

Citation for published version: McCullen, NJ, Bale, C, Foxon, T, Rucklidge, A & Gale, W 2013, 'Modelling the uptake of domestic energy technologies via local networks and integrating real-world data' FutureBuild 2013, Bath, UK United Kingdom, 4/09/13 - 6/12/13, .

Publication date: 2013

Document Version Publisher's PDF, also known as Version of record

Link to publication

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Modelling the uptake of domestic energy technologies via local networks and integrating real-world data

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Introduction

- Companies and policy-makers are in a position to influence residents and businesses to adopt domestic energy measures and reduce energy demand;
- Tools are needed to support decision-makers in achieving their energy and climate change targets [1];
- Quantification and integration of real-world data into mathematical and simulation models is needed for them to be reliable and usable as tools by strategic planners.

Objectives

 To develop tools for modelling diffusion of energy technologies via networks of households, in order to aid decision-making in local authorities;
 To use real-world empirical data to guide the models towards more accurately representing heterogeneous populations and studying the effect this has on the model results.

Modelling Uptake of Innovation

Householder decisions to adopt a particular innovation are based on a combination of factors:



Integrating Real-World Data

- A survey of Leeds residents was undertaken in May–June 2011 in order to populate the model with empirical data.
- The survey gathered information about household type and

Results

(a)

(b)



Total Utility to household[3]: $u_i = \alpha_i p_i + \beta_i s_i + \gamma_i m$, p_i, s_i, m : personal, peer-group and societal influence, $\alpha_i, \beta_i, \gamma_i$: relative weightings given to each factor.

Households are represented as *nodes* on a network.
 People communicate via peer-to-peer interactions.
 Interactions represented by *links* between nodes.



tenure, socio-economic data, geographic location, and questions on who people spoke to (and therefore were connected with) specifically about energy-related issues.

- 1068 valid responses were received.
- The table below shows how empirical data from the survey has been used in the model.

Model Feature	Parameter	Data Source
Network structure	$N, G, M \mid W, L$	Survey Assumption
Individual connections	$I \mid L$	Survey Assumption
Group connections	$G \mid L$	Survey Assumption
Archetypes	$A_i = (lpha_i, eta_i, \gamma_i)$, $P(A_i)$	Simulation
Threshold	$\theta \mid P \theta$	Survey Assumption

- Individual preferences and social network influences are important factors in the adoption of energy innovations; local authorities have the means to potentially harness these influences to their advantage in encouraging increased adoption.
- Since expected 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.



Figure 4: 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 shift in the behaviour demonstrates that the choice of thresholds is crucial to the outcome of the simulations.



Figure 1: Network Model

4. Each node *i* has adoption state variable $x_i = 0, 1$. 5. Dynamical equations determine individual uptake.

Adoption Rule:

 $x'_{i} = \begin{cases} 1 & \text{if } x_{i} = 1, \\ 1 & \text{if } x_{i} = 0 \text{ and } u_{i} > \theta_{i}, \\ 0 & \text{otherwise.} \end{cases}$

• θ_i : threshold (barriers, costs etc.),

Modelling Social Networks



Figure 2: Links established between nodes either

Systematic Investigation of Parameters

Individual simulations *with the same parameters* can depend sensitively on model details and initial conditions:



Figure 3: Examples of 100 individual runs with same parameters but different details and seed.

Need to look at *ensemble averages* over many realisations.
Method:

pick a set of parameters,
perform 20 runs for 36 time-steps,
plot average uptake for that set of parameters,
can study sensitivity to various parameters.

Figure 5: The population is divided into three archetypes $A_j = (\alpha_j, \beta_j, \gamma_j)$. Each point on the plot is for a different set of relative proportions of the population (P(A1), P(A2), P(A3)). (a) Single threshold $\theta = 0.25$. (b) Thresholds are distributed with $\theta = (1, 0.75, 0.45, 0.25)$ with proportions (0.5, 0.05, 0.17, 28). (c) The $\theta = 1$ threshold is lowered to $\theta = 0.45$. The difference between the results is due to the different distribution of archetypes and thresholds.

individually or via groups[4] — social, workplaces, etc. Here there are N = 11 nodes, with node iconnected to G = 2 from a total of W groups overall. There are L = 3 links established per group and individually.

Conclusions

- 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 our basic dynamical network model to integrate empirical data (gathered via a city-wide survey) into the models in order to more closely represents a real social system.
- We have highlighted the need for new data to understand (in a quantitative way) householder barriers and drivers to adoption of energy-efficient innovations.
- The benefits to adopting network interventions are becoming clearer and this is certainly an area where further research is warranted.

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EPSRC EPSRC-funded project "Energy Decision Making for Cities - Can Complexity Science Rise to the Challenge?" (Reference EP/G059780/1)