UNIVERSITY OF CAMBRIDGE
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Agent Based Simulation of Technology Adoption

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Abstract

We present an agent based model of technology diffusion where bounded rational agents are faced with uncertainty about the performance of the new technology versus the old technology as well as spatial externalities. We observe that a wide range of possible phenomena emerge, including modest evolutionary change, 'S-curve' technology adoption, as well as more disruptive "punctuated equilibrium" patterns of adoption. The off-equilibrium diffusion trajectory can be characterised by radical and unstable shifts in the system reminiscent of critical effects in phase transition physics. We also study the impact of a specific form of spatial externality on patterns of technology diffusion, which models some kind of "fashion effect". We find that such externality leads to the emergence of clustering in the adoption of technology. Our model findings are discussed in the light of the changing paradigm of electricity supply, from the current centralised grid supply to decentralised electricity generation technologies based on combined heat and power systems as well as solar panels, whose adoption is believed to be partly driven by such "fashion effect".

Keywords agent based simulation, technology diffusion, fashion, electricity supply

JEL Classification C63, O33

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Agent-Based Simulation of Technology Adoption:

Possible phenomenologies associated with consumer shifts to local electricity generation

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▪ Introduction

The acceptance and spread of new technology in a market is commonly referred to as technology adoption or diffusion. It is an important topic of research in several disciplines, such as marketing, strategy, organizational behavior, economics, and the history of technology (Loch et al., 1999). The classical diffusion model is the *S*-curve model of spreading innovations. This model has successfully been fitted to new product innovations in many industries (e.g., Gurbaxani 1990). However, Abernathy and Utterback (1978) first pointed out that industries often go through cycles of incremental innovations, punctuated by short periods of radical change. As noted by Loch et al. (1999), this pattern has been called "punctuated equilibrium," a term that originated in biology (Eldredge and Gould 1972) and subsequently was adopted in the management literature (e.g., Anderson and Tushman 1990, Mokyr 1990).

As surveyed in Loch et al. (1999), the literature presents a number of obstacles to switching between technologies. For example, organizational inertia and stable industry constellations may prohibit significant innovations for long

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periods until change is forced by a crisis. Cultural “openness” may also foster or inhibit significant technological changes, and interdependencies among multiple component technologies can prevent radical innovations for compatibility reasons. In a groundbreaking paper, Loch et al. (1999) developed a model that offers a different explanation for punctuated technology diffusion. In their theory, punctuated equilibrium may occur among bounded rational adopters who at any point in time choose the technology with the better performance, although with an imperfect capability of evaluation. Loch et al. (1999) demonstrated that punctuation can happen if positive externalities as well as uncertainty in the evaluation of a new technology are present in the system.

In this paper, we use a different modelling approach, based on an agent based simulation, to study further the dynamics of technology diffusion among bounded rational adopters when there are positive externalities as well as uncertainty about the performance of two technologies. A multi-agent model consists of a number of software objects, the ‘agents’, interacting within a virtual environment. The strength of agent-based simulation is that it makes possible the study of the emergence of phenomenologies at the macro level from repeated interaction of simple agents at the micro level. The behaviour of the society is said to ‘emerge’ from the actions of its units.

The paper’s objectives are twofold. First, we aim to assess whether there is the potential for the emergence of “punctuated equilibrium” patterns of technology adoption in an agent based model characterised by positive spatial externalities as well as uncertainty in the evaluation of a new technology; further, we aim to assess whether there is some scope for the system off-equilibrium trajectory to exhibit behaviours characteristic of mathematically complex systems, such as avalanche effects and tipping points. Agent based simulation is particularly well suited to study such off-equilibrium trajectories, as well as the impact of spatial externalities, thanks to the spatial representation of technology adoption on a stylised lattice.

The second objective of the paper is to study the impact of a specific type of spatial externality, which we refer to as the “fashion effect”, on patterns of technology adoption. The penetration of many technologies is indeed driven not only by characteristics intrinsic to the technology, such as its relative performance with regard to the old dominant technology, but also driven by other features such as the impact of a “fashion effect” within a community of users. Examples of the impact of such effect include the disruptive patterns of diffusion of some luxury goods, or fashion related electronic equipment such as mobile phones; the sudden popularity of hybrid cars or hummers in the US can also be attributed to such “fashion effect”. We model this “fashion effect” as a particular kind of spatial externality, which increases the attractiveness of one technology for those agents which have one of their neighbors equipped with the fashionable new technology. The objective is again to study both how the off-equilibrium technology adoption trajectory is influenced by this fashion effect, and to explore the impact on spatial distribution of new technology adopters once a stable equilibrium is reached. We question in particular the likelihood of such “fashion effect” to give rise to spatial clusters of technology adoption.

