well defined when network influences are more strongly weighted, close to $\beta = 1$, in which case the exact behaviour depends more strongly on the network and model parameters. The dividing lines between these regions can also be understood analytically in terms of the degree of the nodes in the network in these homogeneous cases.
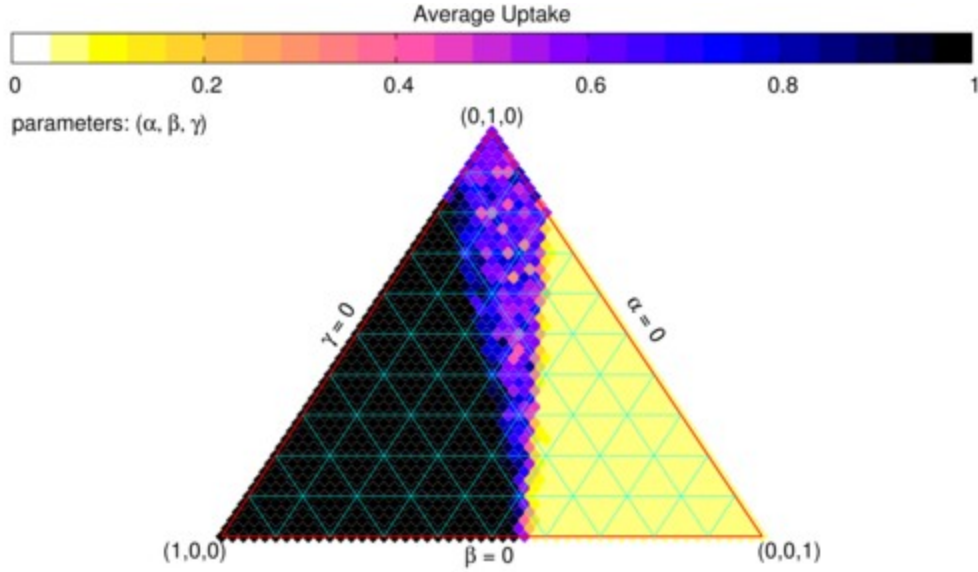
Figure 2. Systematic study of the archetype parameter space for the simplest version of the basic model described in McCullen et al.[11]. Each point on the plot is for a unique set of (α, β, γ) parameter values, which are homogeneous across the network with every node taking the same values. The colours show the average number of adopters after 36 time-steps over an ensemble of 20 realisations of the model, each time randomising the identities of the initial seed-nodes and who is connected to whom in the network, whilst keeping the numerical values of all parameters the same. Other model parameters are fixed to $\theta = 0.25$, $N = 756$, $W = 20$, $G = 2$, $L = 5$.

Variation of Network Connections

We can firstly test the effect of making the model more representative of the real world by connecting each node to others via a different number of groups G_i, rather than all nodes having the same value of *G, and including individual connections*. This has the effect of changing the structure of the network so that nodes have variation in their degrees and the clustering is more irregular across the network. The group association number G_i can be picked from a distribution or based on empirical data. For the results shown in Figure 3 connections were assigned based on the results of our Leeds energy survey, in which we asked people if they communicate about energy issues with others in their social and work groups as well as individual friends and family. These data were used to assign links to nodes based on these *active* group and individual contacts (i.e. those contact they indicated they currently talk to about energy). It can be seen that changing the network structure in this way shifts the critical line in parameter space, the reasons for which can be understood using the insights from our previous work. That is, the critical parameters are the node degrees and the clustering coefficient. Since these factors are difficult to ascertain from data for interpersonal social networks (on the city scale, at least) we must conclude that simulation models such as these have the

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potential to be very useful for comparing the relative effectiveness of different interventions as opposed to making precise predictions on individual outcomes. The situation may be easier for on-line social networks, or smaller bounded communities since data is more readily available or easily gathered in such cases.

