Situated Socio-Cognitive and Ecological Simulation of the Triple-Helix Theory of Regional Innovation Dynamics

by

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Abstract

This dissertation focuses on applying the concept of agent-based ecological simulation to the problem of developing and maintaining regional innovation economies. A simulation model based on a popular model of innovation, the Triple-Helix theory of public-private partnership, is presented. This theory guides the alignment of the three principle sectors of regional and national systems of innovation; academic research, industrial development, and government control. The development and maintenance of systems of innovation has been recognized to be a key driver of economic growth, but the underlying mechanisms which govern these systems have proven difficult for pure statistical analysis to capture.

We introduce an agent-based modeling and simulation approach, which leverages ecological concepts better suited for describing the behavioral mechanisms of multi-agent, environmentally-situated complex adaptive systems. This model extends the basic formulation of the triple-helix to include a new environmentally situated actor, the researcher, which uses indirect signaling to discover and exploit grant-funding. This extension uses principles from classical Predator-Prey interaction and a variant of ant colony optimization, a non-deterministic search algorithm.

The work presents a didactic framework for understanding the role government policy has on innovation-driven productivity and the configuration of resources around centers of innovation. We find that innovation is principally driven by concentrations of mature academic research institutions and is mediated by consistent government support and highly active industrial partners. We also present a unified innovation resilience metric for future cross-model comparison.

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For my parents; Donald King and Vivien Morris, who taught me to value my mind and my self.. For my fiancé; India Napier, who stood by my side through all the upheavals of graduate life and managed to stay (relatively) sane despite fielding five years of my incoherent ramblings. For my friends; we're still digging in the sand, dreaming about robots. I think we did something good here.

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Chapter 1

Innovation Dynamics

1.1 Introduction

Innovation economics is a growing economic doctrine which places knowledge, technology, innovation, and entrepreneurship at the center of economic theories of policy planning. This is a departure from the classic view of these forces, which is often described as external and independent to the formulation of policies and thus unable to be affected directly through their application. Innovation economics rests soundly on two basic tenants: that the core goal of economic policy should be to increase productivity through increased innovation, and that markets relying on resource and price signaling will not always be effective in increasing productivity, and thereby economic growth. Porter (1990) observed that a nation's primary economic goal is to produce a "high and rising standard of living" for its citizens. Predictably, this ability depends on the productivity with which a nation's resources can be exploited and deployed. To this end, a great deal of energy has been devoted to the study of public policies for sustained economic growth.

One well-established engine of productivity is the notion of technological change. Edquist (1997) argues that it is almost universally accepted that technological change, in tandem with other kinds of innovations, are the most important sources of productivity growth and increased material welfare and that this has been the case for centuries. Such change has provided firms with the power to circumvent scarce factors and market disruptions via new products, processes, and services. Efficiency, the reduction of materials, energy and other resource-based inputs, is often a natural byproduct of this change.

The discovery or production of modern materials, inventions, and processes all arise from innovation activities. Likewise, the steady monetization of the product of this creative refinement process results in improved productivity and profit for the country or region. For example, automation and process innovations resulted in a reduction of the labor costs within many industries, implying that access to high technology is more important than low local wages (Porter, 1990). This realization has led many to conclude that it is in a country or region's best interest to promote this parallel system of innovation in order to promote competitiveness.

1.2 Scope of the Thesis & Motivations

The exploration of alternative strategies for the establishment and long term stability of innovation economies and the testing of different ideas and theories before implementation in the real world can result in major economic benefits. The implementation of poorly designed policies or the long-term mismanagement of a region's innovation infrastructure can often lead to social and economic deprivation through the loss of local or global competiveness. Unwinding bad policies or restructuring the built knowledge infrastructure of a region can be a costly endeavor. Thus, it is important to have tools through which one can evaluate the viability of policies which can affect a region's system of innovation.

In this dissertation, we make use of agent-based ecological simulation modeling to study cooperative R&D among public and private firms, represented as university and industry collectives. These collective firms are modeled as agents with heterogeneous behavior when cooperating. To define firms' behavioral micro-foundations (i.e. how firms decide whether to cooperate or not, which kind of partner they would prefer to choose, and the level of trust present in that partnership), we follow the interaction rules laid down in the **triple-helix model of public-private partnership** (Leydesdorff, 2000). The agents in this model are environmentally situated in a two-dimensional physical environment where monetary resources are distributed and managed by a centralized government agent, and the behavior of firms can be observed by the growth and dissolution of clusters. Additionally, we propose a new agent class, the 'researcher', which is monitored and controlled by research firms and serves the dual role of contributing to R&D efforts and discovering environmentally situated resources via swarm mechanics (Ant-colony optimization). Defining the determinants of cooperation to be used between the agents in our simulation system required efforts on collecting appropriate theoretical background as well as analyzing past studies regarding the formation and maintenance of innovation economies.

From the aforementioned definitions of each agent's behaviors we have implemented the model as a two-dimensional landscape where both resources and firms "attract" each other based on their individual characteristics. This physical landscape is then overlaid with several 'virtual' (social) layers representing each additional sphere of the triple-helix. These layers are represented abstractly as asymmetric networks, where firms are represented as nodes connected by their economic relationship with one another. The notion of "attraction" is measured in both physical proximity, network centrality, and a trust metric, where high values eventually result in strong collaboration between firms during R&D partnership (Dongsheng & Yongan, 2008).

Thus described, the motivation for this thesis is twofold. On the one hand, we are interested in answering the basic scientific question of how the interaction of firms shapes the environment within an innovation ecosystem. Previous research focused on the development of computational models which explore individual mechanisms of such a change, but only in models restricted to a single dimension of interactivity (physical or social). Studies have focused strictly on the behavior of individuals in research collaboration (Jordan et al., 2005), the clustering of firms (Butel & Watkins, 2006), the interaction of industrial entrepreneurs (Feldman et al., 2010), or local search for optimal resource siting (Mutiah et al., 1996). However, few computational models have been put forward that capture all of these dynamics simultaneously, and none which investigate their interaction. As a result, the activities of the three helices of innovation production have not been examined in a holistic fashion.

On the other hand we are developing a practical tool, which allows us to test the triple-helix theory and provide insight into the effects of various policies and conditions on the formation and production of stable innovation economies. Its use to simulate these systems—even before the actual creation of policies or firms—makes it possible to determine where a relevant regional management & planning agency may face difficulties, why they face them, and how policies or system features may have to be considered more fully, or changed, to avoid such difficulties. Simulation of human-like behavior in this space is a powerful research method to advance our understanding of the interaction between people, firms, and their environment. It allows for both the examination and testing of models and their underlying theory as well as the observation of the system's macroscopic behavior (Gimblett et al. 1997).

The validation of this approach is done by performing a basic model reduction activity focused on limiting the parameter space to those which are considered germane to the development of triple-helix structures. This reduction process is followed by a sensitivity analysis step. Sensitivity analysis begins with a level reduction on the values of the remaining parameters, whereby three values are selected which represent the upper, lower, and median conditions. Experiment design theory is then used to reduce the parameter combinations to a reasonably (e.g. computable) orthogonal subset, which allows us to explore the search space in a directed fashion. Finally, the results of sensitivity experiments are used to identify the most significant parameters. Significance is determined by the relationship to known empirical works. We are particularly interested in identifying empirical regularities (power laws) concerning the productivity of firms and their relative technological maturity, the growth of trade relationships between research and commercial firms, and the impact of fiscal allocation policies on system growth, diversity, and stability. We compare these results to those distinguished by industry studies in order to validate the accuracy of the model against real-world problems. We believe that the equivalent quantitative outcomes help validate the accuracy of the simulation model while allowing us to test more proscriptive policy strategies.

1.3 Modeling the Innovation Economy

The underlying networks present in an innovation economy have been approached and emphasized in many studies, especially in public policy and evolutionary economics literature (Forfas, 2004; Yang et al., 2009; Gollmitzer & Murray, 2008). However, few works have been done, toward modeling the processes by which these systems are formed and estimation of the outcomes and effects on innovative products, processes, and firm dynamics as they relate to exogenous parameters and cooperative strategy. The complexity of the network dynamics involved and the heterogeneity of the actors make it hard to model this problem using traditional techniques (Metcalfe, 1995). Moreover, modeling techniques such as agent-based cooperative economics often aggregate or ignore cooperation behaviors present in modern knowledge economy configurations (Zhu et al., 1999).

A variety of deterministic (Haynes et al., 1976; Teece, 1980; Giovanis & Skiadas, 1999; Qin & Ljung, 2003; Yildiz et al., 2011) and non-deterministic (Downs & Mohr, 1976; Markus & Robey, 1988; Holland & Miller, 1993, van Laarhoven & Aarts, 1987; Goldberg, 1998, Kauffman et al., 2000) approaches have previously been applied to modeling systems of innovation. Deterministic models guarantee the same solution at different runs with the same parameter values, and the non-deterministic models such as genetic algorithms and simulated annealing generate different solutions due to their randomness (see Chapter 2 for details of previously applied approaches). Butel & Watkins (2006) reveal that ant colony search (ACS) can be applied to problems where actors operate in conditions of dynamic uncertainty, particularly in the business environment, where entrepreneurs must identify and exploit opportunities, and form cooperative clusters.

Agent-based modeling (ABM), which includes flocking models and ant colony optimization (ACO), uses heuristic algorithms to determine solution steps. Heuristic algorithms are especially useful when finding optimal solutions within a limited time is likely to be impossible. These algorithms find results of "acceptable quality" in a short period of time (Maniezzo and Carbonaro, 2001). ACO is a novel optimization method which has been used to solve various real-world problems such as the travelling salesman problem (Dorigo et al, 1996; Corloni et al., 1991; Stutzle & Hoos, 1997), the quadratic assignment problem (Maniezzo et al. 1994), the Job Shop Scheduling Problem (Dorigo et al, 1996), telecommunication routing and load balancing (Sim & Sun, 2003), and others. ACO has been shown to perform well compared to other non-deterministic algorithms such as genetic algorithms and simulated annealing (Dorigo & Stutzle, 2004). Despite this, there have been few applications of this class of algorithm applied to the field of philosophy of science, particularly problems related to information diffusion (Pirolli, 2009) and the development of regional innovation systems (Zhi & Gang, 2006).

Furthermore, little attention has been paid to the granular activity of researchers within the R&D process. Studies on innovation diffusion tend to aggregate individuals in to firms or enterprises, and often ignore the role indirect funding plays in the establishment of new ideas. Government intervention is given equally short shrift in simulation literature, which often focuses on the self-organizing nature of firms in an economy, despite the fact that intervention strategies are well-accepted in economics literature to be a major driving force in building and maintaining regional innovation systems.

Thus, we believe that injecting these two notions is not only important in order to create a holistic simulation of innovation economies, but also affords the application of ecological modeling to the conceptualization and design of the system. This ecological, or ecosystem, view of the system provides a more accurate and holistic architectural framework than analytical and statistical models. Finally, the relation between actors occupying the various (trophic) roles in the ecosystem model provide new analogies for analyzing group behavior, such as foraging, reproduction, and predation.

1.4 Goal & Hypothesis

The goal of this thesis is to develop a computational theory of the triple-helix theory of public-private partnership, which explains how government, entrepreneurial firms, and academic research organizations collaborate both directly and indirectly to build and maintain knowledge economies. The theory uses an agent-based approach and focuses on knowledge in the world in the form of affordances and information, and their utilization by representative agents during the process of innovation creation and sharing. Firms are involved in various activities during this process; therefore, the agent model needs to include different roles whose interplay allow for simulating these activities. For this purpose we turn to ecological modeling, a conceptual technique used to describe the interactions of complex systems with multiple classes of interdependent actors. Hence, we aim to answer the following two questions from the ecological view of system modeling:

1. What is the minimum set of roles necessary to capture the interactions present in the triple-helix model of the innovation economy?

2. What are the critical parameters—affordances and information—necessary to ensure system stability and diversity?

We do not focus on aspects of individual learning and lasting cognitive-map-like representations of the environment, instead we turn to decentralized strategies of information transmission in order to address issues of complexity. Our central hypothesis is:

> The development and maintenance of innovation economies can be explained on the basis of an ecologically driven agent-based model of the triple-helix model of public-private partnership. This model simulates the minimum set of interactions between government, academia, and private industry in a fashion more consistent with their behavioral roles than other traditional agent-based and statistical modeling techniques.

The main hypothesis can be further detailed by the following two sub-hypotheses:

1. Agents need a minimum set of interacting components—knowledge about the world—to meet specific role-defined goals in an unfamiliar environment. These components are its observation schema, agent's state, exploration & exploitation strategies, and rules for interacting with other agents.

2. Knowledge in the world can be represented by ecological affordances and environmental information. The process of innovation creation and transport works on the basis of the interplay between the two.

1.5 Achievements & Contributions

The significance of this research lies in the potential of the developed simulation model, which leverages spatial environments, relational networks, and swarm-based optimization to compose a tool useful for analyzing the effect of resource allocation and intervention policies on the growth of regional knowledge economies arranged in the triple-helix configuration. Further, despite the recent advancements in the fields of innovation systems and agent-based simulation, the following issues have not been directly addressed by other researchers (See chapters 3 for details of previously applied approaches).

- There has been relatively little agent-based examination of the so-called 'triple helix' of public-private partnership.

- Few of the existing simulation models of regional innovation have taken into account an ecological framework for designing agent interactions.

- Existing approaches have addressed neither the activity of individual researchers in the typical RSI, nor the notion of resource foraging among researchers and firms.

- There have been few examples of swarm dynamics applied to address complexity issues inherent to the problem space.

- Most of the simulation models are restricted to innovation diffusion or economic growth.
- Innovation products are almost often treated as homogeneous units, rather than as artifacts with specific attributes.
- Moreover, few of the existing approaches take into account collective social pressures (institutional trust, peer pressure, explorative dogma, etc.) which steer innovation, specifically the creation of funding regimes which favor one or more field of innovation to the detriment of others.

In this thesis, the above issues are addressed. In addition to these issues, the thesis suggests multiple modifications to ant colony optimization and a more formal adherence to ecological modeling principles in the development of future simulations.

First Contribution

Initially, an ecological model of the triple-helix theory is developed taking in to account the presence of individual researchers as well as the interaction rules between multiple actors. From this, a general agent-based conceptual model is formalized following the ecological framework of producer-consumer relationships. An environmental model is also developed as an analogue of the 'funding space' provided by the regional government. A modified version of ant-colony search is developed as a component of the agent behavior in order to provide researcher agents the capability to explore and exploit this theoretic landscape, and diffuse knowledge about its contents and topography to other researchers.

While developing the ant-colony algorithm for the environmentally situated research agents, three modifications have been proposed to better fit the problem domain.

- The first modification is the segregation of communication between swarm populations belonging to each institution. This enables the creation of several pseudo-layers of communication and encourages competition.

- The second modification reduces the size of the search space for each agent to a radius around its originating institution and promoting the convergence of each swarm to local optimum solutions.
- In order to combat the potential stagnation problem brought on by the previous two modifications, the resource pool in the environment may occasionally experience perturbation. This effect is managed by the governor agent.

Second Contribution

In addition to the swarm-based search, a simple marketplace model is introduced which supports policy-based intervention on the part of the government. The relationship rule-set models the trust between university and industry firms. This model takes into account past cooperation in the negotiation of prices and costs for innovation diffusion. In addition, a single government agent monitors the market and engages various strategies to promote productivity, while taxing the profits of enterprises in order to fund basic research. Within the market, each firm attempts to find the price that maximizes its profit through bartering, the government is allowed to intervene in the form of variable subsidies that can ease pressure on both parties and increase the amount of long-term cooperation in the system.

This approach has a long history in real-world scenarios. Governments often subsidize research partnerships between firms in order to promote cooperation or ease market pressures that might hinder new development of promising technologies. Additionally, taxation and indirect research funding act as levers through which a government can enact long-term policies. The introduction of these factors into the broader model of the innovation economy results in an ecological feedback loop which more closely models real systems.

1.6 Outline of the Dissertation

This dissertation is organized as follows: in chapter 2 we provide the theory and concepts of cooperation in innovation, including background on knowledge economies and a brief overview of the triple-helix model and the government grant system. Chapter 3 presents the justification for an ecological approach to agent-based modeling introduced in chapter 1 along with supporting empirical analysis drawn from literature, and serves as the foundation of our design model. In chapter 4 we present our model design, following a formal template to ensure reproducibility. We also provide an initial view of the various behavior parameters and rule-sets that govern agent roles and and activities.. In chapter 5 we present preliminary observations and findings used to justify the feasibility of our modeling approach. In chapter 6 we present a formal experimental design and analysis of our model's behavior with respect to quantifying error and answering questions about its functionality with respect to our initial assumptions. Finally, in chapter 7 we discuss our overall findings as well as future extensions to our work.

Chapter 2

Literature Survey

2.1 Knowledge and Innovation in Economic Systems

In engineering and economic literature the notion of "innovation" comprises the creation or significant technological changes of new or novel products and processes. The early work of Schumpeter seized on the idea that innovative activity was a critical driver of economic growth (Schumpeter, 1942). The act of developing innovation is regarded as a creative "destruction process" because it caused constant disruption to economic systems in equilibrium. In adjusting to equilibrium, other innovations are conceptualized and spun-off, leading to yet more innovation. Through this self-reinforcing process, Schumpeter's theory predicts that an increase in the number of innovations leads to an increase in economic growth. This theory also implies that an increase in the number of centers of innovation will have a similar effect on an economy.

In modern economic parlance, it is accepted that innovation is not strictly generated in the boundaries of a firm or an organization, cooperation between multiple entities with varying degrees of specialty in the activity of generating innovation is an accepted and often desirable strategy for success. Thus, firms are not expected to develop all the relevant technologies without accessing external knowledge sources or entering cooperative relationships with one another. Patents are an example of a "boundary product" between firms (Leydesdorff and Meyer, 2006); while they are largely recognized due to the fact that they offer legal protection, they can also be used as indicators of knowledge production and/or economic value (Fig. 2.1).

As products and processes have become more complex, there has been a steadily increasingly requirement for technological, organizational and marketing search involving many

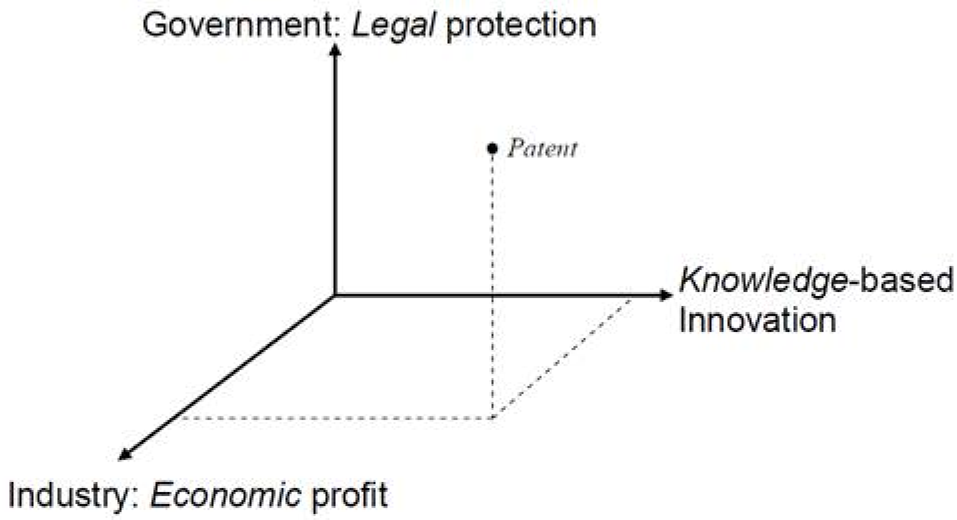


Figure 2.1: Three functional spheres of patenting

players such as suppliers, universities, research institutes, nonprofit organizations and so on. Cooperative innovation is widely considered an efficient means of industrial organization of complex R&D processes (Dachs et al., 2008). The sources of valuable knowledge for innovation may be found anywhere on a firm's production chain and accessing them may be crucial to maintain competitiveness. The positive impact of cooperation in innovation is strongly supported by the extensive literature (Cassiman & Veugelers, 2002; Doo & Sohn, 2008; Miotti & Sachwald, 2003).

While a growing body of research literature supports the notion that cooperation between firms is crucial for innovation and economic development, many studies have identified barriers, which may impede this behavior (Forfas, 2004). Indeed, It is incorrect to assume that this beneficial view of the cooperative behavior is enough for knowledge economies to emerge spontaneously. In order to promote formation and growth of such inter-firm cooperation, governments must be aware of the barriers and play a major role in fostering and creating positive conditions for successful partnership to emerge.

2.2 The Knowledge Economy

A knowledge economy can be defined as the use of knowledge technologies (innovation) to produce economic benefit (Druckter, 1969). While many models for successful knowledge economies have been proposed, perhaps the most influential was the *National System of Innovation* (NSI) proposed by Freidrich List (1841). The NSI can be described as: the set of distinct institutions which jointly and individually contribute to the development and diffusion of new technologies and which provides the framework within which governments form and implement policies to influence the innovation process (Metcalfe, 1995). The growth in size, capitalization, capability, and effectiveness of these institutions comprises the process known as industrialization.

This process accounts for the emergence of the cleavage between developed and underdeveloped countries (Cooper, 1992). Many national systems, which were not among the early pioneer processes of industrialization have continued to struggle in their search for development. Despite this, industrialization after the Second Industrial Revolution has proved to be a significantly different process than that which preceded it at the turn of the century. At the core of the specificities of late industrialization there is a particular focus on technical change processes.

As noted by Porter (1990), innovation is considered the principle engine of capitalist development. Nevertheless, processes of technical change led by innovations are often a privilege of industrialized regions and nations. In industrializing economies these processes are usually limited to the absorption and improvement of innovations produced in other industrialized countries, rather than in support of local firms.

However, the identification of the fundamental distinctions between the processes of technical change of economies at various stages of development has rendered largely uncertain results. This is due to the fact that these investigations are usually hindered by the current tendency towards an increasing conceptual imprecision in the literature on innovation systems. One reason that is often proffered as an excuse for this imprecision is the growing

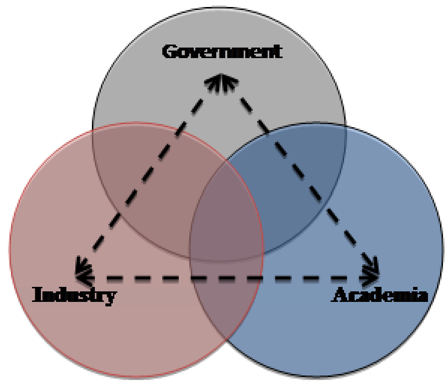


Figure 2.2: Representation of the Triple Helix Model

awareness of the complex interactive relationships that exist between invention, innovation, diffusion, and capitalization (Bell & Pavitt, 1993).

Despite this rich interaction, each of those forms of technical change presents enough differences to justify their independent existence in the conceptual framework of most knowledge systems. Indeed, the relationships between these notions have vast and varied meanings for the competitiveness of firms, industries and nations. Hence, the preservation of the identity of each one of those concepts becomes crucial. It is particularly important, though, to recognize each when building a specific framework for the analysis of technical change in NSIs.

2.3 The Triple-Helix of Public-Private Partnership for Innovation

To more concretely describe the processes through which the co-evolution between technological developments and their cognitive and institutional environments change the knowledge infrastructure, the notion of a triple-helix configuration of public institutions, private enterprise, and government regulatory systems was proposed (Freeman and Perez, 1988; Leydesdorff, 2000).

There are three selection environments, or spheres, specified in the Triple Helix Model (Leydesdorff. 2000):

1. *Wealth generation* (industry)

2. *Novelty production* (academia)

3. *Public control* (government)

A model which captures the cooperation, diffusion of resources, and transport of products across each sphere can be referred to as a Triple Helix Cooperative Innovation (THCI) model. The configuration of successful self-sustaining knowledge economies has been recognized as a key driver of economic growth at the regional and national levels (Tesfatsion, 2002). Evolutionary analysis of the interactions between each sphere in the triple helix focuses on outputs. This can be contrasted with historical analysis, which informs us about how institutions and institutional arrangements carry certain functions (Leydesdorff and Meyer, 2006).

The triple-helix model, like most representations of an innovation economy, is composed of many actors whose collective behavior enables the flow of technology and information among people, enterprises, and institutions (Prevost et al., 2004). In this way it is not dissimilar from an ecosystem, a notion which we will revisit in later chapters. When viewed through the lens of economic theory, an innovation economy is an economic model that effectively promotes the collection and diffusion of knowledge product throughout the system (Holling, 1987). This particular view affords the notion that an innovation economy can be represented principally as a resource management problem. Under neoclassical economics, the exploitation of resources is explained using microeconomic theory (Kreps, 1990). Under this theory various categories of actors make decisions based on the scarcity of available resources (Ferguson, 1969). Models based on this theory have been used to study the way changes in resource density modify the behavior of rational actors (Akaishi & Arita, 2001).

A part of economic literature on resource management is based on a normative approach; a methodology that concerns itself with the measures that must be taken to cause the behavior of the producer or consumer of a resource to reach an optimal solution for resource gathering. This approach implies that some system of supervision or control be imposed by a central entity (Sutinen, 1995). These measures comprise a suite of management tools and controls for restricting access to resources or influencing the costs associated with production. This particular belief is echoed within innovation systems literature, which recognize the importance of this central authority in developing and maintaining the three spheres of the triple-helix. However, the complexity of this model leads to uncertainty with regard to the relationship between environmental and exogenous parameters that affect economic and technological growth. Various methods for addressing this complexity have been proposed, but one recent approach that shows particular promise is known as ecological modeling (Yawson, 2008), which we will discuss in the later sections.

2.3.1 Government Intervention

The role government control plays in the development and long-term management of economies has long been controversial. However, various strategies of government partnership and control are common in most NSI models. These include policy instruments such as:

- Internal R&D.
- Trade taxes
- Grants & direct subsidies

These policy initiatives have the potential to change relative product and factor prices as well as generate shifts in economic resources between consumption and R&D activities.

The long term impacts of a government's use of policy instruments to affect growth of a regional economy are well documented. In fully endogenous growth models, a policy-induced shift in per-capita resources towards R&D activities has been shown to permanently accelerate the rates of innovation and growth. In semi-endogenous growth models this resource shift generates a temporary increase in the rate of innovation. This phenomenon was more formally analyzed in the case of structurally identical industries and countries by Dinopoulos & Segerstrom (1999) and Segerstrom et al. (1990).

The complexity of such systems cannot be ignored. Indeed, the interaction of related economic policy mechanisms can have wildly unpredictable combinatorial effects. Grossman & Helpman (1991) state clearly that, in the presence of asymmetric industries and countries, general equilibrium interactions can reverse the desired effects of several policy interventions. In one example, an R&D subsidy may cause a country to export fewer R&D intensive goods and import more of them, thus creating a dampening effect on local technology firms. In another example, industrial policies that subsidize manufacturing activities in high-technology sectors may have detrimental effects on global long-run innovation and growth because they could raise the aggregate costs of R&D.

2.3.2 Appropriability

Interventions are not limited to cost adjustment mechanisms. Government policy can also affect appropriability or the environmental factors that govern an innovator's ability to captureprofitsgenerated by aninnovation. The portability of new knowledge across an innovation economy has as much to do with the social structure of the system as it does the prevalent economic incentives present. This distinct property is the basis for cooperation between the three helices of an innovation economy. As a result, policies related to the appropriability of innovation not only have drastic economic impacts, but also change the social behaviors, which play a significant role in the economic interaction between firms. Social intervention strategies can generally be thought of as government's economic "soft power" to indirectly manipulate or change behavior by altering the risk-reward calculus in the innovation process without the use of direct capital or labor expenditure.

There is widespread agreement that in a perfect competition setting, that is, a situation in which, among other assumptions, no producer has market power, there is no product differentiation and all firms have immediate and perfect access to the same technologies, the rate of innovation in a market economy would be very low. Thus, the creation and regulation of mechanisms like *intellectual property rights* (IPRs) is seen as the most prominent pillar of government appropriability policy. IPRs have attracted increasing attention both in academic circles as well as in public policy debates over the past decades. This has gone hand-in-hand with their increasing use, particularly (but not only) patents, reforms in the national and international legal frameworks that have resulted in the strengthening of IPRs and the fast growth of sectors in which knowledge, innovation and appropriability play a key role (e.g. biotechnology, information and communication technologies and the cultural industries).

IPRs, including patents, copyright, trademarks, industrial designs, utility models and plant breeders' rights, are some of the appropriability mechanisms that may be regulated by the government. However, as is well known, there are other available mechanisms, including policies related to activities such as:

- exploitation of lead time
- moving rapidly down the learning curve
- use of complementary manufacturing capabilities
- secrecy

A more complete summary is available in Cohen et al. (2000).

Since labor mobility is also a form of technology imitation, labor legislation, contracts and human resource management practices are also very relevant appropriability mechanisms (Hurmelinna & Puumalainen, 2007), although some of those mechanisms could be included under the heading of secrecy. Much of the literature on non-market related government intervention is devoted to issues regarding appropriability of innovation via the patent system.

Some models studying growth of innovation economies have analyzed the dynamic effects of stronger protection of IPRs. In these models, strengthening IPR is captured as either an increase in patent length as shown in Segerstrom et al. (1990) or a reduction in the rate of imitation as shown in Krugman (1979). Both models rely on a North-South Schumpeterian growth model, where two distinct economic zones compete with one another by either innovating internally or imitating innovation in the rival community. Stronger IPR protection was shown to reduce the rate of international technology transfer from innovating North to imitating South. This in turn raised the North-South wage gap, and had an ambiguous effect on the rate of innovation and global growth.

Helpman (1993) showed that even if stronger IPR protection increases the rate of Northern innovation in the short run, it could reduce the welfare of Southern consumers and could raise the welfare of Northern consumers by shifting production from low-price South to high-price North. The IPR model has been shown to be relevant not only in understanding the relationship between industrial firms, but also to the behavior of academic institutions engaged in R&D.