These issues related to technology adoption are explored in the paper in the light of the electricity industry. While this industry is currently dominated by the traditional electricity system, where customers are connected to a grid which brings to them the power produced in a few large power stations, the electricity supply industry is undergoing profound structural change with the emergence of decentralized electricity generation technologies (Patterson, 200X). There is much debate about the penetration speed and patterns of new technologies such as decentralized combined heat and power or solar panels, which could substitute to traditional grid supply. There are many barriers, including technological and institutional lock in, to the adoption of such decentralized power supply technologies. There is also much uncertainty over the performance of such new technologies (i.e. some measure of competitiveness or attractiveness) as compared to the old grid supply technology. Besides, while combined heat and power technology is largely invisible, solar panels diffusion may be subject to different diffusion patterns due to the previously mentioned “fashion effect”.

The paper is divided into five sections. The next section provides a literature review of models of technology adoption and of agent based models. The third section describes our agent based model of technology adoption. The fourth section concentrates on the simulation results and details successively the emergence of “punctuated equilibrium” adoption patterns, the “off-equilibrium” technology adoption trajectory, and the impact of the “fashion effect” on clustering. The fifth section concludes.

▪ Literature review

The classical technology diffusion model in the management literature is the *S*-curve model of spreading innovations. *S*-curve growth (logistical growth) results when growth is proportional to the established base (contagion) and to the remaining untapped potential (Loch et al., 1999). While this model has been successfully fitted to new product innovations in many industries, other industries have also seen more disruptive patterns of technology diffusion. In many industries, long periods of incremental improvement tend to be interrupted by short periods of radical innovation (Abernathy and Utterback 1978, Utterback and Suarez 1993). Kummar and Kummar (1992) observe that the typical application of diffusion *S*curves is to new products or product categories opening up a new market potential, but not to the competition between an established and a new technology. This paper examines how a new technology diffuses in competition with an established technology.

Technology diffusion patterns alternating long periods of incremental improvement and short periods of radical innovation have been called “punctuated equilibrium,” a term that originated in biology (Eldredge and Gould 1972) and subsequently was adopted in the management literature (e.g., Anderson and Tushman 1990, Mokyr 1990). Loch et al. (1999) provide a thorough survey of the management, marketing, and organization theory literature justifications for such diffusion patterns. Loch et al. (1999) categorize the different arguments that have been brought forward to explain the existence of punctuated equilibria in technology diffusion as follows:

> “1. A radical innovation creates uncertainty (for producers as well as users), which needs to be resolved before widespread adoption can occur.
> 2. The new characteristics of the technology may destroy existing firm competences, which contributes to inertia within firms.
> 3. In addition, a new technology may be incompatible technically with other components of complex systems of which it is a part.
> 4. It may also upset the balance of co-operation and interests in the business network that has evolved around the old technology and its complements.
> 5. Finally, it may encounter resistance in society at large”

Our model, similarly to Loch et al. (1999)’s model of technology diffusion, offers a different explanation for the existence of punctuated equilibrium behavior. Loch et al. (1999) show that “even in the absence of inertia or compatibility issues, punctuated equilibrium-type diffusion can happen, provided that two factors are present: some positive network externalities, and uncertainty about the performance of the new technology.” While we use a completely different modeling approach, based on agents simulation, our model is linked to the large literature on so-called evolutionary models of technological change technology adoption pioneered by Nelson and Winter (1982). Similarities between our model and the evolutionary approach include the assumption that actors are profit driven but unable to optimize because of bounded rationality. Actors simply choose the “best” out of the currently available technologies, without being capable of perfect evaluation or of anticipating the system equilibrium.

