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Tao Zhang and William J.Nuttall

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Tao Zhang*, William J. Nuttall
Judge Business School, University of Cambridge
Trumpington Street, Cambridge, CB2 1AG, UK
T.Zhang@jbs.cam.ac.uk

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Abstract

Based on the classic behavioural theory "the Theory of Planned Behaviour", we develop an agent-based model to simulate the diffusion of smart metering technology in the electricity market. We simulate the emergent adoption of smart metering technology under different management strategies and economic regulations. Our research results show that in terms of boosting the take-off of smart meters in the electricity market, choosing the initial users on a random and geographically dispersed basis and encouraging meter competition between energy suppliers can be two very effective strategies. We also observe an "S-curve" diffusion of smart metering technology and a "lock-in" effect in the model. The research results provide us with insights as to effective policies and strategies for the roll-out of smart metering technology in the electricity market.

Keywords agent-based simulation, smart metering technology, the Theory of Planned Behaviour, technology diffusion

JEL Classification C63, C73, D78, O33

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1. Introduction

Technology adoption, which studies the acceptance and diffusion of a new technology in a market or an economy, is an important research area in several disciplines such as marketing, management, industrial engineering and economics [1]. Although the invention of a new technology often comes into being as a single discrete event or a jump, the adoption of that technology often appears as a continuous, long and slow process [2]. A new technology will contribute little in a market or economy until it has been adopted by many users. Therefore, understanding the process of the diffusion of a new technology is of great significance. Rosenberg [3] points out two characteristics in the technology diffusion process: overall slowness and wide variations in the rates of acceptance of different technologies. Rogers [4] theorizes a classical technology diffusion model—the S-curve model of spreading innovations, which suggests that the early users adopt a new technology first, followed by the majority, until the technology becomes common. This model has been successfully justified by studying the adoptions of new technologies in many industries (e.g. [5, 6]). Currently the studies of the diffusion of new technologies mainly focus on econometric models (e.g. [7, 8, 9]). However, as suggested in the Punctuated-Equilibrium Model of Technology Diffusion [1], the diffusion of a new technology is a complex process influenced by a broad range of factors, such as organizational inertia, stable industry constellations, cultural "openness" and uncertainty in the evolution of the new technology. Davis et al. [10] also point out that the acceptance of a new technology is highly related to consumers' psychological factors such as "perceived usefulness" and "perceived ease of use". Therefore, complexity science which studies how the micro-level individual behaviour gives rise to the macro-level collective properties of a whole system appears to be another effective means of studying the influences of factors in the complex process of the diffusion of a new technology.

In this paper, we present an agent-based model to study the adoption of smart metering technology in the electricity consumer market. The motivation of the study is triggered by the fact that the future of smart metering technology in the UK energy consumer market remains a key concern of the government (e.g. the Department for Business, Enterprise and Regulatory Reform (DBERR)), the energy market regulator (the Office of Gas and Electricity Markets (Ofgem)), as well as energy suppliers and consumers. We target the issue by using agent-based computational simulation, i.e. we build a virtual society being comprised of rational software objects, the “intelligent agents”, in a computer. These agents, representing both energy consumers and energy suppliers, interact in the virtual society. As with real households, the energy consumer agents make rational decisions in terms of choosing energy suppliers and metering technologies in the virtual society. Macro-level emergent properties, such as the evolution of the adoption of smart metering technology in the virtual society, can be seen as inferences of the adoption of smart metering technology in the real electricity consumer market.

The objectives of the study are twofold. First, we aim to provide an exploratory and predictive study of the future of smart metering technology in the UK electricity consumer market. Currently all the stakeholders, especially the government (DBERR), energy market regulator (Ofgem) and energy suppliers, are all interested in promoting smart meters in the UK energy consumer market. However, a wide range of barriers and uncertainties make the future of smart meters unclear. A robust exploratory and predictive model can provide very helpful management intelligence for these stakeholders. In other words, the results from the model could potentially help decision-makers see the future of smart metering technology and establish effective strategies and economic regulations to push the take-off of smart meters in the UK energy consumer market.

The second objective of the paper is to develop an effective multi-agent system framework on the basis of the classical psychological/behavioural theories to study all the complex phenomena in the energy consumer market. This model can be seen as a generic multi-agent framework based on which we can study the influences of a number of factors (e.g. word-of-mouth effects in a social network, consumers' perceptions, and the impact of random events) on the issues of most concern (e.g. issues about energy security, technology adoption and global warming) in the energy consumer market. For example, if we detach the model from smart metering technology and apply it to another issue, such as the diffusion of renewable energy technologies, it will still be an effective research approach. Moreover, because a key point in the development of the model—designing algorithms to control the behaviour and interactions of the electricity consumer agents, is based on the classical psychological/behavioural theories, the model can also be seen as another way of validating the classical psychological/behavioural theory.

The paper is comprised of six sections. The second section describes smart metering technology and its current situation of adoption. The third section describes our agent-based simulation model of smart metering technology adoption in detail. The fourth section describes the four scenarios we simulated with the model. The fifth section concentrates on the analysis of the simulation results and their practical implications. The sixth section presents a discussion of the model and concludes the paper.

2. Smart Metering Technology and Its Current Situation of Adoption

2.1 What is a Smart Meter?

"Smart meter" is a catch-all term for a type of advanced and innovative meter (usually an electric meter) which offers consumers information about consumption in more detail than a traditional meter, and optionally interacts with local utility suppliers via some network for monitoring and billing purposes [11]. It could range from a simple display meter which shows consumers how much they spent on the utility, to a high-technology meter which automatically interacts with utility suppliers so as to send accurate meter readings to utility suppliers remotely or help consumers keep track of the carbon emissions caused by their energy consumption [12].

Although currently there is no single unified definition of a "smart meter", some commonly recognised functions are available:

- Display real time information about energy consumption to consumers and send it to energy suppliers directly and remotely [13];

- Provide a more effective way for consumers to understand their energy consumption via a prominent display unit which includes:

  - Cost in £/p
  - Indicator of low/med/high use,
  - Comparison with historic/average consumption patterns,
  - Function to allow data to be accessed via PCs/mobile phones [13].

- Interact with energy suppliers so as to make it is possible for consumers to switch tariffs remotely [12, 13];

- Export metering for domestic micro-generators [13, 14];

- Enhance demand-side management options, such as tariffs which charge more at peak times of the day and less for off-peak times [15];

- Ensure security of energy supply, inactivity monitoring and real time monitoring of gas leaks and CO_2 emissions [12, 13];

2.2 Benefits of Smart Meters

Smart metering technology can potentially offer a broad range of benefits including better information and control of energy use, new service opportunities for companies and other organizations, enhanced power network management facilities, and alternative connections to digital services. These benefits are in line with government's objectives to reduce emissions, keep energy prices competitive, and to encourage electronic trading [13]. The potential benefits that smart meters bring to different stakeholders are outlined below in detail.

- **Energy Efficiency**

  As a basic function, a smart meter can display energy consumption accurately in pounds and pence so that consumers can easily be made aware of the money they are spending on energy. The display is often located in a separate place from where the meter is installed, e.g. in the kitchen or next to the thermostat, in order to provide consumers with easy access to the information [13]. More sophisticated smart meters can interact with electrical appliances around the home and display the exact amount of energy they use, or even control the amount of energy use in a house.

