Using Docking to Verify and Validate Complex Business Innovation Models

Abstract

Complexity models have been increasingly applied in many scientific fields, but lack of verification and validation (V&V) protocols/approaches has been one of the main challenges and criticisms in fully adopting the models. Modelling practice requires checking that model implementation is correct with respect to its conceptualisation (verification) and that corresponds to and explains the real world phenomenon modelled (validation). When numerical data is not readily available, the behaviour of the model cannot be operationally validated and the results are ‘questionable’. Docking/replication is an alternative approach for V&V, in which different implementations of a conceptual model are compared and if they produce similar results, that lends support to the models. This paper reports on the docking experience between two models of innovation in complex business networks, fuzzy logic and agent-based modelling, as part of an extensive V&V process. The positive results are encouraging in further developing the models and show researchers that lack of empirical data in many social complex systems should not be a hurdle in validating their models.

Keywords: Validation, Replication, Docking, Complex Innovation Networks

1 Complex Innovation Networks and Modelling Challenges

Since Powell et al. (1996) argued a network approach, substantive findings have been accumulated to confirm that innovation occurs when actors, in their interactivity, successfully develop new ideas (Gilbert et al., 2001). Each actor/agent has a knowledge base that generates innovations or has resources to leverage the creation of innovations developed externally (Gilbert et al., 2001). This perspective considers the *network* as the medium for generating innovations, rather than maverick individual agents engaging in R&D or with sufficient resources to bring the innovations to market. *In other words, the innovation is not in the agents or in the relationships between them, but is the network of agents* (Watts, 2004). This connectionist, affirmative view (Maguire et al., 2006) is well reflected in the unprecedented growth in collaboration (Powell et al., 1996), the Open Source movement (Bonnacorsi and Rossi, 2002) and in Silicon Valley's clusters (Zhang, 2003) where collective action and coordination, in the absence of central authority, lead to innovation creation and diffusion. Möller and Rajala (2007) also highlighted that value creation occurs at a network level, often through the development of complex business nets, particularly when the value of radical innovation is still unclear.

Innovation networks can be seen as "sets of connected relationships" that "possess advantages beyond the sum of the involved dyadic relations" (Anderson et al., 1994: 1). They have a complex nature (Anderson et al., 1994), being complex business systems (Ritter et al., 2004). In fact, "networks represent the architecture of complexity" (Richardson, 2007: 151). Understanding the complex interactions that occur within networks requires perspectives that consider the whole system and the interdependencies that exist between its parts (Mitleton-Kelly, 2003; Maguire et al., 2006). Interested readers are referred to Mitleton-Kelly (2003) or Maguire et al. (2006) for discussion of the application of complexity principles to organisational studies.

In terms of modelling approaches, complexity consists of a number of theories emerged from the natural sciences (Mitleton-Kelly, 2003; Maguire et al., 2006), requiring multiple ways to address a problem.

Interpretive methods have been used to examine complex network behaviour (see Mitleton-Kelly 2003; Håkansson and Ford 2002; Möller and Svahn, 2005 for examples). However, such methods have limitations when investigating complex phenomena (Purchase et al., 2008): inability to model dynamic, out of equilibrium processes, difficulty to capture non-linearities, emergent consequences, special behaviours, or being mathematically intractable when attempting to include them. Simulation and particularly agent-based modelling have gained a more prominent role in investigating complex systems because they are “more sophisticated, subtle and faithful to the (system’s) complexity” than are more traditional methods (Midgley et al., 2007: 884). Although the development of a simulation is now easier for those without technical skills and the benefits have been demonstrated, ABM is yet to emerge as a common research method or tool (Richiardi et al., 2006; Midgley et al., 2007). The lack of standards for quality assurance (V&V) has been one of the main barriers for its adoption (Wang and Lehman, 2007), especially as traditional validation methods are not always applicable (Wilensky and Rand, 2007; Louie and Carley, 2008). By blending various types of validity with docking, a successful strategy can be formulated, and statistical validation should not be seen as proof of the “absolute” validity of an ABM (Robinson, 2005; Midgley et al., 2007).

After section 2 presents several aspects of validation and verification considered in the study, section 3 describes succinctly the complex innovation models built with the ABM and FL approaches and section 4 outlines the validation procedure used and presents the docking results. Section 5 concludes with a discussion of the results and their implications.