Recognition of the value of public-private partnerships led to the creation of *Institutional Patent Agreements* (IPA), which, among other things, allowed universities and non-profits with approved patent policies to retain title to inventions developed with government funding. This would later be followed by the adoption of thePatent and Trademark Law Amendments Act or theBayh–Dole Act, which expanded these rights. This policy legislation is largely credited for paving the way for the later success of firms transforming of grant-funded scientific research into profitable consumer products, evidenced by the rapid expansion of the country's technology sector.

2.3.3 Government Grant System

Grants are a method of funding whereby one party (Grant Issuers), often a government agency, fund, trust, or other interested firm disburses funds to another entity, business, or individual. While the notion of a grant support at the federal level in the United States has existed in some form going back as far as Federal Tax Act of 1913, regional targeting of grants in support of scientific research is a relatively new concept. The system itself is composed of various classes of issuers and applicants whose relationship generates product in the form of innovation and capital. This architecture of the US government grant system (GGS) is laid out in the Federal Grant and Cooperative Agreement Act of 1977, which states that the principal purpose of the relationship between the GGS and researchers is to transfer a "thing of value" to the government or other recipient (firm) for the public purpose of support or economic stimulation.

Government programs that subsidize commercial R&D are justified on the grounds that profit-maximizing firms underinvest in R&D. Government funding of private R&D projects, however, can increase R&D effort only if the subsidies cause firms to undertake projects that would otherwise be unprofitable. Empirical studies to measure the effect of these government grants typically regress some measure of innovation or firm productivity (e.g., R&D spending or employment) on the subsidy. Many of these studies find a positive correlation between government R&D funding and private R&D effort and employment (e.g., Levy and Terleckyj, 1983; Robson, 1993; Nadiri, 1993; Irwin and Klenow, 1996; and Lerner,1996).

Until recently, most federally funded industrial R&D was directed at government needs, such as large weapon systems. While federal support for private R&D dates back to the 19th century, government-industry R&D programs have become increasingly popular in recent years. Many of these programs aim to help firms commercialize innovations by subsidizing their R&D. Cohen and Noll (1995a) and Nelson and Romer (1996) document the increasing popularity of these programs and the reasons for their rise. Others examine individual government-industry R&D programs. The economic justification for these programs is clear: The social returns to private R&D are often higher than the private returns, some research projects would benefit society but would be privately unprofitable. By lowering the cost to the firm, a subsidy can make these projects privately profitable as well.

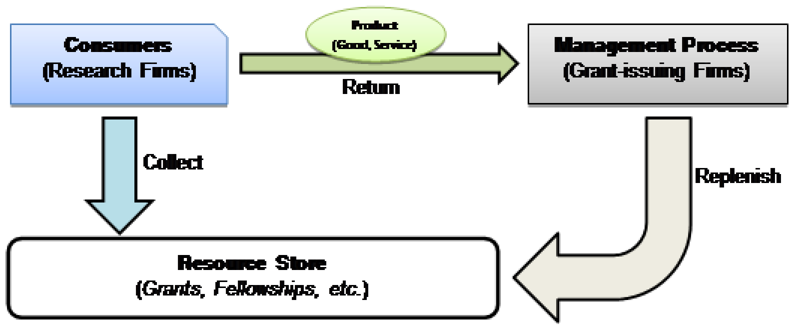


Figure 2.3: Architecture of a grant system.

For the purposes of our investigation, it is useful to regard a grant as a replenishing resource that exists in a notional environment whose connection with institutions and individuals is governed by suitability, or theoretical closeness. This closeness is defined as a relationship gradient between the grant's issuer and potential institutional applicants. The distance between a grant and an institution is analogous to the amount of 'work', which must be done to create a successful application.

In a more concrete sense, grants are both strict resources as well as renewable environmental properties. If one were to represent the grant system as a natural ecosystem, grants would be the equivalent of producers, such as algae or grass. The entities which collect and transform grants are analogous to ecological consumers, which transform environmentally situated resource into higher order products. In this way, the relationship and behavior of the artifacts and firms in the GGS approximate a simple energy flux. This flux can be captured in a variety of natural models, explicitly those that map to grazing or foraging activities. The more general form of this interaction is known as the predator-prey relationship.

2.4 Modeling Innovation Economies

The goal of system modeling is to create a realistic abstraction of the system in question. Due to inherent complexity of real-world socio-economic systems, it is generally not possible for a model to capture every detail. Innovation economies present additional challenges in that their behavior is often unpredictable by virtue of being driven by processes of creative destruction, complex psycho-social phenomenon, and exogenous environmental conditions. Thusly, most models in this domain must be ne-tuned and designed based on a specic hypothesis to be tested for the corresponding system. The basic implication is that models based on the same system can be structured in a myriad of different configurations based on the abstraction chosen by the designer.

In a general sense, modeling has been shown to be very useful in understanding and predicting various properties of complex systems. Stareld et al. (1990) refers to models as "purposeful representations" and "tools for problem solving" they enable the central tenants of a problem to be captured. Most importantly, models help facilitate prediction and understanding of system-level properties. In suitably complex systems these properties may be obfuscated by the behavior of constituent mechanics. The modeling process involves a thorough analysis of the key parameters affecting the behavior of the main components of the system and their interactions with one another. In return, this provides the modeler with valuable insights on the overall patterns of organization within the system.

Robinson (2006) makes the claim that the output product of a model is more than a set of results that match some experimental data. Indeed, the approach as a whole allows us to test the role of mechanisms which may be impossible to manipulate, or even capture properly in the existent systems from which the model in question is derived. Moreover, using models allows for repeated simulation and testing of various mechanisms and scenarios which can be constructed merely by tuning parameters, thus avoiding difficult and time-consuming real-world experimentation.

Deterministic modeling usually involves manually analyzing data and deriving differential equations which approximate and "average: behavior of the system. These approaches often fail to capture a large number of interactions between components which could include factors leading to population-level behavior. Consequently, methodologies focused on the creation of individual-based models have become more en-vogue across the many analytical disciplines which concern themselves with complex adaptive systems (CAS). These models are often considered more realistic and better suited to capture interactions at the individual level and provide deeper insights into the reasons behind population level behavior.

An important aspect which a model designer should remain cautious about is the number of iterations required for a model to be simulated. It is important to have a sufficient number of runs for the system to evolve from smaller parts, otherwise community-level behaviors may not be observed efficiently or effectively. There are two main approaches to modeling complex adaptive systems. These are the top-down, and bottom-up approaches which are discussed in the following sections. Though omitted for brevity, it should be noted that a combination of the two-approaches, referred to as "integrated" or "middle-out" modeling, also enjoys wide use.

2.4.1 Top-down modeling

Based on mainly ordinary or partial differential equations, subject systems are analyzed in a top-down manner in terms of a population of identical individuals. Individual differences in population are ignored and the underlying behavioral rules are usually treated as a "black box", or approximated at the best case. Essentially, this means that the designer is less concerned with the individual mechanics that govern the behavior of a population and instead focuses on the observable changes. The methods through which top-down models, also referred to as state-variable models, are essential and have proven useful in formulation of general theories. One popular example is that of the *Lotka-Volterra* model of the predator-prey interactions. Despite this usefulness, biological and, most importantly, economic systems tend to represent a great challenge for mathematical modelers, due to their inherent complexity and non-linear relationships among individual components. In the study of the social insects, successful applications can be found in the works of (Bonabeau et al., 1998). These models do often successfully describe the behavior of some homogeneous populations, but they also limit the understanding of how patterns are formed. Such models may apparently work well, but in order to understand the exibility and diversity of colony activity, it is also essential to investigate the agents at the individual level. Rather than carrying out a full investigation on the underlying mechanisms of the system, top-down models average individual behavior over the whole population.

2.4.2 Bottom-up modeling

In bottom-up modeling, the system is modeled at the individual level, aiming to study the mechanisms for underlying behavior as well as local interactions between the individuals in a population (homogeneous or heterogeneous). Bottom-up models tend to emerge from low-level components of the system, and are studied in order to understand how the overall pattern of the system emerges. This method emulates the behavior of the system under study in the most realistic way, but can be taxing when used to analyze scale systems with large populations. Recently, bottom-up approaches have started to attract more interest in modeling complex economic systems. This is due to researchers realizing the potential advantages of bottom-up approaches over top-down. In a top-down model, it is not possible for a user to trace back the system properties to the behavior of an individual actor, which is critical when modeling economic systems. In contrast, this is easily achieved in bottom-up models.

Cellular Automata (CA) is a popular method in this regard. CA emulate real physical laws using a small set of simple rules by limiting all properties to a few states, frequently no more than two (Wolfram, 2002). Developed by Ulam and von Neumann, CA was founded upon the notion of one robot building another robot, aiming to address the problem of self-replicating systems. One such classic example is John Conway's 'Game of Life' by which a CA model operating on four simple rules of generations allow individual cells to react and change their states based on their interactions with surrounding neighboring cells. CA has been effectively used to explore many problems in fields such as biology, sociology, and psychology, but suffers when applied economic system models because it treats firms as homogeneous, without any exibility or variability, which are key characteristics of such systems.

Traditional bottom-up models focus on the individual components of a system. Consequently, the set of methodologies conforming to this approach are often referred to as individual-based modeling. Each individual system component is treated as an agent employing certain behavioral rules (agent-based modeling), where over time interactions between these agents will give rise to characteristic patterns at the population level. In modeling social groups (such as insects, societies, etc), successful implementations of such models could be found in the works of Deneubourg et al. (1989). Agent-based modeling is discussed in detail in the next section

2.4.3 Agent-based modeling

Agent-based models (ABM) provide a platform upon which simulations of large number of agents can be constructed. These models encourage bottom-up approaches by allowing the designer to focus on the interaction between individual elements of the system, rather than trying to describe behaviors at the population-level. The characteristic behaviors of the individuals are assigned to agents as simple rules. These rules govern how and where each agent is able to make decisions, as well as providing additional constraints based on the problem domain. As a result of various interactions between the agents through the environment, certain population-level dynamics emerge. The most common use of agent-based models involves mimicking complex systems, in which theoretical lessons could be learned according to the results of the simulations.

In the most basic sense, an agent is a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its design goals (Wooldridge and Jennings, 1995). Once the lowest-level components of a system are identied as agents, simple rules governing their real behavior are applied. These rules

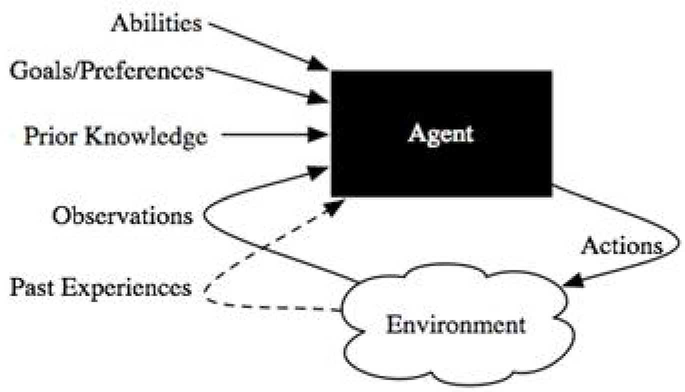


Figure 2.4: An agent interacting with an environment.

then facilitate interaction between the agents and leads to emergent behavior over time. An agent may act both on and within anenvironment.

A system composed of multiple autonomous reasoning agents is commonly referred to as a multi-agent system (MAS). In typical multi-agent systems, an agent's environment includes other agents with which interaction may take place. In this context, an agent together with its environment is called aworld.

Some clear advantages of ABM over traditional modeling approaches, including CA, are the following:

- **Asynchrony**: Agents do not need to simultaneously perform actions at constant time-steps, rather they can follow discrete event queues or a sequential schedule of interactions.

- **Spatial**: The environment does not necessarily need to be grid-based, nor do the agents need a direct tie to the environment, which allows cohabitation of agents with different environmental experiences.

These features are powerful as they allow flexibility in representing systems via abstraction. This is relevant when modeling real-world socio-economic systems which often consist of layered physical and relational (meta-physical) environments which may or may not be linked directly. Biological models also benefit from this loose environmental coupling, as these systems are often decentralized. For example; Ant colonies are known for their decentralized communication system, as they do not have a leader inuencing the colony members. Rather, their colony level behavior emerges from the interactions between the individual ants, which is mainly via pheromones deposited in the environment. It is therefore more appropriate to apply bottom-up agent-based modeling to ant behavior. This way, interesting features emerge over time, which are not pre-determined in the design at all. (Deneubourg et al. 1990).

While many types of agent modeling focus on cognition, the situated multi-agent system (situated MASs) modeling avoids individual intelligence in favor of environmental interaction. Contrary to cognitive approaches of agency where a great deal of effort is devoted to the formalization of agent concepts, relatively little work has been done on the formalization of situated multi-agent systems (situated MASs).

Situatedness is a property of agents adopted by most researchers in the domain of MAS. It is described by Woolridge & Jennings (1995) in their definition of an agent: 'an agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives'. In this case, the notion of situatedness expresses the fact that an agent is not an isolated entity but exists within a conceptually abstract environment. This definition deliberately does not prescribe explicitly what it means for an agent to be situated in an environment, e.g., nothing in the denition explicitly refers to the fact that the existence of an agent in an environment entails a social component.

In situated MASs, agents are considered as social entities. Put more directly, the emphasis in situated MASs is on 'M' in MAS, rather than on 'A'. This view expresses the belief that agents and environment constitute complementary parts of a multi-agent world. In that sense, situatedness expresses the local relationships between agents and objects in the environment rather than strict location. These relationships give the system meaning and structure, driving the evolution of the MAS as it persists. Through its situatedness an agent is placed in a context that it is able to perceive and in which it can interact with other agents. Thus, intelligence in a situated multi-agent system is derived from these interactions, rather than from capabilities of individual agents.

Despite its relative lack of attention within the domain of ABM, the situated approach to MAS design has a long history. Brooks (1987, 1991) identied two central ideas of situatedness; embodiment and emergence of intelligence, while Steels (1990) and Deneuborg et al. (1986) introduced basic interaction mechanisms for agents to communicate and coordinate through the environment: gradient fields, and marks. The work of Maes (1990) introduced robotic principles of reactivity to the field of software MAS. Dorigo (1992), Corloni et al. (1993), and many other researchers drew inspiration from social insects and adopted the principles in situated MASs.

Situated ABMs have been applied with success in numerous practical applications over a broad range of domains, some of which will be explored in greater depth in later sections. Examples of such applications include: manufacturing scheduling (Parunak et al., 1998) and supply chains systems (Sauter & Parunak, 1999), articial worlds and social simulation (Macy & Willer, 2002), network support (Bonabeau et al., 1998) and peer-to-peer systems (Babaoglu et al, 2002). Situated MAS offer very clear benefits, the most important being flexibility, robustness, and efficiency. Despite these affordances, this approach comes with a number of drawbacks which can be attributed to the inherent qualities of the approach, e.g. decision making of situated agents based on local, current information. This means that situated agents by definition have a short-term view of the state of the world. Other unsolved problems stem from complexity issues regarding the engineering of situated agents with respect to desired overall behavior (Rouchier, 1999). Due to the intensely decentralized nature of the system, and the sheer volume of concurrent, often interdependent, interactions between agents, addressing this problem has continued to pose difficulty to ABM designers.

2.4.4 Ecological modeling

Ecology is the study of living organisms and their connection with the environment. These organisms, called species, are divided into semi-homogeneous groups called populations and classified by their general role in the larger ecosystem. Communities are formed from various populations of distinct species that all inhabit the same environment or operate in a dependent fashion. These dependency cycles are often referred to as "lifecycle processes" which, when collected together and viewed in a top-down fashion describe one of ecology's most important and fundamental concepts; the ecosystem (Bosquet & Le Page, 2003).

Tansley (1935) characterized ecosystems as being composed of both the organisms present in an ecological unit and the "... effective inorganic factors of its environment". A major strength of the ecosystem concept is that it is appropriate for any situation in which the biological and physical interact, leading to the broad utility of the concept across many domains (Stepp et al., 2003). Some authors and researchers have sought to stretch the definition of the ecosystem to suit particular problem spaces, leading to concepts such as the human and economic ecosystem views. To perform this transformation, it is often the case that the common definition is expanded with domain-specific concepts. However, because we wish to develop a more fundamental ecosystem model we are principally concerned with the attributes these varying interpretations share.

In general, an ecological system can be said to have several key properties that helps distinguish it from other complex systems:

With these attributes in mind, we can construct a general model of an ecosystem in terms of a lifecycle which connects the members of a community to one another and the environment through a variety of mechanisms and rules which are governed by the nature of the system and trophic levels (roles) available (Costanza et al., 1993). The interplay between the trophic levels may produce cycles that allow energy or material to be transferred through the environmental strata. This transference can also result in transformation activity, which

Ecological Property	Definition
Energy Flow	Energy, in some form or another, is transformed and passed between actors in the system through a series of positive or negative feedback loops.
Role-based Behavior	Species display characteristics that allow them to be categorized by trophic level, or position within the food chain (producers, consumers, and decomposers).
Diversity	Ecosystems are non-homogeneous and operate through the interplay of any number of distinct species.
Emergent Hierarchy	The system provides few endogenous rules besides those that govern the relationships between individuals and species populations (based on their trophic profile), yet over time clear organizational hierarchies emerge between species.
Environmental Feedback	Individuals make changes to the environment that persists between cycles. This cycle allows the formation and maintenance of system-wide services such as regulation, provisioning, and reinforcement.
Social Strategies	Populations use social survival strategies such as cooperation, parasitism, and competition to persist despite fluctuating environmental conditions.
Resilience	The system always attempts to return to equilibrium after perturbation phenomena. The result is often regime change (climax).

Table 2.1 Properties of an ecosystem.

allows high-level products to be synthesized through the cooperation of many low-level actors in a completely undirected fashion.

The concept of energy flow is probably the most central to the ecological model as it acts as the basis for making connections between all the constituent components (species and environment) (McCormack, 2007). The flux of energy, organic, and inorganic material forms the crux of the relationships between trophic levels and is generally regarded as the mechanism through which all systemic change can be measured.

Most ecosystem models adhere to the preceding classification of roles, naturally organizing the dependent relationships in a graph known as a food web (Prevost et al., 2004). Links in a food-web illustrate direct trophic relations among species, but there are also indirect effects that can alter the abundance, distribution, or biomass in the trophic levels. Examples of this can be found in natural systems such as when the over-predation of a primary consumer (such as deer or bison) by an apex consumer results in the aggressive expansion of a previously stable species of plant. In this case, the apex consumer was indirectly influencing the regulation of the plant species through its action on the primary consumer. The net effect of these direct and indirect relationships is called trophic cascade and is separated into species-level and community-level cascades.

The potential for radical environmental change, whether through stochastic models or the activity of communities, introduces a level of uncertainty not often tolerated in engineered systems. This fact, coupled with the lack of a central agency driving the system towards a particular set of goals, allows ecological systems to shift between various regimes while still maintaining equilibrium conditions.

Patten (1978) made a similar observation in his expansion to the Tansley model of ecosystems. However, the Patten view includes both input and output models in the formulation of the environment such that;

$$\text{Input Environment} + \text{System} + \text{Output Environment} = \text{Ecosystem}$$

The resulting model proves to be more easily generalizable beyond the ecological domain. The concepts from which it is derived places an emphasis on the significance of indirect causality, which is realized through complex networks of species interactions and energy flows. This notion permits the exploration of the role of information in ecosystems and more concretely defines the parameters for the feedback cycle which lies at the heart of all ecological systems.

To properly define principles of **ecological management**, we turn to Holling (1987) who lays out three central concepts that have dominated causality in ecological systems and that demarcate the principles for the management of ecosystems. The first concept is based on the notion of equilibrium (balance of nature). The second concept defines several states of stability (nature engineered or nature resilient). This second perception is primarily concerned with dynamics caused by variance (stochasticity), usually attributed to events that occur at small scales.

The third concept is that of organizational change (natural evolution), wherein he notes that not only does the system undergo change (external events lead to perturbation of the system), but also the actors of the bespoke system may, by themselves, change its organization. This is especially true when human interference is taken into account as a feature of the system. This final concept corresponds to the approach adopted by the sciences of complexity: i.e. the general state of a set of interacting entities may converge toward attractors, may be disordered, or may exhibit patterns of organization that change from one to another in an unpredictable way (Wolfram, 1984; Langton, 1992). The study of these systems relies on observations that focus on the connectivity of the ecosystem's elements, their interactions, and their organization across various scales.

2.5 Verifying & validating simulation models

The proliferation of simulation models as problem-solving and decision-making tools has caused serious questions to be raised about the accuracy and usefulness of the information obtained from their operation. Ensuring 'correctness' is paramount. This concern is addressed through model verification and validation (V&V) processes. Model verification can be defined as "ensuring that the computer program of the computerized model and its implementation are correct" (Sargent, 2009), which we will use here. Schlesinger et al. (1979) offers a similarly suitable definition of validation as "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model". These definitions are symbiotic and imply that a model should be developed for a specific application and its verification and validation criteria be evaluated with respect to that application. In the case of validity, a model is considered valid for a set of experimental conditions if the model's accuracy is within its acceptable range. This satisfies the notion that absolute validity is often too time-consuming, expensive, or computationally impossible given development or operational constraints. Formalized model validation approaches vary depending on the domain. Where development teams are involved, the model development team itself may make the decision as to whether a simulation model is valid. In other instances expected users supply validation criteria or provide the validation themselves through direct observation of simulation output. The use of outside observers is common in "independent verification and validation" (IV&V) where an independent third party determines validity (Wood, 1986). Finally, scoring models, such as those proposed by Balci (1989), where weights are determined subjectively

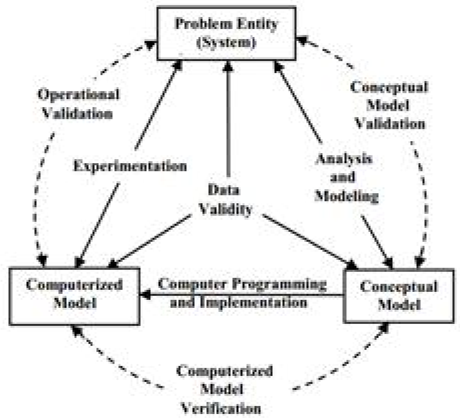


Figure 2.5: Simple version of the modeling process (Sargent, 2005)

when conducting various aspects of the validation process and then combined to determine category scores and an overall score for the simulation model.

Following the 'simple' modeling process (figure 2.4), model validation can be further refined into two main components (Sargent, 2005);

- *Conceptual model validation:* Determining that the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is "reasonable" for the intended purpose of the model.

- *Computerized model verification:* the computer programming and implementation of the conceptual model is correct.

Valid simulation models are constructed iteratively, with each successive model subjected to V&V checks to ensure correctness (Sargent 1984). There exists to-date no algorithm or procedure to select which techniques to use during the V&V stage of each iteration. Instead, this is left to the discretion of the researcher or development team. Some attributes that affect which techniques one might use to make this decision are discussed in Sargent (1984).

In general, agent-based simulation model V&V is difficult. However, those situated in the biological and socio-economic domains present particular validation challenges. Grimm

(1999) reviewed 50 individual-based animal population models, providing a detailed comparison between individual-based and statistical modeling approaches. According to Grimm; the expectations from individual-based models were not fullled. This is because it was expected that once the rules and characteristics of individuals have been assigned to agents, the population and community-level consequences would emerge naturally (DeAngelis et al., 1994). However, out of the 50 individual-based animal population models reviewed, only 36% of them were found satisfactory and the remaining 64% were found to be generally inadequate. Grimm (1999) explains the reason for this disparity was the absence of a general strategy for building and analyzing individual-based models. His suggestion upon this was to start with a very coarse model that reproduces a pattern, followed by refining the model step-wise, and finally checking and testing the model rigorously with each renement. It was concluded that bottom-up approaches alone will not lead to theories at the system level, due to the need for top-down approaches to provide an appropriate integrated view. However, it was also underlined that it will never be possible to fully understand a system's properties unless the mechanistic interactions through which they emerge are well understood.

The solution to this V&V challenge is to express individual-based models in a formal framework (Kefalas et al., 2003), as well as adopt formalized methods for model creation similar to those described in Sargent (2005). The formal specication of a model facilitates model checking, which in turn guarantees completeness of a model with respect to requirements. Merely testing a model via simulation may only reveal surface-level inconsistencies or misconceptions in the model and is insufficient grounds to concretely validate or invalidate a design.

From this survey we conclude that model V&V is performed to assure *quality* as well as *theoretical soundness*. Carley (1996) grouped quality into the five categories seen below:

- *Theoretical validity*: Adequacy of the underlying theoretical model in characterizing the real world.
- *Internal validity*: Whether the underlying assumptions are consistent.

- *Operational validity*: The adequacy and accuracy of the model results when compared with experimental or system data (Sargent, 2005).
- *Cross-model validation*: Comparison of two models against each other.
- *Data validity*: Accuracy of the data (real and computer generated) and the data's adequacy for addressing the issue of concern.

In this research, attempts are made to fulfill each category by taking the following factors into consideration:

- *Face validity*: The model results or simulations 'appear' to be consistent with reality.
- *Parameter validity*: The parameters of the model match available experimental data.
- *Process validity*: The process described by the model corresponds to the observed or implied mechanisms of the socio-economic system (Yilmaz, 2006).
- *Pattern validity*: The pattern of results generated by the model matches the patterns of results from similar studies (where available).

In addition, a number of validation techniques were used. Adapted from Carley (1996) these can be summarized as follows:

- *Grounding*: The simplications made in the model design should not affect providing important insights. Parameters and states should be set in accordance to real rules, and wherever possible it should be demonstrated that the model results and behavior are consistent with the real behavior.
- *Calibrating*: Models should be extensively tuned to the mechanisms of the system under study by parameter estimation and/or altering algorithms and rules within the model.
- *Verication*: The model results are compared graphically or statistically with experimental data and previous related findings.

It should be noted that while model validation requires a close accounting of the parameters and mechanisms of the system, our verification process is constrained to those areas where empirical data is available. Since the domain of innovation system dynamics is new, there will be inevitable gaps in data coverage. To this end we supplement our verification process with a focus on repeatability.

2.6 Chapter Summary

In this chapter we provided a summary of relevant works in innovation economics and agent-based modeling. In section 2.1 we discussed the history of regional and national systems of innovation. In section 2.2 we outlined the role knowledge plays in productivity and competitiveness of economies. In section 2.3 we outlined the triple-helix theory of public-private partnership, paying particular attention to the properties and mechanisms which govern the behavior of the three regimes of control; academia, private industry, and government. We also explored the theoretic environments within which triple-helix actors exist and interact with one another. In section 2.4 we discuss a basic framework for understanding holistic modeling of innovation ecosystems, introducing the principles of ecological modeling as an alternative to top-down or bottom-up interpretations of complex socio-economic systems. In addition we cover the basic tenets of agent-based modeling that we will revisit in chapter 3. Finally, in section 2.5 we address various validation criteria for models and clarify the standards we will use to instill confidence in the conceptual design and experimental operation of our simulation model.

Chapter 3

Agent-based Perspective for Simulating Innovation Dynamics

3.1 An Ecological Approach to ABM

In order to effectively map multi-agent system design methodologies to the ecological model of innovation economies it is important to delineate the criteria through which we cast an ecosystem as a complex adaptive system (CAS). Indeed, Levin (1998) identified three important criteria which a system must satisfy in order to qualify as a CAS:

1. Sustained diversity and individuality of components.
2. Localized interactions among those components.
3. An autonomous process that selects from among those components, based on the results of local interactions.

These properties are simple, yet expressive, and allow us to observe that CAS arise from the conjunction of three main processes: one that creates and supports diversity, one that supports interactions between components (species), and one that selects on the gradient between form and function (Levin, 1998). The final product is the community of components which continuously changes towards a dominance of those best suited to deal with the selective forces and limiting features of the environment.

This mapping also helps us ground the contention that ecosystems are prototypical examples of CAS that not only exhibit a dispersed and autonomous selection process but also continual adaptation (Brooks, 1991). The maintenance of diversity and individuality of components implies the generation of perpetual novelty. This process closely resembles the cycle of innovation creation described in by List (1841). Thus, the preceding listed set of ecosystem processes cleave to the essential definition of features of a CAS while also supporting the central intent and processes of an NSI.

Following on, we also observe in literature that the development of MAS has been intrinsically linked with both the ecological and economic domains for a long time (Baray, 1998). The legacy of decades of cross-pollination between ecology and agent simulation is realized in some of the earliest formative work in the field, such as the ant-hill metaphor (Babaoğlu et al., 2002); which provides an oft used illustration representing concepts of reactive agents and emergent behavior. Later applications would be found in Hogeweg & Hesper's (1983) work on bee colonies and the development of nature-based swarm dynamics such as ant-colony simulation (Dorigo et al., 1999) and Reynolds' (1987) work simulating the migratory behavior of birds which predated organized notions of MAS or Artificial Life. Indeed, the adoption of agent-based simulation techniques was picked up early by the ecological community and mostly used in environmental applications which involved interactions between natural and social dynamics such as land-use management or fisheries (Beckenbach et al., 2008).

From this we can gather that there are properties of agent simulations which afford a mapping between MAS architectures and ecological NSI models. In the context of innovation individual actors and organizations are typically characterized as having bounded rationality, presumed to be acting in what they perceive as their own interests, such as reproduction, economic benefit, or social status (Axtel et al., 2000) using heuristics or simple decision-making rules. From a MAS perspective, some agents may experience learning, adaptation, and reproduction.

The individual agents within MAS have several important characteristics that afford the distributed nature of the problem domain addressed in this thesis, the NSI. These detailed below:

- **Structural Decentralization**: The system displays collectivist behavior, eschewing central behavioral management in favor of local autonomy.