An extensive literature building on Nelson and Winter (1982) has developed on this evolutionary approach to technology diffusion, which Silverberg et al. (1990, p. 75) define as “the diffusion of techniques and new products under conditions of uncertainty, bounded rationality and endogeneity of market structures as a disequilibrium process”. Most of the literature, to the exception of Loch et al. (1999), focuses on *firm* market shares and pioneer advantage, whereas our model emphasizes the *technology* and the possibility of its sudden adoption across the user population. The other strands of literature related to our model of technology adoption are reviewed in Loch et al. (1999), and include the so called path dependence models with positive externalities. Positive externalities are also referred to as “bandwagon” adoptions (e.g., Abrahamson and Rosenkopf 1997). These models emphasize that small initial advantages may determine which one of possibly several competing technologies is chosen by the user community.

The second main difference between our agent based simulation model and the evolutionary approach of technology diffusion models is that we focus on the off-equilibrium behavior of the system, or the system dynamics, until an equilibrium is possibly reached. Human societies, institutions and organisations are complex systems, using 'complex' in the technical sense to mean that the behaviour of the system as a whole cannot be determined by partitioning it and understanding the behaviour of each of the parts separately, which is the classic strategy of the reductionist physical sciences. One reason why human societies are complex is that there are many, non-linear interactions between their units, that is between people. The behaviour of the society is said to 'emerge' from the actions of its units (Gilbert, 2004). Our model aims to assess there is some scope for the technology adoption in a population off-equilibrium trajectory to exhibit behaviours characteristic of mathematically complex systems, such as avalanche effects and tipping points.

There are two fundamental attributes of mathematical complex systems: First complex systems of the type discussed here are based upon a very large number of spatially separated decision agents, each making constrained choices subject to a very simple set of predetermined rules. Second these complex systems are generally extremely resilient, yet nevertheless very small disturbances can generate profound changes. In this way such complex systems can exhibit the famous 'butterfly effect' of chaos theory (Gleick, 1988).

When the interaction of the agents is contingent on past experience, and especially when the agents continually adapt to that experience, mathematical analysis is typically very limited in its ability to derive the dynamic consequences (Axelrod and Tesfatsion, 2006). In this case, agent based modeling might be the only practical method of analysis. Our model allows investigating how large-scale technology adoption arises from the micro-processes of interactions among many agents. As surveyed by Dawid (2005), neoclassical models belonging to the evolutionary approach are indeed limited to explain and reproduce important stylized facts about innovation, technological change and industry evolution. Tier weaknesses have been discussed among other places in Dosi et al. (1995), Dosi et al. (1997), Sutton (1997) or Klepper and Simons (1997). Dawid (2005) demonstrates that quite a few of these observed patterns of technology adoption can be rather robustly reproduced using agent based models. As he points out, "this is particularly encouraging since these patterns are in no way explicitly incorporated into these models, but are *emergent properties* of the aggregate behavior in complex models, which in many cases are built upon rich micro foundations incorporating at least some of the key features of the processes involved in actual technological change."

As noticed by Axelrod and Tesfatsion (2006), agent based modeling is "a method for studying systems exhibiting the following two properties: (1) the system is composed of interacting agents; and (2) the system exhibits emergent properties, that is, properties arising from the interactions of the agents that cannot be deduced simply by aggregating the properties of the agents." Much of the insight into the phenomenology of two-dimensional (2-D) computational models of large-scale systems stems from techniques developed by theoretical and computational condensed matter physicists. It is not our intent in the work reported here to develop physics-based models of socio-economic systems from which we might obtain scientific predictive power. Rather we merely aim to extrapolate from physics-based modelling insights, which although they fall short of a full theory of phase transitions, might provide us with insight into the broad types of system behaviour that might occur – so called phenomenologies. In so doing, we aim to explore the range of possible phenomenologies for these systems and to gain insight into possible robustness and fragility of societal uptake of an innovation.

While it is undeniable that physics is the traditional intellectual discipline with the greatest proximity to the ideas of complexity science, it is important to acknowledge other relevant scientific disciplines (notably ecology and geology) that have done much to push forward our understanding of complexity in the last thirty years. Some work in biology has formalized punctuation as switching between stable equilibria in the system (Foster and Young 1990). This relationship has been described comprehensively and accessibly by Philip Ball in his book *Critical Mass* (2005).

The most famous example of social agent-based simulation has been developed economist and social scientist Thomas Schelling, Nobel Laureate Economics (2005). Schelling's work has demonstrated that racial segregation can emerge in communities from the behaviours of autonomous agents each individually exhibiting only very small racial prejudices (Schelling, 1978). Many hundreds of multi-agent social simulation models have now been designed and built, to examine a very wide range of social phenomena. It is not practicable to review all of these, and even describing a representative sample would be a difficult exercise. However, there are dimensions along which models can be arranged (see e.g. Gilbert, 2004; Hare and Deadman 2004; David et al 2004).