2 Verification and Validation (V&V)

Validation has been defined as “substantiation that a computer model, within its domain of applicability, possesses a satisfactory range of accuracy consistent with the intended application of the model” (Kneppel and Aragno, 1993: 3 cited in Klein and Herskovitz, 2005: 305). Validation is crucial as models’ implementation depend on their credibility. Regardless of the type of model (using inductive reasoning, testing hypotheses, or a combination of them), the arduous process of model building is followed by an even more onerous endeavour for validation. Any model becomes progressively validated by the accumulated confirmations of its results or behaviours. Traditionally, validation requires empirical evidence to check or compare the output of a model. If this does not pass the scrutiny or the test cannot be performed, this is ground for rejecting a model. Comparison with a real system is the most reliable and preferred form of validation, but when the model mimics processes that cannot be replicated in the laboratory (e.g., astrophysical systems, catastrophic natural or man-made events, climate change, social systems) or past history data is insufficiently collected, this is infeasible and validation becomes an issue. Recent literature addresses verification and validation standards and suggests other frameworks for validating simulation models (Klein and Herskovitz, 2005; Richiardi et al., 2006; Louie and Carley, 2008; Moss, 2008). For example, Richiardi et al. (2006) highlighted a framework for validating and reporting agent-based simulation models that has five types of validity, namely: *theory validity* (validity of theory relative to real-world system); *model validity* (model relative to theory); *program validity* (program relative to model); *operational validity* (theoretical concepts relative to their indicators); *empirical validity*. Louie and Carley (2008) however, differentiated three types of validation: *conceptual validity* - the extent to which model theory and assumptions are appropriate for the model, *validity of data* - ensuring data are appropriate, accurate and sufficient for the model, and *operational validity* - related to the fit between model output and the real system being modelled.

It is clear there is no consensus as to what validity is, nor how to address this issue, and that there are degrees of validity (relativity in judging validity) that can be achieved using a combination of instruments or methods. A number of researchers highlighted the need to develop a suite of "best practices" to validate and verify computational simulation models (Wilensky and Rand, 2007:6; Richiardi et al., 2006; Louie and Carley, 2008; Wang and Lehman, 2007; Windrum et al., 2007). Such practices are critical if complex systems modelling approaches are to be accepted by the wider academic community and their findings used by practitioners (Maguire et al., 2006; Louie and Carley, 2008).

This paper reports on a *docking* validation approach (Axtell et al., 1996) comparing results of a fuzzy logic model (FL) and an agent-based model (ABM) built in the innovation networks context, to explore innovation creation and changes in the complex business network resources.

The basic concepts and methods of docking were developed by Axtell et al. (1996). Inspired by docking a spacecraft with an orbital station, the term suggests that perfect coupling/matching of two different entities is necessary for their operation, in other words the results of one model should align with the results of a replicated model. Docking assures the researcher that model outcomes are stable and are not produced by exceptional circumstances (Wikensky and Rand, 2007), allowing the researcher to examine the relationship between the theoretical underpinnings of the model and its results. Replicated models differ across six dimensions (time; hardware; languages; toolkits; algorithms; and authors) (Wilensky and Rand, 2007), with the different mechanisms being the most important aspects of replication (Axtell et al., 1996). Docking requires considerable time and effort to undertake the processes, sufficient description of the models, and same interpretations of the models' theoretical underpinnings, otherwise the task becomes difficult if not impossible (Richiardi et al., 2006; Maguire et al., 2006; Wilensky and Rand, 2007).

In this paper we view docking in a broader sense, as a "cross-paradigm comparison" (Rouchier et al., 2008:2) and beyond internal verification (Boero and Squazzoni, 2009:5), as it assumes conceptual and certain types of data validity already supported. Our intention is not to reformulate general principles and procedures for validation, but to provide an example of practical means of validation based on consistent results from distinct models.