- **Self-Organization**: The system allows agents to define their own hierarchal or relational structure based on their interaction rules.
- **Limited View**: Agents do not possess a global view of the system. This is often a practical concern as the domain is often too complex for a single agent to make sense of in a reasonable period of time.
- **Autonomy**: Each agent in the system acts in pursuit of its own agenda over time and exhibits goal-seeking behaviors.

Since we are observing MAS applied to an ecological model, despite its grounding in economics, we must also concern ourselves with interaction style. There are three major types of interactions in an ecological system:

- Interactions via agent **communication.**
- **Physical** interactions (grow, eat, push, etc).
- Interactions mediated by the **environment**.

Unlike in other scenarios (social, cognitive, etc) direct interaction through the exchange of messages is exceedingly rare in ecological applications. However, some examples of this can be found in literature such as contract negotiations for goods and services among human agents or the communicative predator-prey model put forward by Baray (1998). These behaviors are also prevalent in conflict simulations (Carley & Tsvetovat, 2004). The second type of interaction, physical, is also the most commonly found interactions in an ecological model and is typified through inter-agent behaviors such as predation.

The third type of action, environmental, is a reaction to questions raised by the Artificial Life community, namely; what is the relationship between an object and its environment? In their view, the environment cannot simply be taken to mean all other agents; instead the environment means the physical space and the resources it contains. This notion dovetails with the concept of externality used by economists. The results of an agent's actions transform the environment with a retroactive effect on other agents. For certain mechanisms (stigmergy, etc) the dynamics of the environment become a medium for collective adaptation (Dorigo et al., 1999).

Having generally described the relational mapping between the MAS and ecological NSI model architectures, we proceed on to examine work done to concretize the notion of the agent-based innovation ecosystem model.

3.2 The Agent-based Ecosystem Model

The multi-agent methodology has been successfully applied to problems in a variety of domains through the development and analysis of simulation models (Antona et al., 1998). ABS are especially useful for examining the emergence of macroscopic properties of related communities of actors (Baray, 1998). This analysis is often approached in a bottom-up fashion, with close attention paid microscopic interactions between agents and their collective behavior over time. This more holistic view, which combines top-down and bottom-up strategies, is known as agent-based ecosystem modeling (Picket & Cadenasso, 2002).

Ecosystem modeling has been applied to the analysis of a broad range of natural and artificial systems through the application of theories derived from such disparate areas as non-linear physics and dynamical systems (Parrott & Kok, 2000). The field is, therefore, highly multidisciplinary, bringing together researchers in all specialties, ranging from economics and social policy to biology, physics and modern visual arts (Klomp & Green, 1996). Despite this nexus of expertise, effective applications of ecosystem theories to practical field problems suffer from the lack of knowledge-models and their parameters, as well as uncertainty. Model parameters are often difficult, if not impossible, to measure directly because of time, capital, methodology, scale, or conceptual constraints. Despite this limitation, the development of agent-based simulation models which capture the critical functions of target systems can be used to both discover and quantify parameters of interest (Assad & Packard, 1992).

Natural Ecosystem	Definition	Innovation Ecosystem	Definition
Species	The living organisms that have the growth and bearing ability	*Innovation organizations*	Entity such as private firms, universities, and research organizations
Population	Aggregation of one species	*Innovation population*	Aggregation of one innovation entity
Community	Aggregation of different populations	*Innovation community*	Aggregation of different innovation populations
Producer	The autotrophy that product food with mineral	*Innovation entity*	Organizations that using resources to do technology innovation
Consumer	The living organism that absorb and digest the organic material to survive and multiply	*Innovation consumer*	The organization that absorb and process innovation products to survive and grow
Food chain	The living organism that absorb and digest the organic material to survive and multiply	*Innovation chain*	The relationship formed by the innovation technology transfer among different populations
Environment	The place where living organisms and populations live	*Innovation environment*	The innovation circumstance such as social network, physical infrastructure, geography, and policy structure
Information transfer	The transfer of information in the ecosystem	*Knowledge & information flow*	The flow of knowledge products, practices, and technology in the system
Cooperation	Populations evolve by cooperating and adapting to the environment	*Innovation cooperation*	Populations evolve by cooperating and adapting to the environment

Table 3.1 Comparison of the natural ecosystem and the innovation ecosystem

The work of Leydesdorff & Etzkowitz demonstrated that, at its core, a knowledge economy can be reduced to a theoretic model whose interlocking components display the characteristics of a complex-adaptive system (Leydesdorff & Etzkowitz, 2005). Further investigation has indicated that the relationship of the three spheres in the triple-helix model discussed earlier can be captured in a MAS model (Dongsheng & Yongen, 2008). We also see that the actors within innovation economies can be represented in ecological terms (Dai et al., 2007), and that the macroscopic relationships between classes of THCI system actors approximate that of the classic predator-prey model (Moore, 1993).

3.2.1 Resource Management Models

In the literature on resource management, a common representation of an economic environment is based on an ecosystem model. Under this model, resources are represented globally, and the actions of actors, or agents, upon those resources are represented via a cost function (Antona et al., 1998). Ecological and socioeconomic variables such as resource renewability, demand, harvest intensity and its cost to various agents are synthesized. In this scenario, the harvesting of a resource is the sole objective of the agent. Transformation and exchange are rendered secondary and their rules are often unspecified (Rouchier et al., 2001). Thus the assumption then is that these behaviors are only necessary for setting equilibrium prices and creating synthetic resource artifacts and that the scale at which management operates is at the harvesting stage, directing the activities of uniform agent (Mathevet et al, 2003; Mathevet et al, 2003b).

Alternatively, there are other resource models which are interested in more than just primary harvesting (Janssen & Carpenter, 1999). These models consider that the resource is subject to the derived demand behaviors of final users rather than that of the primary harvester. Moreover, these demands may be for secondary resources which must be synthesized from primary resources. Thus, this representation takes into account not only the heterogeneity of agents, but also that of resources (Costanza et al, 1993). Additionally, this view takes into account agent location with respect to resources and the act of secondary production.

For our model, we chose to represent resource exploitation in the form of *innovation communities*, i.e. agents with various tasks such as harvesting, consuming, and transformation resources (Beckenbach et al., 2008). These communities roughly equate to regional industrial conglomerates in economic parlance. Using this form of representation allows us to formalize exchange and transformation of resources through various stages of the innovation economy. Within economic literature on renewable resources, this representation is typically found in cases where this flow of resources between levels is represented as a series of cost functions (Charles, 1988).

In this model, the method for coordination of the resource model comes through fixed cost functions associated with each agent, with global management policy affecting the placement and amount of resources available at each location in the environment. Because pricing is loosely fixed, we do not observe the market-based dynamics that often act as a balancing mechanism for system behavior at the same scale as have been observed in existing systems

(Rouchier et al., 2001). The precise mechanics of these functions will be discussed in later sections.

Despite the above limitation, the proposed model is relevant to the discussion of management controls as a set of collective rules even if the selection is somewhat limited. The economics of resource management describes two main categories of harvest tools (Nag et al., 2007):

- Those that reduce harvesting intensity or inputs (number of harvesters, input costs, etc)
- Those that directly limit the amount harvested (outputs)

Inputs are reduced by imposing a limit on the number of harvesters or via some taxation scheme imposed on the harvested resource. These use-conditions are particularly relevant in the discussion natural resources (fishery, forest, and aquatic environs), but may be less accurate when dealing in purely economic constructs.

3.2.2 Resource Management Instruments

We will briefly discuss three main instruments in the study; resource spatial positioning, taxation and harvest quotas as they pertain to our model.

Resource positioning provides a simple ecological analogue to environmental configuration. The physicality of resources in relation to actors can be a major factor dictating exploitation in renewable resource models (Tansley 1935). In theoretic models this notion is often described via density ratios, with low density implying local scarcity, and high resource density implying local abundance. This is particularly pronounced in ecological models pertaining to land-use, as the primary driver of action is degree to which environmental resources are utilized by agents (Sutinen, 1993). In economic literature, the cost function associated with resource harvesting often contains some aggregate calculation for work, which accounts for all the activities performed by an actor for the purpose of securing and transporting a resource. In human endeavors, and more specifically in our model, the placement of resources within the grid space gives provides us a metaphor through which to translate this equation (Stepp et al., 2003). Spatial distance within the environment translates to the relative amount of work a harvester must spend to exploit a particular resource. The actual cost associated with extracting resource is a function of distance,

From a management perspective, the modification of this property is akin to diminishing or increasing the coefficient for exploitation (work) in the cost function for harvester agents. As a macroeconomic tool, policies organized around spatial location have profound effects on the behavior of the agent community as well as the nature and timing of regime changes within the system (Pottage et al., 2004). Within the literature pertaining to innovation economies this equates to the strategic allocation of funding around particular industries and institutional programs (Axtel et al., 2000).

Taxation provides a direct means for a central authority to suppress or promote a particular kind of resource utilization or transformation process (Teece, 1998). This action usually comes through the imposition of rates of exchange coupled with some sort of independent loss equation. This formulation differentiates itself from simple waste mechanics in that the product is often collected (rather than dispersed) and can act as a driving mechanic for other activities by the management entity that initiated it (Stiglitz, 1999).

In economic models taxation is often a method for resources to flow out of the system, while in innovation models it is the means by which the governing actor extracts value from inter-agent trade (Cook, 2001). In the latter example taxation is an integral component of the system's renewal subsystem and acts as a direct reward to the system for cooperative behavior.

Our model is principally concerned with examining the direct impacts varying tax rates may have on the system rather than determining an actual effective tax policy. As such, the notion of tax is treated an incentive value which directly affects the individual behavior of agents. Tax is principally active during transactions downscale transactions (i.e. leveraging of products within the market), thus tax is a share of the gain from the sale of product the product of innovation (technology) and is taken from the seller (Parisi, 1997). This share is proportional to the quantity sold. Thus it is possible to examine, through simulation, the effects of redistributing the product of this tax at different stages of the system.

Harvest quotas offer a simple measure through which actor interaction with the environment can be directly regulated by a central authority (Steiglitz et al., 1996). Similar to spatial positioning, quotas act as a barrier to specific exploitative behaviors. By limiting both the amount that can be harvested at once and the amount available to be harvested from a particular spot, the central authority has a mechanism through which it can guide the activity harvesters indirectly. Additionally, quotas can also set minimum bid amounts, ensuring that particular market behavior occur (sales at fixed lot sizes, etc.).

In economic models, quotas exist as hard supply and transport limits that place a ceiling on resource acquisition functions and essentially behave as flow rate limiters across the system (Stigler, 1941). This notion also extends to ecological models in the concept of resource carrying capacity between trophic zones. Within the innovation economy, quotas take on a similar role as seen in pure economic models and are a useful tool for guiding the behavior of consumption and production across multiple communities (Glazer & Hirshleifer, 2005).

In our model quotas merely define the maximum amount product a firm can collect from a single source in its local environment. The interpretation of the quota varies between the helices, but is enacted at the global, rather than individual level. More specifically, this means that a research firm may be limited in the amount of money it may draw from a particular funding source, and that industrial firms may be limited in the number of technological partnerships they are allowed to have, or are capable of pursuing simultaneously.

3.3 Previous Work in Agent-based Innovation Simulation

Because we are interested in the cooperative and competitive behavior of several co-dependent species in an ecological framework, we now turn our attention to examples of relevant developments in the field of agent-based innovation simulation.

Previous efforts in this field largely been grounded in domains such as cognitive theory and social network dynamics. Ecological models of regional ecosystems have been proposed which incorporate innovation concepts in order to capture the effects of human behavior (Hare & Deadman, 2004). However, there have been few studies to date which extend innovation models with ecological concepts, and none which apply ecological modeling methodology to NSI simulation. Despite this, we explored studies relevant to both domains in order to inspire confidence in the applicability of said approach.

Innovation transport and diffusion models

Several investigations have examined the link between transport costs (risk), the likelihood of firms to form partnerships (inter-firm trust), and proclivity to carry innovation forward. Findings point toward several best-practice conditions that must be met in order to maximize diffusion. These included incentivizing individuals and firms with high spatial centrality to buy in, lowering initial cost barriers to tempt wary individuals, and maximizing the visibility of firms within the notional marketplace to extend their trading power (Terna, 2009; Ma & Nakamori, 2005). These results follow the common wisdom that directly addressing risk aversion among firms is a good strategy to promote innovation.

Others suggest that artificially suppressing risk can be costly and may lead to market instability, especially in scenarios where trust between firms is low (Dongsheng & Yongan, 2008). These findings could guide planning agencies in designing intervention strategies that allow public agencies to assume some of the risk in the development of technology, either through seed-grants or partnering with private institutions seeking to bring useful technologies to market. Similar guidance has been offered by Canils & Van den Bosch

(2010), who noted that the partnership between higher education institutions (HEIs) and regional government can help significantly reduce costs during the process of transferring technology to private industry.

Ma & Nakamori (2005)describe this transfer process in more detail via a multi-agent model intended to simulate the low-level mechanics of technological innovation. This model is based on the theory that technological innovation could be viewed as an evolutionary process using Kauffman's NK (hill-climbing) model to handle the mapping from the design parameter space to the performance parameter space (Ma & Nakamori, 2005; Kauffman, 1993). Through the interaction of this evolutionary process and environmental selection criteria, the simulation model is able to inscribe the concept of technological innovation. The environment is represented in the simulation model as a simple market network.

In the NK model, N represents the number of genes in a haploid chromosome and K represents the number of linkages that each gene has to other genes in the same chromosome. The description of the NK model follows Altenberg's (1994) more formalized definition with several slight modifications, namely that the genes are not binary-valued, but rather H_i-valued. This means that an individual gene can take on values contained in set $H_i\,(i = 1, ..., n)$. This represents the notion that there exist multiple designs for a single technology (such as engines, in the automobile example).

In the paper, two factors which prevent producer monopoly are identified through analysis of results obtained from simulation; consumers' incomplete information and diversity of consumers' demand. The author's also show mainly through intuition that industry actors likely operated under sub-optimal technological solutions.

Berger (2001) proposes a spatial multi-agent programming model for assessing policy options in the diffusion of innovations and resource use changes. The model applies a multi-agent cellular automata (MAS-CA) approach by developing and using several heterogeneous farm-household models and capturing their social and spatial interactions explicitly. The MAS-CA model consists of two main components: an economic sub-model and a hydrologic sub-model, which are both tightly connected to a consistent spatial framework represented via a bi-level toroidal lattice. A recursive linear programming approach is implemented wherein each farm-household in the study area is captured in the model and solves its decision problems (whether to adopt or reject innovation) over time autonomously. Results demonstrate that structural change will occur as traditional actors (farmers) will experience persuasive 'pull effects' to leave the farm business as costs and other barriers increase.

Terna (2009) proposes an agent-based framework for examining how innovation and new ideas diffuse among a community, or act to conserve the status quo, in an epidemic fashion. The notion of contagion, or susceptibility to infection of novelty, is borrowed from the studies of infectious disease and is modeled using the chameleon metaphor. While the emergent structure of this model is primarily based on population density, its behavior was show to vary dramatically if agents were allowed to evolve some intelligent behavior, such as a-priori action planning. This evolutionary process is implemented using artificial neural networks supported by reinforcement learning techniques. The development of the structure of the neural network relied on the Cross Target (CT) method which corrects both the guesses about the actions to be done and those about the related consequences.

The chameleon metaphor is described as follows: in the starting phase a certain number of chameleon actors are present in each of three colors: red, green and blue. When two chameleons of different colors meet, they both change their color, assuming the third (non-present) color. If all chameleons in the environment display the same color, a steady state solution is reached. In the context of innovation, the author interprets the metaphor in the following fashion: an agent diffusing innovation (or political ideas) can change itself through the interaction with other agents. Conversely, an agent diffusing epidemics modifies the others without changing itself. Additionally, each agent class' principle intent is to preserve its own color, and attempts to implement different strategies to do so based on the reward structure of the model. The simulation environment is modeled as a, NxN lattice, of which agents are allowed a 3x3 local viewing area.

The reinforcement learning model was constructed using the Swarm Like Agent Protocol in Python (SLAPP) tool and follows the methodological structure laid down by Sutton and Barto (Sutton & Barto, 1998). In this structure S denotes the set of states related to an environment, A denotes the set of possible actions, and R represents the set of scalar rewards for given actions. At any time t an agent exists in state of s_t and can choose action a in set $A(S_t)$. After the action, the agent exists in state $s_{t+1}$with a reward given byr_{t+1} . Rewards are summed over time with a discount factor. Through this transformation the agent is able to map all the possible actions A in a state S to all the related rewards.

The author's results indicate that agents who displayed aggressive strategies (red chameleons) were most successful in preserving their color, implying that innovation diffusion benefits from dynamic, rather than passive activity. This dovetails with earlier findings regarding the importance of first-action in successful clustering.

Knig et al. (2010) demonstrate via empirically-based simulation on a micro-founded network model that small-world networks could be used to model the search for collaboration across a theoretic region. The environmental structure is a relational network of researchers and patents based on Watts and Strogatz (1998) small-world networks and findings gathered empirical surveys of regional collaboration networks. Analysis of the simulation was conducted using the notion of small-world regimes and normalized clustering divided by normalized path length for the largest connected component in each geographical region. The author's results indicate that that links between inventors are established mainly by performing a local search and this effect has become more prevalent over time.

Padgett et al. (2005) propose a hypercycle model of productive systems where goods flow through firms as chemicals through reactors. Eventually, clusters form around production loops, which are reminiscent of Marshallian industrial districts (Belussi, 2005). Interestingly, economies with more than 4 goods require the existence of clusters in order to sustain production.

Page & Tassier (2003) propose an agent-based model where local economies are superseded by chained stores. They observed that the formation of chains arose because they exploit a niche that is profitable at several locations. Subsequently, wherever these chains arise they homogenize the economic structure and beget other chains in (potentially) other sectors. Thus, they observed the process to be a cumulative phenomenon. In addition, they state that final configuration is likely to be suboptimal despite the fact that it is a local optimum in the environment created by the existing chains. They surmise that decay may be the fate of clusters that do not attain world-wide recognition in the globalized economy.

3.3.1 *Behavioral models*

Dawid et al. (2001) analyze the evolution of output decisions of adaptive firms in an environment of oligopolistic competition via an agent-based market simulation. The model is composed of firms which, at each time step, make a decision regarding whether to produce one of several existing product variants or try to establish a new product variant on the market. This decision is driven by aggregate local demand as well as each firm's heterogeneous abilities to develop products and imitate existing designs. Certain estimation rules such as market potential and market founding potential are used along with a measure of stochastic decision-making. Further, the characteristics of the firms are allowed to evolve via "learning by doing" effects.

After sensitivity analysis the simulation model was tested by running the simulation over 64 batches of 100 runs, followed by an additional 36 runs with tuned parameters. The results indicate that the abilities for technological improvement are the dominant factor for the determination of a good innovation strategy. Moreover, firms should choose optimal strategies on their production efficiency relative to the market's need.

Agent-based Nelson-Winter models (NW) have seen limited use with respect to communication mechanisms. A basic NW model is outlined in figure 4.1 and is more fully described in Anderson (2001). Zhang (2003) proposed a NW model which was paired with

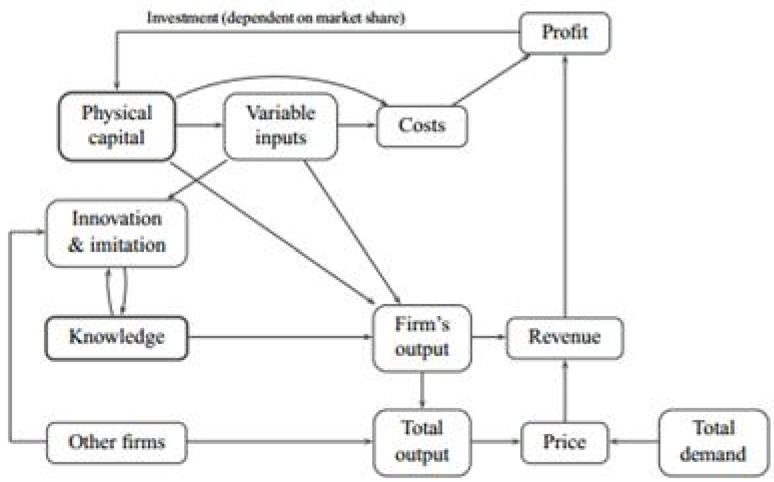


Figure 3.1: Structure diagram of the standard Nelson–Winter model of industrial dynamics. The diagram puts an emphasis on a particular firm, while aggregates are placed in the last row. An arrow from x to y should be read 'x codetermines y' (Andersen, 2001).

an explicitly defined (physical) landscape to study the formation of high-tech industrial clusters. The extended model focuses on social, rather than economic dynamics in site selection and innovation activity between actors and uses cluster metrics to evaluate agent configuration and performance. The problem is defined in terms of Schumpeterian entrepreneurship (Schumpeter, 1934), where economic development is assumed to driven by the activities of a certain class of highly motivated creators. The author's results indicate that entrepreneurial clustering occurs even without the benefit of industrial clusters, such as knowledge spillover. Moreover, the findings reinforce the importance of pioneering actors in the establishment of industrial clusters.

Spatially situated ecosystem models

Case studies involving the application of agent-based models to ecological domains have become more common now that simulation toolkits have become more user-friendly to non-technical researchers. These works have yielded interesting results which incorporate mechanistic themes such as resource exploitation, trophic interaction (Schernewski & Neumann, 2005), spatial configuration (Lansing & Kremer, 1994; Jannsen et al., 2000), and energy transfer processes (Williams et al, 2001) into the multi-agent paradigm.

These simulation models also provide capture the emergent behaviors which drive ecosystem development. The importance of properties such as population mobility (ability for agents to relocate in search of better conditions) and density (agent clustering) were explored by Bosquet et al. (2002), Rouchier et al. (2001), Hoffmann et al. (2002), and many others. These properties were found to be directly correlated with behaviors such as resource exploitation as well as the diffusion of new cooperative and competitive behaviors. This is by no means surprising, as prior work using numerical simulation produced similar results (Mertens & Lambin, 1997).

Of equal importance is the ability of ecosystem simulation to explicitly represent human decision making paradigms. In this context, decision-making refers to the ability of an agent to decide its behavior at any point in time. Agents are able to apply psycho-social knowledge of actual decision-making to agent design that may contrast with the rational homo-economicus of classical economics. This feature is highly relevant with regard to innovation diffusion studies, such as those conducted by Balmann et al (2002) and Berger (2001). These studies proffer model the proliferation of new agricultural and land-use practices through networks of farmsteads. Albino et al. (2004) proposes an agent-based simulation model to investigate how innovation processes in industrial districts (ID) have to be modified to assure their survival in a highly competitive environment. The environment is modeled as a dynamic network where linkages between agents signified relational commitments between various classes of supply and transformational agents. The model was analyzed after being run on four experimental scenarios which varied between low and high demand & and innovativeness parameters. The results indicate that the number of firms within an ID is a proxy of success in a particular competitive context.

These works, and others, show that ecosystem simulation brings forward powerful features such as the ability to capture complex population dynamics, leveraging of individual and group decision-making, systemic resilience, and layered spatial (and non-spatial) contexts.

Otter et al. (2001) developed an agent-based model where firms and households decide where to locate within a multi-layered toroidal NxN lattice according to availability of labor, services, natural resources and recreation areas. The model has two principle agent types, households and firms. The latter of which distinguishes between enterprises operating in heavy industries, in light manufacturing and in services. Both firms and households have imperfect information and can only observe other agents that are within a visibility range.

The environmental model is composed of a 'land-use' and 'attraction' layer. The each cell in the land-use layer has fixed attributes such as 'land', 'natural area', and 'sea'. The initial grid is configured such that no agents are present and each cell registers as empty. Agents are only allowed to locate in empty cells and make their relocation decisions based on the values in the underlying attraction layer. These values are defined by the number of agents and firms present in nearby cells. This interplay is simulates agglomeration phenomena and is similar in execution to the concept of pheromone deposition in ant-colony optimization strategies.

The authors observed the emergence of clusters of firms and households of various size and composition depending on exogenous parameters as well as the initial configuration. Visibility range was shown to be a large determinant in both the size of clusters as well as the time needed to reach equilibrium.

3.3.2 Explicit NSI Simulation

Dongsheng & Yongan (2008) propose an agent-based model for studying the evolution of University-Industry Cooperative Innovation (UICI). Three agent types are identified and modeled following the UICI metaphor; enterprise, university, and government. Enterprise agents attempt to cooperate with university agents to produce technologies, which they then leverage to earn profit. The government agent taxes the earnings of enterprise agents and uses these taxes to fund university agents who promote new research initiatives. The environment consists of a 45 x 45 lattice, within which both university and enterprise agents reside. Universities are only allowed to partner with neighboring enterprises. Both university and enterprise agents are allowed to migrate if local conditions are not optimal (low cooperation rate). In order to evaluate the evolution of innovation between these agents, the authors introduce two variables, named as Success Rate (S_R) and Average Confidence (C_A) respectively. The S_R is the ratio of successful cooperation to all cooperation attempts. The C_A is the arithmetic mean of the confidences of every enterprise to every university. The results indicate that when the Expected Profit (E_P) for university agents is sufficiently, a collapse in trust and cooperation success inevitably results. This implies that strategies which promote more modest profit expectations lead to stable long-term partnership between university and enterprise firms.

Butel & Watkins (2006) propose a model for identifying cluster dynamics for entrepreneurs using an ant-colony optimization strategy of indirect communication. The environment consists of a 50 x 50 lattice, with two types of agents; resources and researchers. The research agents are initialized with no prior knowledge regarding the location of resources of interest and are allowed to operate for a limited number of turns. After each run, successful agents (those that discovered a resource patch) are allowed to increase pheromone along their search path. The results showed that after a training period, clustering occurred quickly, even when unskilled agents were added to the population or the individual search space was reduced. Moreover, agents spent less time searching unprofitable areas. This indicates that under this methodology, the activity of successful agent clusters can negate much of the waste (in terms of unproductive activity) of untrained agents.

3.4 Chapter Summary

This chapter has reviewed concepts relating to the development of our model of the agent-based innovation ecosystems. In section 3.1 we outlined an agent-based approachto ecological and followed with more specific submodels and mechanisms in agnt-ecosystems (section 3.2). Many of the previous agent-based innovation studies discussed in section 3.4 are briefly summarized in table 3.2. The "knowledge-based" column states whether the algorithm is embedded or not with a knowledge-based (e.g. rule-based, etc.) system for selecting a path from the solution set. The last column shows the capability of the algorithm of producing multiple paths in parallel.

We can make several key observations from the algorithms and literature cited above. First, while statistical models of innovation can capture general trends, the behavior centricity of agent-based models has been used to gain insight into the complex forces which drive the creation of knowledge market places. Second, we observe that social factors can play a large role in governing the formation and success of innovation economies. Third, we observe that network and spatial models display different relational characteristics between agents and offer affordances for different types of analysis. This also survey obviates the fact that very few models have been developed which combine these varied approaches, namely using a market-based interaction strategy paired with relational networks in a spatial environment. Due to complexity and hardware limitation issues the computational effectiveness of these approaches varies and in the real world they require many hours of computational time to achieve a satisfactory solution.

In light of the above observations it is notable that few approaches to this problem take advantage of the inherent power of swarm systems to address issues of spatial search. Some simulation models use used classical multi-objective techniques, such as the weighted sum approach or a single-objective function to obtain locally optimum solution, while others leverage neural networks or genetic algorithms. Since there is more than one optimum solution for this sort of problem, many of these approaches are not capable of generating these conflicting optimum solutions (or trade-off solutions). Those that are capable of doing so must operate under severe constraints.

Author(s)	Year	Dimensions	Domain	Environment	Algorithm/Objective Function	Objectives/Constraints
Berger	2001	2D	Agriculture	Lattice	Multi-agent cellular automata	Assess policy options such as cost and peer-pressure.
Albino et al.	2004	N/A	Economics	Network	Reinforcement Learning	Examine changes in relational linkages between firms.
Dawid et al.	2001	N/A	Economics	Network	Reinforcement Learning	Examine the change in output decisions of agents with respect to profitability.
Ma & Nakamori	2005	N/A	General	Network	Hill-climbing	Determine the conditions which create or prevent innovative monopoly in the system.
Zhang	2003	2D	General	Lattice	Reinforcement Learning/Local Search	Examine factors such as cluster size, and early adoption as they relate to the establishment of industrial clusters.
Terna	2009	2D	General	Lattice	Reinforcement Learning	Identify the strategies which lead to preservation of innovation using chameleon metaphor.
Kõnig et al.	2010	N/A	General	Network	Reinforcement Learning/Local Search	Compared results for different search techniques with related success rates (small-world network size).
Otter et al.	2001	3D	Land-use	Lattice	Reinforcement Learning	Analysis of the formation of clusters and the relative equilibrium configuration reached by the system.
Padgett et al.	2005	N/A	Economics	Theoretic	Topological methods	Analysis of cluster formation following the hypercycle model.
Page & Tassier	2003	N/A	Economics	Network	Reinforcement Learning	Cluster analysis applied to the optimality of chains.
Dongsheng & Yongan	2008	2D	General	Lattice	Reinforcement Learning	Comparison of industry trust with the global success ratio for firm partnership.
Butel & Watkins	2006	2D	Economics	Lattice	Ant-Colony Optimization	Cluster analysis applied to the discovery and exploitation of environmentally-situated resources.

Table 3.2 Previous works on simulating innovation economies

Chapter 4

THESIM: Triple-Helix Ecosystem Simulation

4.1 Triple Helix Ecosystem Interaction Model

Ecological modeling provides a novel framework for representing the relationships between the regimes of the innovation economy. It represents the system as an *ecosystem* and utilizes the concept of *energy flux* as a mechanism to capture the transport and transformation of *innovation products* through the system. This agent-based ecological view exposes the relational components of real world innovation systems, and allows individuals within various communities to be included as explicit actors in the model instead of having their collective activity represented deterministically (Grabher & Powell, 2005).