In summary, the contribution of this article lies in the application of agent based modeling to study the off-equilibrium phenomenologies characterizing punctuated equilibrium technology diffusion patterns. The key resulting insight is to show how the combination of positive externalities and performance uncertainty at the micro (agent) level alone may cause a "catastrophic" (that is, sudden and unforeseeable) adoption of a new technology at the macro level, independent of the absolute performance comparison or other managerial and context variables, thereby shedding new light on the micro level roots of such evolution first observed by Loch et al. (1999).

- ## Description of the Model

Context and Premise – Distributed Electricity Generation

In the early twenty-first century the developed world is dominated by concerns for energy security and for climate change. Against these backdrops there is a renewed emphasis being given to possible shifts in the electricity system away from the historically dominate paradigm of large-scale centralised generation, high voltage transmission and distribution and the sale of electricity through suppliers to end-user consumers. Some such as Walt Patterson (1999) argue that our needs would be better served and the adverse externalities minimised if a large proportion of electricity consumers were to break their dependence upon centralised grid-based electricity and rather generate electricity much closer to its point of use. In extremis this proposition suggests that individual residential electricity users and small businesses should consider investing in, and making use of, small scale electricity generation technologies such as solar Photovoltaics and micro-Combined Heat and Power. These and other similar technologies are described in a book Future Electricity Technologies and Systems edited by Jamasb, Politt and Nuttall (2006).

In its White Paper on Energy of May 2007 the UK Department of Trade and Industry gives prominence to distributed electricity generation. Paragraph 3.5.0 of the White Paper states:

> "In the context of the governments overall policy goals, we believe that any action to address these barriers [cost, lack of reliable information, electricity industry issues and regulatory barriers] should:
>
> 1 Stimulate take-up of cost-effective low-carbon distributed generation;
> 2 provide a means of enabling distributed generators to realise a reasonable economic value from their schemes;
> 3 reduce complexity involved in setting up as a distributed generator [...];
> 4 encourage where possible, further development of distributed generation within the licensed framework rather than outside of it."

In extremis this gets down to the level of household generation. It is this possible shift in electricity end use and demand, albeit in a highly stylised form, that we seek to model in the simulations reported in this paper.

The Agent Based Model

In order to model a system involving technology adoption within an agent based framework and investigate the dynamics of such a system, we consider a spatially discrete 'city' populated with interacting, autonomous agents representing electricity consumers. The time evolution of the this system is studied for a given set of initially predetermined rules and conditions. The only non-deterministic element in the model is the perceived relative attractiveness between old and new technologies, which represents the main driver for change and is stochastic in nature. The agents can be of one of two types, either 'residential' or 'business' consumers. This difference is a crucial aspect of the model as the residential consumers are influenced by a spatial externality in the form of a fashion effect, while the business consumers are not. The consumer agents receive electricity from one of three sources: the grid ('Grid' the initial default provider), solar power ('Solar') or from Combined Heat and Power ('CHP'). Each agent repeatedly makes an assessment of the relative attractiveness of the competing technologies leading to a decision whether to stay with the old technology (supply from the grid) or to switch to the new one (decentralized generation at home/business through either CHP or solar panels). The model can be best described by separating its constituent elements into three distinct categories: the global model parameters, the intrinsic attributes of the agents and the criteria used by the agents in evaluating the available technologies.

The model is constructed on a square lattice of N cells, with each cell either occupied by a consumer agent or empty (as shown in figure 1). This stylized city is randomly seeded according to three global parameters: the lattice size, the overall agent density and the ratio of business to residential 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 business to residential agent ratio until the next section. In all other cases involving variation of the lattice size, the overall density or the boundary conditions, the net result is that the 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, a default lattice size of 6400 cells (80 x 80), periodic boundary conditions and an overall agent density of 1 were employed in the simulations presented in this paper.[3]

Time is incremented in 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. It is important to incorporate this asynchronous decision-making as it has been observed, for example by Loch et al. (1999), that a model with consumers making decisions in lock-step is not only unrealistic, but can drastically perturb the very system dynamics of interest in the present study. The net result of this approach is that each agent has 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 w_i (for the ith agent). 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 is weighted heavily in favour 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.