In these results, a homogeneous population of socially motivated nodes are collectively made less likely to adopt the innovation by having these non-uniform group associations, as seen by the region near $\beta=1$ becoming lighter in the plot. This agrees with previous observations that care must be taken when modelling anything which changes the network structure. This is particularly true if we are interested in cases close to the lines dividing different regions of the parameter plot. For example, an intervention would appear more sensitive if it changed individual archetypes to push them over the critical line than if they were modelled too far from this line for this to happen. These results also show that interventions based on encouraging households to have more active communication with their contacts (increasing either the number of active connections or β) could also result in a shift in the uptake for an otherwise fixed population.
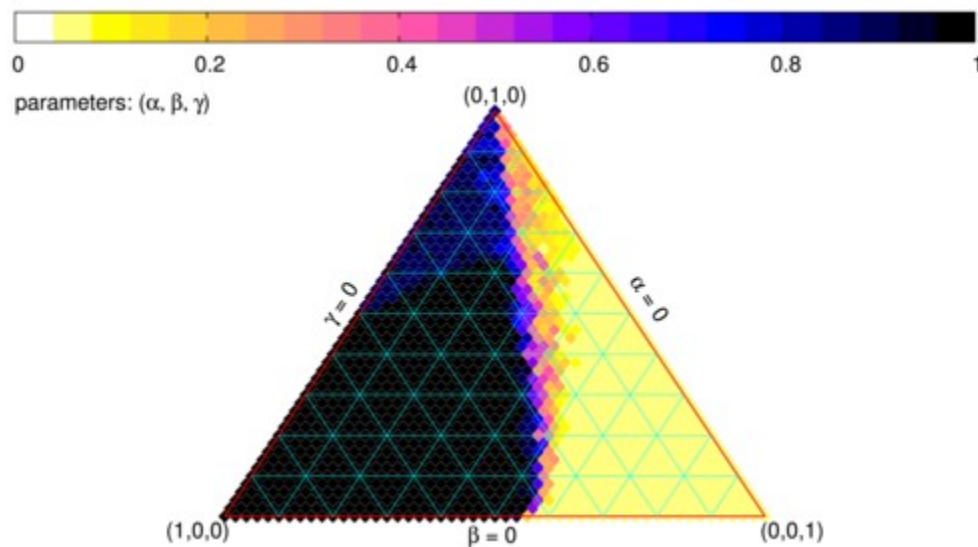
Figure 3. Nodes are associated each to G_i groups based on survey data rather than every node to two, as was the case in Figure 2. Other than this variation, which alters network features such as the node degrees and clustering coefficient (*transitivity*), all parameters are identical to the previous case. For non-work groups the proportions of nodes communicating energy information via association to 0,1,2,3 groups are 89%, 5%, 4% and 2% respectively, with 37% of nodes additionally assigned individual connections. 45% of nodes also have an active work group. The critical line is seen to shift with this variation in the network structure, as compared to the previous case of homogeneous associations.

Distribution of Thresholds

In the real world, individuals and households do not have the same thresholds to adoption of innovations. Therefore, it is natural to consider the effect of introducing a variation in the thresholds assigned to nodes in the network model (c.f. Bassett et al.). For this we can assign two or more discrete thresholds or even a continuous distribution. While it can be difficult to quantify the precise levels of the perceived barriers to adoption from surveys, data can help to provide information on the proportions of individuals with different banded threshold levels. First, we introduce two distinct thresholds, θ_1 and θ_2, and study the outcomes of simulations based on varying the values of these levels for a choice of one homogeneous archetype, as shown in Figure 4. The archetype used here was A=(0.1, 0.8, 0.1), (a point centred two lines below the apex of the triangular archetype parameter plots in Figs. 2 and 3).
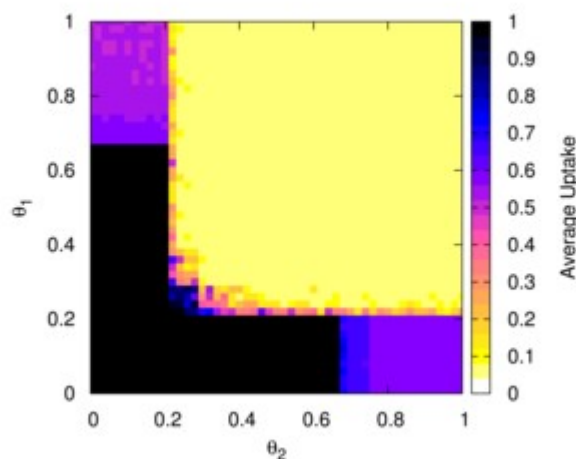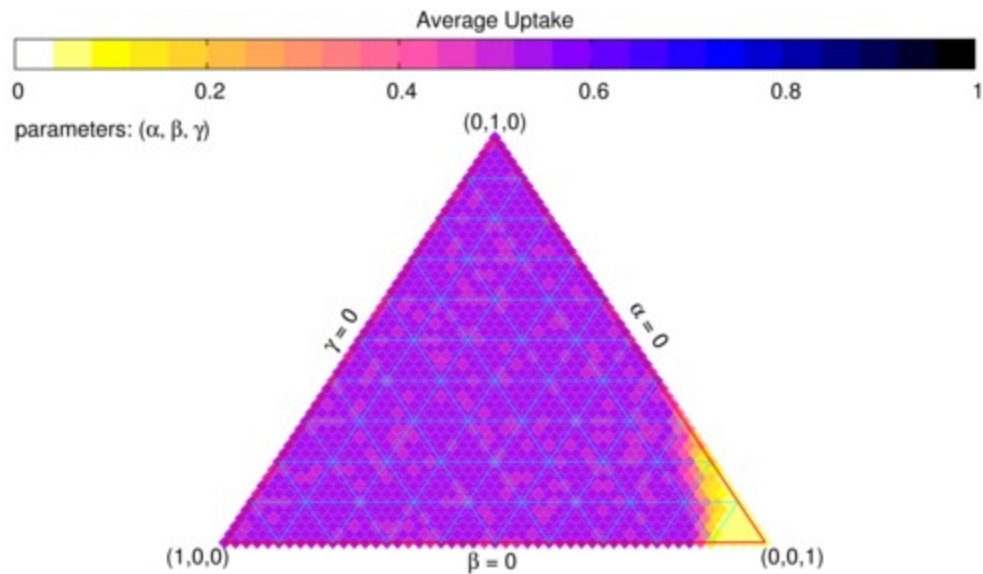

