Agent-based modelling of customer behaviour in the telecoms and media markets

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Keywords *Modelling, Consumer behaviour, United Kingdom, Telecommunications, Broadcasting*

Abstract *Agent-based modelling is a bottom-up approach to understanding systems which provides a powerful tool for analysing complex, non-linear markets. The method involves creating artificial agents designed to mimic the attributes and behaviours of their real-world counterparts. The system's macro-observable properties emerge as a consequence of these attributes and behaviours and the interactions between them. The simulation output may be potentially used for explanatory, exploratory and predictive purposes. The aim of this paper is to introduce the reader to some of the basic concepts and methods behind agent-based modelling and to present some recent business applications of these tools, including work in the telecoms and media markets.*

1. Introduction

One of the most prominent features of the telecom, IT and media markets over the last ten years has been the tremendous amount of change exhibited across the various dimensions of the markets, including technical, regulatory and demand aspects. More than ever, the famous proclamation of the ancient Greek philosopher Heraclitus is apt – the only constant is change. Moreover, these transformations have not always occurred in a proportionate or linear manner. Discontinuity has characterised many of these changes.

Working in this environment has provided great challenges for analysts and managers alike. And while the traditional statistical and equation-based modelling techniques continue to be powerful tools, in certain markets their appropriateness can be called into question, especially for those markets characterized by non-linearity and complexity. In the past, the high degree of structural stability of the telecommunications market allowed econometricians to make reasonably confident predictions of the demand effect of a small change in price. Markets for new telecommunication products, however, have often proved to be highly non-linear, as witnessed, for example, by the explosive growth of pre-paid mobile services and fixed-rate Internet access. Traditional linear demand equations are not appropriate in such situations.

In this new environment, Beaufort International Ltd (Beaufort) has turned to new concepts and techniques in an attempt to understand these new markets from a different perspective. In particular we have begun to employ agent-based modelling (ABM) techniques as an exciting new approach to modelling customer and market behaviour. Conceptually, this work is partly derived from the new interdisciplinary movement known as the "Science of complexity" (Waldrop, 1994; Lewin, 1999). In the natural, biological and social sciences, complexity ideas are being

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applied to systems that are characterized by non-linearity, self-organization, heterogeneity, adaptation, feedback, and emergent behaviour. Agent-based modelling also draws upon advances in computer science, employing techniques from artificial life, connectionism and evolutionary programming.

The key feature of agent-based modelling is that it involves a bottom-up approach to understanding a system's behaviour. Traditional modelling usually takes a top-down approach in which certain key aggregated variables are observed in the real world and then reconstructed in a model. Under this approach a modeller would observe the effects of say a price change on the number of consumers who purchased a product at an aggregated level. This would provide the basis for quantifying the strength of interaction in the model. The modeller would not be interested in how the behaviour of individuals gives rise to this aggregate result. It is the correlation between aggregated variables that is the focus of interest, not the processes that give rise to the system's behaviour.

In the agent-based approach the focus turns to the properties of the individual agents. The term "agent" in the context of business or economic modelling refers to real world objects such as people or firms. These agents are capable of displaying autonomous behaviour such as reacting to external events as well as initiating activities. Of equal importance is the interaction of these agents with other agents. That is, for example, word of mouth communication can alter a customer's belief about a product. Agent-based models can be made arbitrarily realistic by capturing the process or mechanisms that are believed to be driving the individual components.

With ABM the system's macroscopic, observable properties emerge as a consequence of these attributes, behaviours and the interactions between them. They are thus a powerful complement to top-down modelling, particularly because they allow for the implications of assumptions that are necessarily made in top-down modelling.

The aim of this paper is to elaborate on some of the basic concepts and methods behind agent based modelling and why it may be a useful tool for analysts and decision makers. In section 2 we begin by discussing how ABMs are constructed. Although at this stage there is no standard methodology for building ABM, there are some basic steps involved in the development and use of ABMs. In section 3 we elaborate on some of the strengths of this approach, particularly as compared to more traditional techniques. The weaknesses of the approach are discussed in section 4. In section 5 we turn to the issue of how the agents should be defined. This includes a discussion of a possible cognitive framework. Section 6 provides a brief look at some of the software development tools that are now available to assist in the creation of ABMs. In section 7 we turn our attention to some current commercial applications of ABMs. In section 8 we examine a particular ABM project in which the Beaufort International Ltd is working with the cable operator ntl to develop an ABM of the cable pay-TV subscriber market in the United Kingdom. Section 9 concludes the paper.