To study such interactions between industry, university, and research firms on the performance of triple-helix aligned NSI through computer simulation, a model of the simplest NSI in which the three control regimes have no links to one another was constructed.

This simple NSI model (Figure 4.1) consists of two of the three helices of control, industry, university, and government. In the classic triple helix model described by Etzkowitz & Leydesdorff (1997) the government is described as a separately partitioned entity, similar to industry and university. However, in keeping with the ecological view of the system we may also view the government as an actor as well as controlling the environment within which the other helices operate.

After establishing the simplified model of the triple helix NSI, we need to add the interactions among the three regimes. Interpreted from the aforementioned literature, in a triple helix system it is the government's duty to drive industry and university firms to innovate through means such as lawmaking and fiscal measures. Universities provide human R&D

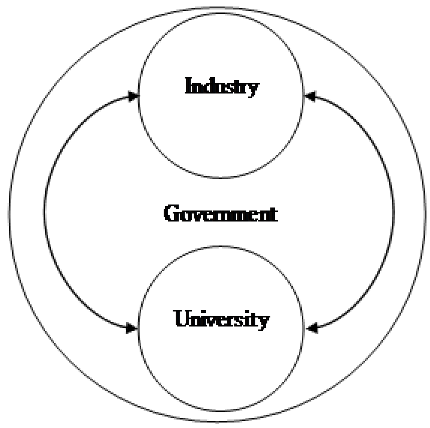


Figure 4.1: Model of a simple NSI.

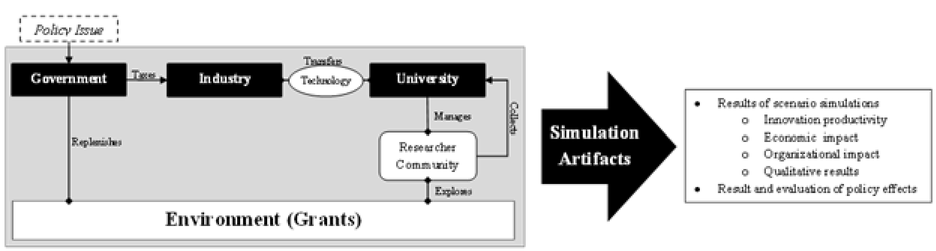


Figure 4.2: Triple-helix ecosystem interaction model.

resources, basic research, as well as technical support to industries engaged in product development (Jaffe & Trajtenberg, 1989). The profits generated by industrial firms are used to provide fiscal support to universities for R&D efforts (Nelson, 1994). Government plays a mediation role between the other regimes by providing funds in support of research, negotiating university-industry partnerships, and imposing control mechanisms on entrepreneurial firms. These relationships form the core of the triple-helix simulation and are shown in Figure 4.2.

Given the mapping between ecological and economic concepts we explored in chapter 3, we observe that co-evolution between the control regimes and their institutional environments change the knowledge infrastructure in unpredictable ways (Uyarra, 2009). Government and industry regimes aim to maximize revenue, while minimizing cost, while the university (or research) regime aims to capture as much funding as possible in order to support large populations of researchers and create new technologies. Public administrators and planners must simultaneously balance these competing agendas to avert economic stagnation or collapse.

Policies provide a rule set for governance which is enacted through mechanisms available to the government. Those policies which drastically alter resource provisions, such as increasing or decreasing funding for basic research or altering return on industrial technological investment through tax policies often have mixed or counterproductive results (Cooke & Morgan, 1998). This relationship is also observable in biological ecosystems, where land management decisions often lead to unintended (and often undesirable) environmental perturbations. In a climate of economic uncertainty where fiscal supply is constrained, policy makers must find other ways to change system behavior to increase productivity. Using ecological modeling to capture the behavioral relationships that modify resource transfer may help obviate the hidden causes of conflict created by such decisions.

Following this basic framework we are able to construct a generalized simulation of the triple helix aligned with NSI. However, more specificity is needed in order to derive specific agent rules necessary to create a complete ABEM model.

4.2 Conceptual Model

In this section we outline a conceptual model for the purpose of defining an agent-based ecological view of innovation economics. The conceptual model is composed of the set of ontologies describing the actors of the system (researchers, universities, etc.), the objects they are acting on (resource patches), the actions carried out by the actors on the objects (foraging, transforming, selling, etc.) and the regulations imposed on these behaviors (tax, waste, etc.).

In our model, an actor may be a member of a large number of formal (university systems, industries, governments, etc.) or informal (research community) institutions. Each institution defines the functioning of its constituents, including its ontologies and norms (Ostrom, 1990). An actor may also be situated geographically within a set of areas that can be embedded within one another. However, we only concern ourselves with areas upon which regulations can be applied, thus implying that formal and informal institutions control these areas. Actors, by virtue of being environmentally situated, are subject to the regulation of these institutions. Thus, an actor is permanently subject to these formal and informal regulations which can contradict one another.

There are two kinds of actors: the *individual actors* and the *collective actors*. In our model, individual actors are the researchers, who exhibit communal foraging behavior and are identified by their affiliation to a particular university. These actors take on the role of harvesters, foraging in the environment for resources which are returned to their university. The act of exploration and exploitation of environmentally situated resources (grants) represents the first stage of ecological energy flux. Collective actors include the universities, entrepreneurial firms representing the industry, and the regional government. Each interacts with the preceding stage by bartering for resources and converting that resource into a higher order product for sale to actors in later stages. Within this model grants take on the role of producers; researchers, universities, and industry actors behave as consumers; while government actors exhibit the characteristics of a decomposer, returning resources back to

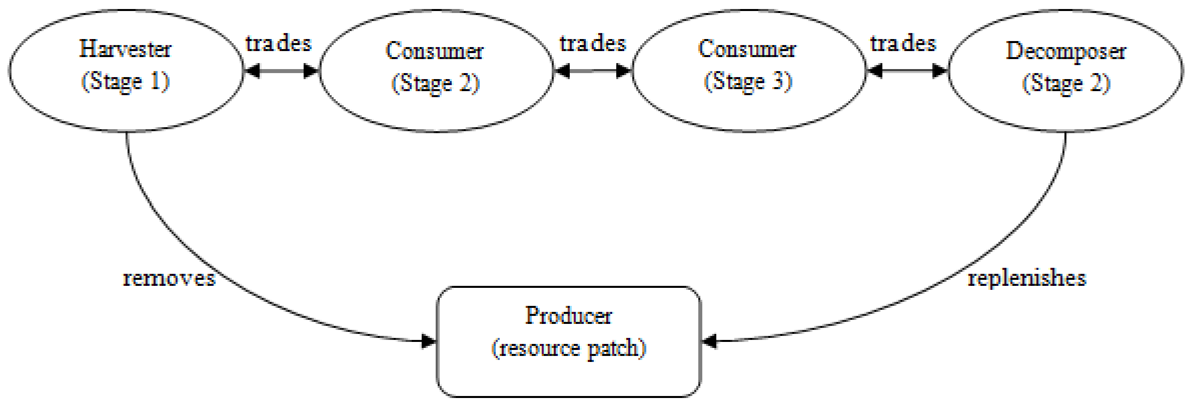


Figure 4.3: Conceptual model of the 'innovation food web'

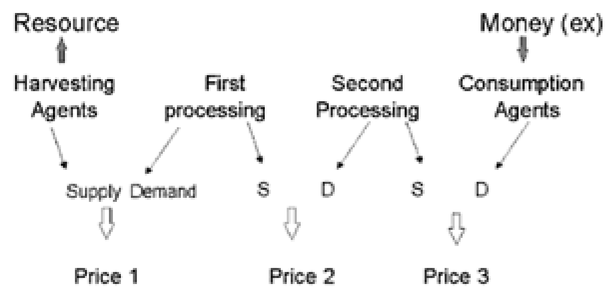


Figure 4.4: Basic resource cycle

the environment. The relationship between the environmental features and various actor classifications forms a resource web, which is displayed in Figure 4.3.

In multi-agent systems, an institution is defined in terms of a set of roles together with the specification of norms, which govern the environmental and social behavior for each role. Using the norms for regulating the interactions with environment as well as other situated agents is a natural extension when dealing with resources management. These norms also define which objects count as a good, a product, etc. Therefore, the norms also define the categories (or roles) in which the objects can be classified (Pottage et al., 2004). Thus, having defined our relational model, we now concern ourselves with the behaviors and norms (regulations) which govern the behavior of our institutions by defining particular actor classifications.

Agents: Each agent belongs to a particular stage of the triple helix, collects or buys resources of a particular type, transforms and sells the resource, or interacts with the environment through directed activity. The first stage (S_1) is the harvester agent which collects the raw environmentally situated resource (currency, in the case of our metaphor). At this stage there is no transformation. At the second stage (S_2) the agent pays affiliated S_1 agents and collects their resources, partially converting it to knowledge product (second-order resource) which it sells to third stage agents. The third stage agent (S_3) buys knowledge product from S_2 agents, converting into currency and innovation product (third-order resource) and currency which is taxed by fourth stage agents. This fourth stage agent collects a tax on all sales as well as monitors the creation of technologies. It receives an imposed quantity of money per round which it disperses back to the environment in the form of grants. This cycle is illustrated in figure 4.4.

4.3 Behavioral Model

Cooperation between universities and industries is one of the most important forms of innovation activity. Besides the two principle actors (universities and enterprise conglomerates, or industries), innovation involves many other agents, such as venture capital, individual researchers, and of course government agents. In the most common model, little attention is paid to the granular actions of constituent agents of the Triple Helix entities (university, industry, and government). It is more common to model their interactions in the form of direct relationships, where super-classifications of entities act on or in concert with one-another to approximate group behaviors. In this model we extend this paradigm to include several lower-order agents (researchers and grants) with the intention of demonstrating the effect of distributed social learning on the behavior of the system.

To facilitate this analysis, we modify the hypotheses presented by Dongsheng & Yongan (2008) to include these social activities:

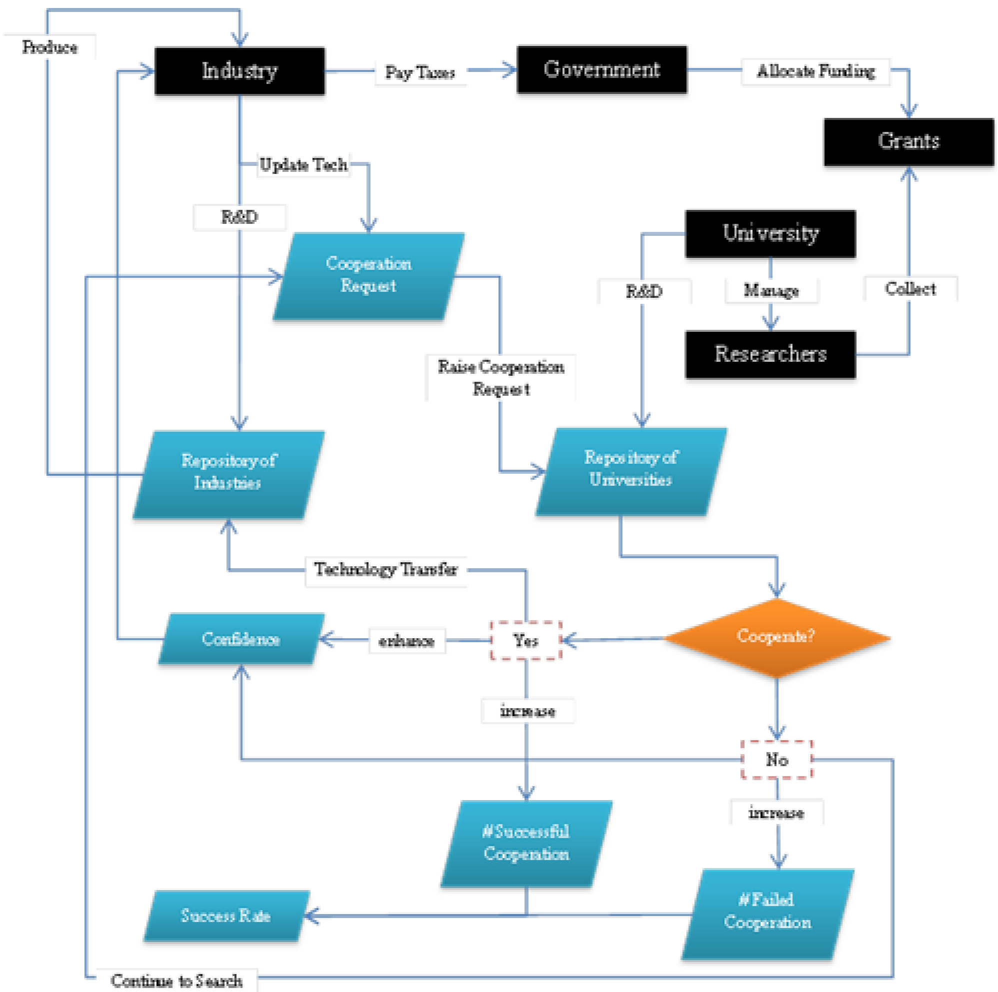


Figure 4.5: Relational Map of agents in the Triple Helix ecology.

- Government actors have no direct connection to universities. Funding for research must be derived from the environment via the collection and distribution of grant resources.
- The actions of researcher agents (grant-seeking) within the environment approximate the function of discovering funding opportunities, making grant submissions, and collaborating with other researchers.
- Each university manages its own distinct population of grant-seeking agents by controlling their population and paying for their upkeep.
- When an agent discovers a grant resource, it makes an attempt to acquire it, and the result is stochastically driven. If successful, it collects funds and then deposits them with its parent university.
- Grant-seeking agents use exogenous communication to facilitate learning and discovery.
- Cooperative innovation is always initiated by industry-level actors. Universities decide to accept or reject these requests. The total number of requests allowed per round is limited to 1.
- Each cooperative request involves only one university and one industry partner, thus there is no direct cooperation between separate industries.
- Each industry has a confidence value for every university. After each cooperative innovation, the value can be changed according to the result of the venture, and the changed value will affect the future cooperation of the agents.

Based on the above analysis and hypotheses on the model, we can summarize the behavior of each agent within the triple-helix cooperative innovation framework. Grant-seeking agents search the environment for funding opportunities and return them to their parent universities. University agents generate technologies, and handle a constant stream of requests as industry agents develop. Industries expect to cooperate with universities rather than innovate by themselves, as this is a dominant strategy for growth. Industries search the local environment for universities to cooperate with. After finding a suitable candidate, the industry actor will propagate a cooperation request to the selected university, according to determinates such as the R&D cost of the technology and confidence (record of past cooperation) between the two agents. The university decides to accept or reject based on its own benefit. If the request is accepted, the technology will be transferred to the industry. Otherwise, no transfer occurs and the industry continues searching for another university to partner with. If the industry fails to find a partner, it will innovate by itself. During the course of innovation, the government involves itself via taxation of industry profits and by the maintenance and replenishment of resources within the environment.

Following this structure we proceed to more fully define the rules which govern agent behavior.

4.3.1 *Agent Behavior Rules*

The behavior rules of agents of different types are as follows:

1. *Rules of grant agents.*

   (a) *Movement*: At the end of each round, grants may migrate to a new (unoccupied) position within the environment. The rules of migration are set by the government agent at the start of the simulation run. Unused grants use random (8-way) movement, while grants which have been utilized will move in the general direction of the university which visited it most often. This creates gravity around well optimized universities.

   (b) *Signaling*: Grants signal their position in the local environment by broadcasting their position to other agents within a local region initialized by the system. When a grant's resource supply is depleted, it will diminish its local signals to divert agents from searching in its local area.

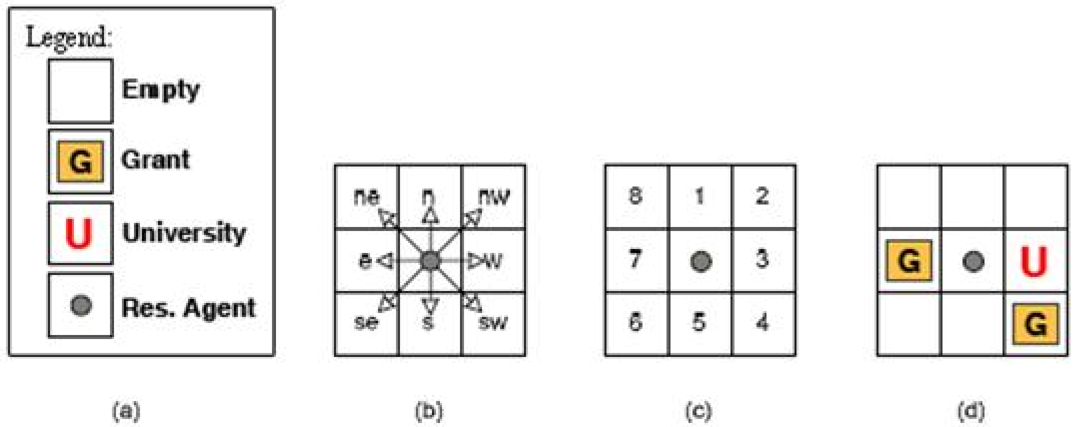


Figure 4.6: The legend of environment (a), agent's movement directions (b), coding sequence for local perception (c), example of local perception (d)

(c) *Supply*: Grants which see high traffic will make requests to the government to increase funding, whereas grants which see little traffic are penalized by having their total funding cut in future rounds and distributed to other sources.

1. *Rules of research agents.*

   (a) *Movement*: Research agents may make a single (8-way) move each turn to traverse their local environment. Agents are allowed only a fixed number of moves before they must return to their parent university.

   (b) *Signaling*: Researchers communicate through environmental signals based on the deposition of a virtual pheromone over the path it follows, marking a trail. This pheromone trail is enhanced by repeat traversals but diminishes at a proportional rate. Agents may use this signal as a determinant in movement decisions or in detecting resources.

   (c) *Innovation*: Research agents are paid by their parent university, and in turn contribute to the development of technologies related to their field of specialization.

(d) *Resource Collection*: If physically adjacent in the environment, researchers may attack grant agents. The success rate of the attack is determined by the difference in specialization field between the grant and the researcher. The larger the difference, the lower the possibility of success. If the agent successfully collects resources from a grant which differs from its base specialization, the researcher has a small chance to change its base research classification to match that of the grant which it consumed.

1. *Rules of university agents.*

   (a) *Management*: The University determines the number of research agents it can support by analyzing its current stored value, income, and expenses. If its pool of researchers is too small, it hires new researchers. The specialization type of these new researchers is determined by proportional probability based on the amount of funding the university has collected from each specialty area.

   (b) *Innovation*: Universities invest money in R&D activities each period. The amount of growth of each technology being researched is determined by the research level of the university. Higher level universities research at a faster rate than those of lower level.

   (c) *Starting new innovation*: At every round, the university creates a certain number of research projects according to its research level and current funding. The parameters of these functions are initiated by the current research level of the university, the distribution of grant funding between the various specialization fields, and random functions.

   (d) *Dealing with requests*: When a university receives cooperation request from an industry, the university decides whether to accept it or not according to its expectation of profit (E_p). If accepted, it transfers the technology at the price proposed by the enterprise. Otherwise the university sends a notice of rejection.

1. *Rules of industry agents.*

    (a) *Updating technology:* Industries submit multiple technology requests each round. The number of requests is governed by the value (financial scale) of each industry. Generally speaking, the bigger the scale of an industry, the more cooperation requests it promotes.

    (b) *Innovation:* Industries invest money in R&D activities at every period. The success rate of R&D is determined by the research level of the industry. Higher level industries research at a faster rate than those of lower level.

    (c) *Production:* Industries produce and gain profit by monetizing the finished technologies they have, including both those innovated by themselves and purchased from universities. After tax is removed, the remaining profit is added to the industry's total money in order to support future purchases and development.

    (d) *Searching for Partners:* When an industry has a technology request, it searches the environment for university partners. The industry then selects the university with the highest confidence value and makes a request for technology. If the university has a suitable technology, the industry agent calculates the transaction cost according to the difficulty of the technology, R&D level, confidence between the two parties, and random functions. If the promoted request is denied, the industry continuse to search. If no suitable partner is found, it conducts the innovation by itself.

1. *Rules of government agent.*

    (a) *Grant management:* At the end of each round, the government evaluates the usage of each grant in the environment and may modify the grant's maximum funding amount, location in the environment, type, and replenishment amount. These decisions are determined by the current goal, strategy, and parameters set at the beginning of the simulation.

(b) *Taking tax:* At the end of each round, the government examines the profits of each industry and takes a corresponding amount of tax. The relative tax rate is specified at the beginning of the simulation.

(c) *Setting innovation goals:* Periodically, the government may set innovation targets in the form of "Create N new technologies in field M".

(d) *Implementing innovation strategy:* During the grant management phase, the government may apply a strategy in concert with its current innovation goal. Strategies may include modifying industry tax rates, or changing the distribution and type of resources present in the environment.

4.4 Overview and Design Concepts of THESIM

A simulation model was developed based on a mapping of the triple helix theory of public-private partnership using the ABEM framework. The resultant conceptual model is described using theOverview, Design concepts, and Details protocol (ODD) proposed by Grimm et al. (2006). This protocol is aimed at facilitating the description of individual-based models in ecology, with attention paid toward its application in agent-based social simulation and other disciplines. The details of this model and of the core structure of the innovation economy theory upon which it is based are presented in the proceeding sections.

4.4.1 *Purpose*

THESIM (Triple Helix Ecosystem SIMulation) is a multi-context agent-based model designed to explore the effects of positive and negative government spatial externalities and psycho-social outcomes. Spatial externalities refer to exploitative land-use activities by university and industrial firms which change the pay-off of other firms in an abstract environment modeled after on a regional government-grant system. THESIM is an abstract model designed for theoretical exploration and hypothesis testing. Specifically, THESIM was designed to extend existing analytical innovation economy theory to examine relationships

Parameter	Brief Description
Coordinates	X and Y coordinates of the grant
Value	Amount of support available in abstract dollars
Utility	Score representing the number of successful awards offered by grant manager
Replenishment	Amount of money budgeted to grant per-round
Target Field	Numeric value representing the field this grant intends to support
Diversity Score	Calculated from awards to researchers outside the targeted field

Table 4.1 Grant patch agent model

between externalities, social behavior, and the efficiency of simple government intervention policies.

The THESIM model functions as an observational tool for identifying the parameter spaces and conditions under which an innovation economy is resilient to environmental perturbation. The policy mechanisms and agent behavior in the model mimic that of the three helices identified in the Mode 2 innovation model (Gibbons et al., 1994), with a technology market model based on the work of Dan et al. (2009) where firms over and under bid for technology products based on trust and risk aversion. The magnitude of these over-and-undershoots diminishes as the model reaches equilibrium but can be disrupted by perturbations in state of each helix.

4.4.2 *State Variables and Scale*

The THESIM Model consists of the following core entities, which are described in the following set of figures (table 4.1 through table 4.5). A run is composed of multiple rounds with each round corresponding to 30 time steps. A single time step in the model is non-analogous to any real-life time scale. Simulations typically run 200 rounds.

4.4.3 *Process Overview and Scheduling*

A high-level diagram showing an overview of the schedule in THESIM is given in Figure 4. More detail on each section in the diagram is provided afterwards. THESIM considers

Parameter	Brief Description
Coordinates	X and Y coordinates of researcher
Success	Number of successful searches versus overall attempts
Value	Valuation of all grants collected in abstract dollars
Cost	Abstract dollar cost to support this researcher per-round
Specialization	Target value for grants
Openness	Determines propensity to explore new funding zones
Employer	The university to which this researcher belongs

Table 4.2 Researcher agent model

Parameter	Brief Description
Coordinates	X and Y coordinates of the university
Budget	Operational funds available in abstract dollars
Researcher List	Population of all researchers managed by the university
Patent List	List of all actively held technology patents
Target List	List of research fields this university is currently targeting
Complacency	Determines likelihood to change focus and/or move
Cost	Total value of all per-round expenditures
Income	Total value of all revenue stream
Risk Aversion	Determines objective ratio of Cost to Income
Break-Even Threshold	The amount of income a university has to make from its revenues to break even

Table 4.3 University agent model

Parameter	Brief Description
Coordinates	X and Y coordinates of the cell over which the firm occupies
Budget	Operational funds available in abstract dollars
Patent List	List of all actively held technology patents
Target List	List of research fields this industry is currently targeting
Confidence List	List of confidence values associated with its university partners, determined by history of successful and unsuccessful partnership requests
Cost	Total value of all per-round expenditures
Income	Total value of all revenue stream
Risk Aversion	Determines objective ratio of Cost to Income
Break-Even Threshold	The amount of income an industry has to make from its revenues to break even

Table 4.4 Industry agent model

Parameter	Brief Description
Budget	Operational funds available in abstract dollars, fixed per-round
Tax Rate	Percentage of industry revenues taxed by government
GDP	Determined by the value of all industry firms.
Grant List	List of grants the government is currently servicing
Industry List	List of all industry firms
University List	List of all university firms
Objective List	List of objectives currently being pursued by the government
Tax Revenue	Total value of tax income

Table 4.5 Government agent model

several main processes in a loop. At the beginning of each step, each agent evaluates its state and then chooses a set of actions based on that state. At the end of each round, each agent performs a diagnostic and may change certain operational parameters as a result of an optimization process. Researcher agents seek to maximize Success, university & industry agents seek to maximize income while minimizing cost, and the government agent seeks to maximize GDP while minimizing waste.

Figure 4.5 illustrates the processes of THESIM at an aggregate level. Exogenous elements (initialization parameters and environmental conditions set by the user) combine with the market model to form various decision cycles within each context. Each agent then selects the highest-valued decision, and additional derived endogenous elements are calculated based on these choices. Resulting changes in social network and landscape patterns then initialize the next time step.

THESIM uses a fixed event-scheduling mechanism, which allows every agent to make an activity decision in each time step (usually consisting of a single move and a resultant action, where possible). This mechanism prevents oscillation, while introducing a minimal amount of additional path-dependency due to stochasticity. Agents are processed sequentially, but updating is synchronous, after each active agent has reached the end of its activity loop.

4.4.4 *Design Concepts*

Emergence: THESIM was designed to explore the relationship between two related emergent phenomena: grant clustering and public-private confidence driven market dynamics. The funding landscape patterns and associated market productivity measures are emergent in the sense that they are the result of the decentralized decisions of distinct populations of autonomous agents.

Adaptation: THESIM models a specific kind of ecological adaptation known as engineered ecological resilience. Each of the individual agent classes modify their endogenous parameters based on their perception of the state of the world. At the macro-level this can be observed in fluctuations in populations, productivity, trade, and social adherence phenomena. Extensions to this model could include more explicit machine learning techniques such as hypothesis generation via genetic algorithms, or a more robust reinforcement learning framework for the decision-making processes governing each agent.

Fitness: At the individual agent-level, fitness is measured differently across role and context. Agents operating within the market context measure fitness by profitability, while those operating in the spatial context use utility. Global fitness is measured through economic welfare statistics (GDP, total surplus, total confidence, and total population), which depend on the degree of resource utilization and market dynamics (price, trust, etc.) as described in previous sections.

Prediction: In the spatial context THESIM agents are generally reactive and do very little to predict the outcome of future events. However, within the market context participating agents predict future outcomes in very simple ways. University agents form an Expected Value for completed technology patents based on sunk costs, maturity level, novelty, and the anticipated fitness (profit) maximizing decisions of Industry agents. In this calculation they assume to know the profit calculations of all other agents. However, this knowledge is incomplete and does not take into account ‘hidden’ metrics such as expected profit and confidence. In this sense they are much more myopic than real-world agents are likely to be.

Interaction: Agents interact indirectly at both a spatial (local) and market (global) level. At a local level, the resource-use choice of one agent affects the behavior and income of its neighbors. At a global level, the agent's choice affects pricing, trust, and competiveness of its partners and competitors.

Sensing: Different classes of agent possess different collections of spatial and relational information. Grant agents only possess knowledge about the 8 neighboring spaces in their local environment. Researcher agents have the same viewing area, but can pass information to one another through environment via stygmergic processes. University agents can only see their space (similar to grant agents), but have a market view that is complete. Government agents are assumed to know the current market network and resource landscape pattern, as well as the positions and endogenous parameters of all other agents. In this instance, information is complete and certain.

Stochasticity: THESIM is subject to a degree of stochasticity that is prevalent across many multi-context ecosystem models. Despite this, efforts were made to minimize path dependence, and the main source of stochasticity is the ability of the end user to generate an initial random input parameters and resource-landscape.

Observation: Observations include graphical display of environmental patterns (spatial and network), metrics measuring the fragmentation and productivity characteristics of the resource- landscape, and metrics that reflect economic outputs (outputs from each university & firm, technology prices, tax revenue, and multiple economic fitness measures).

4.4.5 *Details*

Initialization: The state of the model world is initialized by setting an initial parameter configuration, including a predefined spatial model.

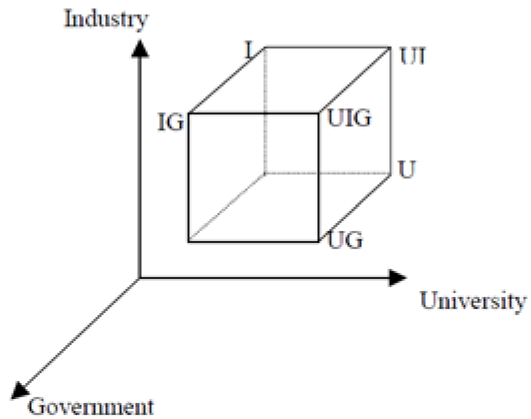


Figure 4.7: University-Industry-Government relations in a three-dimensional space.

Input: Following initialization, environmental conditions remain constant over space and time in the THESIM model. There is no imposed or modeled spatial or temporal heterogeneity, aside from the endogenous variations in market productivity, landscape pattern, and agent choices that are the focus of the model.

