Modelling the Diffusion of Energy Technology on Social Networks

Nick McCullen
School of Mathematics
University of Leeds

With input from everyone on the Energy-Complexity project.

IMA Seminar
22nd March 2011
University of Nottingham

Introduction

Can complexity science contribute to city energy policy?

1. What is a complex system?
    - Multiple interacting individuals,
        - interactions important to system level behaviour,
        - *emergent* phenomena.
    - Tools include computational simulation, network models, dynamical systems ("chaos theory")...
2. What are we trying to model?
    - Interventions to influence the transition to a low-carbon economy.
    - Models can be used to understand which factors are important, and what measures could influence these.

Modelling the Diffusion of Energy Technology on Social Networks

Focus of the Pilot Study

Complex Network Models

Dynamical Models

Model Results

Focus of the Pilot Study

- Study interventions related to adoption of new technology or energy use strategies,
- mediated by social contacts between individuals (as well as through the media).
- This dissemination of technology or ideas can be studied using models of diffusion on networks,
- Theoretical/computational results can then be put into the context of energy technology/use,
    - particular schemes may be considered by public or private bodies.

UNIVERSITY OF LEEDS

Schemes Under Consideration

1. Green Deal provider covers upfront costs of EE tech, paid back from the savings in energy bills;
2. Subsidy for installing EE out of LA budget;
   - word-of-mouth about savings achieved,
   - incentives such as "recommend a friend discounts".
3. Smart meter installation;
   - effects of seeing own use compared to neighbours'.

UNIVERSITY OF LEEDS

Interventions to Consider

Comparisons can be made between various strategies, e.g.:

1. street-by street targeting for installation;
2. focusing on communities to induce a “critical mass”,
    - may then propagate outwards on the network;
3. ‘random’ installation,
    - e.g. via advertising campaign;
4. ‘word-of-mouth’ propagated installation,
    - e.g. incentive to “recommend to a friend”.
5. strengthening network ties to improve communication.

Network Models

- Individuals, organisations, households, . . ., considered as *nodes* on a network.
  - Properties of nodes are associated with variables (states), e.g.:
    - ability to buy (income + subsidy),
    - willingness to buy (personal and social utility).
- *Links* ('edges') are drawn between connected individuals.
  - Information/influence passed along (weighted) edges.
- This is a *complex system* of interacting individuals.
- Dynamics of variables governed by equations (rules) based on own and neighbours' state.

Real-World Social Networks

- Different types of social connection exist; these include:
  - geographical neighbours, distant friendships, family trees, *communities*.

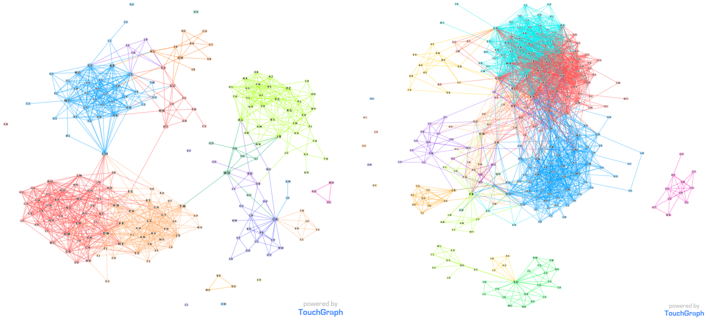


Figure: Inter-friend contacts on the *Facebook* website.

UNIVERSITY OF LEEDS

Community-Structured Networks

- **Communities** are sets of individuals which are more well connected internally than to the rest of the network [1].
  - communities have a distribution over a range of sizes,
  - communities have varying degrees of overlap [2].
- Individual membership characterised by knowing a high degree of the other members.
- Most individuals will be connected to more than one group (work, leisure, children's school etc.).
- Often more than one individual connecting various groups.
- Sometimes even large overlaps exist.
- This creates the cobweb of highly inter-connected groups which exists in the real world.

UNIVERSITY OF LEEDS

Types of Model Network

- Various ways of constructing a random graph,
  - give qualitatively different networks, exhibiting different real-world phenomena.