3 Two Examples of Complexity Models for Innovation: Agent-Based Modelling and Fuzzy Logic Simulation

3.1 Model Development

Both FL and ABM models were developed based on previous research that focused on complex innovation networks. The aim of the models was to see what bundle of network characteristics leads to highly successful innovation networks over extended time periods. Although the network forms an important part of innovation success (Elfring and Hulsink, 2003), it is formed through the connections of individual actors (Herbert, 2006). The models included three types of *actors* (venture capitalists, manufacturers and R&D organisations) who play important roles in the innovation network. To ensure model parsimony other parties, such as trade associations, consultants, and customers were not included. An example of the symbolic network can be seen in Figure 1. Venture capitalists (VC) represent finance partners who invest in new ideas, manufacturers (M) represent organisations that commercialise innovations and R&D companies (R&D) represent science partners in which new ideas are generated (the sources of scientific knowledge). Actors are randomly generated in the network and the landscape is fully connected. Actor size is given by the amount of resources ‘owned’ in the network (i.e. actors owning more resources are considered larger actors) and size acts as a proxy for technology readiness, capacity for new knowledge, functional differentiation (Greenhalgh et al., 2004). As previous research has shown, finance, knowledge and commercialisation are critical processes in the development of an innovation (Pittaway et al., 2004), and actors channel these resources into new projects. The type of knowledge was not specified, but its relevance in relation to innovation was included (i.e., knowledge that has a direct impact on the development of the innovation is considered highly relevant). Knowledge not used is assumed to decay over time – if knowledge is not shared in the network, its relevance diminishes and its importance in the next time period is reduced.

[Figure 1 about here]

Networking is an inherent characteristic/activity of the actors (Ritter et al., 2004, Möller and Svahn, 2005), and their *interactions* embed a myriad of dimensions. By dissecting the links, we identify information processes, communication, collective learning, coordination of resources, capacity to transfer tacit knowledge (Todeva, 2005) all of which are necessary to foster the creation of new ideas. Barriers to innovation are not exogenously introduced in the model. Trust, a shared understanding of problems and objectives and an acceptance of common rules and behaviours have a positive impact on the flow of information and on the consequent innovativeness of the network (Trippl and Tödtling, 2007; Pittaway et al., 2004). Therefore, the inclusion of relational strength is a critical component for simulating information flows throughout the network. A threshold value of link strength dictates when actors can interact (below that value the relationship “dies” - Denize and Young, 2007) and, depending on the resources put together, there is more or less scope for innovation. R&D activities require monetary resources and reduce the capital stock of the VCs or manufacturers, but the capital will be refreshed by successfully introducing a further innovation (which considerably increases knowledge and skills).

Spreading the agents tends to reduce the intensity of the interactions in the network through a gravity function that moderates the links’ parameters (Gilbert and Tierna, 2000). The agents are autonomous, have local, micro-knowledge and hence, their decisions are independent of other actions in the network. The interaction and collaboration between actors does not involve a selective search for potential partners, interaction being modelled as a stochastic element.

The complex network of innovation is conceptualised as the resulting increase in resources throughout the network. Networks in which no or limited innovation occurs have low levels of increases in network resources. For simplicity, we considered financial resources could be easily exchanged to knowledge resources. The model evolves in discrete steps and, at the end of one run/iteration, actors assess their resources and position in the network.

The models also include a moderator – environment, as industries/regions without tradition in innovation are likely to take a different route to innovation adoption and diffusion compared to high technology and speed clusters (Trippl and Tödtling, 2007).

3.2 ABM and FL Models

The ABM model was built in NetLogo 4.0. As indicated, in the network, the interaction/collaboration was not forced by the structure of their relationships because their strength can be manipulated and even reduced to zero. Agents have various capabilities (deterministic and stochastic elementary properties) and we used link parameters to tune the degree of interactivity between them. After specifying the behavioural rules for agents and their interaction, we explored the consequences at a network level: when resources are multiplied and converted into innovation, the network “produces” new knowledge.

The fuzzy logic (FL) model, which was built in CubiCalc 2.0, had the same structure, but inputs were "fuzzified" in a Mamdani system and subject to the knowledge base with rules for operation in order to infer changes in the network (Cordón et al, 2001). The knowledge base includes 486 "IF-THEN" rules expressing the researchers' expert field knowledge. The multiple antecedents were connected by AND, OR, NOT operators and hedges. Multiple rules fired at the same time and may have had various weights. The FL model is not a micro-scale model, and the results reflect the behaviour of the clusters of agents. With FL, we were able to address growth in a comprehensive way through a range of fuzzy factors (the fuzziness about what an agent or innovation really is, the fuzziness of antecedents of innovation and the interactions between agents).