  A significant body of evidence has proven that consumers' behaviour would change if they were regularly informed of the cost of energy they consume [14, 16]. Therefore, arming consumers with better information about their energy consumption could change their behaviour. For example, they may try to find ways of saving money by cutting back on the amount of overall energy they consume, or by reducing energy consumption at peak times. As a result, consumers with smart meters could be more energy efficient. This has been witnessed by studies and experience from overseas including Italy, Ontario, Northern Ireland and Sweden: changes of consumer behaviour have resulted in a reduction of energy consumption by between 3% and 15% [16], with "savings at the upper end often being linked to the provision of energy efficiency information and advice" [13]. Ofgem's analysis based on limited UK information has shown that smart meters could have the potential to deliver, on an annual basis, a reduction in domestic fuel bills by an average of £24 and, if applied in all household, a reduction in overall UK gas and electricity consumption of around 3% [14].

- **Demand-side Management, Micro-generations and Cutting Emissions**

As reported by Energywatch, demand-side management measures and micro-generation technologies can facilitate the establishment of an effective and competitive energy market that delivers reduced carbon emissions, secure energy suppliers and affordable energy for all consumers [13]. Demand-side management enables energy suppliers to offer consumers variable rate contracts which encourage consumers to use energy at off-peak demand times of the day by offering reduced off-peak rates in exchange for relatively high rates at peak demand times of the day. For example, in Italy and Ontario, there are rates for three different periods of the day [16]. Demand-side management measures can decrease the pressure of the distribution network at peak demand times, and also potentially reduce the need for building generating plants to cover the demand at peak times [13].

Micro-generation produces electricity and heat from a low or non-carbon source on a domestic scale. Examples of micro-generation include: micro-CHP (a small domestic Combined Heat and Power unit which produces electricity and heat simultaneously), micro-hydro, micro-wind and photovoltaics. The benefits of wind, solar and hydro micro-generation are the zero fuel cost and that the technologies are carbon free. The development of micro-generation can potentially produce a third of a householder's annual electricity needs thus reducing the load on distribution networks and largely cutting carbon emissions

[13]. As a result, the total cost to consumers will be reduced. In order to capture the benefits from micro-generation, meters must be able to record imported electricity from the distribution network and electricity exported back to the network during the periods when generation outstrips demand. Therefore, smart meters can help boost the spread of micro-generation.

Widespread adoption of smart metering technology can therefore cut CO_2 emissions because:

- "Large uptake of micro-generation would dramatically reduce the need for electricity from major CO_2 emitting power stations. It would also help to smooth out peaks in demand for electricity which would in turn reduce emissions from power stations.

- By encouraging customers to adopt energy efficiency measures and use less energy, this will also help reduce emissions.

- Smart meters could also show how much carbon a household was emitting and this could make customers more aware of the impact of their energy use on the environment" [12].

- **Improving Billing Performance**

As reported by Energywatch, poor billing is by far the largest source of complaints by consumers. In 2004/5, poor billing accounted for 61.5% of all domestic consumers' complaints, equivalent to approximately 40,000 complaints [13]. Since April 2002, the number of consumers seeking advice about billing from Energywatch has increased by 202% [13]. The results from a research commissioned by Energywatch in 2003 shows:

- "Consumers lack confidence in the accuracy of estimated bills;
- 35% of customers receive estimated bills frequently;
- One in five believe that the estimated bills they received are very or fairly inaccurate;
- Almost one in ten said that estimated billing had pushed them into debt with their supplier and for a third of those the debt exceeded £100. For one in four of these the debt was difficult or impossible to pay off" [13].

If there is a suitable information network and infrastructure, smart meters can send accurate real time meter readings directly to the energy suppliers. Therefore, the adoption of smart meters can potentially eliminate the need for manual meter reading and estimated billing. The automatic and remote meter reading and accurate billing will lead to a substantial reduction in energy suppliers' back office costs related to complaint resolution [13].

2.3 Barriers to the Adoption of Smart Metering Technology

Despite a number of benefits that could arise from the widespread application of smart metering technology, the adoption of this new technology is not yet as good as expected. The barriers that have prevented smart metering technology from taking off in the energy consumer market can be summarized in three aspects: economic, technical and regulatory.

- **Economic**

As they are based on advanced technologies, smart meters inevitably cost more then conventional meters, and the more sophisticated the model, the higher the price.

Table 1 shows a comparison between the costs of smart meters and the costs of conventional meters. On the one hand, for consumers, the cost of a smart meter might be up to three times the cost of a conventional meter. On the other hand, currently energy suppliers are also unlikely to roll out smart meters in the whole UK because they may have to pay around £800 million in total for the deployment of smart meters. [14]. Therefore, high absolute cost of replacement of existing conventional meters with smart meters remains a significant economic barrier preventing smart meters from taking off.

Meter Type	Meter Cost	Comments
Standard credit tariff	£50-£70	Combined cost of supply and installation
Standard prepayment meter	£80-£100	Combined cost of supply and installation
Smart "Display" meter	£75-£120	Supply and install. Includes cost of display unit. Potentially additional costs associated with pre-payment token systems.
Smart "AMR/Net" meter (Remote Readable)	£100-£170	Supply and install. Additional infrastructure costs e.g. wireless or powerline communications systems
Smart "Internet" meter	£150 and upwards	Supply and install. Includes costs of TCP/IP stack. Additional infrastructure costs apply directly related to the number of additional services carried over metering system

Table 1: Comparative Costs of "SMART" versus "STANDARD" Meters (Source: [14])

- **Technical**

Although advanced metering technology is already available, there are many options in terms of the types of smart meters. The lack of standardization of types of smart meters can create risk for energy suppliers: a consumer installing a smart meter from one energy supplier may switch to another energy supplier because its new smart meters appear to offer more advanced services [14]. Additionally, the lack of standardization of smart metering technology means that large number of smart meters of different types will work (e.g. collect and dispatch data and instructions, keep track of meter errors, validate and transform the data and store data) under different communication protocols. Currently, this issue remains a big technical challenge for energy suppliers [34]. This barrier is being discussed by both Ofgem and Energywatch, who are currently making efforts to publish international standards covering automatic meter data exchange [18]. The standardization of smart meter technology can overcome this technical barrier and enable energy suppliers to boost the deployment of smart meters in large scale.

- **Regulatory**

With the current regulatory framework, most of the energy meters remain the assets of the energy suppliers, and the prime focus of Ofgem has been the development of metering competition in the energy market. Ofgem suggests that metering competition would advance the interests of consumers by offering more choices, encouraging technological innovation and reducing costs for both consumers and energy suppliers [19]. However, the combination of RPI-X regulations on the ex-PES (the electricity supplier to the extent that the electricity supplier is undertaking activities within its distribution services area), and currently distribution network operators (DNOs) has the effect of exacerbating the trend to install conventional meters with basic functionality, because the regulation can incentivise network operators to deliver their existing services as efficiently as possible in order to maintain their margins [14]. The electricity network operators are reluctant to risk developing innovative services, especially those that can render their current assets (existing working meters) obsolete [14]. Furthermore, the 28-day rule allows consumers to switch their energy suppliers at 28 days notice, which causes energy suppliers to face the risk that consumers may not meet their debts for the meter or services provided, leaving energy suppliers to chase the debt (additionally expenses are incurred for this) [13, 14].