Figure 4 Different choices of two thresholds for a homogeneous archetype A=(0.1, 0.8, 0.1), colours show the mean uptake after 36 time-steps at each choice. All model parameters are as for the results in Figure 2.

This clearly shows a strong dependence of the outcomes on which values are chosen, but will be dependent on the archetype chosen for the investigation. Particular choices of the two thresholds are shown in Figure 5, looking over all archetypes, one where the archetype used in Figure 4 is yellow (no uptake beyond the initial seed) and one purple (just over half adopt, on average). The shift in the behaviour demonstrates again that the choice of thresholds is crucial to the most basic qualitative features of the simulation results. Any comparison of the effectiveness of interventions which shifted a node's parameters would be significantly altered depending on this choice.
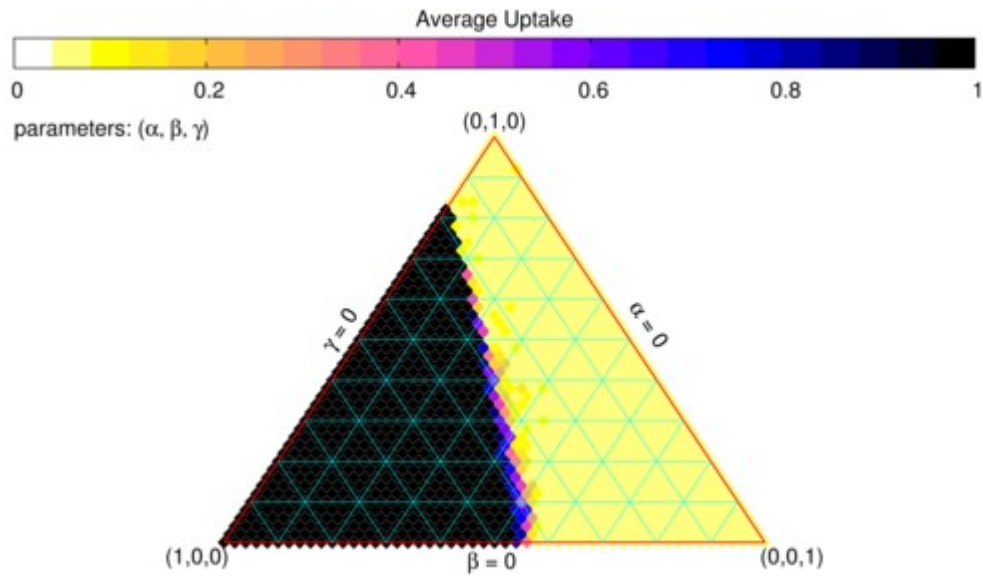
(a)

(b)

Figure 5 Different values of two thresholds, each assigned to half the nodes. (a) $\theta_1 = 0.45$, $\theta_2 = 0.25$ (b) $\theta_1 = 0.9$, $\theta_2 = 0.1$ (the purple region in Fig. 4).