[3]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 multi-node Linux farm.

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 ith 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.

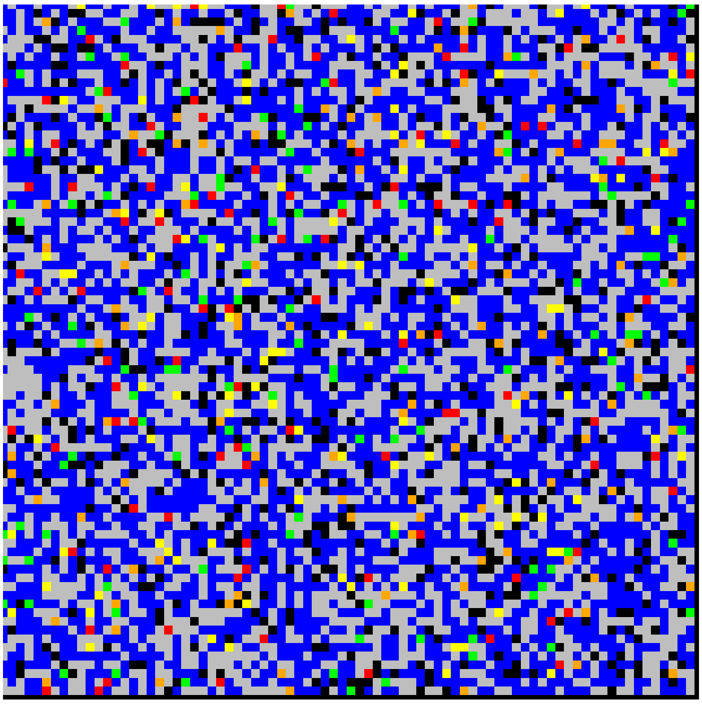

Figure 1: The model 'city' populated with residential and business electricity consumers, where the black squares represent empty sites. At the start, all consumers get their electricity from the grid (blue for residential and grey for business). The consumers can then choose to switch to solar (green/yellow) or micro combined heat and power (orange/red) sources. To eliminate edge effects the model has periodic boundary conditions.

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. If the 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 neighbour interaction. This means that if any of a residential consumer's neighbours has solar power then that consumer's supply preference shifts incrementally in favour of Solar. In other words, the greater the number of neighbours that have moved to Solar the greater the extent to which a given agent will prefer Solar.

▪ Results of the Simulations

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 yield profound effects on the time evolution of the system and the corresponding fundamental dynamics. These are the initial value of the relative attractiveness function ($A_{initial}$) and the ratio of business to residential consumers (R). This latter parameter governs the importance of spatial nearest neighbour fashion effects in the model. It is in some senses equivalent to the overall density.

For the purposes of investigating the system dynamics, we have chosen to focus on the variation of this parameter rather than of the overall density. It is, in our opinion, a more direct and intuitive parameter. Figure 2 shows the three distinct diffusion trajectories which were observed in the model as characterized by these two key parameters, as well as the city in its equilibrium state. For simplicity and clarity, both residential and business consumer agents have the same colour-scheme in figure 2. 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 behaviours appear predictable and stable. Note that most consumers remain with the Grid, and because of the fashion effects more consumers switch to Solar than to CHP.

The second panel of figure 2 illustrates a different case, termed 'Asymptotic'. In this case Ainitial 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 haemorrhaging of consumers from the Grid. This case is therefore very different from the slight evolutionary behaviour shown in the first panel of figure 2. There is a large literature on the now ubiquitous observation of S-curves in technology adoption. Indeed, S-curves have been observed previously in agent-based simulations of technology adoption. Such behaviours were posited by Everett Rogers in his Diffusion of Innovation Theory (1995). 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'. 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 neighbour 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. In this case it is not smooth, monotonic or well suited to trend analysis. Behaviours of this type are to be expected in systems exhibiting the attributes of scientific complexity discussed earlier. These sudden shifts in agent behaviour are 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 system that exhibits typical complex, non-linear effects on the way to achieving a stationary state. The behaviours are simply a direct consequence of the original rules and agent properties established before the start of the simulation. Our extensive analysis has reassured us that the sudden system shifts seen in the bottom panel of figure 2 are not a consequence of any of the stochastic processes occurring during the running of the model.