2.4 Current Situation of Smart Metering Technology Adoption in the UK

The domestic metering market in the UK stands at around 45 million units [14]. Although all the stakeholders (e.g. DBERR, Ofgem, Energywatch and energy consumers) have high expectations with regard to smart meters which can potentially offer a broad range of benefits, smart metering technology is not currently taking off in the UK. According to Ofgem, some trials have been carried out by energy suppliers (e.g. former Seeboard, Severn Trent Water, British Gas and EDF energy), but consumers' acceptance of smart meters does not seem satisfactory [20]. Therefore, the market for smart meters in the UK still remains questionable. In order to promote the adoption of smart metering technology in the UK, Ofgem has proposed pilot studies and they are urging the government to fund the pilots [14]. They suggest that the trials should involve a cross section of society, covering for example, inner city housing, affluent suburban housing, rural areas and a new residential development, to test (i) the social, environmental and consumer benefits of smart meters; (ii) the technical attributes; and (iii) the likely costs both to energy suppliers and consumers of the installation and maintenance of various types of meters and remote switching of appliances [14]. In May 2007, DBERR published a new version of white paper on energy "Meeting the Energy Challenge", which fully addressed the government's ambition in promoting smart metering technology in the UK energy market. In this new energy white paper, DBERR announced its new policies on promoting smart meters: (i) energy suppliers should extend advanced and smart metering services to all business consumers in Great Britain within next 5 years; (ii) a 10-year plan to roll out smart meters to households and, between 2008-2010, smart meters will be available free of charge to any households that requests one.

3. Description of the Model

3.1 The Model

In order to provide an exploratory and predictive study on the adoption of smart metering technology in the UK energy consumer market, we propose to incorporate the research with computational simulation by developing a multi-agent model to simulate the scenarios of the adoption of smart metering technology in the electricity consumer market. The idea of the model is that: based on a two-dimensional spatial map, we will develop a virtual community within which residential electricity consumers and electricity suppliers interact with each other. Each residential consumer can proactively gain information about metering technologies and energy suppliers from other residential consumers and energy suppliers, and can also proactively send information about metering technologies and energy suppliers to other residential consumers. A residential consumer's decision in terms of choosing metering technology and an energy supplier is rationally made based on the information the consumer gains from the social network in which it is involved. The rationality in this process of decision-making is based on the theory of planned behavivour (TpB) [24]. Energy suppliers, on the other hand, will act economically to promote energy and their metering technologies including both traditional metering technology and the new smart metering technology. Whether energy suppliers "push" or "pull" the smart metering technology is economically determined by market situations. The evolution of the adoption of smart metering technology with time can be observed from the virtual community on system level. By adjusting the parameters, we can test and study the influence of management strategies and economic regulations on the adoption of smart metering technology. The simulation model can provide us with an in-depth understanding of the process of smart metering technology adoption and also assist us in predicting the future adoption of smart metering technology.

3.2 The Environment and the Agents

In computational simulation, the environment is a virtual system in which the agents behave and interact in a computer. In the model, we create our 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, as shown in Figure 1. The population in the virtual community is determined by an adjustable parameter called “population-density”.

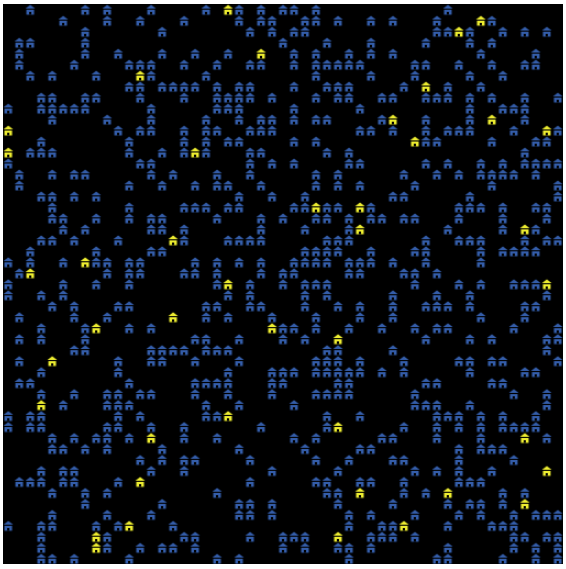

Figure 1: The Environment

Note: In the virtual community, residential electricity consumer agents are randomly populated in the cells (blue or yellow houses), and the black areas are unpopulated cells (non-residential areas). Each populated cell just has one residential consumer agent, and the number of total residential consumer agents is control by the parameter called “population-density”. The blue houses are the residential consumer agents with conventional meters, while yellow houses are the initial participating residential consumer agents (the residential consumer agents who have been initially chosen to install smart meters) in the pilot programme. In order to eliminate edge effects, the square lattice has periodic boundary conditions.

There are two kinds of agents in the virtual community: the residential consumer (RC) agents which appear in form of houses, and the energy supplier (ES) agents which are not visible but interact with RC agents by disseminating price information of energy and smart meters throughout the whole virtual community.

3.3 Behaviour of RC Agents

Since the RC agents are human, they are "smart agents" [21] which have intelligent behaviour in terms of choosing energy suppliers and metering technologies. An RC agent gains information about energy suppliers and metering technologies from both its social network (e.g. neighbours, friends or colleagues) and energy suppliers, processes the information and finally makes decisions. This decision-making process is a complex cognitive process about which scientists of different backgrounds have given different interpretations. For example, in economics, Sugden [22] suggests "rational choice" based on the utility theory; in psychology, McClelland [23] develops the motivation theory; and in behavioural science, Ajzen [24] develops the theory of planned behaviour (TpB). In terms of constructing human agents in an agent-based model, the theories based on which we develop algorithms to control the human agents' behaviour are significantly important because they determine the fidelities of the agents. Previous work on agent-based simulations in the electricity market (e.g. [25, 26]) developed algorithms to control agents' behaviour based on economic theories. In our model, we focus on behavioural science and develop algorithms to control RC agents' behaviour on the basis of the most influential decision-making model "The Theory of Planned Behaviour (TpB)" [24].

The TpB model [24], as shown in Figure 2, suggests that intention is the immediate antecedent of an actual behaviour of a person and it comes from three sources: the person's attitude towards the behaviour, 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 behavioural 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. behavioural beliefs, normative beliefs or control beliefs, which are referred to as a person's personality traits).