2. Building an agent-based model

As indicated in the introduction, the general methodology of creating an agent-based model[1] involves constructing a population of interacting elements or agents. These agents may be people, firms or other objects. The agents interact in some type of environment that may, for example, correspond to a physical or social space.

Agents are designed to mimic their real life counterparts although, as we will see later, different ABMs have different degrees of detail incorporated into the agents. In any case, however, an agent usually consists of:

- Attributes (e.g. age, sex, preferences).
- Behaviours (e.g. actions based on decision making algorithms such a utility maximization).

The attributes and behaviours may not only vary across agents in the model but they may also change within agents during the simulation. For example, an agent-based model may incorporate genetic algorithms or neural nets within the agents which allow the agents to learn throughout the simulation.

Of course, aside from the question of which attributes and behaviours to incorporate into the agents, there is the subsidiary question of how to parameterize these attributes and behaviours. Currently there are two approaches to this issue. One involves using survey data and field research, the other involves making an initial best guess and later calibrating these values by comparing the output of the model with the real world system.

Once the agents are created and parameterised the model can then be run. In agent-based models, time is a discrete variable and in each time-step the agents in the artificial world are programmed to activate their scheduled behaviours (for example, "search for a buyer in the local environment", "update preferences in light of last period's satisfaction'', ''do nothing''). The simulation can run for a set number of iterations or run indefinitely.

During and after the simulation run, output probes can provide information on any particular agent's attributes and behaviours as well as the system's macro-variables. One objective of the simulation is to provide the user with a good idea of how the real system would behave under the conditions portrayed in the model. The simulations of a system offer the model operator a window through which to observe these systems in action under various sets of parameter and variable settings. The effect is similar to a flight simulator – a way to get the feel for how situations develop and important variables interact. The simulation model is thus a laboratory to experiment with various "what-if'' scenarios. You can change various variables including initial conditions, agent behaviours, introduce new types of agents, etc., and follow through the consequences.

When running the model a significant point to remember is that the system's macro behaviour is an emergent feature of the system. When a system displays a particular pattern which is not immediately obvious from the microscopic rules of the system, the behaviour is described as emergent. A graphic example of emergent behaviour is "Boids", a famous simple computer program (often used as a screen saver). This is a simulation of birds in which they have been given three simple rules to control how they interact with each other – essentially collision avoidance rules. At the start of the simulation the birds are given random speeds and directions. However after a few moments the birds begin to fly in a formation that is similar to the flocking formation seen in the real world. The result may seem surprising since this overall behaviour was not explicitly built into the model. By contrast, conventional, top-down, modelling techniques would assume the macroscopic behaviour. The bottom-up, agent-based approach does not make these sorts of assumptions and hence the model can give greater insight, moving away from the problem of just "getting out what you put in".

3. Strengths of agent-based modelling

Compared to most traditional modelling techniques there are a number of advantages of agent-based modelling:

- *System assumptions*. As mentioned above, one of the key strengths of agent-based modelling is that the system as a whole is not constrained to exhibit any particular behaviour (Hood, 1998). In particular, assumptions of linearity and equilibrium are not imposed on the system as they often are in the more common top-down modelling approach. The emergent non-equilibrium, dynamical behaviour of a system is usually one of the most interesting outputs of agent-based models.
- *Realism*. In principle, an ABM can be made arbitrarily "realistic"; after all, the world is indeed made up of interacting entities (Hood, 1998). Similarly, the models can also be arbitrarily abstract (i.e. they can be made caricatures or metaphors for the system of interest). This allows us to undertake qualitative scenario exploration to investigate the structure or morphology of the system independently of the details.
- *Natural representations*. The models are also relatively easy to understand as they have a simple, structural correspondence between the "target system" and the model representation. They are more intuitive and easier to understand than, say, a system of differential equations.
- *Heterogeneity*. ABMs also allow us to introduce a very high degree of heterogeneity (diversity) into our populations of agents. Traditional models – to permit mathematical solutions – often require us to assume homogeneous actors. Indeed, in ABMs it is often the diversity in the attributes and behaviours of the agents that drives the interesting emergent patterns of the systems.
- *Bounded rationality*. There is no need to assume that agents in the model are perfectly rational. Both limited information and limited abilities to process information may be explicitly incorporated into the model. Habit and social imitation may also be included.
- *Communication and social networking*. Another flexible feature of ABMs is their ability explicitly to incorporate communication among agents. Agents can, for example, "talk", share information or imitate other agents in the population. This level of subtlety is usually outside the reach of traditional mathematical models, since social networks quickly make equation-based models so complex as to be insoluble.
- *Object-orientated analysis, design and programming*. Agent-based modelling fits well with the object-orientated analysis, design and programming approaches to business re-engineering, process modelling and software development.
- *Maintenance and refinement*. It is reasonably easy to add new types of agents or new attributes or behaviours of agents without destroying earlier knowledge incorporated into the model.

4. Weaknesses of agent-based modelling

Of course the added flexibility of agent-based modelling does not come without problems and difficulties.

- *Data problems*. One of the most glaring problems of this method is the potential lack of adequate data. This is not surprising since, as mentioned in the introduction, most quantitative research until now has concentrated on "variable and correlation" models that do not cohere well with process-based simulation that is inherent in ABMs. This means that not only is it likely that new types of data are needed to be collected but even theories may need to be recast effectively to take account of the potentialities of agent-based simulation.
- *Identifying rules of behaviours*. Trying to capture the appropriate processes or mechanisms underlying the agents' behaviour may not be an easy task. However, as Hood (1998) points out, the flip side of this is that it forces us to be explicit about our assumptions and forces us to think about extracting the "essence" of the problem.
- *Programming skills*. Any sophisticated, agent-based model requires programming in an object-orientated language such as Java. That is, it requires a level of computing skill beyond simple spreadsheet programming. However, as will be mentioned below, some agent-based software frameworks have been

developed to ease the task of the social scientist or business analyst in building agent-based models.

- *Computational time*. ABMs are computationally intensive, and although it is precisely because of the advances in computing power that we now have the possibility of desk-top agent-based modelling, there are still limits to the level of detail and number of agents that can be run in a simulation in a reasonable amount of time.
- *Unrealistic model expectations*. There is a danger that new users of ABM may expect too much from the model, particularly in regard to predictive ability. Prediction is certainly a possible function of an agent-based model, however it is also certainly the case that many complex adaptive systems exhibit chaos, which make any long-term predictions practically impossible. In these cases, however, an ABM may still provide an important explanatory or exploratory role. For example, by experimenting with the model it may be discovered that under certain conditions the combination of two seemingly unimportant behaviours can sometimes "tip" the system into a different direction – a qualitative system feature that may not have been immediately obvious from examination of the individual behaviours.
- *Lack of prescriptive ability*. In general ABMs provide no mechanism to help us steer or guide the system from one state to another (Hood, 1998). While it is possible to re-run a simulation under differing scenarios in the hope of achieving a specific outcome, there is no simple way to "invert" the model (i.e. to discover what interactions are required for a particular observed property to emerge). ABMs are thus not prescriptive models in the manner that engineering design or some economic models are.

5. Designing an agent

So far we have only alluded to the general flexibility in the design of agents in an ABM. As mentioned in the last section, one of the difficulties of agent-based modelling is capturing the appropriate level of detail of the agents in the simulation. This choice is partly dependent on the system being modelled as well as the type of questions being asked. At one end of the scale, the agents may be very abstract; at the other end we may have agents that have a strong resemblance to real world entities. Hood (1998) has categorized the fidelity of representation into three broad categories:

(1) *Low fidelity*. In this case all the agents in the model have the same behaviour and intrinsic attributes. This situation would not even be categorised as an ABM by many practitioners. It is of interest for problems where the statistics of the collection of entities are of interest. This situation occurs in many physics and chemistry simulations (e.g. the molecular level simulation of material properties or drug design). In these types of model, because of their simpler agent details, usually much larger numbers of agents are employed in the simulations than in a typical ABM. For example, one of the largest astrophysics simulations ever performed consisted of 150 million agents (stellar entities).