4.4.6 *Submodels*

In developing the simulation model, it is critical to identify metrics through which we can evaluate global behavior. To this end we focus on the various intersecting areas of cooperation in order to more fully understand the output of the entire simulation; university-government (UG), university-industry (UI), industry-government (IG), and university-industry-government (UIG). We examine grant clustering as a measure of the degree of UG trust via spatial occupancy of a local Von Neumann neighborhood. We define technology transfer capacity and rates as measures of UI partnership. Individual tax output serves to identify IG success, and we define a global productivity score based on production analysis.

Innovation Production: The creation of technology in both universities and industrial firms are modeled as learning functions. Knowledge artifacts (technology patents) are created at the beginning of each round and incremented until they reach completion. C_N is the cost of incrementing technology N at time t. The equation for is;

$C_N = \frac{Complexity_N}{R_{level}} * R_{cost}$ *Eq. 4.1*

Where $Complexity_N$ is the complexity order for technology N, $R_{level}$is the research level of the institution, andR_{cost} is a constant representing the operational cost of innovation.

Innovation Value: The valuation of technology after completion is represented by a Gaussian function:

$f(V) = Novelty * e^{-\frac{(v-b)^2}{2d^2}}$ *Eq. 4.2*

Where $Novelty$ represents the age and 'freshness' of a technology, $b$represents innovative maturity, and $d$is a constant representing diffusion time of new ideas. Under this submodel, the competitive advantage offered by newly completed technologies is low immediately after adoption, slowly rises in value as their application becomes more well-understood by the firm, then diminishes as competitors become aware of it.

We define return on assets (ROA) as the ratio of after-tax income mode of all available assets, as a percentage. This value is given by the following equation;

$ROA = \frac{NOP-AT}{ModeofTotalASsets}$ *Eq. 4.3*

We use ROA to determine the value of technology available to industrial firms for monetization. This value is held indivudally by each firm and contributes to the market model. When RoA is low, firms are pressured to increase their value by acquiring more technologies.

Acqusisition Process: To understand the dynamics of university-industry (UI) partnerships, it is critical to derive metrics which go beyond trade volume. One such method is to analyze industrial investment in technology and the decisions & processes which drive it. The transfer of technology from research to industry provides us a useful window through which we can quantify the state of the system at a given point in its development.

Transaction Cost Theory states that industries generally incur the cost of communication, negotiation, coordinating, monitoring and enforcing the contract. The communication cost (C) is defined as the temporal and financial spending on searching for cooperative partners. However, due to the fact that industries in this model are not geographically situated and instead can operate across the entire environment, the communication cost is represented by a weighted random function (V_{ij}), which represents the non-fixed cost of communication between industry i and university j. The cost of negotiating and enforcing is enacted because the partners must pay some premium to avoid the risk in the cooperation. In this analysis, we associate the cost with the confidence between enterprise and university (C_{ij}), which takes a value between 0 and 1, where $0 \leq C_{ij} \leq 1$. The larger the confidence value, the lower the cost of negotiating and enforcement that must be paid by the two agents. Moreover, there will still be some uncertain environmental factors that will influence the value of transaction costs. These are represented by a random function (f_{env}). The transaction cost can be expressed as a function of three variables, as shown:

$$T = f\left(V_{ij}, C_{ij}, f_{env}\right) \ \textit{Eq. 4.4}$$

In order to evaluate the evolution of innovation between these agents, two variables are introduced; Success Rate (S_R) and Average Confidence (C_A) respectively. The S_R is the ratio of times of successful cooperation to total number of cooperation attempts. The C_A is the arithmetic mean of the confidence values of every industry to every university.

$$S_R = \frac{T_{Success})}{T_{Success}+T_{failure}}$$

$$C_A = \frac{\sum_{i=1}^{N_E}\left(\frac{\sum_{j=1}^{N_i} C_{ij}}{N_i}\right)}{N_E} \ \textit{Eq. 4.5}$$

Where N_i represents the total count of universities that industry i can cooperate with. C_{ij} represents the confidence of industry i to university j.

Transactional Codependence (Clustering): Technology-led economic development has historically been driven by major research universities, often in partnership with government either through co-development or targeted grant support. This relationship is the bedrock of university-government partnerships By analyzing the growth patterns of grant clusters around universities we can make some analogies to the formation and maintenance of

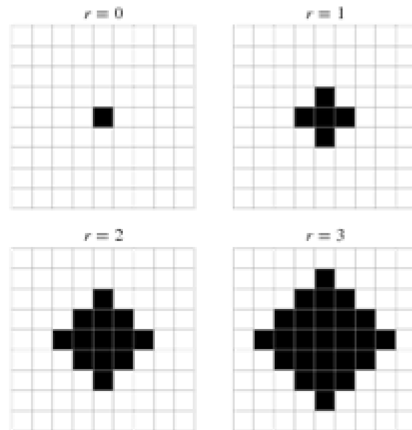


Figure 4.8: Von Neumann Neighborhood for varying values of r.

research communities through partnership with the government via direct funding dispersal (grants). Since the targetting of funds through cluster initiatives and emerging technology funds are accepted and well wrought partnership strategies between universities and federal/state government, this particular metric allows us to quantify the degree of cooperation between those classes of actors in our model.

We represent a cluster as the number of cells occupied by grants in a fixed Von Neumann neighborhood around each university site. The equation for this neighborhood is given as;

$N^{v}_{x_0,y_0} = \{(x, y) : |x - x_0| + |y - y_0| \leq r\}$ *Eq. 4.6*

The number of cells in this range S is given as;

$S_{total} = 2r(r + 1) + 1$ *Eq. 4.7*

To determine the cluster value (K) of a given university we calculate the ratio of occupied to cells to the total number of cells in the neighborhood.

$K_n = \frac{S_{occupied}}{S_{total}}$ *Eq. 4.8*

Thus, the cluster value for the entire model is given as the non-linearized average of K for all universities in the simulation, where N represents all universities, following the formulation model provided by Watts & Strogatz.

$\bar{K} = \frac{\sum_{i=1}^{N_i} K_n}{N_i}$ *Eq. 4.9*

Government Taxation: Generally, we can evaluate the throughput of the system by measuring the downstream returns on initial government investment by following the growth patterns of the industry's taxable income. Specifically, we define return as the net tax extracted from each industry at round n. The marginal tax rate is given by the constant r, which takes a value between 0.1 and 0.5, $0.1 \leq r \leq 0.5$. The total tax (W) is given by the following equation;

$W = \sum_{i=1}^{N_i} income_n * r$ *Eq. 4.10*

Productivity Heuristic: A final metric for validating the entire relationship between universities, industry, and government actors (UIG) can be found the accumulation of earnings from the sale of final products derived from technologies transferred between university and industry partners. To this end we use the common Gross Domestic Product formulation given as;

$GDP\,(Y) = p.cons. + gross.inv. + g.spend.$ *Eq. 4.11*

or

$Y = P + I + G$

In our model, private consumption (P) is assumed to be the value of all derivative sales made by each industry actor i at the end of round n. Gross investment is the total amount spent by all industries to acquire technology artifacts from university partners during each round. Government spending is the fixed cost of investment per round. It is calculated by summing the value of all replenishment to the grant pool. Sector contributions to GDP are also tracked in order to determine the affect of perturbations to the population of grant objects in the environment.

Diversity Index: One of the more interesting corrolaries to our selection of the ecosystem view of the system is that we can investigate the impact of species diversity on overall system behavior. In order to quantify diversity it is often useful define a measure which goes beyond species *richness* (the number of distinct species in a particular ecosystem). The relative abundance of species gives the investigator an indication of the relationship between environmental conditions and particular ecological configurations. The relative abundance of rare and common species is refered to as *evenness*. Species diversity takes into account both richness and evenness, where communities with large numbers of species that are evenly distributed are the most diverse, while those with few species dominated by one species are the least diverse. Various techniques exist to measure species diversity. These techniques are commonly referred to as diversity indices. In the ecological domain, two of the most common diversity indices are Simpson's Index and the Shannon-Weiner Index. For the purpose of this study, we will use the Shannon-Weiner Index as it is more ideal for cases where a greater deal of empirical data is present.

The Shannon-Weiner index was developed from information theory and is based on measuring uncertainty. The degree of uncertainty of predicting the species of a random sample is related to the diversity of a community. If a community is dominated by one species (low diversity), the uncertainty of prediction is low; a randomly-sampled species is most likely going to be the dominant species. However, if diversity is high, uncertainty is high. In our case, we have perfect information regarding the species sample, so we can make stronger claims about the accuracy of the product.

Calculating the Shannon-Weiner Index is straight forward. The index of diversity $H^{'}$ is given by the equation;

$H' = \frac{N \ln N - \sum n_i \ln n_i}{N}$ *Eq. 4.12*

where N is the total number of individuals of all species and$n_i$is the number of individuals of species i. While not part of our basic hypothesis, there is strong correlation between commercial and academic diversity and long-term RSI resilience in the face of perturbation. Thusly, we intend to use this index as a part of our measure of ecological resilience following the conclusions of Holling (1973).

4.5 Chapter Summary

In this chapter we presented a conceptual framework and formal model for THESIM, an agent-based simulation model of the triple-helix theory of regional and national innovation system organization. In section 4.1 we described the interaction philosophy and model of the three control regimes of the triple helix; academia (university), private firms (industry), and government. In section 4.2 we laid out our agent-based conceptual model of the three helices, by defining categories of actors and establishing the resource cycle. In section 4.3 we more fully described agent behaviors and classified them into specific roles based on their ecological characteristics (producer, consumer, decomposer, etc.). These specific roles were then organized in a relational map (Figure 4.3) and a simplified rule set was developed based on their expected behavior. In section 4.4 we formally propose a simulation model based on the conceptual framework laid out in section 3 using a modified Overview, Design concepts, and Details protocol (ODD) similar to the methodology proposed by Grimm (2006). Using ODD we formally present the criteria of parameter selection, behavioral guidelines, and submodels from which THESIM will be developed. These submodels will provide the statistical output for use during experimental verification and validation.

Chapter 5

Model Implementation & Basic Relationships

5.1 THESIM-Repast

In order to test the feasibility of the simulation model proposed in chapter 4 we implemented THESIM using the current version of the Recursive Porous Agent Simulation Toolkit, Repast Simphony 2.0. Repast Simphony is the successor of Repast. We selected this toolkit over other similar packages (SWARM, NetLogo, JADE, etc.) because it provides a user-friendly nterface that allows inexperienced users to rapidly design and implement agent logic and simulation behavior in a flowchart-like interface. Simulation settings are similarly accessible via a simple menu system.

Repast Simphony provides a wide selection of built-in tools for users to track the course of a simulation. The simulation environment also provides customizable graphical output system, access runtime controls (step-wise execution, debugging, live modification of agent setting, etc.), and has interfaces to export data to a broad range of statistical and mathematical programs including MatLab and other Simulink products. Repast Simphony also provides interfaces to the Terracotta Java clustering infrastructure and GRASS GIS.

Repast Simphony models can be developed in several different forms including ReLogo (a dialect of Logo), point-and-click flowcharts, Groovy, or Java. Java was selected as the development language of choice for implementing THESIM due the investigator's familiarity as well as the flexibility provided. The Repast toolkit is integrated with Eclipse, an open-source development platform comprised of extensible frameworks, tools and runtimes for building, deploying and managing software. Eclipse has a well-supported development community and is actively updated. The resultant Repast implementation is referred to as THESIM-Repast.

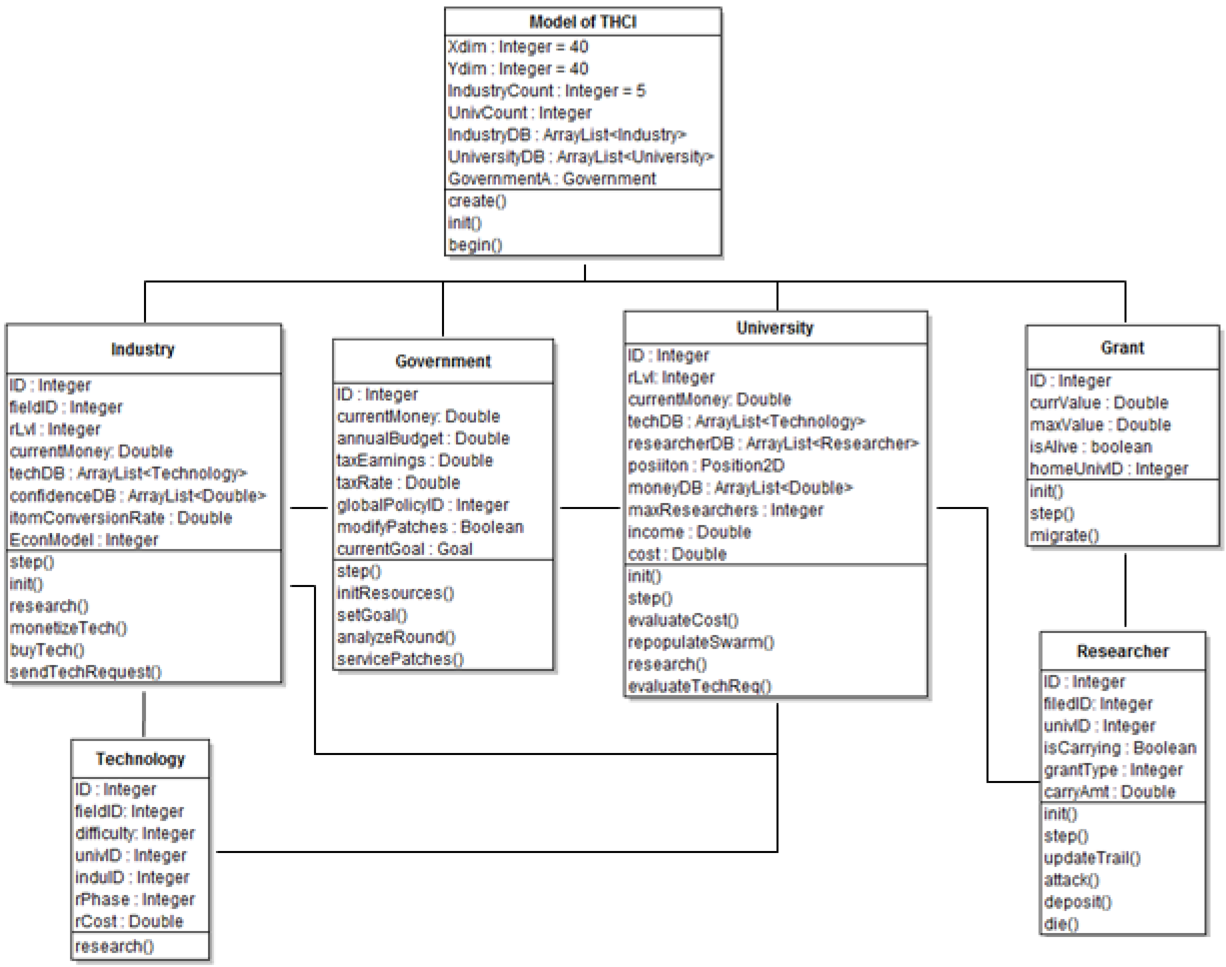


Figure 5.1: UML model of THESIM class relationships

5.2 Class Structure

We begin by identifying the class structure and mapping the relationships between each class to the relational diagram of the model. The resulting class structure can be seen in Figure 5.1. We proceed to label and define the input parameters necessary to initialize the simulation. Finally, we outline and define the simulation's output parameters.

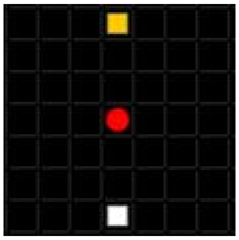
Based on analysis of five different types of agents: government, industry, university, researcher, and grant, we developed five classes describing the characteristics and behaviors of these agents. In addition there are two classes directly associated with the running of the model named THEModel and THEEnviron. The THEModel class handles the creation of indispensable variables, agent scheduling, control of the simulation (start, stop, display, etc.), and the exogenous parameters accessed by active agents. The THEEnviron class contains all the parameters and data-structures associated with the discrete environmental layers visible to agents (resource terrain and market network).

5.3 Simulation Environment

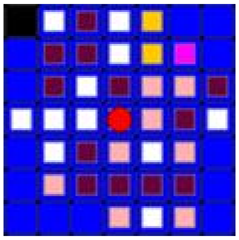
The resource terrain is composed of several discrete two-dimensional grid layers. The physical layer contains a number of grant, researcher, university, and industry agents. Each additional layer is a communication layer corresponding to a specific university. Each grid position in the physical layer may contain several agents simultaneously, with university and industry agents restricted to cells which do not contain resource agents. Cells in communication layers contain no agents, but rather pheromone data-structures used by the ant-colony search variant used by researcher agents to explore the environment.

The grid layers of THESIM-Repast's environment are initialized using variables $Grid_x$and $Grid_y$ to set the dimensions. Agents and decorators are then added to the physical layer based on the input parameters specified by the user via the interface. The visualization of the grid interface is color and shape-coded, red circles represent universities, yellow circles represent industry agents, each small colored square represents a grant agent whose color corresponds to one of five types representing different science and technology sectors. The background color of each cell is determined selecting the pheromone deposition ($P_{x,y,i}$) with the largest non-zero value among all the communication layers.

Using this visualization schema we can see the configuration of grants within the environment overlaid atop the growth and maintenance of the dominant search space for each university's population of research agents. Additional visualization schemas allow us to view more detailed information, such as topological intensity graphs of university search space, market networks (three-dimensional), and charts associated with overall simulation behavior.



a) $t = 0$



b) $t = 150$

Figure 5.2: University's local grant neighborhood $t = 0$ and $t = 150$ respectively.

5.3.1 Activity Scheduling

Agent step activation order is determined by the Repast activity scheduler, which iterates with a simulated concurrency (i.e. in random order). At the beginning of each step agents evaluate their current condition, location, and surroundings then take appropriate action based on their type and status. Time periods are broken up into rounds consisting of a fixed number of time steps specified by the user. Some agent classes (such as the researcher class) perform operations at each time step, while others only perform operations at the start of a new round.

Researcher agents activate once per time step. These agents traverse the environment using movement rules specified in section 4.3 and perform search and resource gathering activities. University agents activate once at the start of the round. They monitor their status, perform management activities on their population of researcher agents, and iterate technological development. Industry agents also activate at the start of the round and develop research partnerships with university agents as well as iterate technologies. The government singleton performs management activities on grant agents on a variable schedule.

Parameter	*Definition*
$Grid_x$	Environment width (cells)
$Grid_y$	Environment height (cells)
n	Total number of simulation rounds (run-time)
t	Marginal tax rate
c_N	Dimensionality constant associated with Von Neumann neighborhood size
$fund_r$	Amount of resource provided to government agent per simulation round
E_r	Expected profit ratio
j	University agent count
i	Industry agent count
β_{ij}	Growth conservation factor
θ_g	Patch Density factor
δ_r	Size drag ratio

Table 5.1 Definition of the basic input parameters within in THESIM-Repast

In the standard configuration, this maintenance step is performed at the start of the round, however the user may specify alternative timing or activity conditions.

5.3.2 Parameters

THESIM-Repast takes a variety of user-specified input parameters which allow for various experimental conditions to be examined. For the purpose of determining feasibility, we performed a down-select on the simulation conditions in order to determine those variables most critical to the development of consistent system stability. The basic initialization inputs can be observed in table 5.1. The simulation requires grid dimensions, information about round duration, simulation length, the size of the academic and industrial bases, and the level of government funding and intervention.

Optional parameters include risk-aversion thresholds, public-private growth target information, and resource proliferation modifiers. These optional parameters are not necessary to initialize a standard run but they allow us to initialize a broad variety of basic condition-testing experiments to validate the individual and system-level behaviors and verify whether the simulation model put forward in chapter 4 indeed results in a system whose characteristics match known innovation economies or are consistent with existent simulation experiments.

Parameter	*Definition*
$\boldsymbol{Y}$	Innovation production score for the entire simulation
$\boldsymbol{G}$	Return on assets (GDP) for the entire simulation
$\boldsymbol{W_j}$	Gross (tax) profit collected by government agent
$\boldsymbol{T'}$	Average transaction cost
$\boldsymbol{cost_i}$	Average investment cost of technology
$\boldsymbol{D_t}$	Shannon-Weiner diversity index at time t
$\boldsymbol{Sr_t}$	Global transaction success rate at time t
$\boldsymbol{Ca_t}$	Global cooperation confidence at time t
$\boldsymbol{RI}$	Return on investment for the entire simulation

Table 5.2: Definition of the output parameters involved in THESIM-Repast

As outlined in chapter 4, THESIM-Repast provides a variety of output parameters used to analyze the behavior of the system. These parameters allow us to validate the activity of the various sub-models of the simulation as well as providing data for experimental verification. Table 5.2 contains a selection of the most salient the output parameters gathered from a typical simulation run. These include; innovation production score, GDP, risk aversion, and diversity calculations. Measures such as resilience and robustness are evaluated from the aggregate data collected over the course of an entire experiment. The full set of input and output parameters are discussed at length in chapter 6, including scenario-building parameters used for stress testing the model.

5.3.3 Preliminary Experiments

Following the initial hypotheses proposed in chapter 1 we constructed an experimental profile intended to investigate two structural conjectures;

1. That the collection of behavioral rules put forward in the THESIM model resulted in agent population and technology production behaviors similar to those observed in statistical models of innovation economies.

2. The social trends present in inter-agent communication are consistent with the expectations of the relevant sub-models (stygmergy, cooperative development, etc.).

3. Parameters associated with environmental fitness are closely tied to system stability and resilience in the face of perturbation.

To evaluate the first objective, we pay close attention to innovation and value production metrics (Y, G, and R respectively). We are also interested in patterns of technology production on a per-round basis, though this is not captured in the simulation output parameters. The second objective is a consistency check against the findings of Dongsheng & Yongen (2008) which is the most relevant model demonstrating socio-economic dynamics between the various production stages within the triple helix. We use the global transaction success rate (Sr_i) and cooperation confidence interval (Ca_i) as measures to evaluate simulation performance in these areas. Finally, the third objective can be captured in the experimental design.

Holling describes the reaction a resilient system displays to perturbation as "positive feedbacks which overcome instabilities and variability experienced by the system, if not of a magnitude sufficient to exceed the systems' resilience." (Allen & Holling, 2008). By instilling regular disturbance into the conditions of the experiment, we can determine the effective carrying capacity of the system by observing the reactions of the agent population. This is accomplished by introducing a randomized resource upheaval at a regular interval during the simulation. By focusing on ecological population metrics such as species richness and diversity (Shannon-Weiner Index) we can strengthen claims about agent-based ecological modeling. Specifically, the notion that using ecosystem models for the behavior of agents and the conceptualization of the environment allows us to better adapt concepts from population dynamics for use in verification and validation.

Additionally, we were interested in determining whether the behavior of THESIM-Repast's sub-models remained consistent with known work in innovation economic simulation despite the differences in the social and environmental models. To this end we chose to focus on broad markers of production, cooperation, and competition. The tests were run

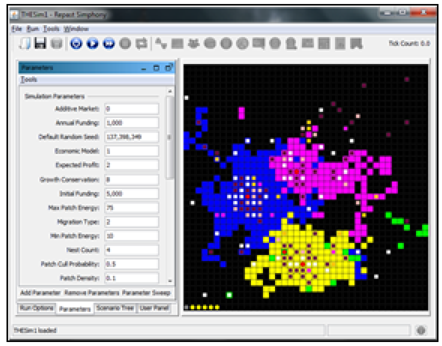


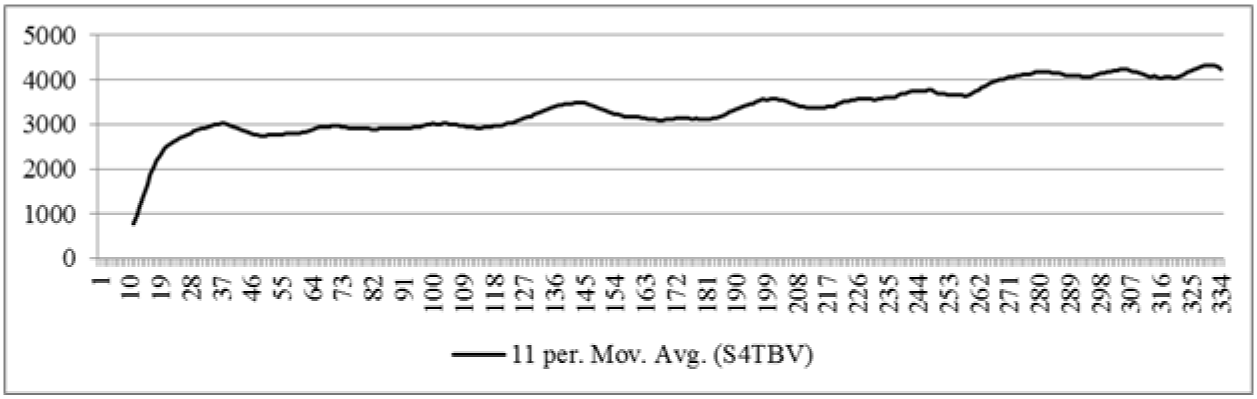
Figure 5.3: THESIM Repast sample output showing grant clustering and exploitation regions in a four university system.

Figure 5.4: System productivity via gross domestic product over time (t)

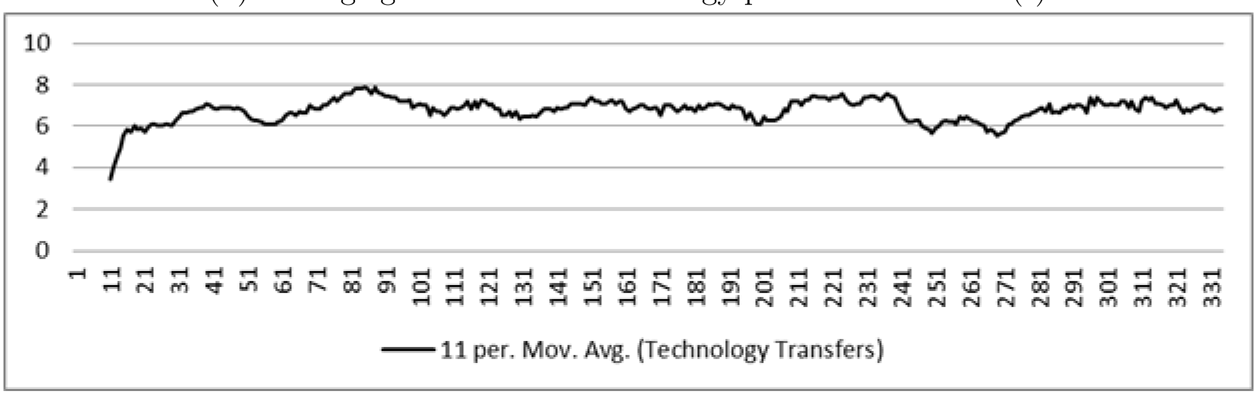
with 'small-world' initialization parameters and a fixed number of university and industry agents.

The simulation was run for 50 trials; each consisting of 10000 ticks (335 rounds) under default parameters. The averaged productivity results are shown in shown in figure 5.5. The GDP curve begins at turn 10 due to the absence of first-products in the system. Universities and industries are forced to innovate alone for the early cycles before they have innovation products to trade and monetize. We can see from the curve that production ramps up early before the growth stabilizes. This is due in part to residual technologies, which depreciate in value as their novelty erodes but nevertheless provide consistent income for industrial firms.

One outcome worth noting is the consistency between the global value of all technologies and the productivity of industry agents seen in figure 5.6. Due to the slow speed of



(**a**) Average global value of technology products over time (t)



(**b**) Average technology acquisitions by a single industry agent over time (t)

Figure 5.5: Behavior and value of technology acquisition among industry agents over time (t)

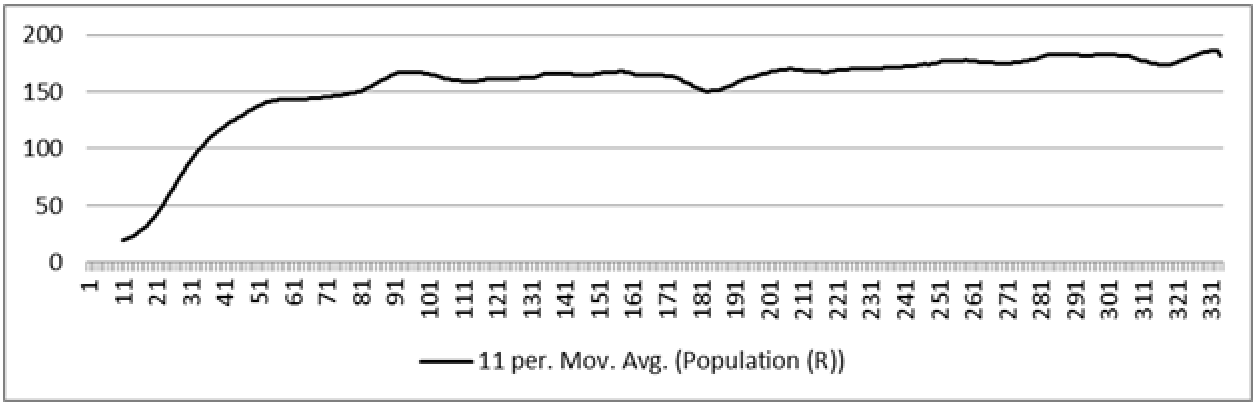


Figure 5.6: Researcher agent population growth over time (t)

solo-innovation, early technology acquisitions are highly valued and provide significant competitive advantage. However, as industries mature and their relationships with university agents solidify, the need to make large, risky acquisitions is overcome by financial constraints and general satisfaction with their level of competitive advantage over their rivals. These results vary somewhat across the agent population but their aggregate behavior is consistent.