Further choices can be made for the number, values and populations of different thresholds. Several of these are illustrated in the results in the following two figures (6 and 7). In many studies, including our own, a population is divided into three levels with respect to barriers to adoption, low, medium and high. These can depend on a number of factors, but estimates of

the number of individuals in each can be made from the responses to survey questions. The Leeds survey was used in such a way to divide the population into three, based on ability to act (e.g. tenancy type and income level). In Figure 6 (a) half the population have a threshold $\theta = 1$, given that they cannot adopt. In (b) these nodes are reduced to the mid-range threshold. This is an example of the type of intervention that could be initiated by local authorities, for those who, for example, rent or are on lower incomes to be enabled to adopt by adding incentives or removing barriers to adoption. Many regions of the archetype parameter space subsequently show much improved uptake rates, although the general structure of the lines dividing regions remains unchanged.
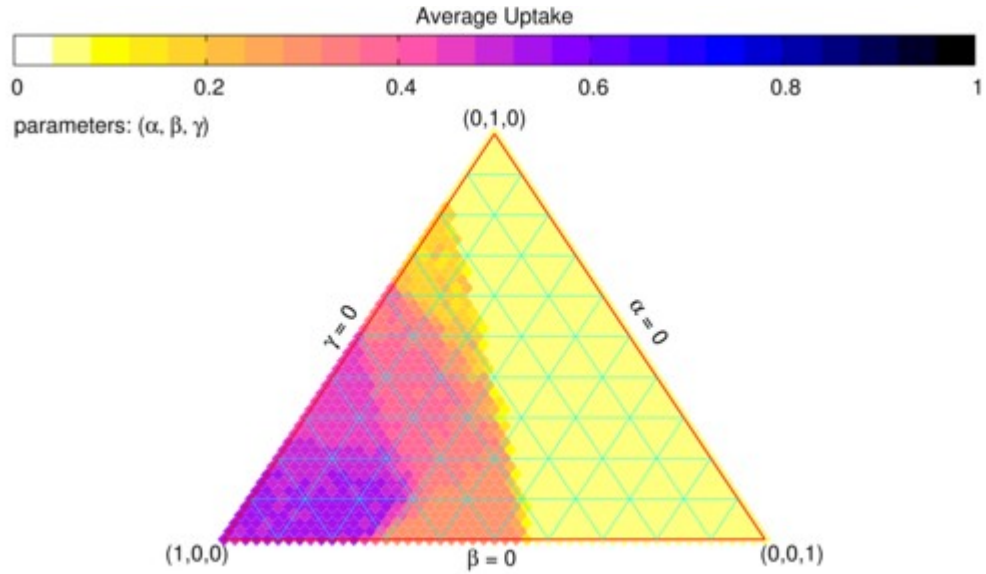
(a)
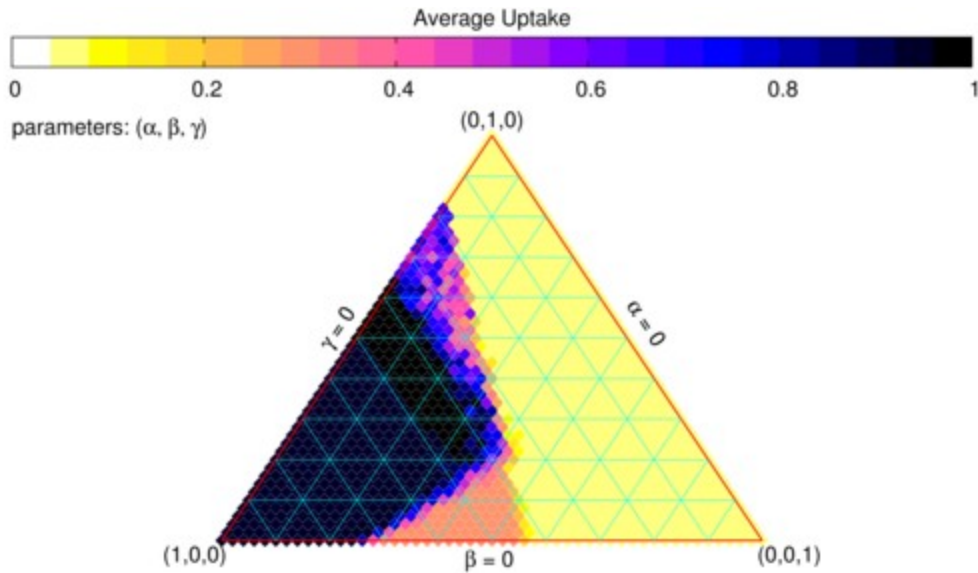
(b)

Figure 6 Thresholds distributed over three values. (a) 28% of $\theta_1 = 0.25$, 17% of $\theta_2 = 0.45$, 5% of $\theta_3 = 0.75$, 50% of $\theta_4 = 1$; (b) 28% of $\theta_1 = 0.25$, 67% of $\theta_2 = 0.45$, 5% of $\theta_3 = 0.75$.