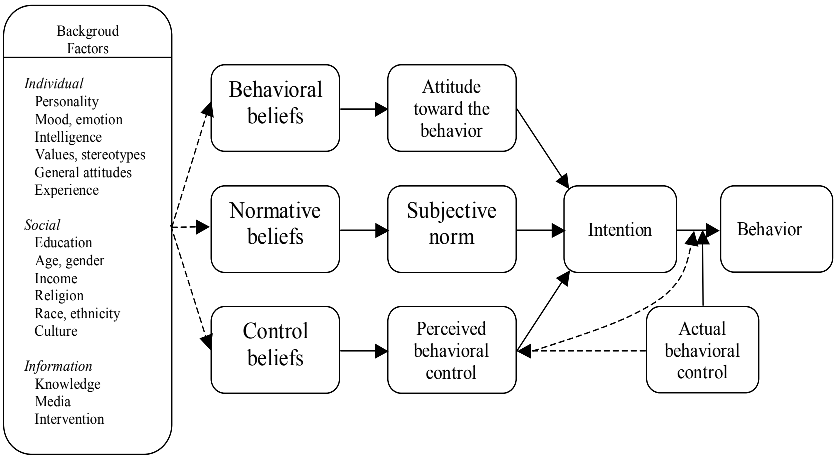

Figure 2: The model of TpB (Source: Ajzen, 1991, p. 181)

We draw on the ideas of the TpB model. In the virtual community, an RC agent has two kinds of interactions (Figure 3). 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 [14], the price information of electricity and smart meters can determine the RC agent's attitude towards its behaviour—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 the external stimuli related to "behavioural 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 Ofgem or DBERR 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.

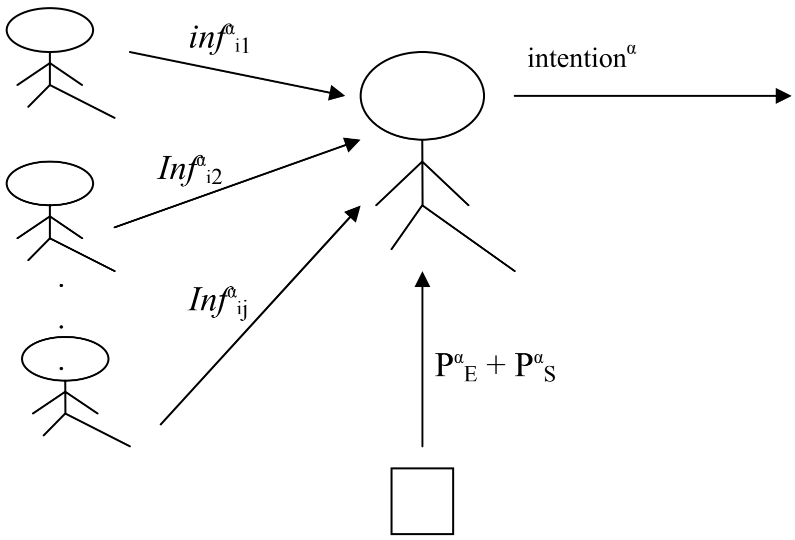

Figure 3: An RC agent's interactions

agent	stimulus	weight	intention
1	$Inf^{\alpha}{}_{i1}$	W_{i1}	$Inf^{\alpha}{}_{i1}$ * W_{i1}
2	$Inf^{\alpha}{}_{i2}$	W_{i2}	$Inf^{\alpha}{}_{i2}$ * W_{i2}
3	$Inf^{\alpha}{}_{i3}$	W_{i3}	$Inf^{\alpha}{}_{i3}$ * W_{i3}
.	.	.	.
j	$Inf^{\alpha}{}_{ij}$	W_{ij}	$Inf^{\alpha}{}_{ij}$ * W_{ij}
ES	$P^{\alpha}{}_{E} + P^{\alpha}{}_{S}$	W_{iP}	$(P^{\alpha}{}_{E} + P^{\alpha}{}_{S}) * W_{iP}$

Table 2: Stimuli, Weights and Intention

Consider an RC agent (agent *i*) interacting with *j* RC agents. Each RC agent sends a stimulus about option *α* (choosing an energy supplier and a metering technology) to the RC agent via the word-of-mouth effect (Figure 3), and the contribution of each stimulus to the RC agent's subjective norm is calibrated by its relevant normative belief. We use different weights to represent these normative beliefs, as show in Table 2. Based on the TpB model, agent *i* subjective norm to option *α* can be formulated as

$$SN_i^{\alpha} = \sum_{j=1}^{n} (W_{ij} * Inf_j^{\alpha})$$

Agent *i* also gains stimuli about option *α* from an energy supplier. If we use $P^{\alpha}{}_{E}$ to denote the price information of energy, use $P^{\alpha}{}_{S}$ to denote the price information of a smart meter if option α includes smart metering technology (if it does not include smart metering technology, then $P^{\alpha}{}_{S}$ is null), and W_{iP} to denote agent i's sensitivity to price (a behavioural belief in the TpB model), agent i attitude towards option α can be formulated as

$$A_i^{\alpha} = W_{iP} * (P_E^{\alpha} + P_S^{\alpha})$$

Combining agent i's subjective norm and attitude towards to option α, its intention to choose option α can be formulated as

$$I_i^{\alpha} = \sum_{j=1}^{n} (W_{ij} * Inf_j^{\alpha}) - W_{iP} * (P_E^{\alpha} + P_S^{\alpha})$$

where we use a minus before the attitude towards the option because price has a negative influence on the RC agent's intention to choose option α. In a the virtual community, if agent i has α options, the one that can give agent i the largest intention is its preferred one, i.e. its final decision on whether to choose a smart meter or not and from which energy supplier. The decision-making can be formulated as

$$\text{decision}_i = \max \{I^1, I^2, I^3, \ldots I^{\alpha}\}$$

3.4 Behaviour of ES agents

As the ES agents are business organizations, their behaviours in a market are economic activities. In our model, each ES agent's behaviour includes: (i) promoting energy and smart meters to consumers by disseminating their price information throughout the whole virtual community; (ii) adjusting prices based on the variation of its overall market share (this differs in different scenarios of experiments).

4. The Simulation

We programmed the model with the agent-based simulation package NetLogo 3.1.4. In terms of an RC agent's interactions with other RC agents, we consider to two kinds (Figure 4). One is the RC agent's regular interactions with its neighbouring RC agents: the RC agent can regularly receive influences from its neighbouring RC agents through regular interactions with them, and the number of regular interactions is controlled by a parameter called "radius". For example, if we make the "radius" larger (a longer radius in Figure 4), the RC agent will have more regular interactions with its neigbouring RC agents. The other is the RC agent's random interactions with other agents in the virtual community: the RC agent can also randomly receive influences from other agents in the virtual community through the random interactions with them, and the number of random interactions is controlled by a parameter called "random-interaction". The purpose of this design is to enable the social networks in the virtual community to have the attributes of both "small-world" effect [27,28] and scale-free power-law distribution [29]. In such kind of social networks, each RC agent can both receive regular influences and random influences from other RC agents and send regular and random influences to other RC agents in the virtual community.

