Exploring innovation networks: two simulations, two perspectives and the mechanisms that drive innovation performance

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Abstract

Business networks are complex systems, made up of interdependent organisations whose managers are each trying to accomplish their own goals whilst simultaneously responding to the actions of others. Understanding the complex interactions that occur within networks requires perspectives that consider whole systems and the complex interdependencies that exist between its parts. Case research methodologies provide the requisite rich perspectives and have been crucial in developing our understanding of business networks. In this paper we show how simulation can be used to complement case-based research to enrich our understanding of the market forms. We develop competing simulations of a prototypical innovation network using two different modelling approaches. We then use these simulations to show how actors' choices impact the distribution of resources within the network and which subsequently produce variations in the innovative performance of the network. In doing this we are able to provide a unique perspective on the mechanisms that produce different network eventualities (i.e. innovation network success and failure).

The alternative simulation approaches we used consider this same phenomenon from two quite different standpoints. First, we develop the theoretical evidence supporting a simple "prototypical" innovation network and the mechanisms that drive it and we explore this network using fuzzy set theory. The model shows how network links, bonds and ties impact on innovation performance, but from a macro system wide orientation. In the competing model we use an agent-based approach (in Netlogo) to reproduce a similar innovation network. But with this approach it is possible to consider the impact on performance for individual actors as well as the overall network. We argue that there are deep mechanisms in innovation networks which drive their performance and that these consistently emerge despite the different simulation strategies and their perspective/frame of reference.

This work has implications for researchers, managers and public policy makers. We suggest that there are specific simple mechanisms that impact on the effectiveness business in developing and commercialising new technologies. Thus we argue that more effective targeting of government funding initiatives can be achieved by considering these mechanisms, furthermore that managers can achieve some degree of independence within the network by developing an understanding of these mechanisms.

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Introduction

Business networks are complex systems, made up of interdependent organisations whose managers are each trying to accomplish their own goals whilst simultaneously responding to the actions of others. Understanding these complex arrays of interactions requires perspectives that consider whole systems and the complex interdependencies that exist between its parts. Thus, simple models that amalgamate all interactions between variables into a single path, rather than reflect numerous individual interactions over multiple time periods, falls far short of providing an adequate explanation of these markets. Case research approaches that employ a range of alternative methodologies and longitudinal data reference frames have been crucial in developing our understanding of business networks. Yet, along with the promise of richer perspectives these approaches offer challenges to the researcher. It is difficult to secure participant cooperation; and integrating and making sense of diverse types of information collect by often radically different methods is problematic. Case research also tends to focus on a small number of actors within the wider network.

This paper attempts to address this problem by considering how simulation can be used to complement case-based research to enrich our understanding on the emergence of different market forms. Simulation offers another way of understanding markets and networks which though necessarily reductionist captures the dynamic and emergent characteristics of complex systems (Maguire et al., 2006). In particular, simulation allows for the investigation of multiple interactions over many time periods, giving the researcher an insight into market emergence and dynamics. Simulation also allows researchers to "vary" conditions and observe possible patterns of outcomes given different market inputs. Other strengths in considering simulation methods as an alternative to traditional research methods for investigating markets will be discussed throughout the paper.

We argue that simulation models can demonstrate deep mechanisms that drive market performance and that these mechanisms consistently emerge despite the different simulation strategies and their perspective/frame of reference. This issue is explored through the results of a simple simulation model that has been developed. We conclude by reflecting on the role that simulation plays in complementing case-based methodologies and the particular insights that emerge from simulation that would not otherwise be identified.

What are markets?

Our perspective is that markets are constructed from the sense-making of the managers operating within them (Ellis et al., 2006). Managers, through their interactions, develop an understanding of "their" market from the language and practices they experience through their interactions. Every actor operates in a "different" market due to individual variation in sense-making and that every actor experiences a unique set of interactions. This concept of markets is similar to performative markets outlined by Araujo et al., (2008), in that markets are ever changing and not static. Our conceptual market encompasses both calculative (knowledge relevance & finance) and social embeddness (relational strength) aspects within each individual actor.

For this research it is important to note that markets are formed through multiple interactions and that there are many possible outcomes for market formation due to the complex multiple interactions occurring. Market emergence, what types of markets emerge and how do different combinations of variables affect market emergence is the focus of the simulation outlined in this paper.

Market emergence

Business networks have been considered from various perspectives and have been the focus of considerable scrutiny since the early 1980's. Despite this there are many unanswered questions about the way these networks function, dynamics involved in network changes and the constant evolution of markets. As we have noted all business networks, are complex systems and are characterised by:

- disequilibrium (never reaching optimally stable condition);
- non-linearity (interactions are more than the sum of the whole and emergence);
- sensitive dependence on initial conditions (butterfly effect);
- emergent patterns at the global level cannot be predicted from properties of the parts (whole is more than the sum);
- parts themselves (ie strategic nets etc) are complex adaptive systems;
- boundaries delimited by the research position, perspective & purpose; and
- behavioural patterns may be constant but there are many paths to numerous possible states (Mitleton-Kelly, 2003; Maguire et al., 2006).