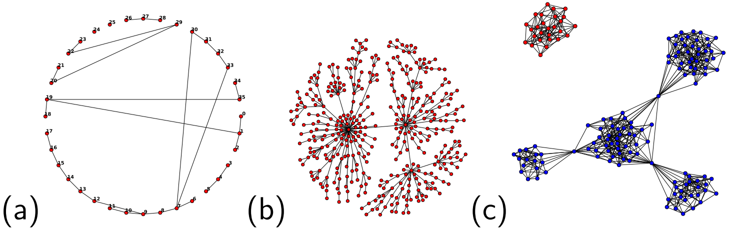


Figure: (a): A *small world* network with 20% rewiring of a regular lattice. (b): A preferential attachment graph which has a *scale-free* degree distribution. (c): A simple model of weakly-connected communities.

Dynamical Models

- Dynamical variables (states) represent properties of individuals (nodes), e.g.:
  - ability to buy (income + subsidy - cost),
  - willingness to buy (personal + social utility - barriers).
- Information/influence exchanged between individuals.
- Need to consider nature of *internal dynamics* and *interactions*:
  - Are internal dynamics of nodes changing continuously or at discrete intervals?
  - Do all individuals interact continuously with all personal contacts or at intervals as discrete events?
  - The types of decision rules on which to base these internal dynamics must be determined from data.

Dynamical Models

Internal Dynamics could include the following factors:

- Rational cost-benefit analysis;
    - dynamical system on nodes,
    - defined decision criteria.
- Decisions based on influence crossing some threshold:
    - fixed number of friends or proportion of contacts.
- Could be probabilistic.
- Would likely have multiple parameters.

UNIVERSITY OF LEEDS

Social Dynamics and Technology Adoption/Diffusion Models

- Many models exist for social dynamics [3].
    - From very simple (e.g. *Voter Model*) to more complicated (e.g. *Axelrod Model*).
- We are more interested in technology adoption models:
    - Again, threshold models are often used:
        - individuals use the technology if a certain number or proportion of the neighbours are using it.
- Can quantify system "effectiveness" counting either:
    - number of individuals who have technology,
    - average opinion of technology.

Other Decision/Adoption Models

e.g.: Simple model scheme using the following rules:

- Threshold model where:
  1. Opinion is changed based on average neighbours' opinion at current time,
  2. technology is adopted when an individual's own opinion exceeds some threshold,
  3. the consumers who have already purchased are given a more heavily weighted influence.

UNIVERSITY OF LEEDS

Models of Social Influences

More realistic models exist, weighting individual's own opinion relative to social contacts [4]:

- *Utility* (benefit) of product to individual i:

$$U_i = (1 - \beta_i)p_i + \beta_i s_i$$

p_i: personal utility: value of product to individual,
s_i: social utility: fraction of other individuals with technology,
β_i: relative weighting of social to personal value.

UNIVERSITY OF LEEDS

Utility Threshold

- When value of utility U_i exceeds cost to individual, technology is adopted:
  - i.e. if benefit exceeds cost.

Personal Utility

Intrinsic to product and individual, could depend on:

- potential savings,
  - relative or absolute,
  - payback time;
- environmental credentials (may vary),
- negative effects of barriers to adoption.

Social Utility

- Data suggests individuals assign different relative value to personal contacts and society [5].
- models based on this principle tested on networks:
  - someone buys when adoption within society and contact network are above respective thresholds,
  - individuals classed as early, majority or late adopters,
  - stance relative to contact network and society can differ.

Archetypes:

- Data on above criteria used to classify individuals,
- user templates used to form archetypes for models.

Aspects to Include in Models

1. Use community-structured networks with wide degree-distribution,
    - can include small group interactions, one-to-one or average of all neighbours.
2. Weight links of different types,
    - strength of influence of different individuals.
3. Use distributions of behaviour archetypes:
    - thresholds for social and personal utility,
    - balance between local neighbour and system average thresholds.
4. Market feedback effects such as *learning-curves*, whereby the unit price reduces with market penetration [6].