(2) *Medium fidelity*. Here an observed distribution of the agents' behaviour is used to "calibrate" the model. This is a very useful middle ground to target for many applications where the tails of a distribution are of interest (e.g. the poorest 10 per cent, the richest 10 per cent). An advantage of working at this level of detail is that it allows ups to capture some of the observed properties of the individual agents without having to resolve the internal workings of the agents (i.e. "what makes them tick").

(3) *High fidelity*. In this case a proper attempt is made to capture the internal workings of the agents. This may include trying to model, among other things, the beliefs, desires and intentions of the agent. At this level of fidelity we may also include an ability of the agent to adapt and learn, such that the agent's behaviours and properties evolve over time as they learn about their environment and what actions lead to success or failure. At this level of fidelity we are thus capturing some notion of a mentalistic or cognitive agent.

While the first two categories of agent representation may be of interest in developing explanatory models of social systems, for the purposes of business applications it is likely that a useful ABM needs to be built on a higher level of representational fidelity.

Of course we are still left with the question of how this representation should be formed, and in approaching this task it is unfortunate that the discipline of psychology does not provide a unified front. There are many behavioural theories that help explain parts of the processes that determine human behaviour. Sometimes we act habitually; sometimes we do private deliberations; sometimes we do things because social norms impel us to act in a certain manner. Up until recently, there has been no convincing attempt to put together a more integrative model that links the various psychological theories together (at least in a form that could be translated into agent-based terms). However, very recently the work of Jager and Janssen (Jager, 2000; Jager *et al*., 2000; Janssen and Jager, 1999) has provided a possible framework. Their "Consumat" approach is a formalization of a meta-model of behaviour, which integrates various theories that are relevant to understanding consumer behaviour.

For the purposes of this paper we will only mention a couple of important aspects of their general model: modes of cognitive processing and the theory of needs and wants.

In presenting their theory of cognitive processing Janssen and Jager (1999) identify two different dimensions. They are reasoned versus automatic processing, and individual versus socially determined processing. For the reasoned versus automatic processing, a key issue is whether the consumption of a certain good or service is highly satisfying (given the resources that we have to spend on it). If it does easily satisfy our needs (or has large consumer surplus, to use an economics term) then we are less likely to bother to think hard about seeking other possibilities (i.e. default to automatic processing). On the individual versus socially determined dimension, the key issue is the level of certainty involved in the consumption. If we are uncertain what exactly we are going to get from a good or service, we are more likely to look around us to see what other people are doing.

Given these two dimensions, Jager and Janssen classify four possible modes of cognitive processing:

(1) *Repetition or habit* (individually determined and automated processing). This mode occurs with those goods for which we have a high degree of satisfaction (there is no urgent need to look around for other satisfiers) and low level of uncertainty (we know what we are going to get when we buy the good). An example would be buying toothpaste. In psychology, classical and operant conditioning are the research areas that study this phenomenon.

(2) *Deliberation* (individually determined and explicit reasoning). This mode is likely in situations where there may be low satisfaction with a good (compared with what we have to give up for it) and, as such, we are prompted to consciously think about what we are actually getting and what the alternatives are. However, with a high level of certainty of outcomes (if we do decide to buy the good we are pretty sure we know how much it is going to satisfy us) we have no need to look at what other people are doing. Classical decision theory in economics, and the theory of planned behaviour in psychology are the research areas that concentrate on this mode of behaviour.

(3) *Imitation* (automated thinking and socially determined). This mode occurs when there is a high level of satisfaction from a good or service but because there is uncertainty about the outcome we automatically follow what others are doing. Social learning theory and the theory of normative conduct in psychology are relevant to this area.