Previous research has highlighted that all of these principles are evident in business networks (Håkansson & Ford 2002, Ritter *et. al.* 2004, Wilkinson & Young 2005). Interested readers are referred to Mitleton-Kelly (2003) or Maguire et al., (2006) for discussion of the application of complexity principles to organisational studies.

Understanding complex behaviour requires a specific way of viewing reality, and this perspective differs from the deterministic paradigm that is evident in most of the current research (Mateos de Cabo et al., 2002). But, complexity isn't a single theory; it consists of a number of theories that have emerged from the natural sciences (Mitleton-Kelly, 2003; Lissack, 1999; Maguire et al., 2006). So, by its very nature, complexity is difficult to examine and requires multiple approaches to the problem, similar to the interplay outlined by Schultz and Hatch (1996).

In contrast, the epistemological approaches that are often used in marketing and business research make deterministic presumptions of stability, additivity (properties add to each other in a linear way) or at least multiplicity, and a principle of strong causation (predictability). The frequently employed structural equation modelling (SEM) approaches are aimed at developing a single picture of the world and they assume linearity and a stable equilibrium. While these approaches offer limited help to researchers and mangers they do not deal with complexity. These models cannot be used in changing and turbulent business environments where organisations need models to better help them understand different scenarios and strategies to cope with future unforeseen changes (Robertson, 2003). Practitioners are now demanding that complexity be incorporated in all of their strategic and tactical development (Bryan and Joyce, 2007; Heywood, Spungin and Turbull, 2007), thus requiring researchers to also incorporate complexity in their philosophical approach to research.

Interpretive methods such as case studies, discourse analysis and action research enable researchers to describe emergence and interactions pertaining to complex systems (Maguire, et al., 2006). For example, Mitleton-Kelly (2003) investigated complex behaviour through case analysis within the banking industry. Emerging interpretative approaches, such as discourse analysis, also offer opportunities for considering complex behaviour (e.g. Ellis, et al., 2006). The IMP group have embraced these approaches and they have informed much of our current understanding of networks (Håkansson & Ford 2002, Ritter *et. al.* 2004) and innovation networks in particular (Möller & Svahn 2003, Möller & Svahn 2005, Möller *et. al.* 2005). However, incorporating complexity into business network research is not without its problems. We note that despite the use of these techniques much of the extant research fails to employ rigorous case methodology (as discussed in Welch, Plakoyiannaki and Piekkari (2007)) a corollary of which is its failure to properly address complexity. Nevertheless, when used by complexity researchers, these qualitative approaches do give rich

descriptions of complex behaviour.

Despite its mystic persona, simulation is a process in which most people have engaged: we simulate real-world situations through theatre and movies, children simulate life through games, stories simulate the imagination of the authors and readers, teachers simulate real-world situations through role playing, while computer modelling simulates the interactions in the phenomena under investigation. Computer simulation is a process of developing rules that model interactions between actors and allows researchers to learn about the interactions in their systems. Simulation is being increasingly used to examine network problems. For example, agent-based models have been used to investigate banking (Roberson, 2003), and Norwegian and Icelandic fishing networks (Følgesvold and Prenkert, 2007). In other work, Purchase *et al.* (2007) examine innovation networks using simulation and fuzzy set theory. Simulation provides an alternative way of understanding complex systems because it attempts to imitate real-world systems (Banks, 1998), dealing with emergence, non-linearity and unpredictability (Maguire et al., 2006; Lissack, 1999).

This paper highlights the use of simulation which we feel is suitable for investigating markets where multiple interactions take place. To highlight the contribution simulation methods can make to the investigation of markets we highlight an example of a simulation conducted on a simple network. This example is reductionist to ensure simplicity. But this simple network does not limit our argument that simulation methods can contribute to the investigation of markets.

Research Context

A central concern in network research pertains to the capacity of the network (and innovating businesses) to successfully develop and commercialised new technologies and processes. The extant literature has shown that relational governance (Ferguson *et. al.* 2005, Rickne 2006) and the network capabilities of managers are significant factors in innovation "success" (Möller *et. al.* 2005). In other work the structures of networked 'organisations' have been identified as crucial in navigating start-up, growth and commercialisation of innovations (Elfring & Halsink 2003). The work reported here investigates how actors' choices impact the distribution of resources within the network and subsequently produce variations in the innovative performance of the network. In doing this we are able to provide a unique perspective on the mechanisms that produce different market eventualities (i.e. market success and failure).

We begin by considering a prototypical innovation network comprising three types of actors; venture capitalists (VC), manufacturers (M), and research and development organizations (R&D). Each actor exists in various proportions in the prototypical network and are assumed to be sufficiently familiar with each other to develop resource links/ties – for two different types of resources, knowledge and financial resources. Each of the different actors has different levels of resources; each according to their operation: VCs are assumed to have high levels of financial resources and low levels of innovation knowledge, while R&Ds have high levels of innovation knowledge, but lack financial resources. Manufacturers are assumed to have low to moderate levels of both types of resources.