Model Specifications

1. The individual households are nodes on the network.
2. Their weighted "opinion" of an EE product is bundled into a *utility* variable:
   - $U_i = (1 - \beta_i)p_i + \beta_i s_i$
   - s_i is sum of both:
     - average weighted "opinion" $\frac{\alpha_i}{K_i} \sum \sigma_{ij} U_j$ over individual's K_i *neighbours*, with individual "trust" weightings per contact σ_{ij}
     - weighted society average "opinion" $\frac{1-\alpha_i}{N} \sum_{i=1}^{N} U_i$
3. When U_i is greater than the cost (minus any incentive) then a purchase is considered.

UNIVERSITY OF LEEDS

Model Specifications

4. Time-scales for updating opinion (τ_1) and making purchases (τ_2) may be different:
   - τ_1 opinion updated after interacting with friends and taking in media (e.g. weekly),
   - τ_2 purchase decisions made less frequently (motivated by monthly pay-day, weather, prices, breakages etc.).
5. U_i varies continuously as an opinion until purchase made, then fixed at higher value U^* on purchase (reflecting stronger value given to opinion backed by experience):
   - $U_i(t+\tau_1) = (1-\beta_i)p_i + \beta_i \left(\frac{\alpha_i}{K_i} \sum \sigma_{ij} U_j(t) + \frac{1-\alpha_i}{N} \sum_{i=1}^{N} U_i(t) \right)$
   - if $U_i(t = n\tau_2) \geq C - I$: $U_i(t+\tau_1) = U^*$, with cost C, incentive I.

UNIVERSITY OF LEEDS

Modelling Interventions

1. Measure effect of different interaction network:
    - test for sensitivity to and correctness of model network,
    - possibility of enhancing network contacts.
2. Measure diffusion with and without a given intervention.
3. Compare possible interventions:
    - reduce costs by providing incentives,
    - targeting communities and opinion leaders,
    - encourage communication using “recommend a friend” schemes.

UNIVERSITY OF LEEDS

Example: Threshold Model of Opinion

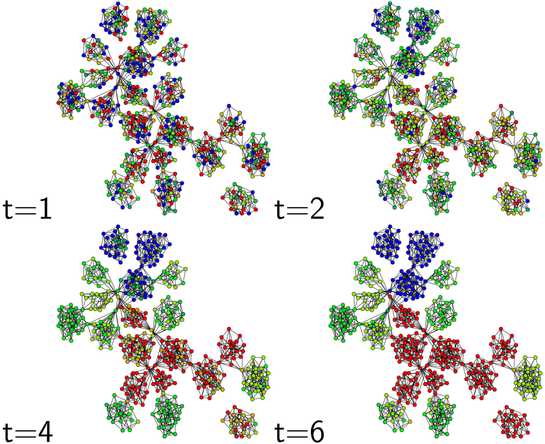
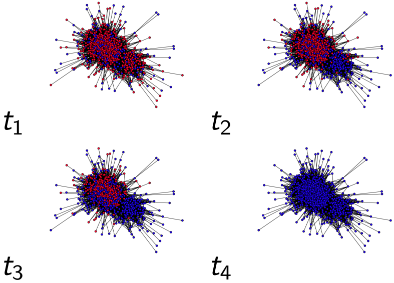


Figure: Individuals are *for*, *against* or *undecided*, and take the average of their neighbours in the next time-step.

