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# Sociophysics Simulations of Technology Adoption and Consumer Behavior

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## Abstract

This paper makes use of spatial agent-based simulation techniques inspired by theoretical condensed matter physics. These techniques form part of 'sociophysics' an approach that has emerged slowly, but with increasing speed, over the last thirty years. This paper reports on two studies by the authors relating to the adoption of new technologies by a stylized virtual community comprising thousands of agents. The first case emphasizes the physics aspects of sociophysics in seeking to assess how a social system responds when confronted with potentially fashionable new technologies. In that example one of two new technologies is visible to neighboring residential agents and complex phenomena are seen to emerge depending upon the initial parameterization of the society. These phenomena are reminiscent of phase transition physics. The second set of examples, while modeled entirely separately, has a similar starting point, but seeks to give its agents a more realistic decision rule. Building upon ideas from marketing and the social sciences the agents in this latter work form their decisions according to Icek Ajzen's 1991 Theory of Planned Behavior. Both sets of simulations reveal lessons of possible benefit to policy-makers concerned with technology adoption. The work reported here uses exemplary scenarios relating to one such area of technology policy – the need for new electricity end-use technologies, which favor significant reductions in greenhouse gas emissions.

**Key words:** Complexity, Agent-Based Simulation, Sociophysics, Small World, Technology Adoption

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## 1. Introduction

The work presented here falls into the domain of applied complexity science, taking methodological inspiration from lattice model computer simulation of problems in two-dimensional condensed matter physics. As such, it forms part of a literature sometimes called 'sociophysics'. The origins of sociophysics have been recorded and commented upon by Serge Galam [1]. In recent years sociophysics has emerged alongside econophysics as a significant new domain of inquiry. The emergence of sociophysics has been ably summarized by Philip Ball in his Aventis Prize winning book *Critical Mass* [2]. The part of sociophysics of interest to us in this paper draws inspiration from canonical examples in theoretical condensed matter physics include the Ising model of magnetism, higher order Potts models and continuous XY models.

The journey to sociophysics included the application of techniques from theoretical condensed matter to problems outside the conventional boundaries of physics, but still within the domain of the natural sciences; these included forest fire models (e.g. [3]) and consideration of avalanches and earthquakes. In seeking to apply these techniques to human societies and individual human agents the physicists found that the economist Thomas Schelling had arguably got there first with his pioneering studies of racial segregation [4].

## 2. Nearest Neighbors and Small Worlds

Following in the traditions of sociophysics we consider stylized approximations of human settlements – essentially low-rise cities. In these frameworks the computer agents play the role of householders with local neighbors and possible farther-flung acquaintances. Unlike much agent based simulation in the social sciences where there are relatively few agents in play, each with a sophisticated decision rule, we make a natural extrapolation from physics and consider populations of many thousands of agents each operating with very simple decision rules and with limited interactions.

In terms of a residential agent's interactions with other agents, we shall here report on two approaches. First three of us (Hamilton, Nuttall and Roques) stay close to physics and consider whether such a sociophysics system might exhibit interesting kinetics, interesting equilibrium end-states and possibly even something akin to phase transition behavior. Hamilton, Nuttall and Roques construct a scenario in which householders seek to generate their own electricity locally and hence disconnect themselves from the electricity grid [5]. In this case it was posited that residential agents might stay with the grid, install a combined heat and power (CHP) system or install solar photovoltaic panels. The key difference is that the CHP is a private matter while the decision to install solar panels is very visible to nearest neighbors. Sight of a neighbor's decision might in turn affect a householder to follow suit, generating possible 'fashion effects'. The nearest neighbor interaction is shown by the blue arrow in Figure 1. Householders observe changes to nearby dwellings. Note that in Figure 1 the blue arrow denotes the direction of influence and not the direction of the agent's observation. The second approach revolves around a series of models developed by Zhang and Nuttall [6,7]. In this case the stronger inspiration came from the social sciences, as they sought to give greater realism to agents' decision-making and communication. By modeling 'small world' systems, see figure 1, they have been able to assess the relative merits of possible methods by which governments might most effectively and efficiently seek to facilitate the roll-out of a new technology such as smart technologies in electricity metering.