The nature and strength of the ties/relationships is assumed to affect the exchange and creation (and sometimes the reduction) of resources. We assume that when actors are strongly connected to each other (close ties and trustful relations) and when knowledge resources have high relevance, there will be growth in both financial and knowledge resources within the network. Conversely, when a lack of social capital exists between actors or knowledge relevance is low there will be no fertile ground for growth within the innovation network. Rule development was based on the following literature:
- The report "Innovation in Australian Business" (ABS 2005) identifies a further broad group of actors who may be involved in innovation relationships including customers and

suppliers.

- Market performance measurement are based on established rubrics around changes in financial and knowledge resources (see for example Cowan & Jonard 2004, Nielsen 2007, Short *et. al.* 2007).
- Generally, strong relationships are necessary for the co-production of tacit knowledge (Augier & Vendelø 1999) and strong relationship are required for learning and such learning has as significant positive association with performance (Powell *et. al.* 1996, Selnes & Sallis 2003).
- Literatures clearly establish the significance for knowledge creation as the sharing of information and knowledge (Nonaka 1994, Nonaka *et. al.* 2000, Pittaway *et. al.* 2004). Knowledge exchanges have also been found to have significant positive implications for financial performance (Ferguson *et. al.* 2005)

The main parts prototypical innovation network, which were used in the simulation (input control variables), are described below:

1. Proportion of different actors.

2. Resources with the system (amount of knowledge and financial resource within the overall network). For the purpose of the simulation knowledge and financial resources have a one-to-one exchange value.

3. Relevance of knowledge resource exchange – this captures the "usefulness of knowledge in decision making within the innovation process" acting as a catalyst for increase or reduction of innovation.

4. Knowledge decay describes the perishability of knowledge – more relevant knowledge decays quickly while less relevant knowledge decays more slowly. NB: Financial resources are not perishable)

5. Relational strength – reflects the closeness of the ties between actors, this may be conceptualised as trust or as a cumulative measure of the relational ties, bonds and links between actors of different types.

Simulation Methods

The two approaches we use for modelling address some of the constraints and issues associated with complex systems/ problems. They are fundamentally different from the traditional approaches; the truth values we manipulate and interpret differ depending on the technique we apply, the mechanisms for illustrating/describing changes/processes vary, as well as the way we represent/acknowledge "ignorance" on the representation of the system and its inherent ambiguities. Fuzzy logic is an alternative for some kind of uncertain knowledge ("What is a strong tie between two firms"?, "What role(s) is the firm adopting in its relationships with other firms in the industry, its clients, supplier/customers?") and the main motivation is to represent qualitative propositions, beliefs that do not have an equivalent in classical models. On the other hand, the agent-based model provides the interaction between firms at the dyadic level, showing conditions that create the premise of innovation creation. We will now outline each approach and conclude by summarising the differences between them.

Fuzzy Set Theory

In classical set theory an object is either in the set or it is not. That is, an organisation is either an R&D firm or it is not. In contrast fuzzy set theory defines membership (of the set R&D firms) as a

probability distribution (Zadeh 1965). In practical terms this means that an organisation might have attributes that were typical of an R&D firm while simultaneously having attributes that are more characteristic of a manufacturer (in the terms of our prototypical network described above). Thus fuzzy set theory is particularly useful when the phenomena under investigation are ambiguous and imprecise (Ragin and Pennings, 2005), as is the case in innovation networks (indeed any networks).

Simulation using fuzzy set theory can be used to 'model complex and diverse constellations of case aspects and to assess set-theoretic relations' (Ragin and Pennings, 2005, p. 425). That is, it allows the researcher to develop logic based rules to guide the simulation from empirical case based research and theory despite the uncertainty and vagueness of natural language (Nguyen & Walker 2000; Ragin and Pennings, 2005; Hage 2007).

Simulation using fuzzy set theory can also be easily applied when the relationships and connectivity between the phenomena are non-linear. This is a particular benefit in most social research as the phenomena of interest are hardly ever linear. Finally and by no means least, using fuzzy set theory is easy—it doesn't require in-depth technical knowledge (Hage 2007).

When taken together simulation using fuzzy set theory enables an holistic analysis of complex cases—it enables researchers to model behaviours in ways that are typical of "real" firms. In these simulations actors sometimes perform particular behaviours and at other times they do not, even in contextually similar situation. Although this approach has been used in business research context (see for example Denize et al. (2007); Kvist (2007) and Hage (2007)) it is rather new and not yet well established. For a more detailed discussion on fuzzy set theory please see Purchase et al. (2007).

Agent-based modelling

Agent based modelling is considered the 3rd way of science (Bonabeau 2002). It has been used to investigate phenomena that are dynamic and require researchers to consider change as an important aspect of their model. This approach to simulation offers the researcher a number of advantages: its ability to model non-linear relationships between heterogeneous agents (Tay and Lusch, 2005), analyse multi-dimensional phenomena including feedback relations, to include asymmetry of relationships between agents; handle bounded rationality and incremental learning (Axtell, 2000; Edmonds and Moss, 1999; Kiel, 2005); conduct sensitivity analysis of initial conditions; investigate extreme events (Axtell, 2000). A more detailed discussion of these benefits is provided in Purchase and Olaru (2006).