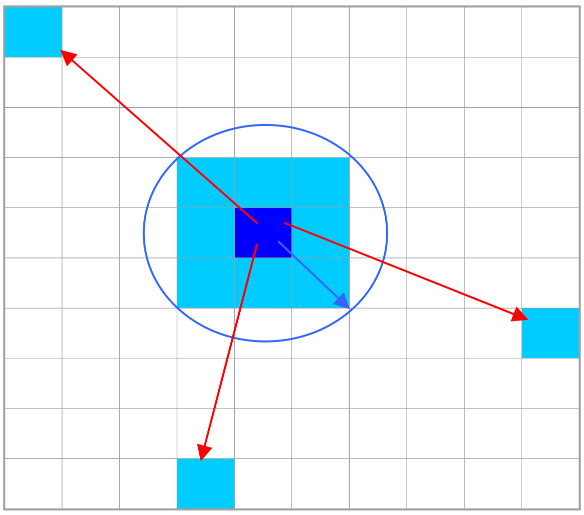

Figure 4: An RC agent's regular (blue) and random interactions (red) with other RC agents

We simulate four scenarios. The time steps in the evolution of the four scenarios are the same, with each time step being defined as 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 two time steps (simulating the 28 days rule in the energy market [14]). In the first scenario, we simulate one possible pilot for promoting smart meters in a monopoly market. An RC agent has two options in the virtual community: (i) conventional metering technology, and (ii) the new smart metering technology. The initial conditions of Scenario 1 are given in Table 3:

parameter	value	comments
number of ES agent	1	There is only one energy supplier in the virtual community
population-density	0.40	40% of the cells in the virtual community is populated, i.e. there are 25000 (62500*0.4 = 25000) RC agents in the virtual community
random-interaction	10	Each RC agent has less than 10 random interactions in the virtual community
radius	2	Each RC agent regularly interacts with other RC agents less that 2 times of radius away from its position
percentage	0.10	Initially in the pilot, the ES agent **randomly** chooses 10% of its RC agents **at geographically dispersed sites** to install smart meters

Table 3: Initial Conditions in Scenario 1

In the second scenario, we simulate a second pilot scheme for promoting smart meters in a monopoly market, with initial conditions the same as that in Scenario 1. An RC agent also has two options in the virtual community: (i) conventional metering technology, and (ii) the new smart metering technology. The only difference between Scenario 1 and Scenario 2 is that in Scenario 2, the ES agent chooses 10% of its RC agents in a centralized controlled area to install smart meters, as shown in Table 4.

parameter	value	comments
number of ES agent	1	There is only one energy supplier in the virtual community

population-density	0.40	40% of the cells in the virtual community is populated, i.e. there are 25000 (62500*0.4 = 25000) RC agents in the virtual community
random-interaction	10	Each RC agent has less than 10 random interactions in the virtual community
radius	2	Each RC agent regularly interacts with other RC agents less that 2 times of radius away from its position
percentage	0.10	Initially in the pilot, the ES agent chooses 10% of its RC agents **in a centralized controlled area** to install smart meters

Table 4: Initial Conditions in Scenario 2

In the third scenario, we simulate a pilot scheme in a duopoly market. The two ES agents promote smart meters with cooperation, i.e. they set a unified price for smart meters and neither of the two will unilaterally adjust the unified price of smart meters. A RC agent has four options in the virtual community: (i) conventional metering technology with ES agent A, (ii) smart metering technology with ES agent A, (iii) conventional metering technology with ES agent B, and (iv) smart metering technology with ES agent B. The initial conditions of Scenario 3 are shown in Table 5.

parameter	value	comments
number of ES agent	2	There are two energy suppliers (A and B) in the virtual community
population-density	0.40	40% of the cells in the virtual community is populated, i.e. there are 25000 (62500*0.4 = 25000) RC agents in the virtual community
market-share-A	0.50	Initially ES agent A has 50% market share
market-share-B	0.50	Initially ES agent B has 50% market share
random-interaction	10	Each RC agent has less than 10 random interactions in the virtual community
radius	2	Each RC agent regularly interacts with other RC agents less that 2 times of radius away from its position
percentage-A	0.05	Initially in the pilot, the ES agent A **randomly** chooses 5% of its RC agents to install smart meters
percentage-B	0.05	Initially in the pilot, the ES agent B **randomly** chooses 5% of its RC agents to install smart meters

Table 5: Initial Conditions in Scenario 3

The fourth scenario also simulates a pilot of promoting smart meters in a duopoly market. However, it is different from Scenario 3. In Scenario 4, the two ES agents promote smart meters with competition, i.e. they will always adjust the price of smart meters based on the variation of market shares. Every six months the two ES agents check their overall market shares, and if one ES agent finds that it is losing in its market share, it will slightly lower the price of smart meters in order to gain more RC agents; if it finds that its market share is increasing, it will slightly raise the price of smart meters in order to gain more profit. An RC agent also has four options in the virtual community: (i) conventional metering technology with ES agent A, (ii) smart metering technology with ES agent A, (iii) conventional metering technology with ES agent B, and (iv) smart metering technology with ES agent B. The initial conditions of Scenario 4 are given in Table 6.

parameter	value	comments
number of ES agent	2	There are two energy suppliers (A and B) in the virtual community
population-density	0.40	40% of the cells in the virtual community is populated, i.e. there are 25000 (62500*0.4 = 25000) RC agents in the virtual community
market-share-A	0.50	Initially ES agent A has 50% market share
market-share-B	0.50	Initially ES agent B has 50% market share
random-interaction	10	Each RC agent has less than 10 random interactions in the virtual community
radius	2	Each RC agent regularly interacts with other RC agents less that 2 times of radius away from its position
percentage-A	0.05	Initially in the pilot, the ES agent A **randomly** chooses 5% of its RC agents to install smart meters
percentage-B	0.05	Initially in the pilot, the ES agent B **randomly** chooses 5% of its RC agents to install smart meters

Table 6: Initial Conditions in Scenario 4

5. Simulation Results

Through the four experiments we observe the evolution of the adoption of smart metering technology under different conditions, which gives us possible phenomenological information about the future of smart metering technology in the real UK energy consumer market.

Figure 5 from Scenario 1 shows that if the ES agent at the outset randomly and dispersedly chooses its RC agents to have smart meters, the smart metering technology will be adopted by those RC agents outside the pilot group in a very effective way. The market share of smart meters evolves to around 100% in about 40 time steps. Figure 6 from Scenario 2, however, presents a very different situation. The adoption of smart metering technology is very slow if the ES agent initially chooses its RC agents in a centralized controlled area, even though in Scenario 2 the percentage of RC agents initially chosen to install smart meters is the same as that in Scenario 1. Figure 7 shows a comparison between the evolutions of the adoption of smart metering technology in the two scenarios. One conclusion we can draw from the comparison is that in the pilot of promoting smart metering technology, choosing the initial participating RC agents (the RC agents who have been chosen to install smart meters at the beginning of the pilot programme) on a random and geographically dispersed basis is a more effective strategy than choosing initial participating RC agents on controlled and geographically centralized basis.

Figure 8 presents the evolution of smart metering technology in a scenario of cooperation (Scenario 3), and Figure 9 presents the evolution of smart metering technology in a scenario of competition (Scenario 4). Although the two scenarios are different, a common pattern of the adoption of smart metering technology appears. However, if we make a comparison between the evolutions of the adoption of smart metering technology in the two scenarios (Figure 10), we can find that in competition scenario (Scenario 4), the adoption of smart metering technology can be quicker and when the market reaches a stable state, smart meters in competition scenario can possess a larger market share than that in cooperation scenario. Moreover, Figure 12, Figure 13 and Figure 14 show that competition can also help an ES agent to maintain its overall market share, because the difference between the two ES agents' overall market shares in the competition scenario is evidently smaller than that in the cooperation scenario. Therefore, we can draw another conclusion from the comparison: competition is a more effective way than cooperation in terms of both promoting smart metering technology and maintaining ES agents' market shares.