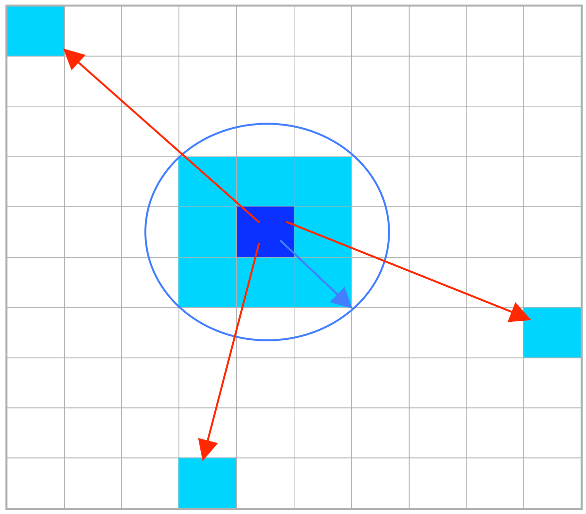

Figure 1: Small World. Nearest-neighbor interactions are shown by the blue arrow only. The red arrows represent longer-ranged random interactions. Taken together these nearest neighbor and extended interactions forming a 'Small World' model.

## 3. Modeling Consumer Choices in Electricity

### *3.A. Nearest Neighbor Model of Visible Householder Behaviors*

In one study Hamilton, Nuttall and Roques have considered consumer adoption of a new technology, simulating an agent-led move to distributed electricity micro-generation [5]. The model underpinning this work makes use of the Swarm tools originally developed at the Santa Fe Institute, NM USA for the simulation of collections of concurrently interacting agents (www.swarm.org). The simulations make use of a set of open-source libraries written in both Objective-C and JAVA. The model was constructed on a standard desktop Linux PC and run on a Linux Farm.

The Hamilton et al. nearest neighbor model simulates a city evolving with time under a set of initially predetermined rules and conditions (the exception to this being the stochastic behavior of a parameterized relative attractiveness function between the competing technologies described below). Hamilton and coworkers considered that spatially located consumer agents might be of one of two types, either 'residential' or 'business'. The distinction being that, unlike the 'residential' agents, the 'business' agents are not influenced by nearest neighbors' technology choices, i.e. the 'fashion effect'. Both types of consumer agent can obtain their electricity from one of three sources: the grid ('Grid' the initial default provider), solar power ('Solar') or from Combined Heat and Power ('CHP').

The model is constructed on a square lattice of N cells, with each cell either occupied by a consumer agent or empty. This stylized city is randomly seeded according to three global parameters: the lattice size, the overall agent density and the ratio of residential to business consumers. Detailed sensitivity studies have been performed to assess the impact of varying these three parameters, as well as the effect of employing periodic or non-periodic boundary conditions. We postpone a discussion of the significance of the residential to business agent ratio until later, noting that in all other cases involving variation of the lattice size, the overall density or the boundary conditions, the net result is that the time evolution and system dynamics remain unaltered and only the time required before the system reaches equilibrium is affected. In order, therefore, that many different configurations of the model could be studied in a computationally efficient manner, and without altering the generality of the results, a default lattice size of N = 6400 cells (80 x 80), periodic boundary conditions and an overall agent density normalized to 1 were employed in the simulations presented in this paper.

Time is incremented in notional twelve-hour periods, with agents updating their own evaluation of the competing technologies continuously but making decisions to change to a particular technology asynchronously according to a Poisson process. This results in each agent having its own internal clock with respect to the global clock. It is assumed that all agents are identical in the sense that they measure performance in the same fundamental way, although each agent has its own threshold for change. These thresholds are normally distributed among the agents around some appropriately chosen common value.