Agent based modelling is the most natural technique for describing and simulating a system composed of behavioural entities (Axtell, 2000; Bonabeau, 2002). This is because it allows unanticipated, "enigmatic" behaviours to emerge (Bertels and Boman, 2001; Macy and Willer, 2002) and has a result the simulation exhibits complex behaviour patterns offering valuable information about the dynamics of the real-world system that it emulates.

There are four key assumptions outlined by Macy and Willer (2002, p. 146) that are important to consider. Agents are (i) autonomous, (ii) interdependent, (iii) follow simple rules and are (iv) adaptive and backward-looking. The first three of these assumptions are common to both fuzzy set theory and agent based simulations. Of particular importance for this paper is that agent based models are adaptive and backward-looking. This means that the previous time-period affects how the rules operate in the next time period. When researchers are interested in the dynamic properties of networks, agent based models are particularly useful. However, like fuzzy set theory, agent-based models are yet to be established as mainstream approaches for considering business networks. Notable exceptions include the work of Tay and Lusch, (2005), Robertson, (2003); Ladley et al. (2007); Kirman and Vriend (2001); and Følgesvold and Prenkert (2007).

In summary, in both models we aimed to measure the growth / decay of total network resources, in

particularly financial resources and knowledge resources. The starting values for each input variable were randomly generated and the rules system was constant in each model, and in both cases features of the model allow for emergent behaviour to occur. But there were differences between the two simulation approaches.

Fuzzy set theory allowed for multiple truths, that is, actors can differ in how they perceive the same situation and the membership functions reflect this. For example for one actor can consider relationship strength to be high while at the same time another actor might consider the level medium. Further, the agent based model presented here allowed the rules to spark over three time periods, suggesting that the adaptive and backward looking aspects of these models may come into play.

The following table summarises the main differences between the two simulation approaches.

Table 1: Model Comparison

Fuzzy rule based model	Agent-based model
Capture uncertainty in fuzzy sets (the main difference between approaches)	Simulate and see changes for manipulated inputs
Enables reasoning with vague information	Uses Boolean logic
View of the network from the perspective of a type of actor (mesoscopic to macroscopic level)	Microscopic view identifying each actor and tracing its behaviour; fully observable behaviour of any (autonomous agent) in their competitive and cooperative actions
Middle-up approach to derive knowledge for the behaviour of the whole network	Bottom-up approach to summarise the emergent behaviour
More than one situation (as described by the IF-THEN rules) are simultaneously active, with different outcomes (fuzzy inference)	Only one IF-THEN rule applies in the "crisp" model
Results aggregated at the network level by type of actor	Results provided for each agent, then aggregated at any level depending on the research interest

As set out in Table 1 (and above) the main difference between the models is the ability of fuzzy set theory to capture uncertainty and ambiguity in concepts such as relational strength and relevance of information. The main advantage of agent based modelling is the ability to provide results for each individual (atomic perspective) and to include learning algorithms and feedback. Although it is possible to do so, the learning/reasoning and feedback loops however have not been incorporated into this stage of our agent-based model.

Methodology

The fuzzy model was built using CubiCalc software (HyperLogic 1990-1996)) and the agent-based model was developed in NetLogo (Wilensky 1999). The same assumptions were applied in both models. Both simulation models show the magnitude of resources in the network after simulation compared to the level of resources at the beginning of the simulation. The agent-based simulation complements and validates the findings of fuzzy modelling by replicating the fuzzy reasoning. As the fuzziness cannot be incorporated, our closest approach is to manipulate input elements and investigate their impact on the set of actors. We ran for several hundred times the models to simulate

as many scenarios as possible (including extreme situations) and trace the actors to see how they performed in the network.

By way of illustration we provide the graphical user interface for the agent-based model. Figures 1, 2 and 3 illustrate this interface.
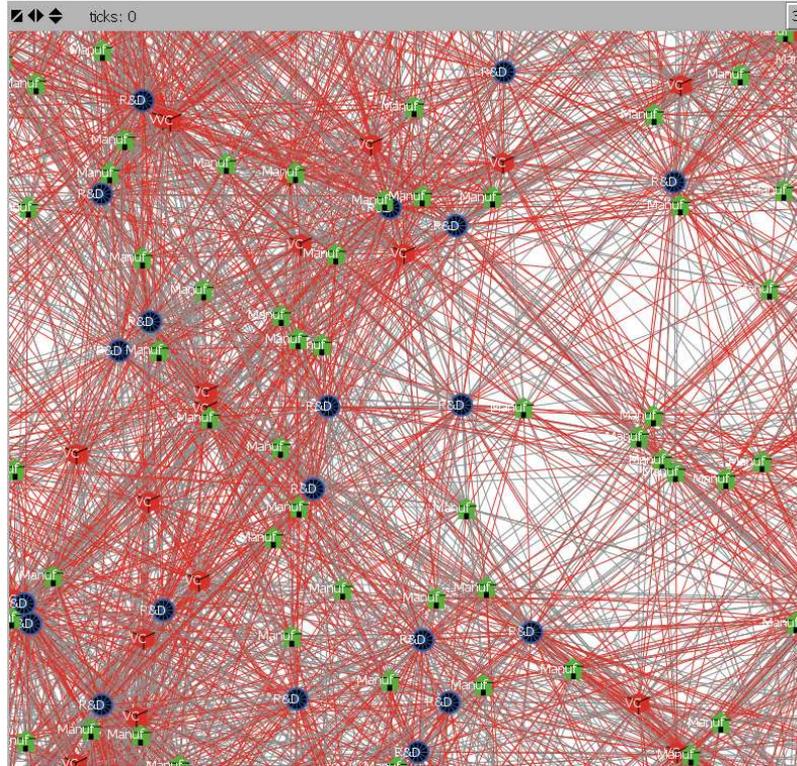
Figure 1: Setup of the agent-based model