As a final example, we can pick all thresholds from a continuous distribution, rather than discrete fixed values. In Figure 7 this is shown for a case where thresholds were picked uniformly from zero to one. In this case all structure has disappeared and all homogeneous archetype parameter values take some intermediate value for the average uptake.
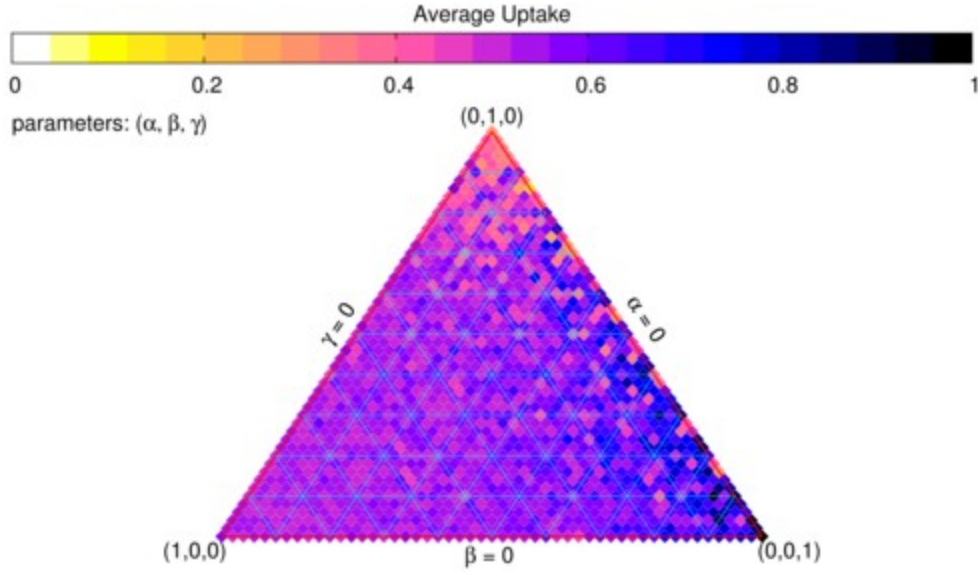
Figure 7 All nodes take different threshold values randomly from a uniform distribution, across the range [0:1].