The model reproduces the "S-curve" model of technology diffusion [4]. The evolutions of the adoption of smart metering technology in all four scenarios have the common pattern of an "S-curve" (Figure 7 and Figure 10). Our empirical observation from the Telegestore Project of promoting smart meters carried out by Enel in Italy also shows the "S-curve" model of technology adoption (Figure 15). Our simulation results show that the increasing rates of the four "S-curves" are different. This is due to the highly different management strategies (methods of choosing initial participating RC agents) and economic regulations (competition and cooperation). Under these different management strategies and economic regulations, individual RC agents have different perceptions (which is reflected as highly different values of "attitude towards the behviour", "subjective norm" and "perceived behavioural control" in the TpB model) towards smart meters and energy suppliers. As a result, they have different behaviour at individual level (whether choose smart meters or not and with which energy supplier), which then gives rise to the different system level properties (different rates of the four "S-curves").

Another very interesting emergent result is the appearance of a "lock-in" effect [30]. The "lock-in" effect is a very interesting phenomenon in marketing. It describes a state of an evolving market in which consumers prefer one of two or more competing products and that this preference persists for a long time beyond what would be economically rational [31]. The "lock-in" effect in the adoption of smart metering technology in our model is an emergent property of the whole virtual market which originates from the behaviour of individual RC agents and their interactions. Empirical observation from the real UK energy market shows a typical "lock-in" effect does exist between the major electricity suppliers (Figure 16). The appearances of the "lock-in" effect in different markets have attracted many marketing scientists and a huge volume of literature on the studies of the "lock-in" effect has been published (e.g. [32, 33]).

However, most of them are based on traditional top-down techniques on analytical mathematical models. Our computational simulation model offers another way of generating the "lock-in" effect: based on our bottom-up agent-based model, we can further study how the RC agents' interactions in the social networks contribute to the "lock-in" effect.

6. Conclusions and Future Work

Our model shows the robustness of agent based simulation in terms of coping with uncertainties and complexities in the adoption of smart metering technology in the electricity consumer market. As our results show, with the model, we can carry out experiments to test the effectiveness of different management strategies and economic regulations in the process of promoting smart metering technology. The results from the experiments in the virtual community might be used to infer the results in the real electricity market. This can help us to gain insights into the future of smart metering technology and optimize our management strategies and economic regulations so as effectively to boost the take-off of smart metering technology in the real energy market. For example, given that the benefits of smart meters exceed their costs, our experimental results can have two practical implications: if we carry out pilots to promote smart meters in the UK energy market, we should (i) choose the initial participating households on a random and geographically dispersed basis; and (ii) encourage competition between energy suppliers in the smart meter market.

The appearance of the "lock-in" effect and "S-curve" model of technology diffusion in the virtual community can be seen as two validations of our model. The appearances of the "lock-in" effect and the "S-curve" enable the model to bear resemblance to empirical observations from real electricity markets, and further signify the validity of the model. Additionally, because the model is developed based upon classical behavioural theory, the robustness of the model can also been seen as a validation of the TpB model. As the TpB model is a generic behavioural theory, our model can also be seen as a generic reference agent-based model that can be applied to deal with other issues in the energy market. For example, it might be possible to separate the model from smart metering technology and then apply it to another issue with similar properties, e.g. the adoption of micro-generations in the energy market.

Our further research will evaluate the effectiveness of DBERR's new policies on promoting smart meters set in the new energy white paper in May 2007. These new policies raise some interesting issues in the energy market. For example, to what extend should these policies be publicized to households and how can energy suppliers take the advantage of initial enthusiastic smart meter users to roll our smart metering services. We will target these issues via agent-based computational simulation and provide policy implications for promoting smart metering technology in the UK energy market.

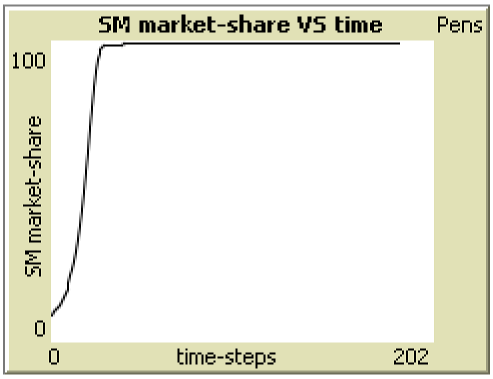

Figure 5: Scenario 1

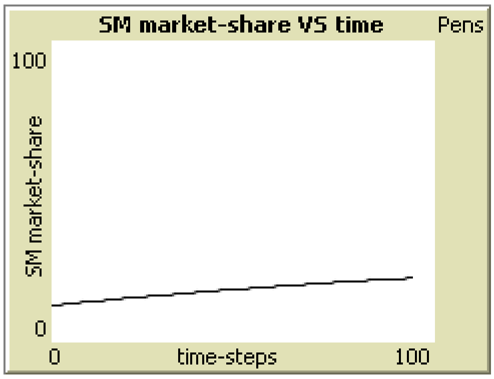

Figure 6: Scenario 2

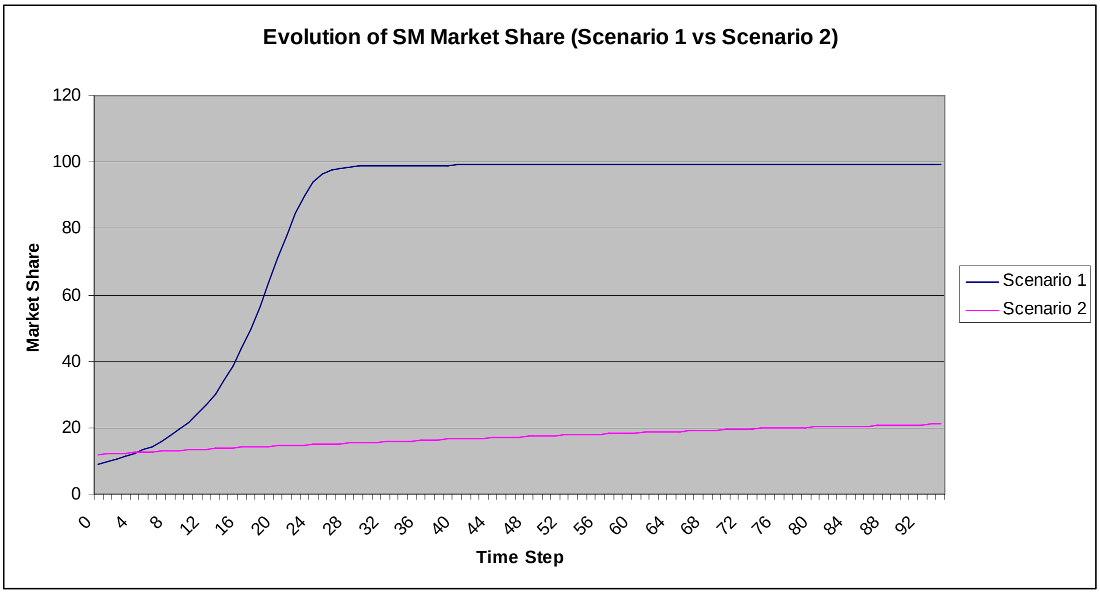

Figure 7: A Comparison between Scenario 1 and Scenario 2

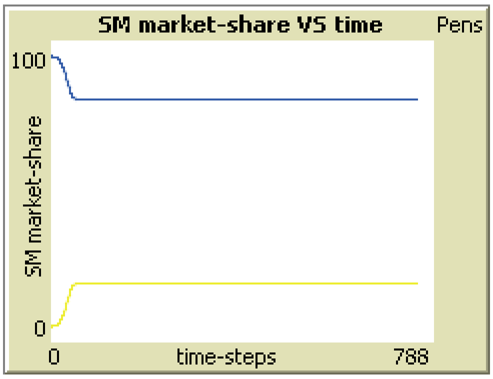

Figure 8: Scenario 3 (cooperation)