It is further assumed that there are no switching costs between the various technologies, and that agents choose to switch technologies based solely on their perception of the relative attractiveness of the old technology (the grid) compared to the new technologies (CHP and solar panels). A global parameterized attractiveness function A(t) is therefore introduced, which characterizes the relative attractiveness of the new versus the old technology. The 'attractiveness' of one technology can be interpreted as the imperfect perception by an agent of the relative benefit to it of using the technology in question. This benefit may be, but need not simply be, regarded as the relative economic competitiveness and performance of the technology in question. The attractiveness function is weighted heavily in favor of the old technology at the start of the simulation and is stochastic with some minimal spread, in order to reflect the uncertainty over the impact of technological progress on the performance of the new versus the old technologies. As the simulation progresses, the magnitude of the relative attractiveness function decreases in proportion to the number of agents switching away from the old technology, while the stochastic spread becomes greater.

All agents start the simulation by getting their electricity from the grid. Their evaluation criteria (for both residential and business consumers) are determined at an individual agent level and depend on their imperfect perception of the relative attractiveness between technologies. The following factors, which are established and fixed before the simulation starts, represent the agents' perception regarding the competing technologies and therefore control their decision-making. The $i^{th}$ agent's level of 'satisfaction' with the old technology is represented by a continuous function $S_i(t)$ that can take values between 0 and 1. For each time-increment dt, the agents update their level of satisfaction according to the formula:

$$S_i(t + dt) = K_i\, S_i(t)$$

where $K_i$ can hold one of three values $K_i^+$, $K_i^-$, or 1:

$K_i = K_i^+$ corresponds to the situation where the grid is relatively attractive, $S_i(t) > A(t)$;

$K_i = K_i^-$ corresponds to the situation where the grid is relatively unattractive, $S_i(t) < A(t)$;

$K_i = 1$ is a normalization correction to ensure S remains between 0 and 1 at the extremes.

Here, $K_i^+$ and $K_i^-$ are coefficients for the rise and fall in consumer 'satisfaction', the values of which are normally distributed around appropriately chosen values in order to reflect a spread in the willingness among the agents to switch technologies. To incorporate the fact that the status quo is usually preferred over change, these coefficients are chosen to be correspondingly asymmetric. Like the threshold parameters, the satisfaction coefficients are assigned to the consumer agents before the start of a simulation run. The final step in the process occurs when it becomes time for an individual agent to make a decision as to whether to switch away from the grid. At this point, determined by the agent's internal clock, a simple comparison is made between the level of satisfaction and the threshold for change; if the satisfaction has dropped below the threshold the agent switches to one of the new technologies.

The final element in the model involves incorporating a spatial externality in the form of a fashion effect. All consumer agents have a 'supply preference' probability, which attempts to capture the visual and fashion elements entering into the formation of social preferences, which in turn shape agent's individual choices beyond rational economic and performance criteria[2]. If an agent, as described in the previous paragraph, is to switch the source of its electricity supply away from the grid then the supply preference probability determines whether it will move to Solar or CHP. For the business consumers there is an equal probability for each throughout the entire simulation, representing the fact that business consumers in our simple model are not influenced by any kind of fashion effects. This is, however, not the case for the residential consumers. These agents are subject to fashion effects that take the form of a nearest neighbor interaction. The fashion effect is modeled such that if any of a residential consumer's neighbors has Solar power, then that consumer's supply preference shifts in favor of Solar. The greater the number of neighbors that have moved to Solar, the greater the extent to which a given agent will prefer Solar.