Introducing Different Archetypes

The next aspect to evaluate in making the model more realistic is to remove the restriction on the homogeneity of the archetypes. To do this we divide the population into a number of different groups with distinct archetypes, randomly assigning a certain proportion of nodes to each. In the real-world it is known that people fall into categories such as "innovator", "majority" or "laggard" (Rogers, 1983) depending on their propensity to favour adoption of an innovation based on its individual merits, the fashion amongst ones peers or the prevalence in society as a whole, respectively. These types of behaviour can be seen in our previous results (as explained in McCullen et al.[11]), with certain sets of parameter values being more or less likely to adopt than others. To keep the parameter space manageable, as well as making the results easier to visualise and interpret, we restrict ourselves to three separate archetypes in each case, varying the relative proportions ($P(A_1)$, $P(A_2)$, $P(A_3)$) assigned to each of the three archetypes ($A_1=(\alpha_1, \beta_1, \gamma_1,)$, $A_2=(\alpha_2, \beta_2, \gamma_2,)$, $A_3=(\alpha_3, \beta_3, \gamma_3,)$) and performing an ensemble of simulations at each set of these proportions. For the results shown in Figure 8(c) we choose archetypes based on results shown previously (Figure 2). Three archetypes were selected from regions of the parameter space where the uptake rate was sensitive to the choice of parameters, rather than extreme archetypes where uptake was either completely successful or not at all (from Figure 2). In the first case we choose archetypes consisting of a mixture of pure $\alpha = 1$, $\beta = 1$ or $\gamma = 1$ types, to contrast with the case of homogeneous archetypes. For Figure
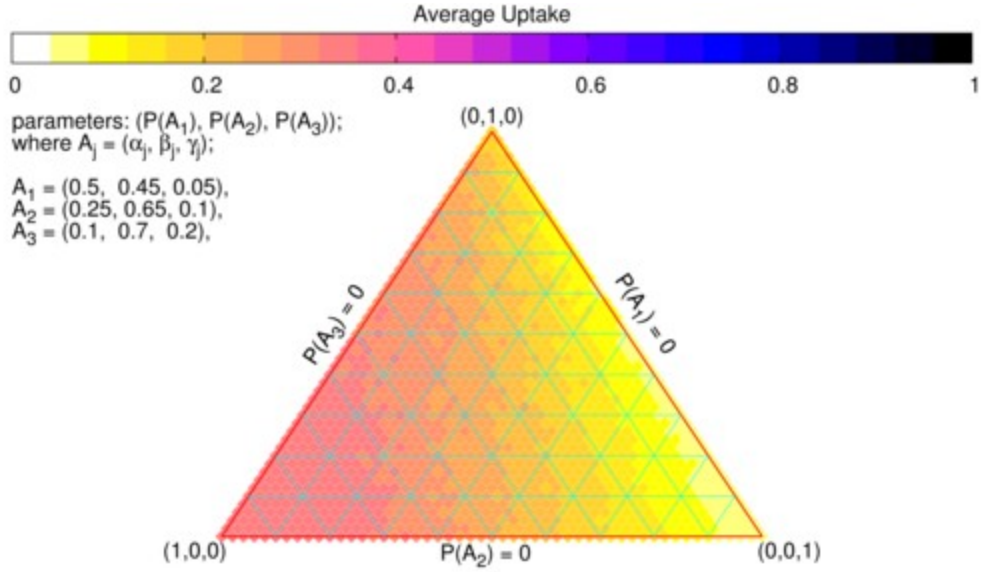
8(b), $\theta = 0.25$ for all of the population, whereas for Figure 8(c), $\theta = 1$ for 50% of the population, i.e. the difference between Figures 8(b) and 8(c) is largely due to the different distribution of thresholds. The reduction of the $\theta = 1$ threshold to $\theta = 0.75$ results in the picture seen in 8(d).
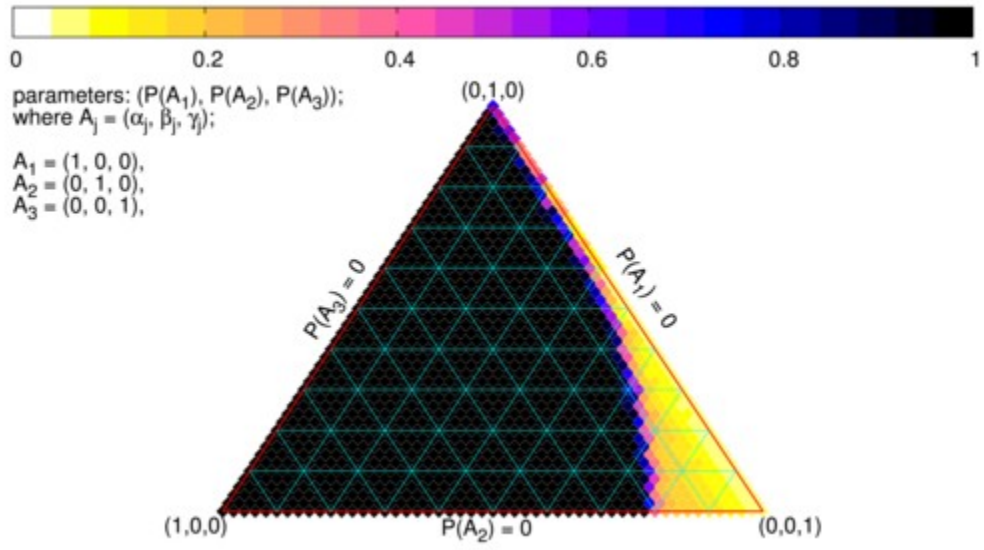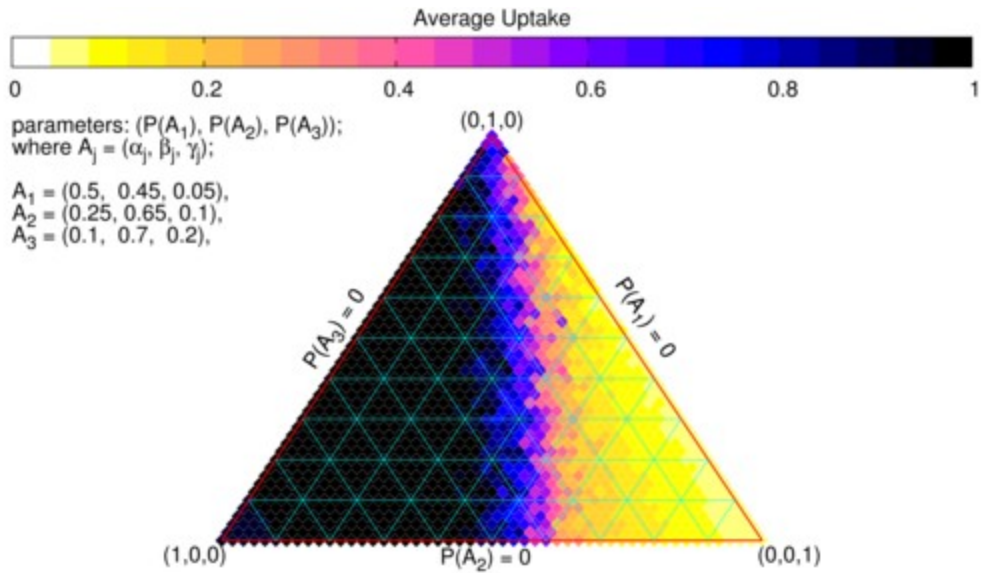
(a)
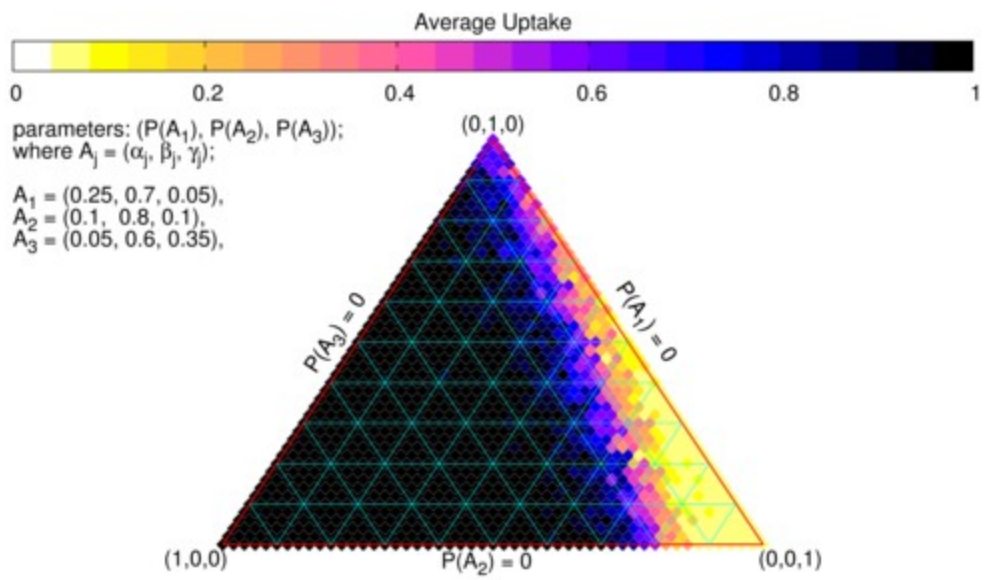
(b)