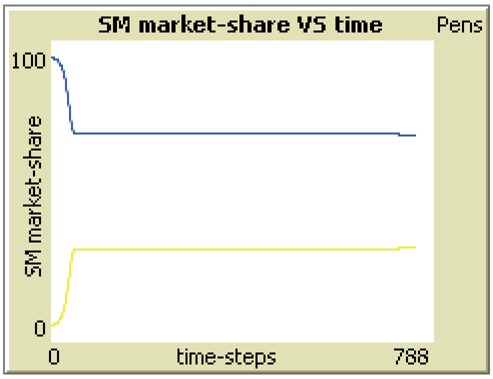

Figure 9: Scenario 4 (competition)

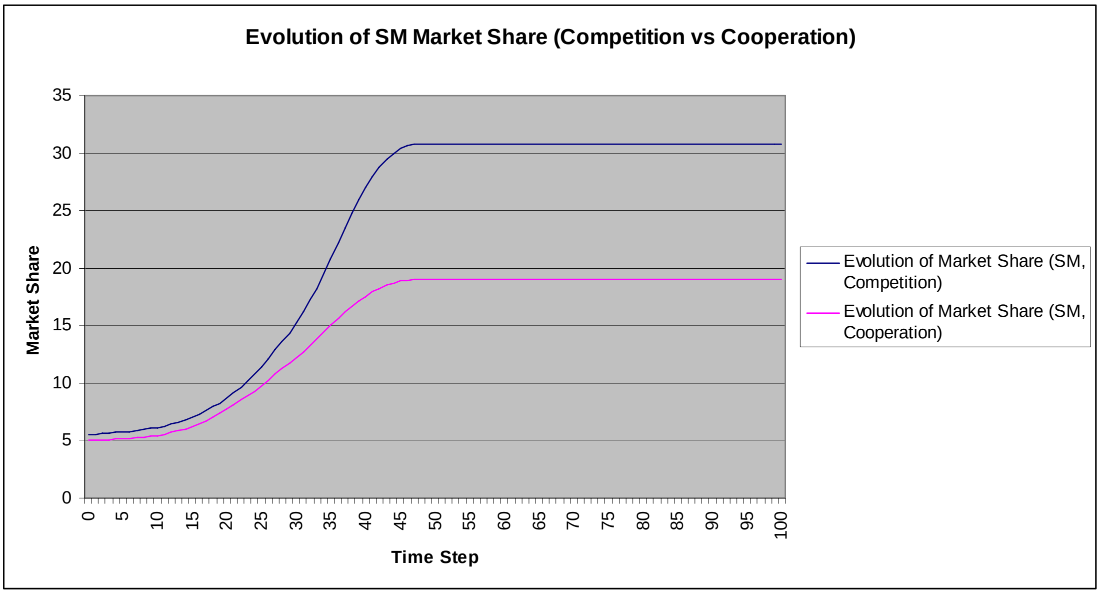

Figure 10: A Comparison between Competition (Scenario 4) and Cooperation (Scenario 3)

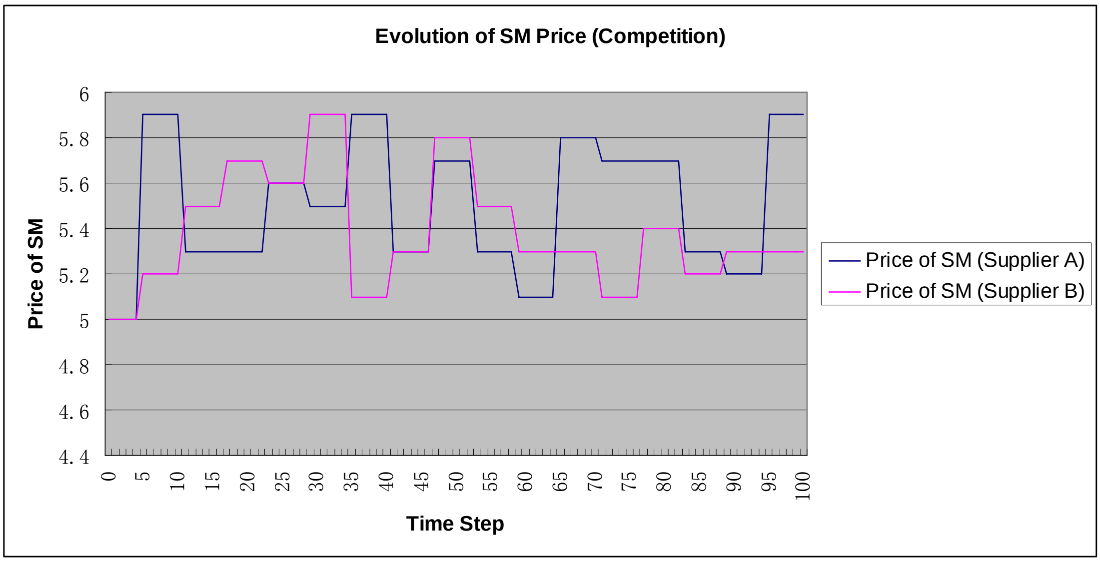

Figure 11: The Evolution of SM Price in the Competition Scenario

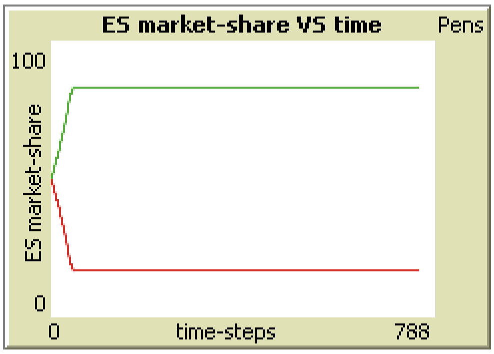

Figure 12: Market Shares of ES Agents (Scenario 3)

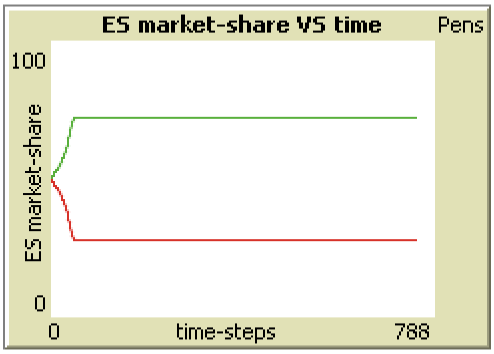

Figure 13: Market Shares of ES Agents (Scenario 4)