Our choice for ABM and FL was driven by the characteristics of these modelling approaches, deemed appropriate for our complex system. Both ABM and FL are alternatives to classical thinking in which a systems' evolution is expressed using functions, equations and algorithms.

ABMs operate with agents, environment and objects that interact with each other. In addition to providing a natural and intuitive description of complex[1] systems (Mitleton-Kelly, 2003), ABMs capture emergent behaviour (Bonabeau, 2002; Macy and Willer, 2002; Watts, 2004) and the aggregated behaviour of a system is not a magnification of single agent behaviour at a larger scale. Emergent behaviour is particularly important for radical innovations as new value systems need to emerge (Möller and Rajala, 2007). Heterogeneous adaptive agents (such as our three types of actors) interact, leading to complex spontaneous dynamics (Pyka and Fagiolo, 2005) in which large changes can be driven by subtle modifications, imperceptible to individual actors (Windrum et al., 2007). In other words, network cognition, rather than individual actor cognition, is the focus of the research (Goldstone and Janssen, 2005).

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[1] Complexity is used here in the technical sense that the "behaviour of the system as a whole cannot be determined by partitioning it and understanding the behaviour of the parts separately, which is the classic strategy of the reductionist physical sciences" – Gilbert (2004):3.

The widespread use of ABM in many fields is a response to the complexity of real world phenomena, facilitated by data availability and increased computational advances (Bonabeau, 2002; Macy and Willer, 2002; Mitleton-Kelly, 2003; Pyka and Fagiolo, 2005; Louie and Carley, 2008).

The second modelling approach, FL, provides an ideal framework to deal with independent layers of data of varying degrees of uncertainty/confidence, ‘imprecision’ or membership (Zadeh, 1965). FL is another paradigm that departs from traditional mathematical approaches and opens the door to a new way of defining knowledge using statements that can be true to a certain degree. Born to deal with degrees of truth (instead of binary Boolean logic), tolerant to ‘ambiguous’, noisy data and operating with linguistic expressions for reasoning, FL has spread into numerous domains (Cordón et al., 2001; Purchase and Olaru, 2006). Mathematical set theory and logic are augmented in FL by making fundamental changes to the ideas of set membership and to the logical operations. The motivation for FL came from the need to represent propositions such as: “Agent 13 and agent 7 are close friends.”, “Many R&D do not use a large amount of financial resources.”, “Current market conditions are not favourable.”, or “This information is not relevant at all.”

4 Unfolding the Process of Validation

Validation is a challenging task, but one that can be met by using a sound approach. In this research we adopted a hierarchical approach with six stages of validation before docking. Although the selection may be subjective, it produces a body of evidence for models’ quality, which may be useful for the larger research community. Our suggested route starts with a conceptual validation, followed by data calibration and validation (assumptions, input parameters validity, distributions), and operational assessment for each model (output values and conclusions). Only at the end of those we performed the docking of the two models.

i) ***Conceptual validity*** – was based on an examination of existing theories. The structure of the model is supported by past research (Denize et al., 2007) and case analysis confirmed the main relationships incorporated.

ii) ***Expert judgement*** – was based on interactions with colleagues in various forums (seminars and conferences) in that discussed the representation of each dimension in the model and the various hypotheses. We relied on existing case studies and peer-feedback for developing concepts and simulation rules. As Gilbert (2004) and Bonabeau (2002) have noted, the validation of ABMs of social processes have a degree of arbitrariness and subjective or expert judgement and this was accepted in the present study.

iii) ***Input validation*** – ensuring the fundamental conditions in the model reproduce aspects of the real system. This ex-ante verification of the models' ranges of the parameters (e.g. the decay of irrelevant information and the relativity between financial and knowledge resources for the three classes of actors) was supported by case studies that suggested the inputs were consistent with real-world processes.