A very large number of simulations have been run over the full possible range of initial parameter settings. As a result it is found that the variation of only two parameters yields profound effects on the time evolution of the system and the corresponding fundamental dynamics. These are the initial value of relative attractiveness function ($A_{initial}$) and the ratio of residential to business consumers (R). This ratio, R, is fixed in a given simulation as business consumer agents cannot become residential consumer agents, or vice-versa. The parameter, R,

[2] These aspects will be developed further in the second set of simulation examples discussed later.

governs the importance of spatial nearest neighbor fashion effects in the model. Figure 2 summarizes three distinct types of behavior observed in the model as a consequence of the initial settings for the two key parameter values. The first case is termed 'Stable' and is characteristic of simulations in which $A_{initial}$ is very large and the fashion effects are weak (i.e. there are relatively few residential consumer agents). In such systems a stationary state or equilibrium is achieved straightforwardly and rapidly. The time evolution of such a system would hold few surprises for policy makers in our fictional world. It is a slight evolutionary shift from the pre-existing status quo. Trends are good and behaviors appear predictable and stable. Note that most consumers remain with the Grid and because of the fashion effects discussed earlier more consumers switch to Solar than to CHP.

The second panel of figure 2 illustrates a different case, termed 'Asymptotic'. In this case $A_{initial}$ is very small and fashion effects are very strong (i.e. there are a very large number of residential consumer agents). Once again a stationary, equilibrium, state is reached straightforwardly and rapidly. In this case however we see a large-scale disruptive adoption of Solar technology and a hemorrhaging of consumers from the Grid. This case is therefore very different from the slight evolutionary behavior shown in the first panel of figure 2. There is a large literature on the now ubiquitous observation of S-curves in technology adoption[3]. S-curves have been observed previously in agent-based simulations of technology adoption [8]. In the case of this work we regard the S-shape of the curve revealed in the middle panels of figure 2 to be nothing more than a direct mathematical consequence of the normal distributions adopted for the distribution of consumer agent thresholds. Nevertheless by a logical inversion the emergence of S-curves might be argued to validate our selection of normally distributed consumer agent thresholds.

The lower panels of figure 2 reveal the most interesting effects and these form the main basis of the work presented here. These data correspond to a case intermediate to those considered previously and described as 'Near-Critical'. In this case $A_{initial}$ is neither exceptionally large nor exceptionally small. Similarly nearest neighbor fashion effects are neither dominant nor negligible. As in the other two cases a stable stationary, equilibrium state is achieved although it takes longer than in either of the other two cases. What is most dramatic, however, is the nature of the shift from starting conditions to final stationary state. Behaviors of this type are to be expected in systems exhibiting the attributes of scientific complexity. These sudden shifts in agent behavior appear to be an emergent property of the complex system and are not the result of sudden shocks to the system. That is, they occur without specific trigger events and any policy-maker in our stylized fictional city looking for explanation would be well advised to avoid looking for targets to blame or for a sudden collapse of the rules and policies governing the system. The sudden shifts observed are merely a phenomenon to be expected in a complex system of this type and phenomenologically similar behaviors have, for instance been observed by Robert Axelrod in his *Dissemination of Culture* model [9]. The observed behaviors are simply a direct consequence of the original rules and agent properties established before the start of the

[3] For an introduction to S-curves in technology adoption see: http://www.inrialpes.fr/prospective/ECVision-innovation.pdf