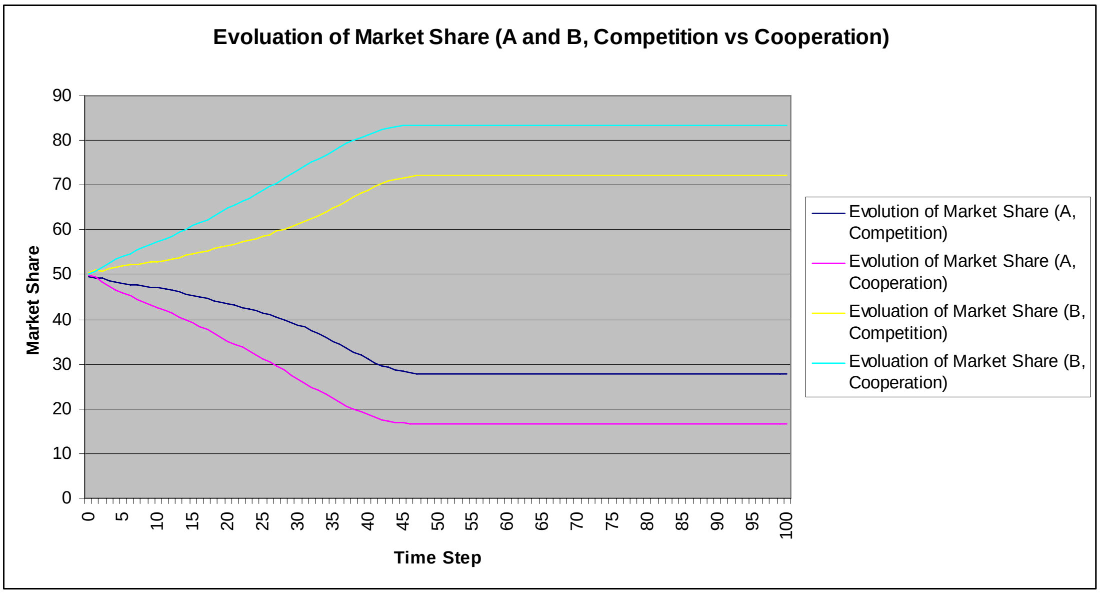

Figure 14: A Comparison between Competition (Scenario 4) and Cooperation (Scenario 3) in ES Agents Market Shares

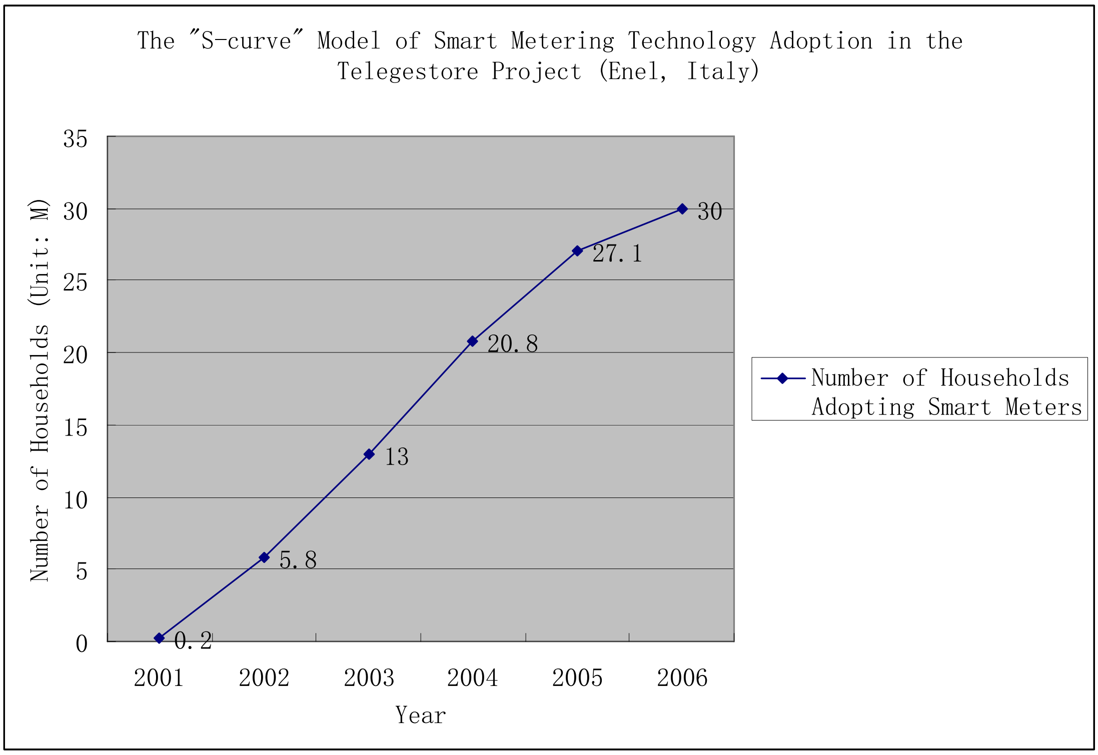

Figure 15: The "S-curve" Model of Smart Metering Technology Adoption in the Telegestore Project (Data Source: Enel, Italy)

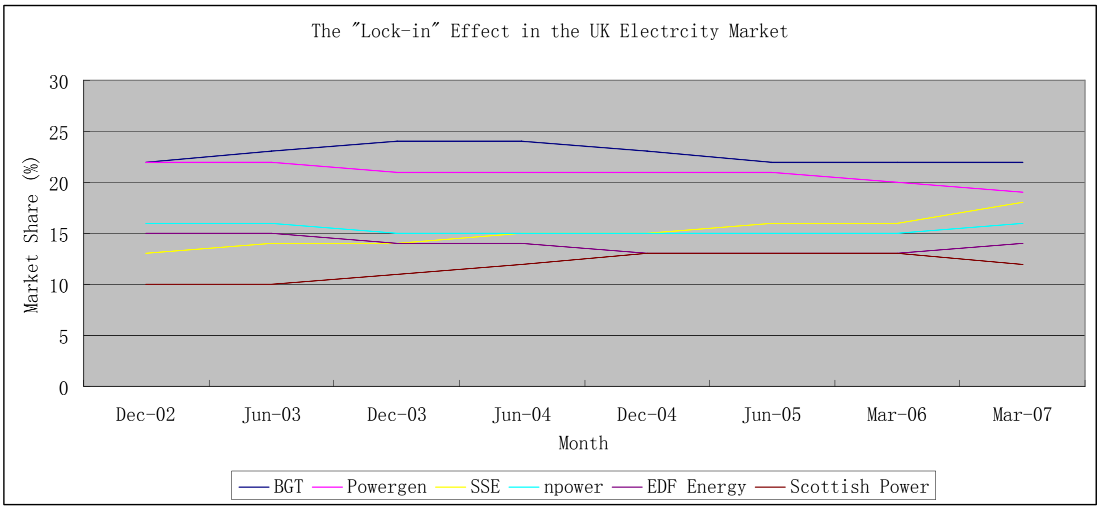

Figure 16: The "Lock-in" Effect in the UK Electricity Market (Data Source: Domestic Retail Market Report, Ofgem, June 2007)

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