Figure 1 shows the prototypical network where 100 actors (in red – VCs, in blue - R&Ds, and in green – Ms) are randomly generated for a network with different resource ties.

Figure 2 (see over page) shows how ties and resources of the actors exchange and modify depending on the context and the interaction between actors. The distance between actors' change as the simulation progresses reflecting how their relationships become stronger or otherwise, modifying the configuration of the network as well. Clearly, one of the benefits of ABM is the high resolution view of the world, where each actor can be seen in its interactions. Figure 3 (see below) traces over time the amount of resources in the network using the agent based model.

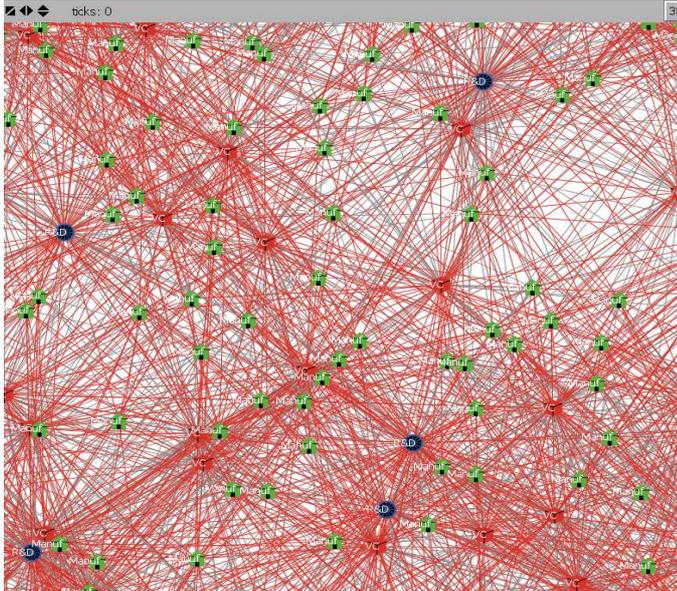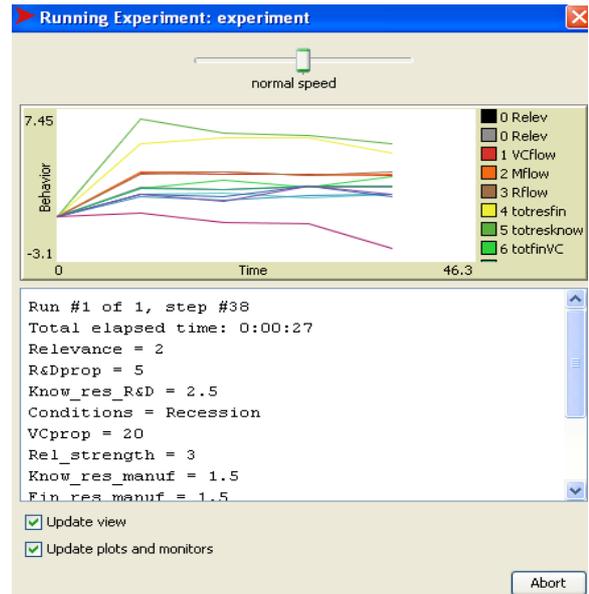Figure 2: Links between actors (simulation end)   Figure 3: Change in resources over time

The fuzzy set theory approach uses a different graphical interface and method for generating the data (i.e. inputs and changes in network configuration are not visual).

Figure 4 a) and b) (below) shows graphically the changes in the overall network resources in the fuzzy model (a) and in the agent-based model (b).