For the purposes of instilling confidence in the population model as it relates to ecological domains we turn to metrics for analyzing communities of researcher agent. Looking at the curve of Figure 5.7 we can observe a fairly typical population curve whose growth bounds are reasonably well defined and resemble real-life examples. Agents well optimized to exploit the types of natural resources present in the environment persist and encourage the hiring of additional agents of similar quality, while those that do not are eliminated from the workforce. This workforce growth is limited by the amount of resources available in the environment. As the capacity is reached, the population stabilizes (with minor fluctuations). While this competitive mechanism is simple, and does not capture more complex notions such as tenure, university-level research diversity initiatives (for example; it is unlikely a university would eliminate the mathematics program simply because its research staff was less successful acquiring federal grants), and long term research initiatives it does provide a proxy through which ecological questions can be asked.

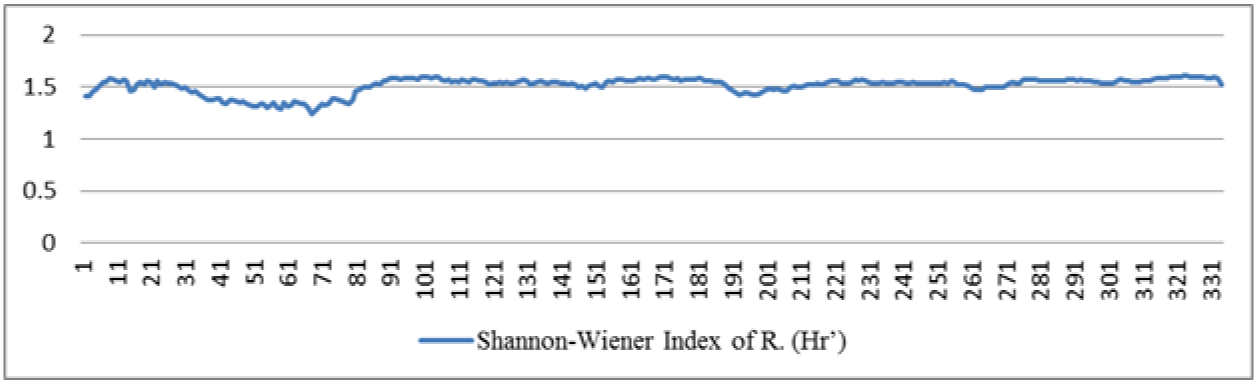
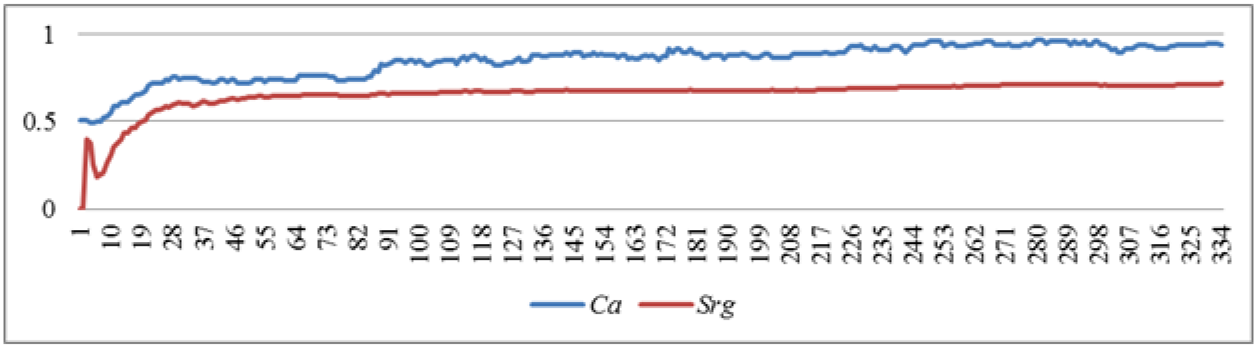


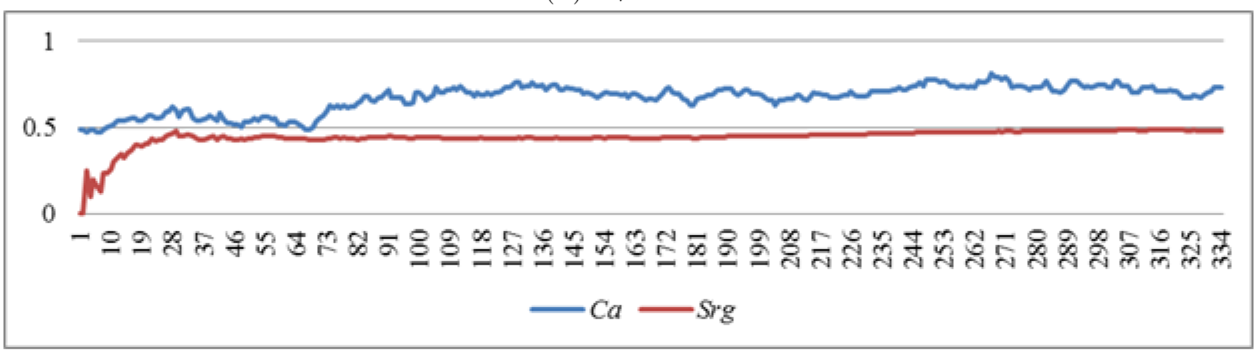
Figure 5.7: Shannon-Wiener index of researcher agent population (H_R') over time (t)

We look at the changes in H_R'(where R is the population of researcher agents) to give us some insight into the population dynamics at work within the simulation model. Researcher-agent hiring and firing (equivalent to ecological birth and death rates) are tied to search performance. Biologically realistic H' values range from 0 (only one species present with no uncertainty as to what species each individual will be) to about 4.5 (high uncertainty as species are relatively evenly distributed). In theory, the H' value can be much higher than 4.5, although most real world estimates of H' range from 1.0 to 3.0. H' values close to 2.0 are considered normal and indicate a moderate amount of volatility in species density and diversity. In general, it is thought that more disturbed and less stable environments should have lower H' values. Looking at the curve of H_R' in figure 5.7 we see very little fluctuation, with averaged values ranging from 1.281 to 1.53. This is in line with the resource model, which is initially evenly distributed across all types, and expectations of agent population dynamics.

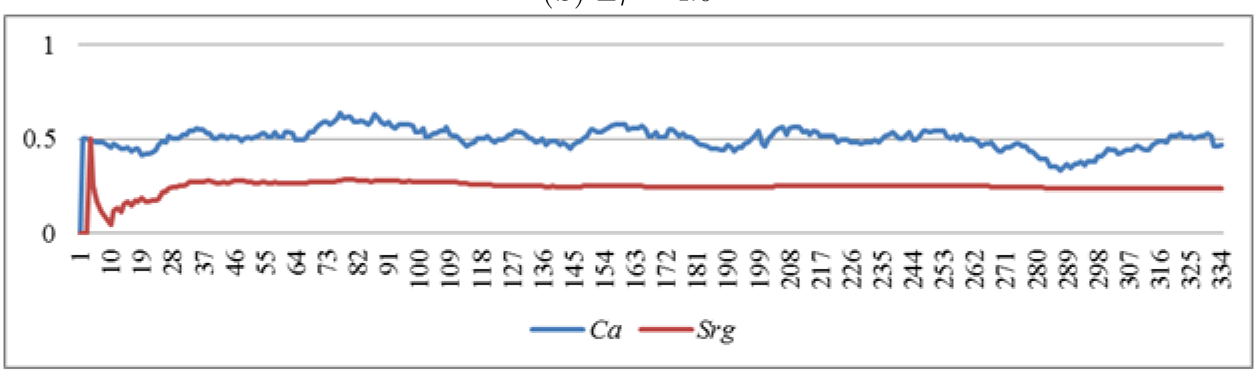
Finally, we are interested in correlating our work with existing studies of innovation economy simulation. To this end we made a deliberate effort to pattern our technology acquisition process on the work done by Dongsheng & Yongen (2008), who proposed a specific model for evaluating trade deals between university and industry agents whose output could be measured as the ratio of successful to unsuccessful transactions and a trust metric which influenced likelihood to finalize deals. Our model extends this theory by allowing the



(**a**) $E_r = 2.0$



(**b**) $E_r = 4.0$



(**c**) $E_r = 5.0$

Figure 5.8: The Success Rate (Sr) and Average Confidence of industry-university partnership (Ca) under conditions of risk-aversion (E_r) over time (t).

opportunity for limited government intervention to help 'sweeten' deals which risk-averse partners might otherwise decline. However, in this first experiment we have disabled this functional interaction in order to gauge the consistency of our sub-model with the results gathered in the 2008 study.

Much like the earlier work, we can observe that the curves of Srg and Ca vary with the industry agent's expectation of return (given by $E_r = 2.0$, 4.0, and 5.0, respectively). The rapid increase of cooperation during the early phase of the simulation can be attributed to the need on the part of industry firms to address their competitive needs by acquiring new technologies (as they start out with none). However, these early ventures are often costly, and depending on the level of risk-aversion may sour these firms to future cooperation or at least reduce the amount they are willing to bid. Low bids, combined with high risk aversion results in fewer successful transfers which in turn depresses the success rate. A feedback reaction exists between acquisition success or failure and adjusting of trust values (successful bids raise trust, unsuccessful bids lower trust). Thus we observe an effective sensitivity threshold in E_r such that high risk aversion engenders consistently lower trust between firms. Lower values of E_r result in higher degrees of consistent and stable cooperation, while higher values cause this relationship to fall to ruin. We also see that Sr reaches a stable value gradually after a period of evolvement. From this we draw a similar conclusion with the authors of the similar study, which is that industry and university agents are able to form a stable cooperative relationship.

Chapter 6

THESIM Experimental Design & Analysis

6.1 Introduction & Objectives

Our experimental goal is to explore four facets of knowledge ecosystem development; system productivity, carrying capacity, resilience, and inter-agent relational structure. This follows the overall aim of our thesis; the development a computational theory of the triple-helix theory of public-private partnership. To this end, we can revisit the initial hypothesis guiding the work as stated in chapter 1;

H_a: The development and maintenance of innovation economies can be explained on the basis of an ecologically driven agent-based model of the triple-helix model of public-private partnership.

- H_{a1}: Agents need a minimum set of interacting components to meet specific role-defined goals in an unfamiliar environment.
- H_{a2}: Knowledge in the world can be represented by ecological affordances and environmental information. The process of innovation creation and transport works on the basis of the interplay between the two.

While the development of the THESIM model following ecological agent-based modeling has provided satisfactory resolution to H_{a1}, H_{a2} requires dedicated experiments designed to more fully investigate the claim.

Principally, we can validate our resolution of H_{a2} by providing clear analysis of our computational model that indicates how the transformation of a set of system variables by our implementation of the simulation model results in the innovation creation and conservation behavior described by triple helix theory. In particular, if we can show that there is some small *set of critical variables* that control key model output parameters we can falsify the null hypothesis that the system's behavior is indistinguishable from a random distribution of values (i.e. all relevant system output is noise). It is therefore instructive to develop a comprehensive experimental model to structure our inquiries regarding simulation behavior and performance.

For the purpose of completeness and replicability we follow the guidelines and recommendations given in support of a systematic design of experiments (DOE) as detailed by Lorscheid et al. (2011). DOE increases the transparency of simulation model behavior and the effectiveness of reporting simulation results. This technique is well suited to socio-economic simulation and has been applied successfully to multi-agent market models (Meyer & Troitzsch, 2012; Klingert & Meyer, 2012).

6.2 Systematic Model Analysis

This section illustrates the application of DOE principles for structured experimental analysis of the THESIM model. We proceed from the standard reporting template provided by Lorscheid et al. (2011), paying specific attention to the variable description and selection process due to the exploratory nature of the proposed experimentation. For the communication of results, we make use of standardized output formats described in the aforementioned work and detailed in later sections.

As described in Chapter 5, the THESIM model is used to examine the structure and functionality of Triple-helix aligned knowledge ecosystems. Therefore, the performance of the system under simple policy and environmental constraints are analyzed and compared. The simulation experiment has three objectives: First, the effects of inter-agent innovation trade on system productivity are analyzed through a relative comparison of the performance several experimental models with differing endogenous environmental parameters. Second, the optimum carrying capacity in terms of innovation production, agent-population, and

Simulation Parameter (main class)	DOE	Variables	Parameter Type
Integer minPatchEnergy			Support parameter
Integer maxPatchEnergy			Support parameter
Integer initialFunding			Support parameter
Integer annualFunding	✓	S4 Annual Funding	
Double s3KnowledgeValue	✓	S3 Knowledge Value	
Integer patchMaintenancePolicy			Static policy model
Integer econModel			Support parameter
Integer gridX			Environmental parameter
Integer gridY			Environmental parameter
Integer updatestyle			Behavior parameter
Double patchDensity			Support parameter
Double patchCullProbability			Support parameter
Integer patchDistributionPolicy			Static policy model
Integer patchMaintenancePolicy			Static policy model
Integer minPatchEnergy			Support parameter
Integer maxPatchEnergy			Support parameter
Integer initialFunding			
Integer annualFunding	✓	S1 Annual Funding	
Double s1AnnualPayRate	✓	S1 Annual Pay Rate	
Double s3MaintenanceRate	✓	S3 Maintenance Rate	
Double s3ItoMConversionRate	✓	S3 Innovation-to-Money Conversion Rate	
Double s4TaxRate	✓	S4 Tax Rate	
Integer migrationType			Static policy model
Double expectedProfit	✓	Expected Profit	
Integer randomNest			Support parameter
Integer nestCount	✓	University Count	
Integer shakeUpTime	✓	Shake-up Time	
Integer runLength			Initialization parameter
Integer growthConservation			Support parameter
Integer additiveMarket			Static policy model

Table 6.1 Simulation DOE full parameter selection.

system configuration in the given model scenario is determined to enable the comparison. Third, we examine the system's overall resistance to shock by introducing environmental stress and calculating a resilience threshold for the base configuration of the model.

To prepare our experiment, the variables of the THESIM model are classified in two steps. We begin by enumerating all the independent, dependent, and control variables present in our experimental model. These values are taken directly from the source-code defining THESIM operation and are more comprehensive then the basic set presented in chapter 5. These simulation parameters are used as reference points to identify all model variables (Table 6.1).

We proceed to identify all parameters which influence model behavior and include them in the DOE as independent variables. Parameters deemed necessary to evaluate the simulation model are entered as dependent variables. Support parameters are included as control variables as they are necessary for calculating the simulation outcome but do not vary between simulations. As they are required for implementation purposes only, they are not included as model variables.

Independent Variables (x_i)

- Government Annual Funding: x_1)
- Researcher Annual Pay Rate: (x_2)
- Industry Knowledge Value: (x_3)
- Industry Maintenance Rate: (x_4)
- Industry Innovation-to-Money Conversion Rate: (x_5)
- Government Tax Rate: (x_6)
- Expected Profit (Er): (x_7)
- University Count: (x_8)

- Shake-Up Time: (x_9)

Control Variables (C_i)

- Economic Model (C_1)
- Grid XY-dimension (C_2)
- Update Style (C_3)
- Patch Density (C_4)
- Patch Cull Probability (C_5)
- Patch Distribution Policy (C_6)
- Patch Maintenance Policy (C_7)
- Minimum Patch Energy (C_8)
- Maximum Patch Energy (C_9)
- Patch Migration Policy (C_{10})
- University Random Distribution (C_{11})
- Run Length (C_{12})
- Growth Conservation (C_{13})
- Additive Market (C_{14})
- Government Initial Funding (C_{15})

Dependent Variables (R_i)

- System GDP: (R_1)
- Researcher Population Count: (R_2)

- Researcher Population Diversity Index: (R_3)
- University Size: (R_4)
- University Innovation Creation: (R_5)
- Industry GDP: (R_6)
- Industry Partner Count: (R_7)
- Technology Transfer Count: (R_8)
- Network Structure Graph: (R_9)

After classification, these variables are then collected in order to develop an overview of the model components (Table 6.2). This allows us to determine areas for potential experimentation on the model.

Based on the classification of variables, the investigated relation in the model can be described as the effect that different (x_1-x_9) environmental and behavioral parameters have on the (R_1, R_6) *GDP*, (R_2-R_5) *population dynamics*, (R_5, R_7-R_8) innovation carrying capacity, and (R_9) *network structure graph* of the triple-helix knowledge ecosystem. This can generally be represented in the diagram below below (Figure 6.1).

The variation of potential independent variables (C_1) *economic model*, (C_4) *patch density*, and other policy-based options are not of interest for the given exploratory exercise. As a result, these parameters remain fixed as control variables in the model. The variable (C_1) *economic model* contains all endogenous agent decision parameters associated with fiscal distribution and that form the basis of the experimental model. Environmental variables (C_2 -C_{11}) can be combined into a more general *environmental model* for the experiment. These features remain constant across the lifetime of the experimental run and can be referenced by agents for the purpose of local competitive decision-making.

The variable (C_{13}) *growth conservation* sets a maximal distribution of new researcher agent creation and destruction by university agents based on their current size. This tuning

Independent (Input, x) Variables	Control (Fixed, C) Variables	Dependent (Response, R) Variables
(x_1) Government Annual Funding	(C_1) Economic Model	(R_1) System GDP
(x_2) Government Tax Rate	(C_2) Grid XY-dimensions	(R_2) Researcher Population Count
(x_3) Researcher Annual Pay Rate	(C_3) Update Style	(R_3) Researcher Population Diversity Index
(x_4) University Count	(C_4) Patch Density	(R_4) University Size
(x_5) Industry Knowledge Value	(C_5) Patch Cull Probability	(R_5) University Innovation Creation
(x_6) Industry Maintenance Rate	(C_6) Patch Distribution Policy	(R_6) Industry GDP
(x_7) Industry IMC Rate	(C_7) Patch Maintenance Policy	(R_7) Industry Partner Count
(x_8) Expected Profit (E_r)	(C_8) Minimum Patch Energy	(R_8) Technology Transfer Count
(x_9) Shake-Up Time	(C_9) Maximum Patch Energy	(R_9) Network Structure Graph
	(C_{10}) Patch Migration Policy	
	(C_{11}) University Random Distribution	
	(C_{12}) Run Length	
	(C_{13}) Growth Conservation	
	(C_{14}) Additive Market	
	(C_{15}) Government Initial Funding	

Table 6.2 Formal classification of THESIM DOE variables.

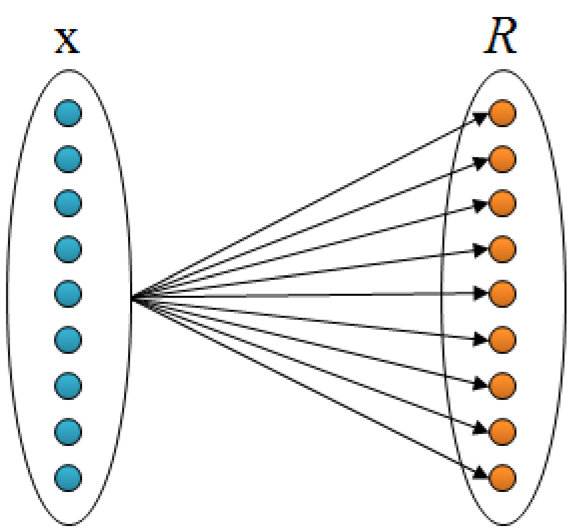


Figure 6.1: Goals: Relationship Mapping of x_i to R_i

parameter allows for the introduction (or reduction) of population volatility across the system by limiting the rate at which universities can add, remove, or replace researchers in their pool. *Run length* (C_{12}) defines the number of time steps per simulation. In our experiment, it states that the number steps in a single run is initialized to 1000. The variable (C_{14}) *additive market* allows an experiment-defined fraction of profits to be return to the system at the end of each round. Finally, *government initial funding* (C_{15}) is held constant across each simulation run.

The dependent variables are (R_1) *system GDP*, (R_2) *researcher population count*, (R_3) *researcher population diversity*, (R_4) *university size*, (R_5) *university innovation creation*, (R_6) *industry GDP*, (R_7) *industry partner count*, (R_8) *technology transfer count*, and (R_9) *degree centrality*. *System GDP* denotes the total economic productivity of the system and is calculated by combining the total value of all technological assets and profits generated by innovative behavior.

Researcher population count is running total of all active researcher agents active in the system at the end of each time step. Meta information for each agent is retained for the purposes of more granular investigation into the properties of sub-populations. Additionally, *researcher population diversity* is the Shannon-Weiner diversity index of the researcher population at the end of each time step. *University size* is a list of all active universities within the system and the size and composition of their researcher population. University innovation creation tallies the total number of new technologies completed by all universities in the system.

Industry agent-specific productivity information is collected by the variable *industry GDP* which indicates the total productivity of industries represented in the model. *Industry partner count* represents the total number of unique universities that have completed successful transactions. Following on, *technology transfer count* indicates the total number of successful technological transactions between universities and industry across the lifetime

Factor	Experimental Variable	Level -1 (low)	Level 2 (high)
Government Annual Funding	x_1	1000	5000
Government Tax Rate	x_2	0.2	0.7
Researcher Annual Pay Rate	x_3	10	20
University Count	x_4	2	15
Industry Knowledge Value	x_5	20	100
Industry Maintenance Rate	x_6	0.5	0.9
Industry IMC Rate	x_7	2	20
Expected Profit	x_8	1	9
Shake-Up Time	x_9	1	334

Table 6.3 Goals: Description of DOE factors and factor levels.

of the simulation. The *network structure graph* provided by the simulation isan xml documentrecording the links incident upon each university and industry agent in the graph representation of the system along with performance metadata for each agent. These graphs are stored for future network structure analysis and data visualization efforts.

Within the simulation experiment, the described model variables are analyzed as *response variables* with distinct factor levels. To accomplish this, the model variables need to be transformed into factors whose factor level ranges are defined following factorial reduction strategy (Table 6.3). To accomplish this, we begin with a basic 2^k experimental design. In this case, for the set of response variables R_i we outline an experimental case designed to evaluate the combinatorial effect of each independent factor x_i (as indicated in Figure 6.1). This exhaustive approach to the evaluation of the Top-Level-DOE represents the final step towards answering the research questions;

1. What is the minimum set of factors that describe the response variance of the model?

2. What are the critical thresholds of these factor-levels that define different response configurations?

For the purpose of developing a tractable set of early experiments to evaluate these questions we temporarily contract our independent variable range by pegging the variable shake-up time (x_9) to its first factor level for the sake of simplicity. This variable is only relevant for

Factors	Factor Level Ranges	Responses
Government Annual Funding	1000-5000	(R_1) System GDP
Government Tax Rate	0.2-0.7	
Researcher Annual Pay Rate	10-20	(R_2) Researcher Population Count
University Count	2-15	(R_3) Researcher Population Diversity Index
Industry Knowledge Value	20-100	(R_4) University Size
Industry Maintenance Rate	0.5-0.9	(R_5) University Innovation Creation
Industry Innovation-to-Money Conversion Rate	2-20	(R_6) Industry GDP
Expected Profit	1-9	(R_7) Industry Partner Count
		(R_8) Technology Transfer Count
		(R_9) Network Structure Graph

Table 6.4 Top-level DOE chart.

Table of preliminary design points for the estimation of error variance

Design Points	Factors x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	Definition by
1	1000	0.2	10	2	20	0.5	2	1	1	Low factor levels
2	3000	0.45	15	8.5	60	0.7	11	5	167.5	Mean factor levels
3	5000	0.7	20	15	100	0.9	20	9	334	High factor levels

Table 6.5 DOE Effect Matrices.

specific experiment types (system reaction to perturbation) and can thusly be treated as a control variable for the purpose of early experimentation. The resulting model gives us a 2^k model where ($K = 8$) that can be represented using a Top-level DOE chart. This model can be represented by an effect matrix (table 5).

6.3 Sub-DOE THESIM-Sensitivity 1st-iteration

In order to proceed toward answering the first question (finding a minimum set of factors), basic estimation of error variance and variable sensitivity must be performed on the model in order to reduce the number of factors in our experimental design to a more tractable set. Sensitivity analysis of a model is performed to determine how outputs vary with changes of input parameters, in order to identify the relative importance of parameters and to help in optimization of the model. Traditionally, this is performed using the one-factor-at-a-time (OFAT) method. However, the results of OFAT are unreliable if there are significant interactions between parameters (Mikhael & Funnell, 2005). Therefore, we incorporate the Taguchi method of sensitivity analysis in to our experimental design as an alternative to OFAT or full-factorial selection. This method employs only a small number of all the possible combinations of model parameters to estimate the main effects and some interactions. An orthogonal array (OA) is used to reduce the number of simulations (Taguchi, 1987) but still obtain reasonable information.

The procedure for applying the Taguchi method is as follows. Minitab 16 was used for the calculations.

1. Select parameters and interactions of interest.

2. Select parameter levels.

3. Find a suitable OA with the smallest number of runs. This normally involves looking up a predefined OA based on the numbers of parameters, interactions and levels.

4. Map the factors and values to the OA.

5. Run simulations based on the OA.

6. Analyze the simulation results.

The eight relevant independent variables (x_1-x_8) were selected for this analysis, with shake-up time (x_9) omitted for the sake of initial relevance. This process can be summarized in table 6 via an OA L_8 2^{12} , representing 8 two-level parameters, and a total of 12 simulation configurations.

The eight outputs investigated (R_1-R_8) are summarized in the previous section. A total of 12 static finite-element simulation models were input and each was performed 30 times in REPAST; Their results are summarized in Table 6.6. The experimental designation for this trial is recorded as TKGL12-2.

	Factors								Responses							
Run	*x1*	*x2*	*x3*	*x4*	*x5*	*x6*	*x7*	*x8*	R_1	*R2*	*R3*	*R4*	*R5*	*R6*	*R7*	*R8*
1	1000	0.2	10	2	20	0.5	2	1	1718391	16.73	1.49	1.12	0.90	1848.80	0.91	1330.23
2	1000	0.2	10	2	20	0.9	20	9	2853673	49.61	1.60	12.40	0.88	1789.16	0.90	12201.30
3	1000	0.2	20	15	100	0.5	2	1	4369685	9.54	1.46	0.48	0.86	1365.31	0.81	1321.63
4	1000	0.7	10	15	100	0.5	20	9	55123060	123.39	1.57	6.17	0.77	1776.84	0.72	4844.40
5	1000	0.7	20	2	100	0.9	2	9	2637093	8.39	1.49	4.20	0.84	1729.52	0.80	1288.77
6	1000	0.7	20	15	20	0.9	20	1	48427325	107.85	1.60	5.39	0.77	1566.79	0.72	4257.07
7	5000	0.2	20	15	20	0.5	20	9	13112785	44.60	1.59	2.23	0.75	3309.43	0.71	3928.27
8	5000	0.2	20	2	100	0.9	20	1	4272136	6.80	1.49	0.34	0.91	1261.02	0.92	1098.93
9	5000	0.2	10	15	100	0.9	2	9	2553907	103.44	1.60	5.17	0.76	937.43	0.71	4070.87
10	5000	0.7	20	2	20	0.5	2	9	2204245	6.71	1.43	0.34	0.85	416.71	0.80	1032.10
11	5000	0.7	10	15	20	0.9	2	1	7747609	104.61	1.59	5.23	0.89	661.89	0.89	4116.90
12	5000	0.7	10	2	100	0.5	20	1	16077425	14.69	1.47	0.73	0.91	971.73	0.92	1078.47

Table 6.6 OA L_8 2^{12} table for investigation and simulation results.

Next, the effect analysis of all factors is conducted for the simulation data. For a systematic analysis of the factor effects, the analysis proceeds in two steps. First, factors are tested for significant effects on each simulation response. Second, the strength of all identified significant factor effects is calculated. For the first step, testing the factor effects for significance, a generalized linear model (GLM) was developed for the model outputs based on the L8 Taguchi test matrix. Table 6.7 shows the p-value output of the GLM with respect to each response. In statistical significance testing p represents the probability of obtaining a test statistic at least as extreme as that which was actually observed in the simulation.

Because this level of testing will be focusing on main effects in a fairly complex model, we relax the confidence interval for significance by apply additional gradations of p. We establish that weak significance is attributed to $p \leq 0.25$ (75%), moderate significance is attributed to $p \leq 0.1$ (90%), and strong significance is attributed to $p \leq 0.05$ (95%). The strong significance class follows the general ANOVA model for p and will be most relevant in later iterations which will be more tightly focused.

Due to the size of the model and the number of initial response variables, only first-order response interactions were performed. By summing the p-values for each factor across

Factor	DF	$R1_p$	$R2_p$	$R3_p$	$R4_p$	$R5_p$	$R6_p$	$R7_p$	$R8_p$	Sum
Gov. A. Funding (x_1)	1	0.464	0.308	0.46	0.471	0.227	0.518	0.15	0.374	2.972
Gov. Tax Rate (x_2)	1	0.483	0.069	0.242	0.841	0.618	0.203	0.58	0.405	3.441
Res. A. Pay Rate (x_3)	1	0.496	0.226	0.968	0.227	0.577	0.42	0.32	0.326	3.56
Uni. Count (x_4)	1	0.571	0.037	0.042	0.644	0.343	0.096	0.176	0.063	1.972
Ind. K. Value (x_5)	1	0.606	0.112	0.127	0.362	0.196	0.531	0.262	0.059	2.255
Ind. Maint. Rate (x_6)	1	0.353	0.386	0.179	0.37	0.173	0.302	0.092	0.417	2.272
Ind. IMC Rate (x_7)	1	0.311	0.121	0.222	0.263	0.702	0.106	0.772	0.073	2.57
E$_r$ (x_8)	1	0.453	0.676	0.205	0.398	0.74	0.411	0.789	0.405	4.077

Table 6.7 p-value results from GLM of TKGL12-2.

the respective response parameter in this model we immediately see that there are clear disparities in predictive significance. This significance of factor effects can be read from the GLM response table. While there is no clear main effect on all responses from any single factor, it's clear that x_4, x_5, x_6,and x_7 display relative importance indicating potentially hidden interaction effects for each response. We also see that several factors have main effects approaching or within the strong interval (x_2, x_4, and x_6 respectively). This immediately indicates that we might be well served focusing our investigation on these factors.