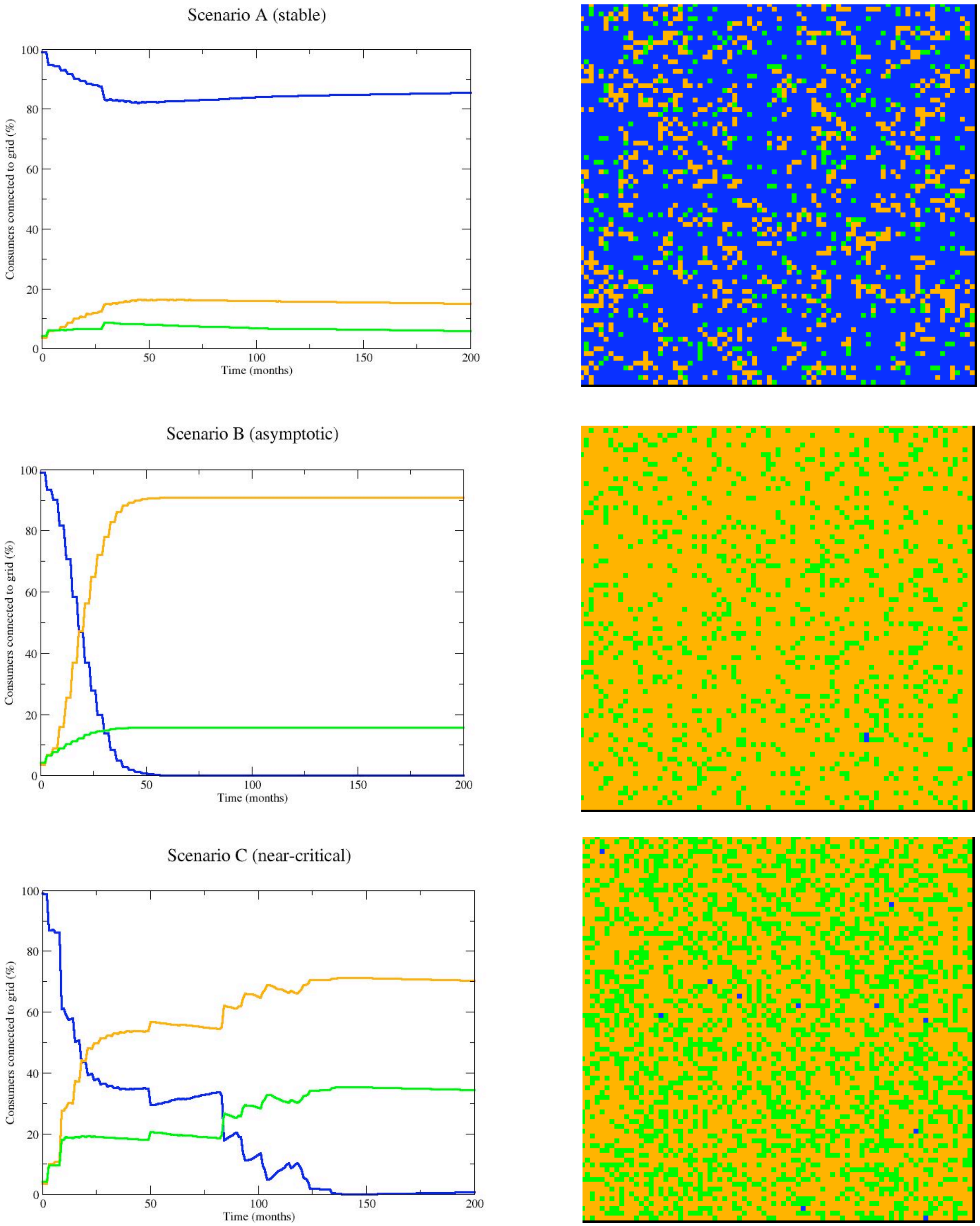


Figure 2. Comparison of three scenarios. Grid connected consumers are shown in blue, solar panel users in orange and combined heat and power users in green. Source: Hamilton et al. [5]

simulation. Our extensive analysis has reassured us that the sudden system shifts seen in the bottom panel of Figure 2 are indeed intrinsic to the model as specified and are not an exogenous consequence of any of the stochastic processes occurring during the running of the model.

In Figure 2 only two of the model parameters were varied in order to make this comparison: the grid availability and the ratio of business to residential consumers (i.e. the percentage of consumers influenced by their neighbors). Scenario C ('critical') exhibits typical complex, non-linear effects on the way to achieving a stationary state. For simplicity and clarity no graphical distinction is made between residential and business consumer agents in the figure.

