Energy Decision-Making for Cities

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Future energy decision making for cities:  
Can complexity science rise to the challenge?

- Using complex systems methods to understand energy decision-making at the city level

1. Network modelling
   - consumer behaviour models\(^1\),

2. Agent-based simulation
   - Modelling electricity consumption in office buildings\(^2\)

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1: McCullen et al., IJBC (2011)
2: Zhang et al., Energy and Buildings (2011)
• Local authorities (LAs) are willing to think strategically about energy interventions but need the tools to do so.

Bale et al., Energy Policy, (2012)
Network models: Role of social networks in domestic sector uptake of energy-efficiency innovations

N. J. McCullen.
Role of social networks in domestic sector uptake of energy-efficiency innovations

- influence of social networks not previously considered.

- We use complex networks to model innovation diffusion mediated via social network interactions.
Modelling adoption of innovations

**Households** are *nodes*.

*Links* represent *interactions*.

- Households adopt based on various factors:
  - personal + social benefit\(^a\).
- Intrinsic benefits to household.
- Social benefit combination of both\(^b\):
  - personal social network,
  - mainstream social norm.

- Total *utility* to individual household \(i\):
  \[ u_i = \alpha_i p_i + \beta_i s_i + \gamma_i m \]  
  (1)
  - \(p_i, s_i, m\): personal, peer-group and societal influence.
  - \(\alpha_i, \beta_i, \gamma_i\): relative weightings given to each factor.
  - Adoption occurs if \(u_i\) exceeds a *threshold* \(\theta_i\).

\(^a\) Delre *et al.* (2010); \(^b\) Valente (1996)

Parametrising the models using survey data

- Survey data including info on behaviours.
  - Over 1050 valid responses received from residents of Leeds.
- Data used as a guide rather than definitive source,
  - used to narrow choice of structure and parameter values,
  - also to illustrate potential applications.

<table>
<thead>
<tr>
<th>Model element</th>
<th>Parameter</th>
<th>Question / Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network</td>
<td>number of active individual / group connections.</td>
<td>Q. on who talks to whom about energy.</td>
</tr>
<tr>
<td>Threshold</td>
<td>$\theta$</td>
<td>Q. on house type, tenancy and income.</td>
</tr>
<tr>
<td>Node archetypes</td>
<td>$\alpha, \beta, \gamma$</td>
<td>Defra types of pro-enviro. behaviour</td>
</tr>
</tbody>
</table>
### Modelling Scenarios

- Different **scenarios** studied by varying *dynamical model* and *network parameters*.

<table>
<thead>
<tr>
<th>Model Param.</th>
<th>Baseline</th>
<th>Seeded</th>
<th>Community</th>
<th>Incentives</th>
<th>Snowball</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do Nothing</td>
<td></td>
<td>Give efficiency measure to some (random) individuals</td>
<td>Give efficiency measure to whole communities.</td>
<td>Advertise a money off scheme.</td>
<td>Recommend-a-friend discount voucher scheme.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Links</th>
<th>Data based</th>
<th>–</th>
<th>–</th>
<th>–</th>
<th>Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>Data based</td>
<td>–</td>
<td>–</td>
<td>Lower</td>
<td>Lower</td>
</tr>
<tr>
<td>Initial Seed</td>
<td>Unforced</td>
<td>Random</td>
<td>Target</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>
Example model results

Baseline

Seeded

Community

Incentives
Example model results

Baseline

Uptake vs Time (months)

Snowball

Uptake vs Time (months)

Seeding Level

Average Uptake vs Initial Seeding

Snowball + Extra

Uptake vs Time (months)
Agent Based Simulation: Role of user learning in council-led smart meter deployment

T. Zhang

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Role of user learning in council-led smart meter deployment

• Smart metering is one of the key interventions that local authority can take to manage and control the energy consumption in Leeds.

• Deploying smart meters to council-owned properties is a type of authoritative technology adoption.

• User learning (i.e. transit from zero knowledge about smart meters to making the best use of them) is very important in this process.
Theoretical Basis

• Technology adoption decisions:
  • Optional Innovation-Decision
  • Collective Innovation-Decision
  • Authority Innovation-Decision

• User learning

The form of the function is

\[ P_A = M(1 - e^{-kt}) \]

where:

- \( P_A \) is the probability of purchasing Brand A,
- \( M \) is the maximum attainable loyalty to Brand A,
- \( k \) is a constant expressing the learning rate,
- \( t \) is the number of reinforced trials

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\(^1\)Bennett and Mandell (1969)
Overview of the ABS model
Behaviour of Residential Energy Consumer Agents

- Empirical data for the simulation model from Leeds survey.
- Developed archetypes of residential energy consumers\(^2\).

\(^2\)Zhang et al., 2012
Simulation Experiments

- Simulated Load Curve vs. Real Load Curve:
Simulation Experiments

- The effect of smart metering
Simulation Experiments

- Continuers vs. Discontinuers
Insights and lessons learned

- Developed complexity science models of city level domestic energy users:
  - network and ABS models of different aspects,
  - populated with data from real-world.
- Network models comparative rather than predictive.
  - social network interactions are important,
  - trust in various sources of information matters.
- ABS can produce simulation results to reflect real-world,
  - use to predict future effect of smart metering,
  - can look at possible effect of discontinuers.
- Complex systems models could be used for aiding policy decisions.
References


