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

Nick McCullen\textsuperscript{1}, Catherine Bale\textsuperscript{1}, Timothy Foxon\textsuperscript{2}, Alastair Rucklidge\textsuperscript{1} and William Gale\textsuperscript{1}
\textsuperscript{1}EDEn research unit, University of Bath, UK. \textsuperscript{2}Energy, Earth & Environment, \textsuperscript{3}Maths, University of Leeds, UK.

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 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
1. To develop tools for modelling diffusion of energy technologies via networks of households, in order to aid decision-making in local authorities;
2. 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:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td></td>
</tr>
<tr>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>0.6</td>
<td></td>
</tr>
</tbody>
</table>

Data Source

<table>
<thead>
<tr>
<th>Data Source</th>
<th>G</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Uptake

<table>
<thead>
<tr>
<th>Uptake</th>
<th>10%</th>
<th>30%</th>
<th>50%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 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.

<table>
<thead>
<tr>
<th>Model Feature</th>
<th>Parameter</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network structure</td>
<td>G, M</td>
<td>Assumption</td>
</tr>
<tr>
<td>Individual connections</td>
<td>L</td>
<td>Assumption</td>
</tr>
<tr>
<td>Group connections</td>
<td>G</td>
<td>Assumption</td>
</tr>
<tr>
<td>Archetypes</td>
<td>( \alpha_i, \beta_i, \gamma_i )</td>
<td>Simulation</td>
</tr>
<tr>
<td>Threshold</td>
<td>( \theta )</td>
<td>Assumption</td>
</tr>
</tbody>
</table>

- 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 a decision of individual behaviour of individuals connected on a social network, in order for us to investigate potentially successful interventions, a complex-systems perspective is needed.

Systematic Investigation of Parameters

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

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Modelling Social Networks

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

Adoption Rule:

\[
x_i' = \begin{cases} 
1 & \text{if } x_i = 1, \\
1 & \text{if } x_i = 0 \text{ and } u_i > \theta_i, \\
0 & \text{otherwise}.
\end{cases}
\]

\( \theta_i \) threshold (barriers, costs etc.).

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 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.

<table>
<thead>
<tr>
<th>Model Feature</th>
<th>Parameter</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network structure</td>
<td>G, M, W, L</td>
<td>Assumption</td>
</tr>
<tr>
<td>Individual connections</td>
<td>L, L</td>
<td>Assumption</td>
</tr>
<tr>
<td>Group connections</td>
<td>G, L</td>
<td>Assumption</td>
</tr>
<tr>
<td>Archetypes</td>
<td>( \alpha_i, \beta_i, \gamma_i )</td>
<td>Simulation</td>
</tr>
<tr>
<td>Threshold</td>
<td>( \theta )</td>
<td>Assumption</td>
</tr>
</tbody>
</table>

- 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 a decision of individual behaviour of individuals connected on a social network, in order for us to investigate potentially successful interventions, a complex-systems perspective is needed.

Results

A selection of results is shown here.

Figure 1: Network Model

Figure 2: Links established between nodes either individually or via groups \( i = 1 \) — social, workplaces, etc. Here there are \( N = 11 \) nodes, with node \( i \) connected to \( G = 2 \) from a total of \( 15 \) groups overall. There are \( L = 3 \) links established per group and individually.

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

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

Figure 4: Different values of two thresholds, each assigned to half the nodes. (a) \( \theta_0 = 0.45, \theta_2 = 0.25 \)

(a)

(b)

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 \( \theta = 0.1, 0.25, 0.5 \) with proportions \( (0.5, 0.05, 0.17, 0.28) \).

(c) The \( \theta = 1 \) threshold is lowered to \( \theta = 0.15 \). The difference between the results is due to the different distribution of archetypes and thresholds.

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 have 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.

References