(c)

(d)

Figure 8. The population is divided into three archetypes and individual nodes are each assigned to an archetype $A_j=(\alpha_j, \beta_j, \gamma_j)$. Each point on the plot is for a different set of relative proportions of the three archetypes in the population (P(A1), P(A2), P(A3)), and individuals are assigned according to this distribution. All other parameters are identical to previous cases. (a) Extreme values for the archetypes of [A1=(1, 0, 0), A2=(0, 1, 0), A3=(0, 0, 1)] In order to study the effect of having mixtures of purely personal, peer-group and societal archetypes for the different nodes, with varying proportions. (b) The set of three archetypes here are less extreme [A1=(0.25, 0.7, 0.05), A2=(0.1, 0.8, 0.1), A3=(0.05, 0.6, 35)], and guided by simulations on homogeneous populations (e.g. Fig 2). (c) Here the thresholds are distributed, with the same values as used for Fig. 6(a), and archetypes guided by the results therein, i.e. thresholds θ = (1, 0.75, 0.45, 0.25) with proportions (0.5, 0.05, 0.17, 28), and archetypes (A1=(0.5, 0.45, 0.05), A2=(0.25, 0.65, 0.1), A3=(0.1, 0.7, 0.2)) with proportions of each being the loc-

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ation of data in this plot. In (d) the $\theta = 1$ threshold is lowered to $\theta = 0.45$, as for the results in Fig. 6(b).

The results in (a), with homogeneous thresholds, shows a similar spit between regions of success and otherwise, with a fairly distinct dividing line. However, these will depend on the exact choice of archetypes and other model parameters. For the more realistic case of distributed thresholds shown in (b) the behaviour changes completely. Here the picture is much simplified, showing much lower sensitivity to the proportions of archetypes for the model. However, when the inaccessible subset of nodes ($\theta = 1$) have their thresholds lowered to allow them to adopt, the critical behaviour is again apparent. This again shows the importance of the threshold distributions used in the model.

DISCUSSION

The structure of the network is important to dynamical processes on it, and in this specific application of innovation diffusion the clustering (transitivity) is particularly so. Through our survey work we have gathered some information on the active network connections (those who participants indicated they do talk to about energy-related issues), both individual and group, which has certainly helped give a representational structure of a real-world network for the influence of energy information on which to base out models.