iv) ***Believability test*** **-** checking the correspondence between what emerged from the model and what was expected to be seen in the real world. Although this is not sufficient to conclude a model is correct, the fact that model components adequately represent a real behavioural effect is of paramount importance for a model's "temporary acceptance". We judged the model output through network density effects and the analysis of extreme conditions. Denser networks created clusters with an enhanced ability to innovate, showing that geography is important. Both models generated similar clusters. When resources for each type of actor were reduced to zero, or a type of actor was non-existent, the network became unstable and collapsed.

v) ***Internal validity*** **-** ascertained by comparing results from simulations with various random seeds and changing the type of the noise in the data. Statistical tests confirmed the repeatability of results when pseudo-random number generators had various seeds as there were no statistical difference between runs and we obtained a normal distribution of effects in all situations (checked by Kolmogorov-Smirnov tests). Similarly, when the parameters of the normal distributions were changed or the normal distributions were changed to uniform distributions (Richiardi et al., 2006), the results remained consistent.

vi) ***Sensitivity analysis*** – what-if scenarios to ascertain the effect of inputs upon the model's output. We examined the results to changes in network size, the proportion of the actor groups, the strength of relationships and the exchange rate between financial and knowledge resources. Sensitivity analysis revealed the most important effects:

- stronger ties between agents are associated with the generation of new ideas and the adoption of innovation if relevant knowledge flows between R&D to users of innovation;
- knowledge is “lost” if there is no good soil to seed it (at least a moderate strength of interactions and resources to develop or implement the innovation);
- an imbalanced number or proportion of the three types of agents may hinder innovation;
- smaller, denser networks (50 actors) have greater innovation than larger networks (100 or 200 actors).

4.1 Docking

The ABM innovation model built late 2008 is an incremental replication of a FL model built in 2007. Ad-hoc adjustments based on a theoretical foundation and discussions with peers helped us to obtain a better representation of an innovation network and to understand the network’s factors and assumptions.

The models have the same structure and inputs, but they operate in different paradigms. Therefore it is necessary to delineate the extent of the replication we achieved during the docking and the equivalence of the results obtained. Axtell et al. (1996) suggested three criteria for performance, namely: *numerical identity* (results that are numerically the same in the two models), *distributional equivalence* (distributions of results are statically indistinguishable), and *relational alignment* (same patterns of interactions in the models). Over 1,000 runs for the FL model and over 5,000 runs for ABM showed distributional equivalence between the two innovation models. As both models used the same parameters, we believe differences in results arose only from relaxing the restrictive assumptions in the FL or ABM models. Fuzziness was not possible in the ABM, while emergence and extended time periods were not possible in the fuzzy logic model. The stochastic ABM generated a distribution of outcomes caused by random encounters among agents, while FL generated an ensemble of crisp values as a result of multiple rules of interaction being applied simultaneously.

The simulation models produced similar clusters. An "awesome" cluster included actors with a higher level of knowledge resources and greater relevance of those resources, with stronger ties or collaborations with other actors that had a more privileged position in the network. This cluster included the highest proportion of R&D companies, which are the generators of knowledge. A "vulnerable" cluster included actors with fewer knowledge resources and weak ties, in often-imbalanced networks, while a "steady and mixed" cluster had an average structure in both models. Multivariate analysis of variance highlighted that the clusters were associated with statistically different resources, relations and change, but the type of model did not have a significant effect on the results. The main finding is that the relevance of the knowledge and its flow through strong ties drives the multiplication of capital stock.

5 Findings and Conclusions

5.1 Managerial implications

The models have benefits for managers and policy making. ABM and FL models highlighted that awesome networks are built on strong relationships that transfer confidential and innovation specific knowledge. The models showed how network bonds impact on innovation performance from a macro-system wide orientation. There are deep mechanisms in complex innovation networks that drive their performance and government-funding initiatives are likely to be more effective if they consider these mechanisms. Further, managers could achieve some degree of independence within their network if they developed an understanding of these mechanisms and regard the network as a complex system of resources and capabilities. The significance of the strength of interactions and of the relevance of knowledge suggests that successful networks require enduring commitments between agents.

5.1 Academic implications

The models are particularly useful in shedding light on the relations between agents, on the emergent behaviour in the innovation network, and in generating synthetic data that represented possible situations in real world innovation networks. The ABM enabled us to examine relationships that are not easily modelled by traditional approaches in ways that are more realistic representations of complex dynamic systems. The FL provided the opportunity to incorporate the unavoidable fuzziness in describing the role of each actor, their relationships and interactions.