Hamilton, Nuttall and Roques has considered the final stationary state proportion of consumers remaining as customers of the electricity grid as a function of the full range of parameter values for $A_{initial}$ and R, the two quantities which are found to produce significant effects. In the parlance of phase transition physics we term this proportion of remaining grid customers to be the 'order parameter' of the equilibrium state. Fundamentally Hamilton et al. see a phase space of these two parameters a set of 'states'. This will form the basis of a later publication Hamilton, Nuttall and Roques.

*3.B. Small World Model of Consumer to Consumer Influence*

In separate work Zhang and Nuttall have adopted a Small World approach when considering consumer choice in a model where consumer to consumer interaction mimics conversation rather than just simply observation [6,7]. Zhang and Nuttall has adopted a well established framework from marketing theory and psychology – Icek Ajzen's Theory of Planned Behavior (TpB) [10]. Zhang and Nuttall have for the first time systematically applied it in a context of Agent Based Simulation for studying the effects of policies on innovation (e.g. smart electricity meters) diffusion. The TpB states that human actions are driven by a behavioral intention. That intention is shaped by three fundamental beliefs: behavioral, normative and control. Each individual has his or her own traits in these areas and these differences of beliefs mean that each person responds differently to common stimuli – i.e. knowledge. This work has used Ajzen's insights to frame agent decision rules.

The TpB model as summarized in Figure 3 suggests that intention is the immediate antecedent of an actual behavior of a person and it comes from three sources: the person's attitude towards the behavior, the influence the person perceives from his/her social network (the subjective norm), and the person's perception of his/her ability to perform the behaviour (the perceived behavioral control, which may be facilitated or impeded by unexpected or random events). External stimuli's contributions to the three sources of intention are calibrated by their relevant parameters (e.g. evaluation of behavioral beliefs, motivation to comply with normative beliefs or perceived power of control beliefs, which are referred to as a person's personality traits).

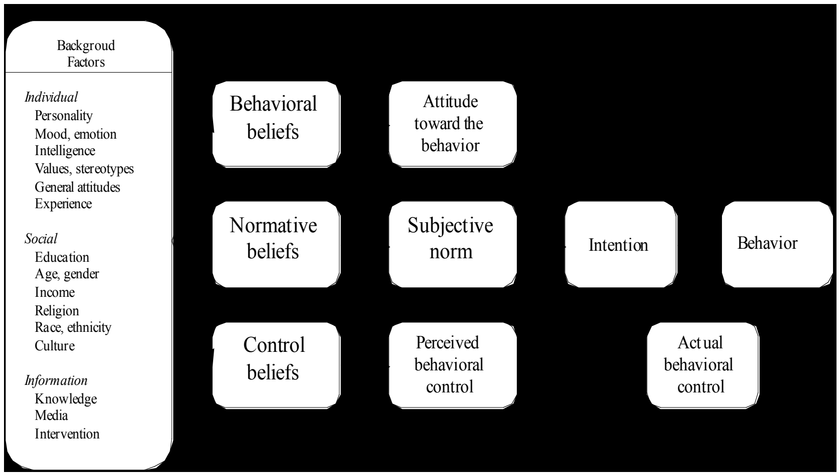


Figure 3 The Theory of Planned Behaviour – a Schematic Representation
(Source: Ajzen, [10], p. 181)

Zhang and Nuttall draw on the ideas of the TpB model. Zhang and Nuttall create a virtual community comprising of two types of agents: residential consumer (RC) agents and electricity supplier (ES) agents. In the virtual community, an RC agent has two kinds of interactions. One kind, in the form of price information of energy and smart meters, is the interaction between the RC agent and ES agents. The other kind, in the form of word-of-mouth effects, is the interaction between the RC agent and other RC agents. As competition between suppliers in the energy supply market has so far been based primarily on price comparison, the price information of electricity and smart meters can determine the RC agent's attitude towards its behavior—choosing a smart meter or not, and from which energy supplier. Therefore, based on the TpB model, the price information of electricity and smart meters can been seen as external stimuli related to "behavioral beliefs". The influences from the RC agent's social network through word-of-mouth effects can positively or negatively trigger the RC agent's intention to make a decision on whether to choose a smart meter or not, and from which energy supplier. Therefore, they can be seen as the external stimuli related to "normative beliefs" in the TpB model. Energy and technology policies made by an energy market regulator or a government department are the external factors that can facilitate consumer's decisions on choosing smart meters. Thus these policy effects can be seen as external stimuli related to "control beliefs" in the TpB model.