6.3.1 Main Effect Analysis

In order to reduce our model's parameter space to make it more tractable for traditional analysis of variance we first examine the factor effects in more detail by examining effects plots for both individual factors. First-order interaction effects for each factor were also calculated and charts containing this information are available in the appendix. For the purpose of this exercise we will restrict our analysis to main effects. Further DOE iterations will examine specific interaction effects of interest.

This form of analysis differs from the p-test included with the GLM in that we are interested in the slope of the graph. In the main-effects graphs, nearly-horizontal lines indicate little effect, while the degree of slope indicates the strength and direction of main effect. Comparisons of 'weak', 'moderate' and 'strong' are relative to the set of response plots

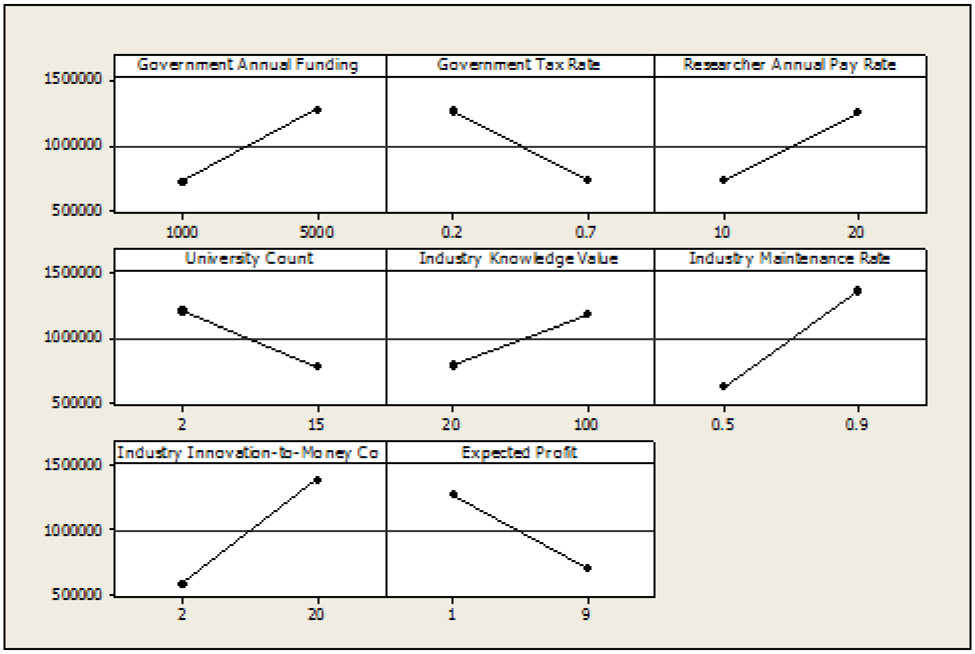


Figure 6.2: Parameters' main effects on System GDP (R_1).

and do not imply correlation with particular p-values. This correlation step is restricted to higher-order analysis with respect to factor interactions. We also use some analytical nomenclature to describe the effects in terms of the domain, innovation ecosystems for the purpose of providing a summary of the trends in main effects.

Parameter main effects on system GDP (R_1) Tested parameters have strong confounding main effects on system GDP (Figure 6.2). No clear dominant set of factor responses appear present among main effects.

- Strong negative effect from higher taxation (x_2).
- Strong negative effect from higher expected profit (x_8).
- Strong positive effect from higher industry maintenance overhead (x_6).

Parameter effects on researcher population count (R_2)

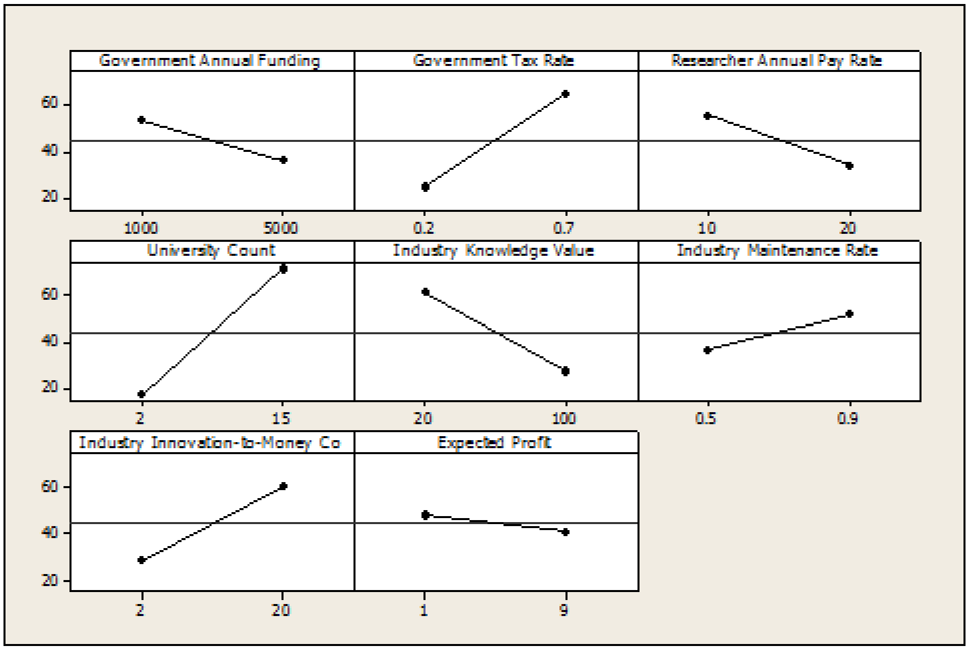


Figure 6.3: Parameters' main effects on researcher population count (R_2).

- Compared with the other 6 parameters, government tax rate (x_2), university count (x_4) and knowledge value (x_5) have the greatest main effects on system productivity (Figure 6.3).
- Strong positive effect from increased taxation.
- Strong positive effect from increased university count.
- Moderate negative effect from increased knowledge value.

Parameter main effects on population diversity (R_3)

- Compared with the other 6 parameters, university count (x_4) has the greatest main effects on system productivity (Figure 6.4).
- Strong positive effect from increased university count.
- Moderate negative effect from increased knowledge value.

Parameter main effects on average university size (R_4)

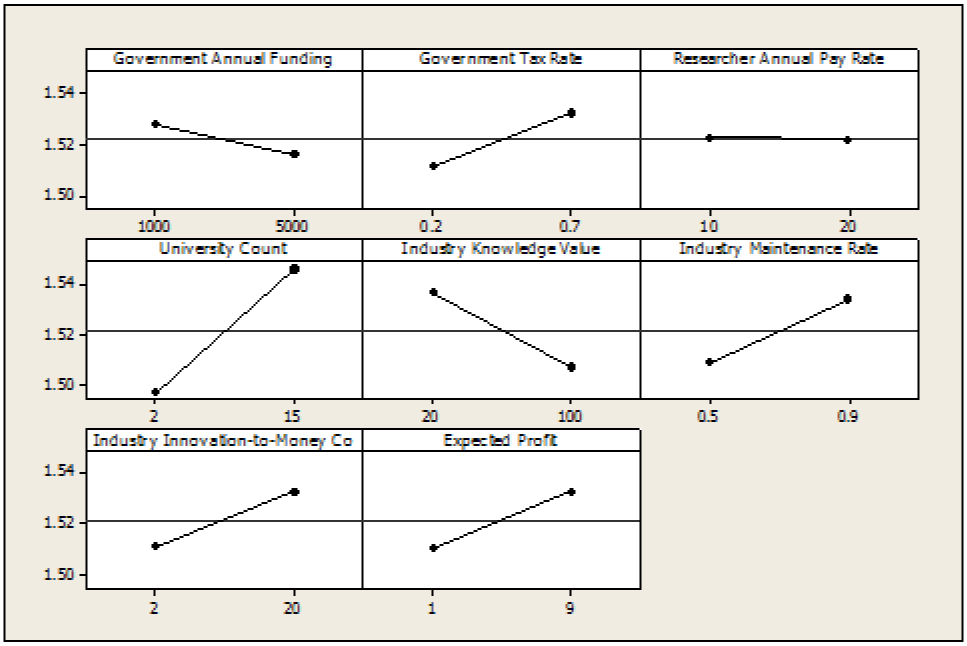


Figure 6.4: Parameters' main effects on researcher population diversity (R_3).

- Compared with the other 6 parameters, researcher annual pay rate (x_3) and industry IMC rate (x_7) have the greatest main effects on system productivity (Figure 6.5).
- Strong negative effect from increased researcher salaries.
- Strong positive effect from increased industry IMC.
- *Moderate negative effect from increased government funding.*
- Moderate positive effect from increased risk sensitivity (x_8).

Parameter main effects on university-industry trust (R_5)

- Compared with the other 5 parameters, government funding (x_1), industry knowledge value (x_5), and industry maintenance rate (x_6) has the greatest main effects on university-industry trust (Figure 6.6).
- *Strong positive effect from increased government funding.*
- Strong positive effect from increased knowledge value.

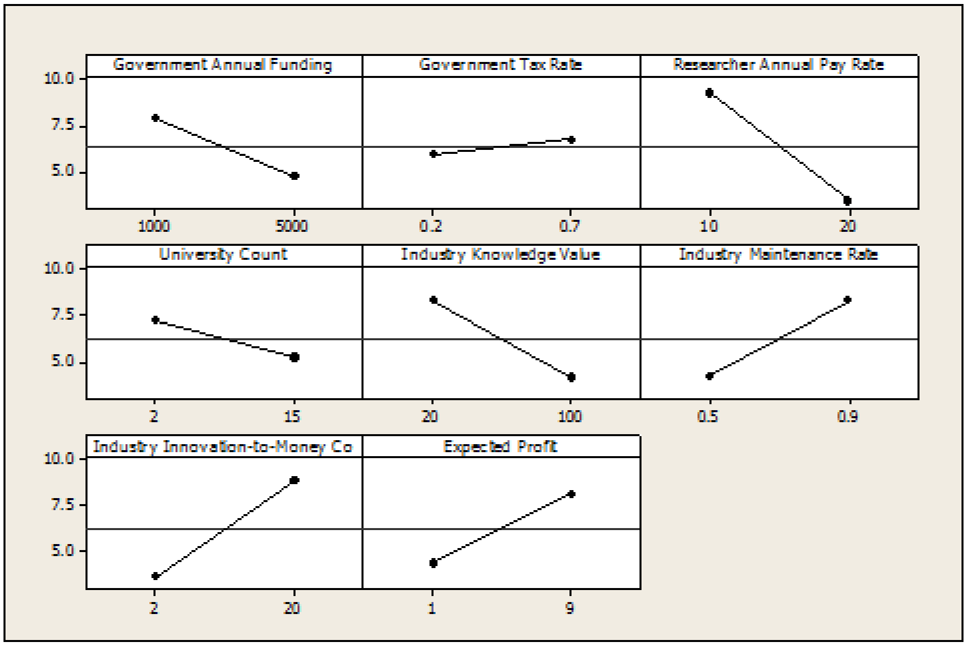


Figure 6.5: Parameters' main effects on average university size (R_4).

- Moderate positive effect from reduced industry maintenance efficiency.

- Moderate negative effect from increased university count.

Parameter main effects on average industry GDP (R_6)

- Compared with the other 6 parameters, university count (x_4) and industry IMC rate (x_7) have the greatest main effects on average industry GDP (Figure 6.7).

- Strong positive effect from increased university population.

- Strong positive effect from increased industry IMC.

- Moderate negative effect from increased taxation.

Parameter main effects on average on industry partnership success rate (R_7)

- Compared with the other 5 parameters, government funding (x_1), university count (x_4), and industry maintenance rate (x_6) have the greatest main effects on industry partner count (Figure 6.8).

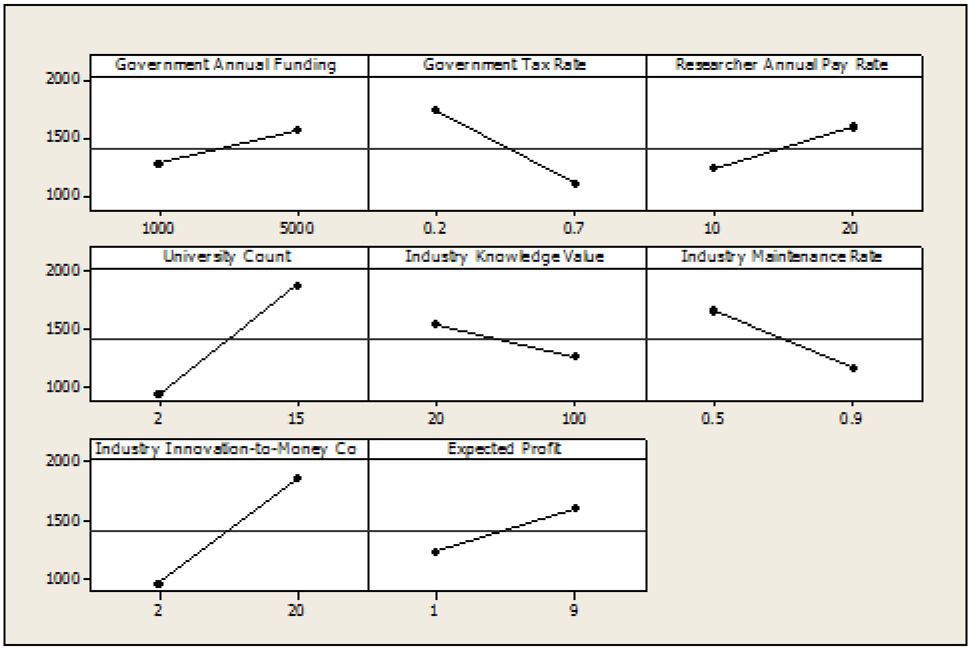


Figure 6.6: Parameters' main effects on university-industry trust (R_5).

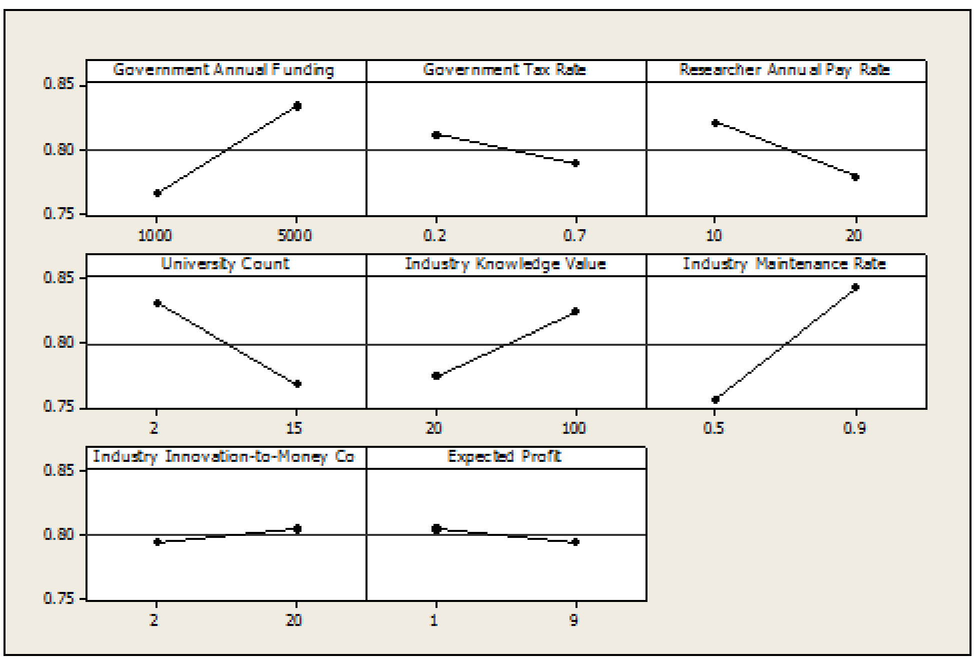


Figure 6.7: Parameters' main effects on average industry GDP (R_6).

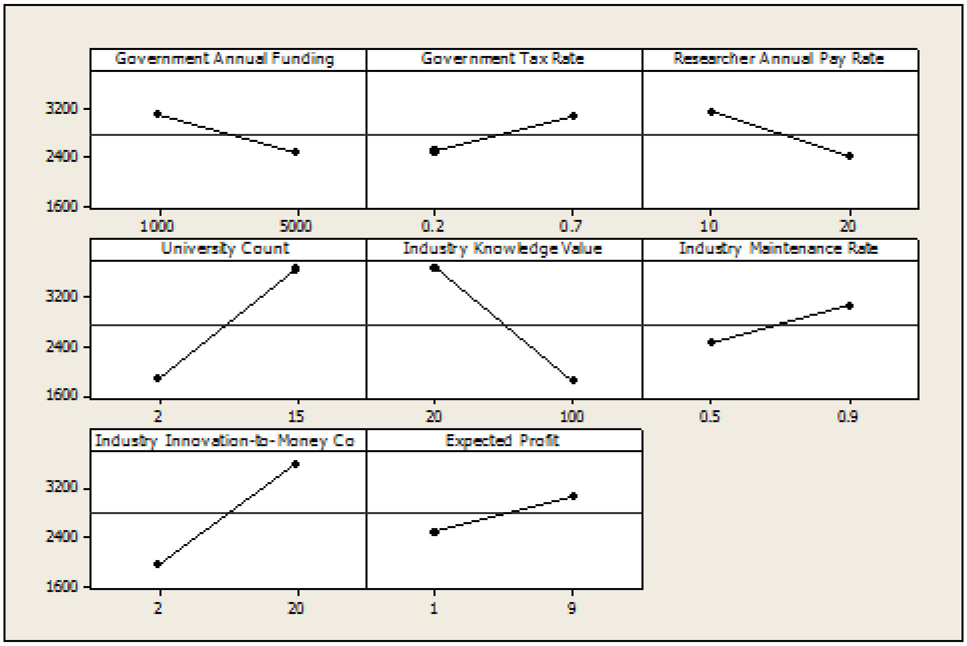


Figure 6.8: Parameters' main effects on industry partnership success rate (R_7).

- Strong positive effect from increased government funding.
- *Strong negative effect from increased university count.*
- Strong positive effect from reduced industry IMC.
- Moderate positive effect from increased industry knowledge value.
- *Negligible effect from increased risk sensitivity (x_8).*

Parameter main effects on average on technology transfer count (R_8)

- Compared with the other 5 parameters, university count (x_4), industry knowledge value (x_5), and industry IMC rate (x_7) have the greatest main effects on industry partner count (Figure 6.9).
- Strong positive effect from increased university count.
- Strong negative effect from increased industry knowledge value.
- Strong positive effect from increased industry IMC.

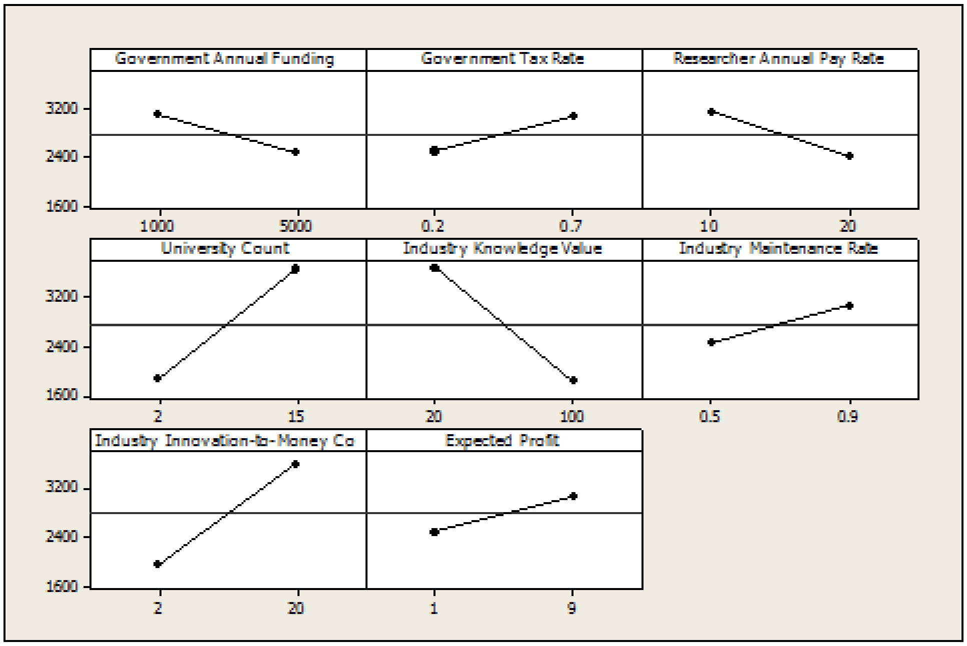


Figure 6.9: Parameters' main effects on technology transfer count (R_8).

6.3.2 Sub-DOE THESIM-Sensitivity 1st-iteration Summary

While a broad range of interesting effects are presented, a key finding of this initial experimentation indicates that while most responses are tightly bound to an identifiable set of interactions between factors, several (R_1, R_4, and R_5) display no strong factor effects or confounding effects. This implies that there is some other, hidden effect (or mixture effects) governing their behavior. Though useful for our analysis, the interaction graphs for each response have been omitted from this chapter for brevity, they are available in the appendix (Appendix 1).

In light of this observation, it is helpful to represent this data in terms of general effects on response data. By isolating each interaction and applying a minimum exclusion threshold, we can build a table of effectiveness to give us a rank-order notion of the interactions taking place within the model (table 6.8).

In the above figure '+' represents a positive effect, '−' represents a negative effects, and '=' represents a null effect. Darkened cells represent moderate to strong effects, while empty

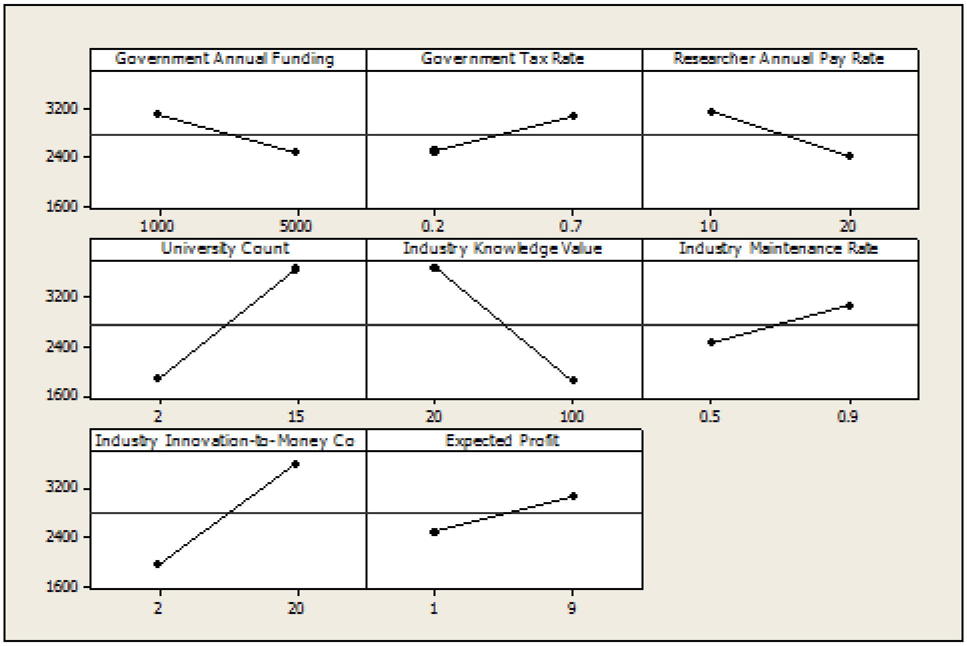


Table 6.8 Sign representation of main-effects of factors in GLM of TKGL12-2.

cells represent weak effects. Combining this view with the p-values in Table 6.7 we can make the case for reducing our the factor-scope of our experimental design down to x_4, x_5, and x_6 as these factors seem to carry the strongest effect across the response variables of interest. While efficacious, x_7 seems to operate as a scalar calibrating effect and could be fixed for greater experimental simplicity. Following this observation we can fully omit those factors which have only weak or calibrating effects on model response.

At this point, the analysis process is pursued iteratively. With these factors fixed, the analysis can be continued by running more simulation experiments with further factor level combinations on a smaller variable-set to find best possible performance for each response of interest.

It should be noted that this first step satisfies our first question, namely that we can represent a demonstrably large set of model response output through activity on this reduced set of input factors. However, in order to answer the second question we must isolate the factors of interest and determine discrete thresholds for system behavior across our responses.

Factors	Level Ranges	Factor Levels	Representation
x_4	∈ [0, 1]	{5, 20}	(-, +)
x_5	∈ [0, 1]	{20, 100}	(-, +)
x_6	∈ [0, 1]	{0.3, 0.8}	(-, +)
x_1	∈ [0, 1]	3000	Control variable
x_2	∈ [0, 1]	0.45	Control variable
x_3	∈ [0, 1]	15	Control variable
x_7	∈ [0, 1]	11	Control variable
x_8	∈ [0, 1]	5	Control variable

Table 6.9 Factor levels for $2k^3$ factorial design of Sub-DOE.

6.4 Sub-DOE THESIM-Sensitivity 2nd iteration

As stated, the goal for this iteration is to identify criticalities among the remaining factors of interest. We do this partially in order to instill confidence in our model, but also to determine if the interaction is consistent with empirical knowledge regarding real-world systems.

The starting point for this step is once again selecting an appropriate factorial design. New factor levels around the previously successful levels are defined for the next simulation experiment iteration with the ultimate goal of identifying the most successful factor levels in the factor screening process. As per our initial analysis in the main DOE we were able to reduce the scope of our DOE to three factors; x_4, x_5, and x_6 (Table 6.9).

Due to the mixed effects of each factor on our response variables we peg the control factor levels at the mean values described in Table 5 to mitigate variance.

The combinations of the new factor levels yield a total of eight (2^3) new design points. They define the simulation experiment as shown in the new design matrix (Table 6.10) which is referenced as $2k^3E$. The values depicted in the design matrix enable the two-step process outlined above for analyzing all factor effects and their effect strengths. The effect matrix captures the outcome of the effect analysis.

Run	x_4	x_5	x_6	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
1	2	20	0.3	1141766.349	12.48643	1.464021	6.243214	0.724129	1102.88	0.666864	1293
2	2	20	0.8	1142268.7279	12.35908	1.472242	6.179541	0.714273	1082.2678	0.646945	1294.933
3	2	100	0.3	1139163.308	12.17625	1.467636	6.088124	0.740988	1081.237	0.683212	1267.333
4	2	100	0.8	1139336.641	12.21417	1.467982	6.107086	0.710886	1057.643	0.659258	1268.733
5	25	20	0.3	1560391.864	106.2924	1.474433	4.251697	0.525944	1859.133	0.505252	5618
6	25	20	0.8	1669308.297	113.4345	1.578083	4.537381	0.552121	1908.509	0.533793	5962.533
7	25	100	0.3	1514291.864	98.28375	1.425833	3.920197	0.601944	1727.133	0.604148	5274.2
8	25	100	0.8	1782911.864	128.2837	1.425833	5.03742	0.55093	2059.386	0.694468	6106.2

Table 6.10 $2k^3$ Factorial Sub-DOE simulation p-value results.

6.4.1 Response Analysis

In this iteration we eschew main effect plots in favor of more traditional effect matrices due to the fact that we want to differentiate between specific main effects and interactions across the experiment. In the prior iteration such plots were not tractable as there were far too many factor interactions to appropriately attribute effects in this fashion. Each effect matrix displays the crosswise comparison of main effects and interaction effects (p-values) in a fashion similar to the example (Table 6.11). In the discussion of each table, 'positive' and 'negative' effects refer to sign (direction) of the slope of the effect plots. The individual slope computations for each effect are omitted from this section for the sake of brevity, but are included in the discussion via short-hand nomenclature.

For this iteration we tighten our confidence interval to the range more traditionally associated with ANOVA, with weak effects attributable to $p \leq 0.15$, moderate effects attributable to $p \leq 0.05$, and strong effects attributable to $p \leq 0.01$. To avoid confusion with prior terminology, we will speak generally about significance and attempt (where possible) to link this analysis to prior findings in the experiment set.

Analysis of $2k^3E$-R_1

The high factor level of x_4 stands out with its positive effect on R_1 (Table 6.11). Thus, a further testing of factor x_4 around the high factor level ('+' = 20) might lead to a better

Factors	x_4	x_5	x_6
x_4	0.047	0.755	0.228
x_5		0.797	0.501
x_6			0.227

Table 6.11 $2k^3$E R_1 effect matrix.

Factors	x_4	x_5	x_6
x_4	0.000001	0.839	0.311
x_5		0.865	0.495
x_6			0.312

Table 6.12 $2k^3$E R_2 effect matrix.

system productivity than $R_1 = 1782911.864$ which is the best value observed so far (see Table 6.10, design point 8). Weak interactions are observable but fall outside of our significance threshold. The factors x_5 and x_6 have only minor effects on R_1 within the given factor level interval. Hence, for further study on R_1 they should be fixed as control at their mean values.

Analysis of $2k^3E$-R_2

Similar to the findings from R_1, we see that x_4 has a substantial effect on R_2 (Table 6.12). The effects of x_5 and x_6 respectively have minor impact on R_2 within the given factor level. A p-value less than 0.01 indicate that the performance of the R_2 is tightly correlated with x_4. This supports the prior recommendation that further analysis around the high factor level ('+' =25) might lead to higher performance of R_2, the best being R_2=114.1078. The factor x_5 appears to have little impact on R_2 and it is recommended that any further investigation on this response fix x_5 at its mean factor-level.