We have demonstrated the importance of the parameters for the threshold (θ) and the split of archetypes. However, we are currently limited in applying the model as a decision-support tool for local authorities by the availability of appropriate data, although as we have shown elsewhere[12] our dynamical network approach could be used as the conceptual basis of a decision-support tool for local authority interventions in domestic energy demand reduction.

The work presented here has highlighted that further data is required in order to develop these types of models, although valuable insights can be gained by adopting a systematic approach to exploring the parameter space, as we have shown. We summarise in table 2 the specific types of quantitative data that would be needed to develop the model further. Whilst data is available on those types of household who do adopt energy innovations, we do not currently have any quantitative data to distinguish between those who would fall into the different archetype groups and, therefore, who would exhibit weightings towards α, β or γ (as discussed

earlier). Additional data on the barriers to adoption for specific energy innovations is warranted.

Table 2 — Specific data requirements for further model development.

Model parameter	Data needed	Comments
Threshold (θ)	Segmentation of households' barriers to specific energy technologies. Linked to physical and economic barriers to adoption e.g. house type, tenancy, cost. May potentially include understanding/awareness of the technology.	This would be different for different technologies e.g. solar panels cannot be adopted if the household does not have a south-facing roof.
Personal benefit (p)	Likely economic and personal benefit to adopting a technology	This would not solely include cost savings, but could also include thermal comfort or fit with pro-environmental lifestyle choices.
Archetypes (groups with different α, β, γ weightings)	Segmentation of households' weightings for personal, personal social influence and social norms.	This does not need to be technology specific.
Social Network properties	Average node degree, transitivity and link weightings for connections specific to energy technologies.	This may also be different for different technologies e.g. solar panels are more visible than loft insulation.

There are potentially many modifications and enhancements that could be made to the model developed so far, which support the assumption that there is potential value in these methods as a basis of decision-support tools. An example of an enhancement is given. In the current model, network connections are all equally weighted. In the survey, we gathered information on levels of trust regarding energy information that people placed in different groups of people (e.g. friends, family, work colleagues etc.). This information could be used to weight

different network connections, i.e. introducing a measure of each connection's ability to influence.

Aside from further developments, experimental methods for validating the model would be invaluable and network interventions need to be tested in either restricted laboratory or real-world settings. As noted by Valente[10], the options for network interventions have been dramatically enhanced by electronic communications and online social networks. While there are some questions as to whether electronic network interventions are as effective as face-to-face [25], the online networks could provide an easier means of setting up and monitoring a network intervention as well as providing the data on the initial (and developing) network structure. An online experiment, for example, implementing a scheme for users to recommend a friend to receive a voucher offer for an energy-efficient technology could be monitored and associated data on the participants gathered. This would provide a controlled environment with a bounded network of participants to be studied and would provide a valuable means of validating theoretical models.

CONCLUSION

In this work we have developed a model for exploring the parameter space to investigate what factors are important in the diffusion of innovations on a real-world social network. We extended the previous implementation of our basic dynamical network model, which represented households as homogeneous nodes, to integrate some empirical data (gathered via a city-wide survey) into the models in order to express a heterogeneous population which more closely represents a real social system. In applying a systematic approach we have examined the relative effect that different parameters have on the behaviour of the system. This development exhibits a significant advance over previous models which contain a homogeneous population of nodes on a network. The method presented enables investigation the relative significance of personal preferences versus social influence, both from the peer-group and wider population networks.

The emergent behaviour arising in the system indicates that a complexity-based method is required to understand the decision-making of households, where interactions can play an important role.

This methodology has been developed further and used for exploring different network interventions that could be implemented by a local authority for enhancing uptake of energy-technologies, and identifying those that would be more likely to lead to an increased uptake[12]. In addition, with relevant modifications based on empirical data this model could also be used to investigate diffusion of a variety of energy-efficient behaviours that may have different properties in terms of the associated level of personal preference and social influence. For example, it is plausible that solar panels are associated with a higher degree of social influence compared with loft insulation, as they are visible on the property.

We have highlighted the need for new data to understand (in a quantitative way) householder barriers and drivers to adoption of energy-efficient innovations. However, the models developed to date provide a useful means of drawing insights into the factors affecting the emergent behaviour of a social system. This, in itself, provides a constructive starting point for designing effective interventions to increase uptake of energy-efficient innovation in cities and supporting efforts to mitigate climate change. As observed by Valente[10] 'the science of how networks can be used to accelerate behaviour change ...is still in its infancy'. Nonetheless, the benefits to adopting network interventions are becoming clearer and this is certainly an area where further research is warranted.

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