The simulation model of this work makes use of NetLogo originally developed at the Centre for Connected Learning and Computer-Based Modeling, Northwestern University, IL USA. In a NetLogo computational simulation, the environment is a virtual system in which the agents behave and interact in a computer[4]. In the model, Zhang and Nuttall created a model based on a square lattice of 62500 cells (250*250) with periodic boundary conditions. Cells can either be blank or be occupied by residential electricity consumers. The population in the virtual community is determined by an adjustable parameter called "population-density". The model was constructed and run a on a standard desktop Windows PC.

[4] Programming was done using NetLogo version 3.1.4

There are two kinds of agents in the virtual community: the residential consumer (RC) agents and the energy supplier (ES) agents which are not visible. The ES agents interact with the RC agents by disseminating price information of energy and smart meters throughout the whole virtual community. The starting condition for a technology roll-out program could be where a technology (i.e. a 'smart' electricity meter) is given to consumers spread in some way across the 'city'. The majority of residential consumer agents would have conventional meters, while others would be initial participating residential consumer agents in the pilot program, i.e. those that have been given a smart meter. Zhang and Nuttall have studied cases of random allocation of free meters, clustered distribution and dilute distribution targeted at technology 'enthusiasts'.

In the investigation of the Small World TpB model, Zhang and Nuttall simulate four scenarios. The time steps in the evolution of the four scenarios are the same, with each time step representing one month. In all the four scenarios, if an RC agent chooses a smart meter, it cannot switch back to a conventional meter or switch to the other ES agent within 2 time steps (simulating the 28 days rule in the English energy market [11].

This approach has yielded insights into how policy makers should allocate scarce resources when seeking to promote a new and disruptive technology, such as an electricity smart meter. Such approaches provide valuable depth of understanding beyond the well-established notion of an S-curve posited by Everett Rogers in his Diffusion of Innovation Theory [8]. In Rogers' model technology adoption starts slowly with the 'innovators' followed with greater take-up coming from the 'early adopters'. The highly non-linear S-curve ends with the final slow adoption of the technology by the 'laggards'.