Figure 4: Changes in the network resources a) fuzzy model and b) agent-based model

a)   **b)**
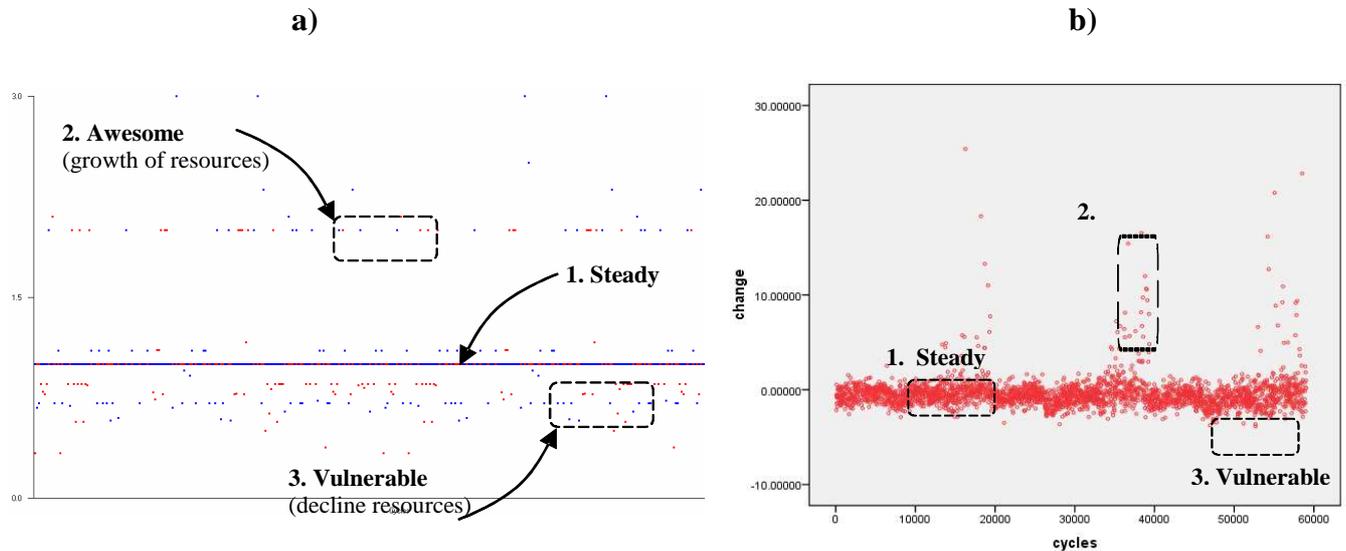
Results

We performed hundreds of simulations with both models and we analysed the results using multivariate techniques. First, cluster analysis on the output generated from both simulation approaches was used to identify groups of similar types of outcomes. Note that here we have aggregated the individual outcomes from the agent based model to provide an overall network picture of the changes to resources (i.e. to compare with the fuzzy set model). Next profiles of each of three possible outcomes were produced using MANOVA. Table 1 summarises the profiles of three types of network configurations: *vulnerable*, *steady*, and *awesome*, that emerged from the behaviour of the network and identified in Figure 4 (above).

Table 2: Clusters of firms based on the changes in the network.

Network Attribute	Network Outcomes (Fuzzy model / Agent-Based model)			
	Vulnerable	Steady	Awesome	Total
Relational strength	<u>1.34</u> / <u>1.95</u>	1.72 / 2.0	<u>2.58</u> / <u>2.09</u>	1.83 / 2.0
Financial resources	1.96 / 1.99	1.83 / 1.98	1.82 / 2.01	1.87 / 2.0
Knowledge resources	1.81 / 1.98	1.86 / 1.99	<u>1.99</u> / 1.99	1.88 / 1.98
Relevance of knowledge	<u>1.21</u> / <u>1.96</u>	2.32 / 1.98	<u>2.72</u> / <u>2.18</u>	2.08 / 2.02

(underlined values are reflect differences significant at p=0.000)

Table 2 shows the lowest (underlined) and the highest (double underline) values of attributes identified as statistically significant in the MANOVA analysis. We noticed that regardless of the type of actor, the level of financial and knowledge resources plays a less important role in the redistribution of network "worth". In contrast, strong ties and relevant/useful information flows seem to be crucial in producing different network outcomes.

When comparing the fuzzy model (first value in each cell) with the agent based model (second value in each cell), the dispersion of the values is larger in the fuzzy model, reflecting the multiplicity of roles the actors can embrace and the uncertainty of relation characteristics. While in the agent based model, because it uses crisp rules, it is expected to obtain less "chaotic" behaviour. Importantly we note that the general findings are consistent in both models.

The network characteristics were also analysed by type of actor and the conclusions hold at this level as well. We note that all types of actors who participate in awesome clusters have significantly higher relational strength, similar to networks in general. Between actors, relevance of knowledge was a significant indicator (p=0.000) for venture capitalists and manufacturers participating in awesome clusters but not for R&D firms, perhaps because R&D firms produce "relevant knowledge" and because for VC and Manufacturers to participate in innovation networks knowledge relevance must be sufficiently high to warrant the risks.

Table 3 (see over page) presents the three clusters of changes (vulnerable, steady, and awesome) by type of actor.