Figure 3 shows the percentage of consumers which remain with the Grid once equilibrium has been reached, which in the parlance of phase transition physics we shall term the the 'order parameter' of the equilibrium state. This variable has been calculated from the average value obtained from three separate simulation runs for each bin. The nature of each equilibrium stationary state, and hence the value of the order parameter, has been binned in the two key parameters Ainitial and R. Fundamentally we see the phase space of these two parameters to show two states, the first a state in which at equilibrium effectively no consumer agents remain as customers of the grid. The second a state in which a clear proportion of grid consumers remain. The transition between the two is not particularly sudden or abrupt and this leads us to conclude that this model system may indeed reveal 'critical phenomena' in phase transition terms. For states where only a small, but non-zero, number of customers remain on the grid we expect that relatively unusual phenomena might occur that in the absence of the insight from this work might perplex analysts and policy makers. It is our intention to extend and broaden our investigations into these and related phenomena. In so doing we hope that we might be able to draw insight and inspiration from complexity science to the very real challenges facing our modern energy systems.

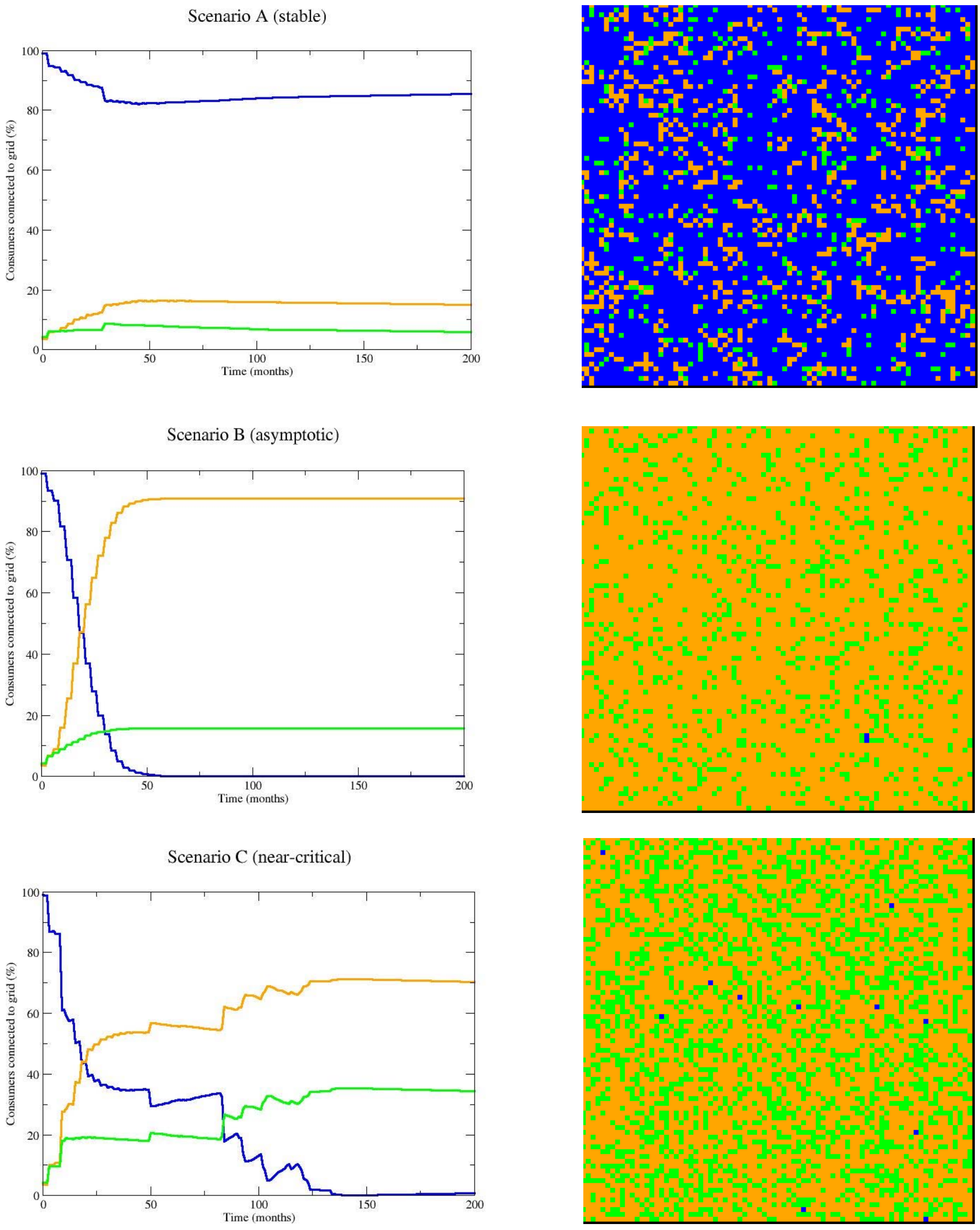

Figure 2: **A comparison of three different scenarios. Only two of the model parameters were varied in order to make this comparison: the relative attractiveness between technologies and the ratio of business to residential consumers (i.e. the percentage of consumers influenced by their neighbours). The overall agent density is 1 and the colour-scheme is the same for both business and residential consumers (blue for grid, orange for solar and green for CHP).**