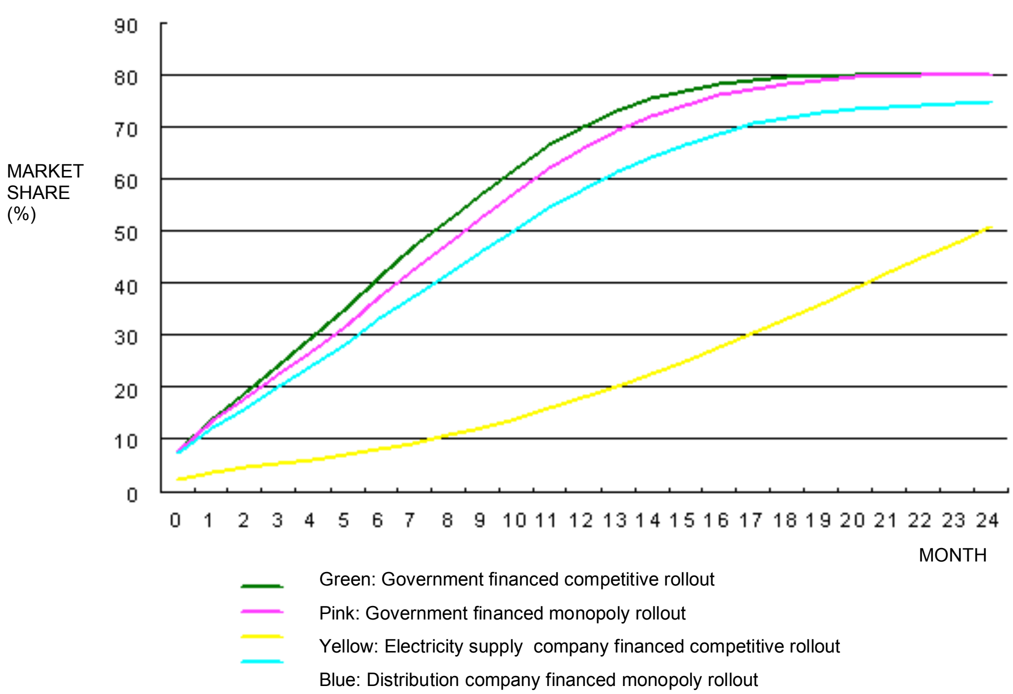


Figure 4: The Trends of Electricity Retail-Time Visual Display Diffusion under Different Policy Scenarios. 'Enthusiasm' parameter is active in all cases. Source: Zhang and Nuttall [7]

Rapid consumer take up is favored by policies in which the new technology is spread thinly across the population as a whole, rather than first deployed in a pilot neighborhood. Secondly Zhang and Nuttall have studied the effectiveness of rollout strategies from monopoly and competitive sources and funded in various ways, see figure 4 [7]. Zhang and Nuttall observe benefits if the dilute spread of the government subsidized items can be arranged such that the technology is first made available to those with a pre-existing enthusiasm for technology through retail competition. This last approach is similar to that coincidentally adopted by the UK government in its 2008-2010 policy for the diffusion of free real-time electricity use display devices to domestic electricity users. It is also interesting to note the strategies adopted by the various electricity supply companies in response to this policy from government. In this case these companies are also agents in our model, but they are not spatially localized on the lattice.

## 4. Conclusions

The work of Hamilton et al. illustrates that interesting effects are observed in the non-equilibrium kinetics of the system as it approaches its equilibrium state. In some cases dramatic effects emerge after relatively long periods of apparent stability. As is often the case in complex systems dramatic change can arise from negligible proximate causes or without any immediate cause at all. In this observation we believe that there are lessons for policy makers. Hamilton et al. use this observation to posit that policies can be put in place that appear to have been implemented smoothly and without dramatic disruption to the system as a whole. However months, or years, later dramatic unanticipated changes can occur. The work reminds policy makers that the fundamental cause of the problematic and dramatic change is not to be found by a narrow examination of events leading up to the crisis, but rather that the seeds of the crisis were sown long before with the original policy design. In a complex system an extended period of stability should not be confused with an equilibrium state.

Zhang and Nuttall's work reveals the methodological benefit of complexity science for policy assessment. Through spatial agent based simulation, Zhang and Nuttall have observed the dynamics of technology deployment (e.g. smart electricity meters) under different policy options. By considering such emergent systems-level phenomena, policy makers might gain insight into the effectiveness of policy design for promoting innovation diffusion. The earlier examples discussed in this paper give emphasis to the physics aspects of sociophysics (e.g. phase transitions) while the latter examples give emphasis to the social sciences (e.g. the Theory of Planned Behavior).

We conclude that while it is not possible to replicate the behaviors of real human communities, highly stylized spatial agent based simulations can, as part of sociophysics, provide insights which can act as warnings to policy-makers who might otherwise operate with insufficient sensitivity to the attributes of complex systems. We do not merely argue that that complexity science provides metaphors through which we might better understand the real world, although it might. Rather we go further and suggest that it is possible to construct useful simulations of, admittedly highly stylized and simplified, human societies. These virtual societies exhibit phenomena which, we suggest, may be of possible interest to those concerned with real societal questions. Working at a phenomenological level these simulations do not need to be fully realistic in order to be useful.

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