(4) *Social comparison* (explicit reasoning and socially determined). Like imitation, people are again looking around at what others are doing, but here, because of low levels of satisfaction, people are prompted consciously to reason about the consumption decision. In this reasoning process, agents will try to infer some information about the good from the level of interest other agents have for the good.

The papers by Janssen and Jager cited above should be examined to see how these cognitive processes can be quantified in an ABM.

A second aspect of the cognitive agent that is examined by Jager and Janssen is the classification of wants and needs. The classic work in this area is Maslow (1954), who proposed that everyone has a hierarchy of needs, starting with physiological needs such as hunger and thirst, then safety needs, belonging needs, and so on, up to needs of general fulfilment. However Jager and Janssen point to a more recent work by Max-Neef (1992) as a possibly more appropriate classification for agent-based modelling. Max-Neef identifies nine fundamental needs that he claims all people have: subsistence, protection, affection, understanding, participation, leisure, creation, identity and freedom.

We will not elaborate on this classification or whether the breakdown of needs and wants is always appropriate compared with a more simple unitary measure. However, it is interesting to consider how a telecom service such as a mobile phone may relate to these needs. Certainly there may be elements of participation (via connectivity), leisure (games and pleasure talking to friends), identity (mobile phones as a status symbol), freedom and protection (e.g. emergency location finders). For a given modelling task it may be too complex to model such multiple needs but there could also be occasion where interesting system behaviours emerge from the distribution of these needs as they relate to, say, demographics, with implications for market targeting and diffusion in sectors.

These ideas of Jager and Janssen are offered here to present a flavour of the generality and flexibility available in modelling the attributes and behaviours of agents. Undoubtedly, as agent-based modelling becomes more popular, new frameworks and techniques will be developed.

6. Software development tools

Business analysts and managers are not computer programmers. However, an ABM of any serious detail cannot be modelled on a spreadsheet – the typical tool used by analysts and managers. As such, one of the inhibitors of the popularisation of agent-based modelling has been the high level of computing skills required in the software development of an ABM. This problem is being alleviated as generalized agent development tools become more readily available.

One of the most popular frameworks, around which there is a growing community, is Swarm, developed at the Santa Fe Institute – a highly regarded centre of complexity science research. Swarm is a system of software libraries developed by a team led by Chris Langton (the founder of artificial life). It was the first real attempt to produce a general ABM toolkit that can be used for a wide variety of modelling experiments.

Swarm is freely available under the terms of the GNU licence and offers a wide spectrum of tools combined with a kernel that drives the simulation. Researchers are free to customise the general-purpose objects of Swarm to model systems of interest (Swarm is object oriented, and so customisation of these objects is relatively easy). Swarm provides objects for discrete, two-dimensional lattices, arbitrary graphs, many analysis tools (histograms, graphs, the ability to probe an individual agent), the ability to nest objects (swarms of swarms) and a very general method for scheduling events in the simulation. Already Swarm has been used in many application areas, including economics, ecosystems, and anthropology[2].

However Swarm still requires the modeller to know Java or the Objective-C programming language. Although Java is a very popular language it still requires some investment of learning. In response, at least two institutes have created a simpler higher-level language for agent-based modelling. These are MAML (Multi-Agent Modelling Language), developed at the Central European University Systems Laboratory (www.syslab.ceu.hu/maml/maml.html), and Ascape, developed at the Brookings Institute (www.brook.edu/es/dynamics/models/ascape/ReadMe.html)[3].

7. Applications of agent-based models

ABM is a novel technique and we are still in the very early days of its development. Many of the models that have been developed so far have been of a more academic nature, focusing on the explanatory role of ABMs. Nevertheless there have been some recent applications of ABMs for commercial purposes. We will briefly look at four examples here[4].

Shopping stores

As application of an ABM where the interactive environment is a physical space is SimStore developed by Ugur Bilge of SimWorld, Ltd, Mark Venables of J. Sainsbury in London, and the complexity scientist John Casti (Casti, 1999; Venables and Bilge, 1998). SimStore is a simulation model based on a real British supermarket – the Sainsbury's store at South Ruislip in West London. In this simulation, agents are provided with shopping lists derived from real-world data and make their way round the store, picking products off the shelves according to rules such as: "Wherever you are now, go to the location of the nearest item on your shopping list" and "act to avoid congestion". Using these rules, SimStore generates the paths taken by customers, from which it can calculate customer densities at each location.