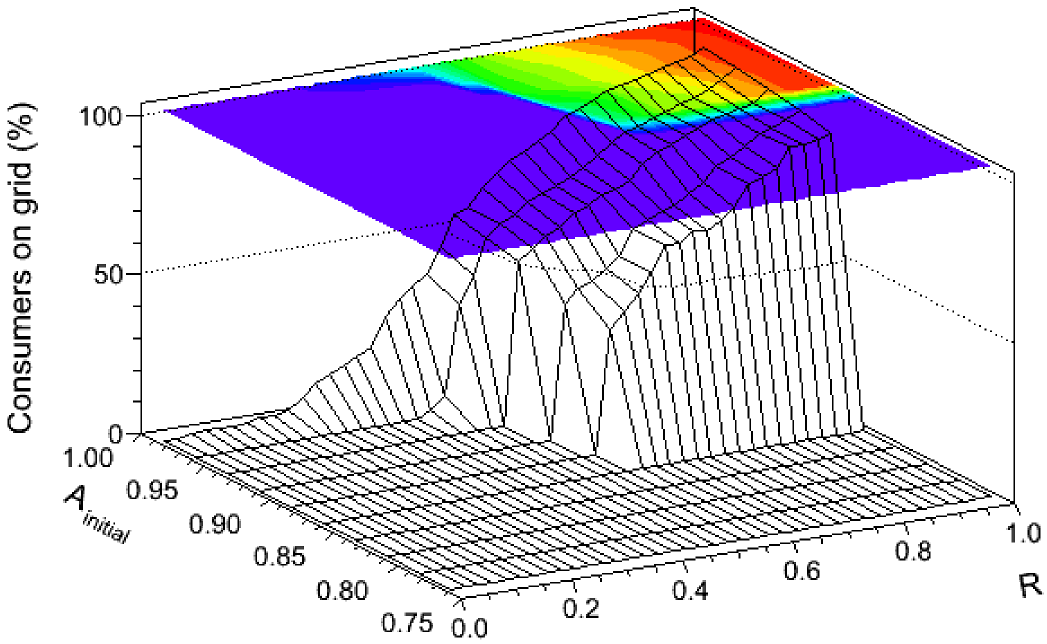

Figure 3: **Phase diagram showing the percentage of consumers remaining on the grid at equilibrium as a function of both the relative attractiveness ($A_{initial}$) and the ratio of business to residential consumers (R).**

- ## Conclusions

In this work we present results obtained from a simple and highly stylised agent based simulation of consumer attitudes to electricity supply. The main motivation for this work is the demonstration that micro-interactions and the subsequent system dynamics and can play an important role in technology diffusion, a role which is not included in the management literature paradigm based on equilibrium states alone. The model adopted involves a very large number of simple agents making decisions based upon current conditions. No money or agent memory is involved in the model. The model is therefore unrealistic in that it possesses no inter-temporal effects that might arise from the banking of money, a time preference of money or a memory of previous conditions. We find that in this simplified model the dominant factors driving the system dynamics are the degree to which the competing technologies are perceived to be relatively attractive and the significance of a nearest neighbour interaction modelling a fashion effect. We observe, depending on these initial conditions: small evolutionary changes; S-curve technology adoption and the elimination of the customer base for the grid; and, in a situation highly reminiscent of phase transition physics, states where profound shifts occur in response to negligibly small triggers.

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