Table 3: Changes in the network by type of actor (Fuzzy model / Agent-based model)

Type of actor	Vulnerable	Steady	Awesome	Total
Venture Capitalists	-0.431 / -0.225	-0.110 / -0.035	0.640 / 0.518	0.015 / -0.030
Manufacturers	-0.180 / -0.484	-0.010 / -0.300	0.024 / -0.110	-0.047 / -0.360
R&D Firms	-0.025 / -0.220	-0.130 / -0.034	2.170 / 0.525	0.396 / 0.020

Overall, we note that the network changes are significantly different (p=0.000) across the types of actors. Again, we observe a higher variability in the distributions of results from the fuzzy model compared to the agent-based model. Table 3 suggests that VCs and manufacturing companies experiencing decline in resources (in vulnerable networks) are at risk of higher loses compared to R&Ds. In awesome network configurations, VCs and R&Ds benefit the most, while in steady conditions none of the actor types stands out.

We notice that the two models show differences in the magnitude of changes for manufacturing firms, with higher results in the fuzzy model. This again may be explained by the ambiguous behaviour of manufacturers, frequently presenting financial and knowledge resources that may be characteristic for the other two types of actors.

Examining the agent based model more closely (i.e. for individual actors) it is possible to consider the network structure and composition Our analysis shows that the awesome cluster includes significantly more VCs and R&Ds (16.5% and 16.71%), and the vulnerable cluster more manufacturers (69.66%).

Discussion

The discussion section will highlight two themes which pertain to the special track of markets and market formation. Firstly, we will discuss the results of the simulation in the emergence of 3 different types of markets and how different aspects of the market affect the different market types. Secondly, we will highlight how we think simulation methods as outlined in the examples given can complement the current case based methods for considering markets.

Market Emergence

Despite the simulation method used, the results show that three different types of markets may emerge: awesome, steady and vulnerable. Within each of these broad categories there were numerous possibilities, but for the sake of this discussion we will limit the level at the three broad categories. Awesome markets indicated that resource combination within the network increased dramatically. Awesome markets are the types of markets that many government departments, and private R&D companies aim to achieve. It should be noted that awesome markets don't mean that every resource combination was positive, but it does show at the network level a net positive resource growth.

Steady markets were markets where the net resource combinations didn't result in an overall high growth or loss within the network. The highest proportion f of possible outcomes tended to be within the steady market scenario, as shown in figure 4. This means that usually a steady market possibility is more likely to occur than either awesome or vulnerable. Steady markets although not optimal, are

neither the less not a negative outcome.

Vulnerable markets were markets where the net resource combination is likely to be decreasing, that is the different resource combinations are unlikely to grow the market. Vulnerable markets have been witnessed in the past where innovations have not been successful. For example, beta video systems (VHS dominated); lotus operating systems (Microsoft dominated) and IBM mainframe technology (desktop computers dominated) etc.

The important question to ask is what different combination of resources resulted in the different types of markets emerging? Both models highlight that financial resources and knowledge resources have little impact on the performance of the network when compared to relational strength and relevance of knowledge. Also, both models highlight that awesome networks are built on strong relationships that transfer confidential and innovation specific knowledge. When comparing the individual actor types in each cluster similar patterns emerge from both models.

We therefore suggest that there are specific simple mechanisms that impact on the effectiveness of businesses engaged in developing and commercialising new technologies. The relevance of information and strong relational ties emerge as significant. These results present some interesting aspects, firstly it indicates that both social embeddedness (relational strength) and calculative aspects are important in market emergence. This result shows that markets are formed through both social forces and calcultive forces, rather than solely one or the other. This diverges slightly from the concept of markets that are "ever-changing performances …. shaped by multiple and distributed calculative agences" (Araujo et al., 2008, 8). We agree that they are ever changing performances given the wide variety of different market forms that were generated, but we disagree that **only** calculative agencies were involved. Social embeddedness forces also played an important role in market formation.

Thus, we argue that more effective targeting of government funding initiatives can be achieved by considering these mechanisms, furthermore that managers can achieve some degree of independence within the network by developing an understanding of these mechanisms.

Complementing case based methods

We now consider the how simulation can complement case based methods for investigating markets. Complexity is an area that is based on the study of connections, non-linear dynamics and emergence (Mitleton-Kelly, 2003). Interpretative research, such as case based research, is typically used by IMP researchers to describe complex behaviour within business networks. Yet, how do such approaches work with simulation, as outlined in the paper?

All approaches have some similar philosophical underpinnings. For example: the heterogeneity of actors under investigation is an important criterion; the ability to "predict" outcomes is impossible as there are many possible outcomes that can emerge when considering complex systems; importance is placed on the relational aspects and interactions rather than the actors themselves; dynamics of the interactions is particularly important in considering the situation etc. Therefore, given the similar philosophical underpinnings they are not dichotomous approaches where never the twain shall meet. Having similar philosophical underpinnings they complement each other and allow for paradigmatic interplay and cross over (Schultz and Hatch, 1996).

Simulation modelling in conjunction with interpretative research (here we mean case-based, discourse analysis and/or action research) is required if the phenomena of complexity science is to emerge as an important approach to considering phenomena. Maguire et al., (2006) outlines six ways in which interpretative research and agent-based models can complement each other (these also apply to fuzzy models).