By analysing the paths taken by the agents in the store the model can identify the most popular paths used by the customers. Then by using optimising techniques such a genetic algorithms, the location of where the products are stacked in the store can be changed so as to minimise, or maximise, the length of the average shopping path. Minimizing paths is obviously to the convenience of shoppers who wish to get their shopping done quickly. Maximizing paths, however, can benefit the store sales by increasing the opportunity for more impulse buying. The ABM provides a powerful tool to explore this trade-off. Among other uses, the creators of this model hope it will provide unexpected insights into the dynamics of activities like customer behaviour in stores, patterns of customer demand, and be useful in redesigning stores so as to generate greater customer throughput, reduce inventories, and shorten the time that products are on the shelves.

Consumer apparel market

An interesting ABM in a clearly fashion driven market is the research of Evelyn Brannon and her colleagues at Auburn University who are building an agent-based simulation of the consumer apparel and textile market (Brannon, 2000). Their ABM, called InfoSUMERS, models the interaction between external influences (advertising, promotion, and product placement in media) and personal influences (social communication), and between fashion leaders and fashion followers. The agents in the model are adaptive and the effects of external influences both diffuse and evaporate.

At the beginning of a simulation, parameters can be set for the rate of diffusion and evaporation of the external influences, the number of each kind of agent, and the number and kind of fashion looks available for adoption. Each agent evaluates the situation and determines the action at each time step according to its individual rule set. The rule sets include probability functions so that each decision is unique and adaptive. During each run of the simulation, data are gathered at each time step on the agents' segmentation and their adoption profile. Validation procedures for the simulation include comparing the results from the simulation with published results from studies of diffusion of innovation. Sensitivity analysis is used to determine the relative importance of the assumptions underlying the simulation. When fully implemented InfoSUMERS will be used to perform computer experiments to investigate differences in patterns of diffusion among various consumer segments.

Currently experiments are being run with InfoSUMERS to investigate two issues: the effect of competitive activity and the effect of marketing expenditures on diffusion patterns. By setting the parameters for diffusion and evaporation in the simulation space and the rule sets for three categories of agents – change agents, fashion leaders, and fashion followers – the researchers are investigating various scenarios and aim to determine the factors that bolster or impede diffusion to the population of agents.

Japanese CD sales market

Another example of agent-based modelling in a fad or fashion driven market is the work of Hakuhodo Inc. and Pricewaterhouse Coopers. They developed an ABM to predict CD sales in the Japanese pop (J-Pop) market (Makoto, 2000). As they point out, the J-Pop market is a very difficult market to predict sales for because of the short life cycles, skewed distribution of sales, strong emotional element in choice, and the importance of peer pressure. Standard linear models cannot predict behaviour in such markets.

In developing their model agents were constructed using data on demographics, preferences and social connectivity of J-Pop buyers. Input (predictor) variables included: artist characteristics (product), exposure to TV advertising and tie-in program (promotion), and retailer expectations (place). In the model the synthetic consumers were exposed to TV advertising and program, radio airplay and retail promotion, and then formed perceptions toward a certain CD. In addition each agent belonged to a network of friends, whom she/he trusts and vice versa, regarding choices of music. Word of mouth thus flowed through these networks, further affecting the agent's purchasing decision.

The model was created with 75,000 agents using a mainframe computer. The model was calibrated using 135 single CDs released from 1998/4 to 1999/3. The results of the model were quite impressive, with correlation coefficients between actual and predicted sales ranging from 0.8 to 0.9 for forecasts performed one week before.

The model is a particularly good example of an attempt to explicitly model consumer interaction via word of mouth. Recent marketing literature has identified the importance of word of mouth in spreading ideas and information across a population. These include Cadwell (2000), Farrell (2000), Rosen (2000) and Godin (2000). ABM would appear to be a powerful tool to formalize this important aspect of consumer behaviour.