Through multiple stages of validation and consistent results produced by docking, we gained confidence in the algorithms and implementation. Within their domain of applicability, the models had satisfactory accuracy and supported our hypotheses about innovation creation. Using an applied science perspective, we offered an example of validation procedure, which rendered robustness to our innovation models. Docking is seen in this paper from a broader perspective, as a technique building upon other types of validation, which were examined separately for each of the docked models.

In addition to achieving validity, docking provided complementary views about the mechanisms operating in complex innovation networks. As Rahmandad and Sterman (2008: 1001) stated, the two distinct models can be seen as “regions in a space of modelling assumptions, not as incompatible modelling paradigms”. Through docking we obtained a deeper understanding of the complex behaviour of the system as a whole and identified limitations of the models.

The docking exercise has been successful and we appreciate this approach should find a wider place for discussions among researchers. We consider it as a valuable item in the V&V toolkit and will continue recommend it to our colleague modellers. To conclude, there are various positions in the philosophy of science with respect to validation ranging from extreme objectivist (in which model validation can be separated from the model builder and its context) to relativist (where the “model and model builder are inseparable” and “validity is a matter of opinion). In this study we share the perspective that simulation modelling should not follow a prescriptive set of approaches to validation but, rather, that modellers should “responsibly and professionally argue for the warrant of the model.” (Kleindorfer et al., 1998:1097).

6 References

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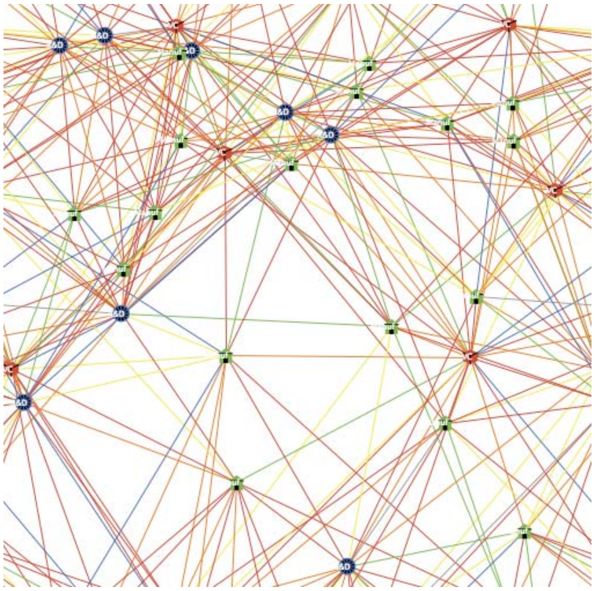

Figure 1: Network structure (VC – red nodes, M – green nodes, R&D – blue nodes; colour of the links indicates strength of relationships - from blue the weakest to red the strongest links)

(Figure 1 in black and white on the following page)

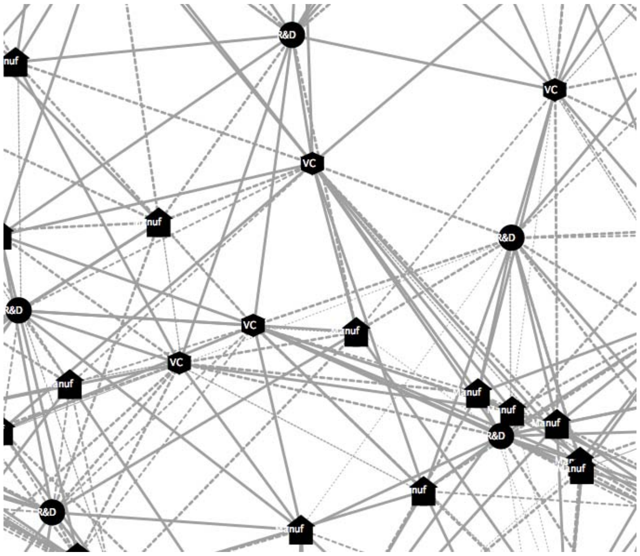

Figure 1: Network structure (type of the links and thickness indicate strength of relationships **-** dotted thin lines for the weakest links to thicker solid lines indicating the strongest links)