1) Interpretative research offers rich descriptions from which the rules for models can be developed. Rule development needs to emerge from prior theory building which given the wide range of variables and interactions and this is usually interpretative research. Rule development with limited or no theoretical underpinnings leads to a plethora of inconsistent and weak models leading to credibility issues. Therefore, well developed interpretative theory building approaches are vital for the development of credible models. Rule development for the models outlined in this paper came from case based research that highlighted the interactions involved in innovation networks. The rules do not come from a single case, but rely on access to multiple cases.

2) Modelling researchers also need to investigate case-based research if they are to *validate* their models to different real-world situations. Model validation is an important step in the modelling process. Validation can be conducted in a variety of ways. One of which is docking as outlined in this paper. The results of this paper highlight that the models are robust as both models produced similar clusters of vulnerable, steady, and awesome. Another way of validating models is to examine how the model results align with similar cases conducted by interpretative researchers—Are the patterns emerging of the models similar to those to real-world cases? If not - what variables need to be included/ deleted in the model? The validation against real-world cases in the next step in this research project and the researchers expect to begin developing cases over the next 12 months.

3) Modellers and interpretative researchers can work together to experiment with interpretative findings to further elaborate on possible futures or experiment by manipulating situations to determine whether different outcomes may have emerged. Such a process provides researchers with avenues to examine what/if scenarios. The models presented in this paper are at the early stage of development and scenario experimentation has not yet begun.

4) Agent-based models (but not fuzzy models) can be used to study dynamics in ways that interpretative researchers are unable to follow. For example interpretative researchers are often resource limited and can not follow the full flow of information through the network, while simulation models allow for many dynamic multiple interactions. Therefore, agent based models are particularly useful for assisting with interpretative research in elaborating on the flow of resources and interactions. We found this aspect particularly useful in our models as we were able to investigate networks that would not "survive". Networks that dissolve / cease to exist are difficult to conduct case base research on as the network participants are often dispersed or taken new positions elsewhere making them difficult to get access. Also, managers are reluctant to discuss failures within networks again making interpretative analysis a difficult task.

5) Interpretative researchers provide an excellent platform for critiquing and challenging the results of simulation models that are developed. This is particularly important in considering long-term applications or models that are developed on one particular cases and further generalisation is required. Simulation model developers need to present the results of their models to interpretative researchers allowing them to critically evaluate them for consistency with their empirical work. Here conferences and collaborative workshops that bring together modelling and interpretative researchers play an important role in providing the platform for these conversations.

6) If generalisation is important for the research project, then models allow further generalisation of results to other situations, particular other environments such as say a change in economic conditions. This feature of simulation is similar not unlike scenario building. Scenarios can be built for different initial conditions, say developing country networks rather than networks in developed countries. Again the models presented in this initial paper are at a very early stage of development and scenario building has not been integrated into the rule development.

Limitations

The results presented in this paper were considering the emergence of simple markets. Therefore,

some market situations were excluded to keep the simple structure. One of these was the importance of weak ties and their ability to span structural holes (Granvettor, 1985; Burt, 1992). Both of these concepts have been shown to be important in some market scenarios, particularly when information sharing and information dissemination is important – as shown in our results. We acknowledge this limitation and hope to incorporate this in future simulation modelling.

Network size and network boundaries were not varied in this research. Although, network size and there strategic net boundaries lie are important criteria covered in previous research, we have not included them in order to keep the simulation model simple. It is possible to include network size etc within simulation development and would be an area of future research.

It is assumed that total network resource is the simple addition of all actor resources have each time period of change. One unit of knowledge resources is equivalent to one unit of financial resources. We are currently conducting further qualitative research into this aspect and expect to improve this in future model development.

Conclusion

Our work is early in its development and we anticipate further work in a number of areas. Agents behave according to a general set of rules established by researchers. The rules are based on case studies and the results passed both the "common sense" test and the docking, however no quantitative data was available for setting any parameters in the model; new information collected for an industry can be crucial for updating the information and getting more details on the "plans" agents may use in their decision making. We also note that our model does not include optimisation by agents; we envisage extending the model by tagging actors to see their dynamics and by introducing an objective function for actors to be considered in their rule selection. As presented here, agents are not learning, reasoning, their way of "evolving" is simply governed by the rules imposed for operation for each category of actor; future research based on more information foraging may include learning mechanisms and feedback relations. Finally, we note that the system/network we analyse is "closed" in the sense that it represents the internal affairs within a particular industry, domain, or even geographical area; a natural extension would be to incorporate the exchanges with the "larger world";

This paper has shown that simulation of networks is a complementary form of inquiry to the interpretative approach currently used in IMP, when considering the complex behaviour of business networks. Using simulation modelling in conjunction with interpretative approaches allows researchers to investigate the issue of complexity from a variety angles, thus building on our understanding of interactions, and the behaviour of emergence within these networks. Simulation models need to be developed in conjunction with interpretative approaches if they are to be grounded in theory and real-world phenomena.

Given that the simulation approaches discussed in this paper and interpretative methods, such as case analysis; action research and discourse analysis have a similar way of considering the world then these approaches should be able to build on each other to develop an interesting approach for considering complexity behaviour within business networks.

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