Telecommunication services diffusion

Another interesting area of agent-based modelling research that hinges on the importance of social networking has been undertaken by BT Laboratories. David Collings and his team have been using agent-based models to study the rate of adoption of telecommunications services (Collings *et al*., 1999). In conventional modelling of the diffusion process, there is no way to describe how the microscopic attributes of the members of the social system give rise to the observed rate, extent or order of the diffusion process. A particular issue explicitly examined by Collings and his colleagues in their model is how customers interact to learn about a service through their communications with other customers. Using agent parameters based on real field data, they show how the different structure, dynamics, and distribution of social networks affect the diffusion of a service through a customer population. Their model shows how the real world adoption rates of a telecommunication service are a combination of these mechanisms which interact in a non-linear and complex manner. They argue that the complex systems approach provides a very useful way to decompose these interactions.

8. Pay-TV subscriber model

In 2001 ntl, the UK's largest cable television operator, asked Beaufort to build an ABM of the potential pay-TV subscriber market in the UK. The objective was to have a scenario tool that can be used to investigate various questions relating to possible changes in regulatory and other market conditions. The cable TV market has changed dramatically over the last few years and it was reasoned that traditional econometric techniques relating to aggregate long-term price elasticities and package-size elasticities would be very difficult to measure and be of dubious value. This is especially so given that, unlike the USA, there are very few cable operators in the UK, preventing any possibility of cross-sectional analysis across cable companies.

The approach that Beaufort has adopted is to begin with a very simple model of subscriber behaviour and, as confidence in the model is built up, the model can be extended to include more sophisticated behaviours. As mentioned earlier, one of the advantages of agent-based modelling is the relative ease with which the model can be extended and refined. Currently the attributes of the model agents (which include channel preferences, age, sex, marital status and social grade) have been constructed from monthly survey data of existing and potential subscribers. In particular certain questions in the survey have been used to identify the strength of channel preferences for each agent (a relative utility measure). The survey information has also been used to create a measure of dissatisfaction that consumers have in being required to purchase channels (as part of a package) that they do not watch.

So far a simple decision-making algorithm is being used by the agents in the model, involving the aggregation of utilities offered by the package of channels and comparing it with the price. Around this set of first-approximation assumptions we have built a scenario analysis tool for studying the impact on demand behaviour from price changes, package-content changes and package-size changes. The ABM is being used to study the relative effects on demand of these changes, particularly as they may relate to potential new "must carry" rules. We are currently working on calibrating the model and are looking to introduce more sophisticated behavioural assumptions into the model such as inertia in consumer behaviour, word-of-mouth effects, and marketing influences on subscriber behaviour. As mentioned before, a strength of these models is their scalability and ability to be refined with relative ease.

9. Conclusion

Practical, large-scale, agent-based simulations of the type discussed in this paper are in their infancy. But even the preliminary work outlined here shows the great promise of using the ideas of complexity science along with modern computing technology to provide a complementary basis for analyzing rapidly changing markets such as the telecom, Internet and media markets. The positive response from early users of these technologies indicates that these first steps hold great promise that agent-based modeling may one day become a standard technique of business analysis, particularly in emerging and rapidly changing markets. ■

Notes

1 There are a growing number of interesting Web sites devoted to agent-based modelling and complex adaptive systems which the reader is invited to explore to gain a more in-depth understanding of agent-based modelling. Seven sites especially worth browsing are:

- Agent-Based Computational Economics (ACE) http://www.econ.iastate.edu/tesfatsi/ace.htm
- Individual Based Models by Chris Reynolds, http://www.red3d.com/cwr/ibm.html
- Journal of Artificial Societies and Social Simulations, http://jass.soc.surrey.ac.uk/JASSS.html
- Complexity in Social Science, http://www.irit.fr/COSI/index.php
- Simulation for Social Scientists, http://www.uni-koblenz.de/~kgt/Learn/Textbook/NewBook.html
- Centre for Policy Modelling, http://www.cpm.mmu.ac.uk/
- Centre for Research on Simulation in the Social Sciences, http://www.soc.surrey.ac.uk/research/simsoc/simsoc.html

2 See the Swarm Web page – www.swarm.org – for more information about the projects that have been developed using this framework.