Example: Simple Threshold Adoption Model (with random purchases)



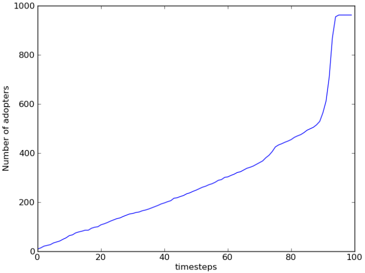


Figure: t_1=50, t_2=75, t_3=85, t_4=95

UNIVERSITY OF LEEDS

Example: Weigted "opinion" Model on Community Network

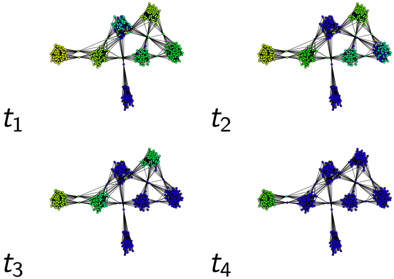
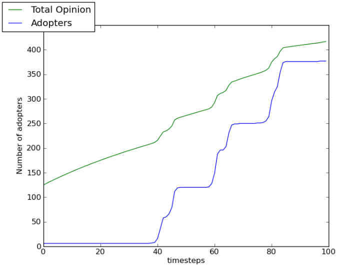


Figure: t_1=45, t_2=60, t_3=75, t_4=90



- See community penetration in steps.

UNIVERSITY OF LEEDS

Comparing Different Transitions

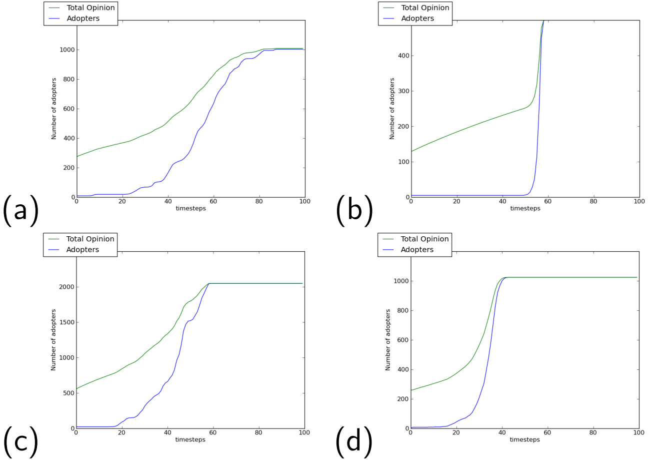


Figure: **(a)**: Weakly connected communities. **(b)**: Inter-community *bridges*. **(c)**: Large, weakly bound groups. **(d)**: Distributions of thresholds.

Possible Conclusions

In this simple example:

- Fast transitions are seen wherever tightly bound communities interact with more than a few others.
- Transition to technology adoption can be slowed when:
  - communities are not tightly bound,
  - communities do not interact strongly,
  - a lot of individuals have high resistance to uptake.
- To ensure a fast transition increase:
  - strength of links,
  - inter-community ties,
  - information about whole system.

UNIVERSITY OF LEEDS

Potential Recommendations

- Increase network ties for swift transition:
  - incentivise people to spread the word, e.g. by:
    - money back for recommending a friend,
    - money off for groups investing together.
- Make energy more visible to consumers, e.g.:
  - smart meters, showing neighbourhood averages, time-averaged individual (monthly/weekly) spend,
  - potential savings from EE measures,
  - show prevalence of EE measures in society to encourage people into the 'trend',
  - attract *early adopters* by predicting future trends.

S. Fortunato and C. Castellano.
Community structure in graphs.
2007.

G. Palla, I. Derényi, I. Farkas, and T. Vicsek.
Uncovering the overlapping community structure of complex networks in nature and society.
Nature, 435(7043):814–818, 2005.

C. Castellano, S. Fortunato, and V. Loreto.
Statistical physics of social dynamics.
Reviews of modern physics, 81(2):591–646, 2009.

S.A. Delre, W. Jager, T.H.A. Bijmolt, and M.A. Janssen.
Will it spread or not? The effects of social influences and network topology on innovation diffusion.
Journal of Product Innovation Management, 27(2):267–282, 2010.

T.W. Valente.
Social network thresholds in the diffusion of innovations.
Social Networks, 18(1):69–89, 1996.

S. Cantono and G. Silverberg.
A percolation model of eco-innovation diffusion: the relationship between diffusion, learning economies and subsidies.
Technological Forecasting and Social Change, 76(4):487–496, 2009.

UNIVERSITY OF LEEDS