3 For more references to available software for agent-based modelling see Leigh Tesfatsion's link page: www.econ.iastate.edu/tesfatsi/acecode.htm

4 Some other agent-based modelling references not discussed here include: Nagenda-Prasad and Chartier (2000) who discuss the use of agent-based models in understanding organizational dynamics; Bunn and Oliveria (2000) who develop an ABM of the new electricity trading arrangements in England and Wales; and LeBarron (1999), who discusses a number of recent papers on artificial financial markets.

References

Brannon, E. (2000), "Agent-based simulation of the consumer's apparel purchase decision", research proposal available at www.humsci.auburn.edu/ca/research/ntc/00_agent_based.pdf

Bunn, D. and Oliveria, F. (1999), "An application of agent-based simulation to the new electricity trading arrangements of England and Wales", *IEEE Transactions on Evolutionary Computation, Special Issue on Evolutionary Modelling of Economic Systems*.

Cadwell, M. (2000), *The Tipping Point*, Little, Brown & Company, New York, NY.

Casti, J. (1999), "Firm forecast", *New Scientist*, 24 April.

Collings, D. *et al.* (1999), "Agent based customer modelling", *Computing in Economics and Finance*, Society for Computational Economics, No. 1352.

Farrell, W. (2000), *How Hits Happen*, Texere Publishing, Chicago, IL.

Godin, S. (2000), *Unleashing the Ideavirus*, Do You Zoom, London.

Hood, L. (1998), "Agent based modelling", available at www.brs.gov.au/social_sciences/kyoto/hood2.html

Jager, W. (2000), *Modelling Consumer Behaviour*, doctoral thesis, Centre for Environmental and Traffic Psychology, University of Groningen, Groningen.

Jager, W., Janssen, M.A, De Vries, H.J.M., De Greef, J. and Vlek, C.A.J. (2000), "Behaviour in commons dilemmas: Homo Economicus and Homo Psychologicus in an ecological-economic model", *Ecological Economics*, Vol. 35, pp. 357-80.

Janssen, M. and Jager, W. (1999), "An integrated approach to simulating behavioural processes: a case study of the lock-in of consumption patterns", *Journal of Artificial Societies and Social Simulation*, Vol. 2 No. 2.

LeBarron, B. (1999), "Building financial markets with artificial agents: desired goals, and present techniques", in Karakoulas, G. (Ed.), *Computational Markets*, MIT Press, Cambridge, MA.

Lewin, R. (1999), *Complexity: Life at the Edge of Chaos*, University of Chicago Press, Chicago, IL.

Makoto, M. (2000), "Forecasting hits in the J-Pop market: a practical application of multi-agent simulation in Japan", *SFI Business Network: Tutorial on Complexity and Agent Based Modeling*, (2000/1/25), available at: www.comdig.de/ComDig00-03/JPOP-summary-E.htm

Maslow, A. (1954), *Motivation and Personality*, Harper, New York, NY.

Max-Neef, M.A. (1992), *Development and Human Needs. Real Life Economics: Understanding Wealth Creation*, Ekins, P. and Max-Neef, M. (Eds), Routledge, London, pp. 197-214.

Nagenda-Prasad, M.V. and Chartier, D. (2000), "Modeling organizations using agent based simulations", available at: citeseer.nj.nec.com/261838.html

Rosen, E. (2000), *Anatomy of Buzz*, Harper Collins Business, New York, NY.

Venables, M. and Bilge, U. (1998), "Complex adaptive modelling at J Sainsbury: the SimStore supermarket supply chain experiment", *The LSE Strategy & Complexity Seminar*, 30 March, available at: www.lse.ac.uk/LSE/COMPLEX/Seminars/1998/report98mar.htm

Waldrop, M. (1994), *Complexity*, Penguin Books, New York, NY.

Further reading

Axtell, R. and Epstein, J. (1996), *Growing Artificial Societies – Social Science from the Bottom Up*, MIT Press, New York, NY.

Terna, P. (1998), "Simulation tools for social scientists: building agent based models with SWARM", *Journal of Artificial Societies and Social Simulation*, Vol. 1 No. 2.