Analysis of $2k^3E$-R_3

While there is no clear correlation within the established confidence intervals, R_3 (population diversity) seems to operate as a function of the interaction between x_4 and x_5 (Table 6.13). Returning to table 6.7, we initially saw that the behavior of this response appeared to be correlated with the main effects of all three factors. However, further study seems to

Factors	x_4	x_5	x_6
x_4	0.792	0.285	0.502
x_5		0.283	0.452
x_6			0.45

Table 6.13 $2k^3$E R_3 effect matrix.

Factors	x_4	x_5	x_6
x_4	0.063	0.718	0.264
x_5		0.873	0.431
x_6			0.279

Table 6.14 $2k^3$E R_4 effect matrix.

indicate only moderate complimentary interactions between these factors. Indeed, several factors not contained in this iteration may play a larger role in the outcome of R_3 than was indicated by the initial this test. This suggests that further experimentation focusing on these omitted factors would be prudent. These first-order interactions can be observed in interaction graph for R_3 (Appendix).

Analysis of $2k^3E$-R_4

The high factor level of x_4 (Table 6.14) stands out with its positive effect on R_4 (university researcher-population size). This result is actually unsurprising, as increasing the number of universities in an environment with a fixed resource quantity would suggest greater competition and a general reduction in the average population size per university. This reduction appears to behave in a scalar fashion (Table 6.10) which could be determined by further testing around factor x_4. Interestingly, while the values lie outside strict confidence intervals set by this iteration level, there appears to be a weak interaction (negative) interaction between x_4 and x_6 within the given factor level. Finally, x_5 seems to have little bearing on the response. In further studies it is suggested that x_5 be fixed as a control to its mean factor-level.

Analysis of $2k^3E$-R_5

Factors	x_4	x_5	x_6
x_4	0.055	0.476	0.835
x_5		0.365	0.337
x_6			0.459

Table 6.15 $2k^3$E R_5 effect matrix.

Factors	x_4	x_5	x_6
x_4	0.057	0.849	0.385
x_5		0.951	0.507
x_6			0.458

Table 6.16 $2k^3$E R_6 effect matrix.

While x_4's contribution to R_5 (inter-firm trust, C_a) is near enough to the confidence interval (95%, or p=0.05) to imply strong correlation, it should be noted the factor x_1 (annual government funding) which was included in the DOE iteration as a control displays a significant positive main-effect on the outcome of this response (Table 6.9, design point 4). Despite this, increasing x_4 has a predictably negative impact on R5 (Table 6.15). This indicates that increased competition via the addition of more universities has a curiously negative effect on the mean trust across the system. However, this outcome may belie more dynamic trends within the model that are not captured in the response, as R6 measures the mean of C_a rather than the distribution. Further refinement of model response output may be necessary to fully extract the granular behavior of the system under the factor-levels included in this iteration. Due to the relatively minor impact of interaction effects, it is suggested that future iteration on R_5 fix x_5 and x_6 and their respective mean factor-levels.

Analysis of $2k^3E$-R_6

Observing the results in Table 6.16, x_4 displays a strongly positive main effect on R_6 (average industry GDP). While the affect appears to be scalar, further analysis around the high factor level ('+' = 25) might lead to higher performance of this response, the best being R_6=2059.386 (Table 6.10). A minor interaction is observable between x_4 and x_6, but its

Factors	x_4	x_5	x_6
x_4	0.13	0.177	0.245
x_5		0.143	0.542
x_6			0.459

Table 6.17 $2k^3$E R_7 effect matrix.

Factors	x_4	x_5	x_6
x_4	0.013	0.586	0.172
x_5		0.485	0.501
x_6			0.172

Table 6.18 $2k^3$E R_8 effect matrix.

effect seems to be dominated by the action of x_4 on the response. Due to the relatively minor impact of interaction effects, it is suggested that future iteration on R_5 fix x_5 and x_6 and their respective mean factor-levels.

Analysis of $2k^3E$-R_7

Interestingly, while x_4 and x_5 exhibit strongly positive main effects on R_7 (inter-firm trade success rate, S_r), countervailing negative interaction effects exist between x_4 and x_5/x_6 (Table 6.17). This suggests a more complicated relationship between the three factors. The response data in Table 6.6 and Table 6.7 indicates a correlation between R_5 (C_a) and R_7 (S_r), as proffered by Dongsheng & Yongan (2007). and may indicate that whatever mechanisms impact one response may indeed work upon the second in similar fashion. Because of this observation, it may be worth re-examining the interaction effects between x_4, x_5, x_6 and x_8 (E_r) which was identified in prior as a bounding factor governing the behavior of R_7.

Analysis of $2k^3E$-R_8

Both x_4 and x_6 display strongly positive main effects on R_8 (technology transfer count), as well displaying a moderate positive interaction effect (Table 6.18). , further analysis around the high factor level ('+' = 25) might lead to higher performance of this response, the best being R_8=6106.2. This positive interaction is of particular interest when combined with observations on R_1, as it strongly supports the main supporting argument of innovation ecosystem development; the development and transfer of new technology from academia to private industry is a key driver of economic growth. The factor x_5 appears to have little impact on the response and it is recommended that future studies fix this factor to its mean value.

6.4.2 Sub-DOE THESIM-Sensitivity 2nd-iteration Summary

A key finding of this iteration is that, unlike the first iteration, the impact of x_4 on the broad range of system responses is strong. The notion that increased regional university count (or by proxy, density) is a strong indicator of innovation production capacity is well documented and is supported by literature (Cooke et al., 1997; Varga, 1998). There is an obvious cleavage in the response data recovered from the experiment set that indicates that increasing the number of universities in the model has a positive impact on virtually all factors and may dominate the contribution (positive or negative) from most other factors.

In a majority of the experimental cases we recommend fixing the values of x_5 and x_6, leading us to the general conclusion that the factor level of x_4 accounts for a majority of the variation across most of our included response variables. However, the degree and direction of this variance does not appear to be scalar, and in fact there are several interesting response interactions that would benefit from further DOE iteration.

The most curious result can be seen in the behavior of total researcher population (R_2), which appears to be the response most tightly bound to x_4. While relatively pronounced with respect to the other responses, this finding is interesting when observed in context with system GDP output (R_1) and average university size (R_5). One would expect, given the negative impact of inter-university competition, that R_3 would be relatively static as a 2-university system would result in two very large agent populations of similar total size to that in a system with more universities (i.e. that researcher population is a function of resource quantity). Instead, increasing x_4 to its '+' factor level results in a significantly larger total population. In context, this suggests the presence of 'hidden' interactions.

The first relates to the local-search dynamic of each researcher agent, which has a set search time (round length) in which it can make only a single move. This effectively limits the visible area of researchers belonging to a particular university to a radius potentially smaller than the bounds of the environment. This means that in a 2-university system with randomly distributed resources, it is possible that many grants are simply impossible to reach, resulting in bounded growth.

The second may be more subtle, as we also see an increase in the total number of technology transfers in the system. This implies that R_3 is actually a function of available environmental resources, university search space, and (most critically) industry participation in technology trade. Determining the validity of this observation requires more focused testing on independent values of x_4 and perhaps observation on a different set of response variables than those selected for the general model analysis.

Another interesting observation comes from our analysis of population diversity (R_3). It is clear from results that the factors included in this iteration do not appear to strongly impact the outcome of this response. This is actually expected, as the diversity index closely reflects the fact that the government agent selects grant funding types using a stochastic function which follows a normal distribution. As a result, there is no inherent favoritism of one field of funding over another over the course of a simulation run resulting in an evenly balanced population.

Indeed, a closer look at granular data from individual runs indicates that our researcher agent model quickly trains itself to match even minute changes in grant distribution, and this training speed can be roughly treated as a resilience measure. However, to fully quantify the behavior of this response requires specific experimentation which can be pursued in a separate iteration once the main factor interactions are explained. In particular, this experimental model should include the omitted input factor 'shake-up time' (x_9).

The final exception to the primacy of university count's response dominance can be observed in the negative impact on university-industry trust (R_5). This finding at first seems counter-intuitive from a pure innovation perspective, but upon examination actually fits with the concept of economic and ecological competition. Consider that the competitive space (grant environment size) and total available resources remains fixed between the test groups, but x_4 is increased. This leads to greater competition for resources which in turn reduces the average researcher population per university in the model.

Since technology production and iteration operates as a function of the maturity level of the university which itself is tied to its researcher population size, this means that in denser models each individual university actually produces fewer technologies more slowly. Because our implementation of *Transaction Cost Theory* introduces downward pressure on universities to accept technology transfer requests at reduced rates when their store of technologies and iteration speed is higher, scenarios which negatively impact those two internal factors result in more rejections. In order to quantify the particular dynamics of this relationship further iteration on this design point is necessary.

In summation, this iteration step obviates the notion that the university count is responsible for a majority, but not all, of the model's response variance. In order to quantify the specific effect, we perform a final iteration before looking at the special cases discussed previously.

6.5 Sub-DOE THESIM 3rd-iteration

As explained by prior analysis, factor x_4 has been shown to be the dominant effect on response variables R_1, R_2, R_4, R_5, R_6, and R_8. In the previous iteration of the model's DOE, we also observed only weak interactions which were outside the chosen significance thresholds. Therefore, in this iteration new factor levels are defined for x_4 for the subsequent analysis with all other factors designated as control variables and restricted to their mean factor-value (Table 6.19).

Factors	Level Ranges	Factor Levels	Representation
x_4	$\in [0, 1]$	{5, 8, 11, ..., 41}	{5, 8, 11, ..., 41}
x_5	$\in [0, 1]$	60	Control
x_6	$\in [0, 1]$	0.5	Control
x_1	$\in [0, 1]$	3000	Control
x_2	$\in [0, 1]$	0.45	Control
x_3	$\in [0, 1]$	15	Control
x_7	$\in [0, 1]$	11	Control
x_8	$\in [0, 1]$	5	Control

Table 6.19 Sub-DOE third iteration factorial design.

Thirteen new factor levels around the former successful high factor level of x_4 ('+' = 25) are chosen (Table 6.20). This gives us a fairly wide window to compare effects of incrementing this value step-wise.

Because we are looking for patterns rather than maximizing any single response, we can immediately identify two countervailing trends in response behavior. Maximal values for average research population size (R_4) and average trust (R_5) can be seen about $DP2$, with very clear falloff as university count (x_4) increases. Maximal values for system productivity (R_1), researcher population (R_2), average industrial firm productivity (R_6), and technologies transferred (R_8) emerge around $DP11$. This indicates that for future experiments looking to maximize quantities in R_4 and R_5, low values close to $DP2$ should be considered. Alternatively, experiments looking to maximize quantities for R_1, R_2, R_6, and R_8 higher values of x_4 close to $DP11$ should be considered.

Given that policy-makers are mostly interested in boosting economic productivity, growing more robust business communities, and increasing technological competitiveness, we can strongly recommend $DP11$ as the best factor level for x_4. Moreover, an analysis of these results indicates that above $DP5$, R_1 is a semi-scalar predictor for R_2, R_6, and R_8.

	Factor	Responses					
Design Point	x_4	R_1	R_2	R_4	R_5	R_6	R_8
1	5	1259273.803	30.98802	6.197605	0.642826	1171.689	2202
2	8	1358810.2802	48.67964	6.084955	0.644606	1424.3821	3036
3	11	1453129.901	64.27545	5.843223	0.604623	1424.123	3873
4	14	1545005.403	81.94611	5.853293	0.580289	1512.439	4768
5	17	1626433.761	96.06886	5.65111	0.578276	1569.032	5460
6	20	1590119.312	95.08683	4.754341	0.564655	1657.195	5240
7	23	1677595.092	110.5868	4.808123	0.546675	1909.428	6149
8	26	1717023.081	120.5599	4.636918	0.526131	2396.833	6608
9	29	1682945.782	116.015	4.000516	0.571231	2200.927	6099
10	32	1787490.438	135.5988	4.237463	0.545252	3056.789	7051
11	35	1812086.911	146.0599	4.173139	0.528961	2887.147	7523
12	38	1806795.265	148.1048	3.897494	0.525827	1498.385	7407
13	41	1801880.275	142.6707	4.040748	0.506766	2678.449	7307

Table 6.20 Sub-DOE third iteration analysis of selected response variables versus change in x_4.

	Factors								Responses							
Final DP	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
"Best performance"	3000	0.45	15	35	60	0.5	11	5	1812087	146.06	1.59	4.17	0.53	2887.15	0.53	7523

Table 6.21 Optimal parameter combination.

6.5.1 Sub-DOE THESIM-Sensitivity 3rd-iteration Summary

In this iteration we focus on the behavior of the university count factor (x_4) and establish a bidirectional trend in the response factors of interest. We were able to establish the tight coupling of x_4 to the behavior of R_1, R_2, R_4, R_5, R_6, and R_8 and isolate two design points for x_4 which promote optimality of two subsets of response data.

We establish the primacy of maximizing R_1, R_2, R_6, and R_8, and we also observe that R_1 is a predictor for the remaining factors. In the given scenario of $R_1 = 1812086.911$, 35 emerges as the best factor level for maximizing relevant simulation output. The final step for factor screening is to set the factor level for all sub-factors at the highest measured response for R_1 (Table 6.21). The response variable values of this parameter combination will serve as the performance value for the simulation model in the Top-level DOE. All Sub-DOE of our sample model have been analyzed in the described way. On this basis, the calibrated sub-factors with the best performance can be entered in the Top-level DOE as the factor level values for the subsequent experimental scenarios.

6.6 DOE Analysis & Observations

The observed trends lead us to the following set of conclusions about the model;

The set of input factors can be initially reduced to the following set;

- Government Annual Funding: (x_1)
- Researcher Annual Pay Rate: (x_2)
- Industry Knowledge Value: (x_3)
- Industry Maintenance Rate: (x_4)
- Industry Innovation-to-Money Conversion Rate: (x_5)
- Government Tax Rate: (x_6)
- Expected Profit (Er): (x_7)
- University Count: (x_8)
- Shake-Up Time: (x_9)

The set of response factors can be reduced to the following set;

- System GDP: (R_1)
- Researcher Population Count: (R_2)
- Researcher Population Diversity Index: (R_3)
- University Size: (R_4)

- University Innovation Creation: (R_5)
- Industry GDP: (R_6)
- Industry Partner Count: (R_7)
- Technology Transfer Count: (R_8)

A large class of these response factors is significantly impacted by variation on a single factor, university count (x_4).

There are, however outliers to this trend. The behavior of response factor R_3 is largely a function of the distribution of grant-types in the environment and therefore is independent of the factors chosen for experimentation. x_4's impact on R_1 is significant but complex and may require additional study to accurately quantify.

x_4 acts strongly on responses R_2, R_4, R_5, R_6, and R_8 which are the responses of interest in this model. The action of x_4 on the remaining variables is bidirectional in nature:

- High values of x_4 corresponding with high performance of R_1, R_2, R_6, and R_8.
- Low values of x_4 corresponding with low performance of R_4 and R_5.

Because R_1, R_2, R_6, and R_8 are of principle importance to policy makers and investigators, the top-level DOE design should fix these factors at the values recommended in table 6.21. Further experiments should now focus on environmental configuration or policy-designs.

6.7 THESIM-ER Ecological Resilience Experiment

Following our formal description of a Top-level DOE we can now initiate experiments designed to better quantify the ecological factors in model behavior alluded to in Chapter 1. Of principle interest is the notion of structural ecological resilience in complex socio-economic systems driven by human activity (Alberti & Marzluff, 2004). In the DOE, we

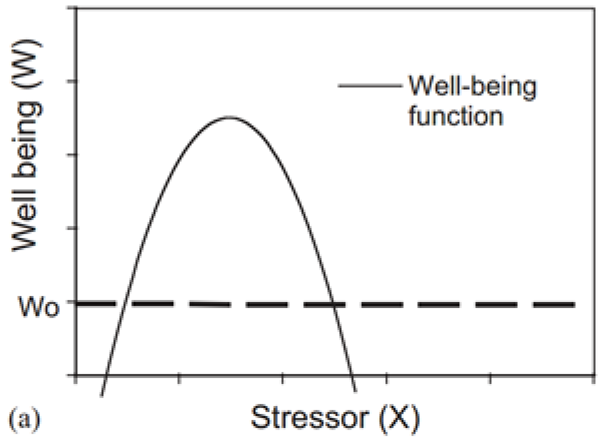


Figure 6.10: A hypothetical well-being function for an idealized system.

establish the relationship between the input parameters and establish tuning thresholds for system performance based on a set of response variables of interest.

In this regard, we develop an experiment to measure the ecological resilience of our model using the technology yield Y of a system experiencing periods of stress. In this approach stress is represented as an across-the-board resource disturbance and reduction approximating drought-like conditions. The two environmental variables of interest are disturbance frequency (D_f) and disturbance duration (D_l). This sub-model is an attempt approximate the impact of shifting policies on a regional innovation ecosystem and brings forward vulnerability metrics as described by Luers et al. (2003) and the general idea of Total Regional Technological Resilience ($TRTR$) which has been adapted from Rose (2004).

To develop our factor space we return to the findings from sub-section 6.5.1 which allows us to establish baseline input values for our model (Table 6.21). We proceed on the basis that this configuration is representative of a stable, productive system from which will vary environmental configuration in order to induce periodic system stress.

Thus we can define the factors of this sub-model as an extension of the prior experimental framework with two additional stress factors. We define system stress as the periodic occurrence of negative externalities on our system. From the ecological parlance we choose

Factors	Level Ranges	Factor Levels	Representation
D_f	$\in [0, 1]$	{0, 1, ..., 8}	{0, 1, ..., 8}
D_l	$\in [0, 1]$	{20, 40, 60}	{20, 40, 60}
x_1	$\in [0, 1]$	3000	Control
x_2	$\in [0, 1]$	0.45	Control
x_3	$\in [0, 1]$	15	Control
x_4	$\in [0, 1]$	35	Control
x_5	$\in [0, 1]$	60	Control
x_6	$\in [0, 1]$	0.5	Control
x_7	$\in [0, 1]$	11	Control
x_8	$\in [0, 1]$	5	Control

Table 6.22 Factorial Deisgn of THESIM-ER.

the 'drought' metaphor, in which government support for technological research is reduced by a static factor (50%) for a set period of time, For this purpose we introduce two new environmental control factors to our model:

- Disturbance Frequency, D_f – How often environmental stress occurs in a single run.
- Disturbance Duration, D_l – How long (in rounds) a typical disturbance lasts.

The total time of disturbance becomes a useful catch-all expression to describe change in overall system stress. (D_t) can be found by the following equation:

$D_t = D_f * D_l$ *Eq. 6.1*

While we will use D_t to describe overall system stress, it should be noted that unpacking this function into its constituent components helps differentiate between scenarios. For example a scenario with high disturbance frequency and low duration may have a similar D_t, but engender vastly different internal behavior.

To evaluate model output, we will focus on the total number of technology transfers (R_8) and redefine it as our yield, Y. To build a general resilience metric, we analyze the ability of the system to absorb shock and mitigate stress. Rose (2004) provides several flexible resilience metrics which we paraphrase for this work. *Direct regional technological resilience* ($DRTR$) is the extent to which the estimated direct output reduction deviated from the likely maximum, which is the equivalent to the percentage technology transfer disruption in a linear approach to baseline estimation of model output:

$DRTR = \frac{\%\Delta DQ''' - \%\Delta DQ}{\%\Delta DQ'''}$ *Eq. 6.2*

Where $\%\ \Delta DQ'''$ is the maximum percentage change in direct model output with respect to it's optimal conditions (as provided in Table 6.21) and $\%\ \Delta DQ$ is the estimated percent change in direct output. Estimates are based on a linear fit of simulation output

DRTR gives a general resilience rating for an individual simulation runs which we modify to provide a generalized evaluation measure for technological resilience. Our measure of *total regional technological resilience* ($TRTR$) to environmental disruption of funding allotment is described by the following equation:

$TRTR = \frac{\%\Delta TQ''' - \%\Delta TQ}{\%\Delta TQ'''}$ *Eq. 6.3*

Where $\%\ \Delta TQ'''$ is the maximum percent change in total output and $\%\ \Delta TQ$ is the estimated percent change in total output. Thus we can provide a holistic response metric that can give us an approximation of our model's behavior that can be compared to future refinements or new implementations.

6.7.1 THESIM-ER Analysis & Summary

The model was run for each orthogonal permutation of Df and Dl 30 times each and their yield output was compared to a general compared to the linear model of expected yield, Y'. This operation resulted in 27 independent data-points for Y (Figure 6.11), with additional materials available in the appendix.

This initial view provides us confidence that the system's reaction to disturbance falls within believable bounds. Significantly, we see the expected shift in response on Y with respect to increased funding scarcity. The most relevant observation from this data set confirms the maximum yield at the lowest disturbance levels, both in terms of overall time as well as frequency and duration.

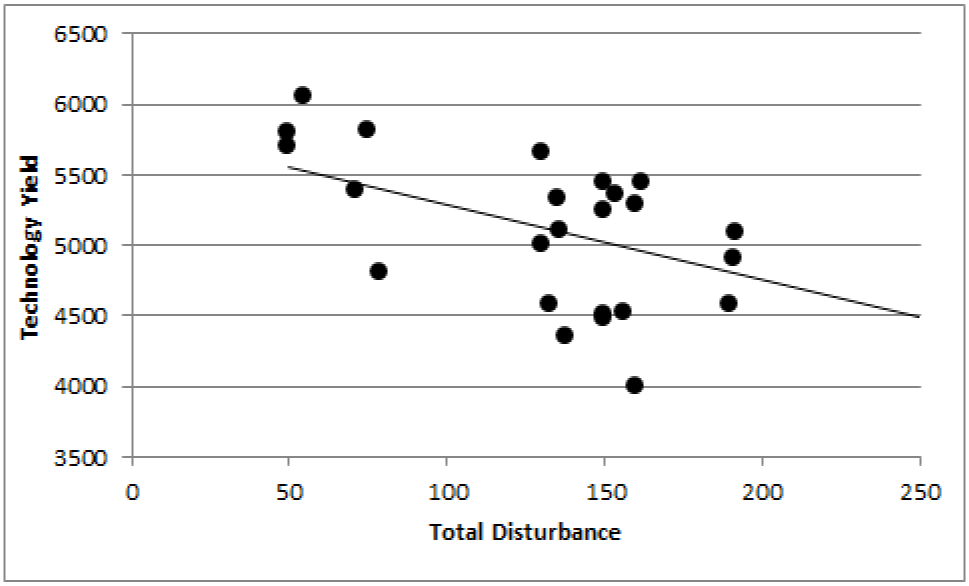


Figure 6.11: Linear-fit of Y under increasing system stress.

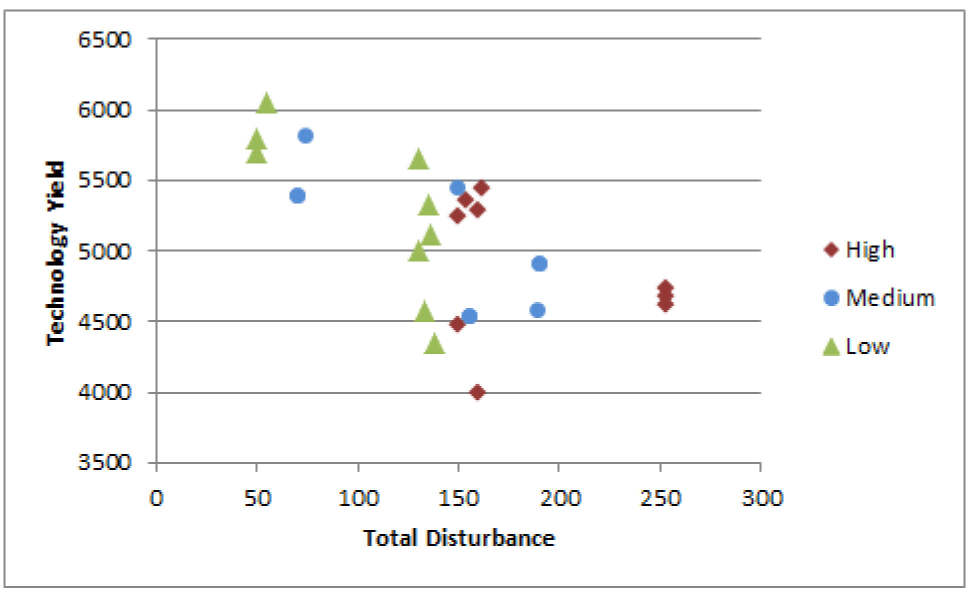


Figure 6.12: Y with respect to D_f.

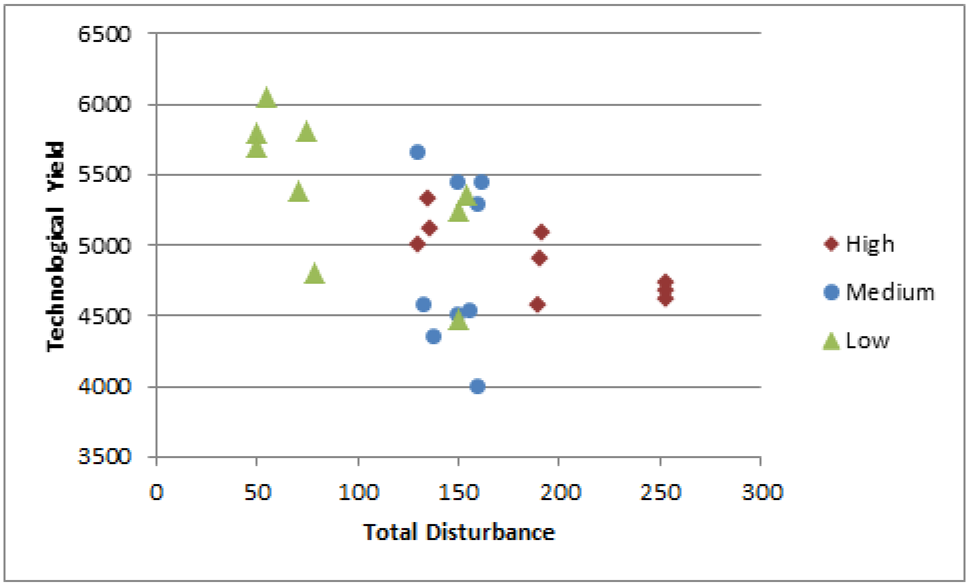
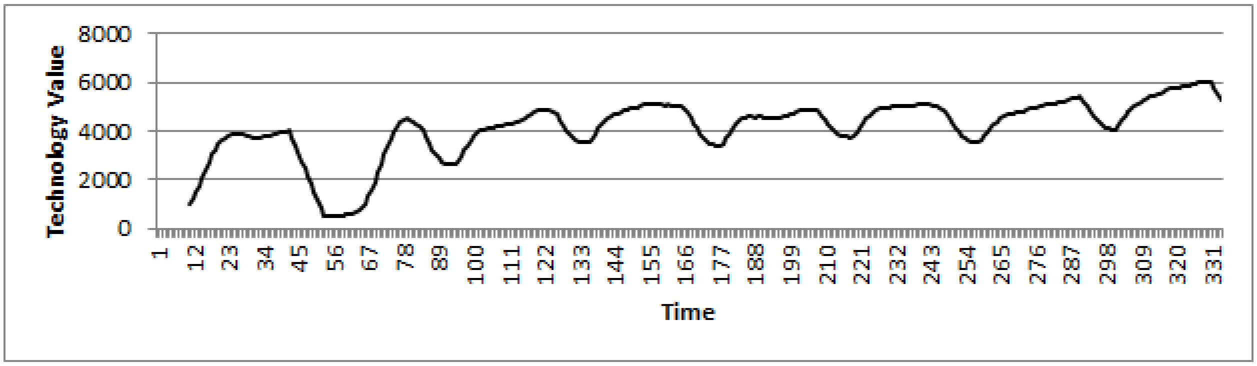


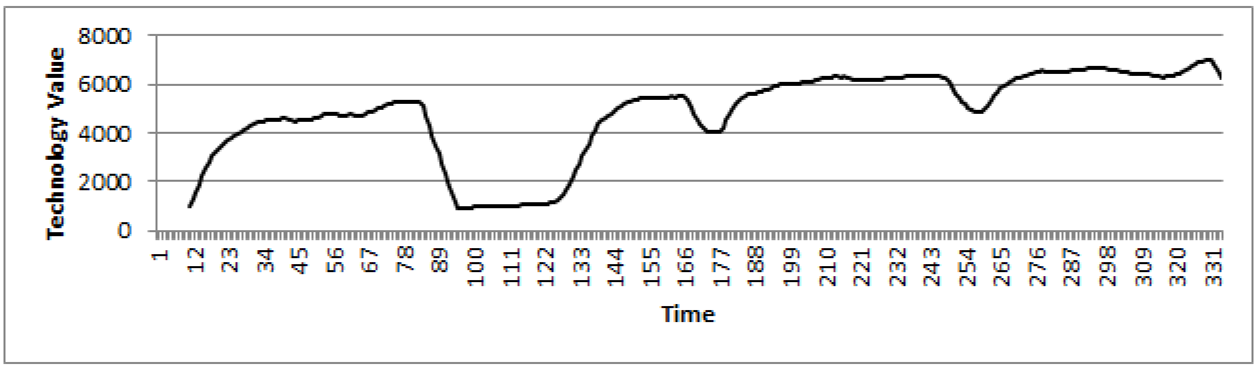
Figure 6.13: Y with respect to D_l.

A more interesting set of features can be observed when we separate the yield response with respect to disturbance frequency. We see here that there are clear response bounds that delineate the reaction of the system under low, medium, and high-stress configuration. Each frequency class displays regimes of effectiveness which overlap at regular intervals. While the plots are not remarkably different, it becomes clear that the model is more vulnerable to disturbances which are infrequent but longer in duration those that are shorter and more frequent, even in the case where the total length of disturbance is identical. This can be seen even more clearly in the individual plots of technology transfers (Figure 6.14a-c).

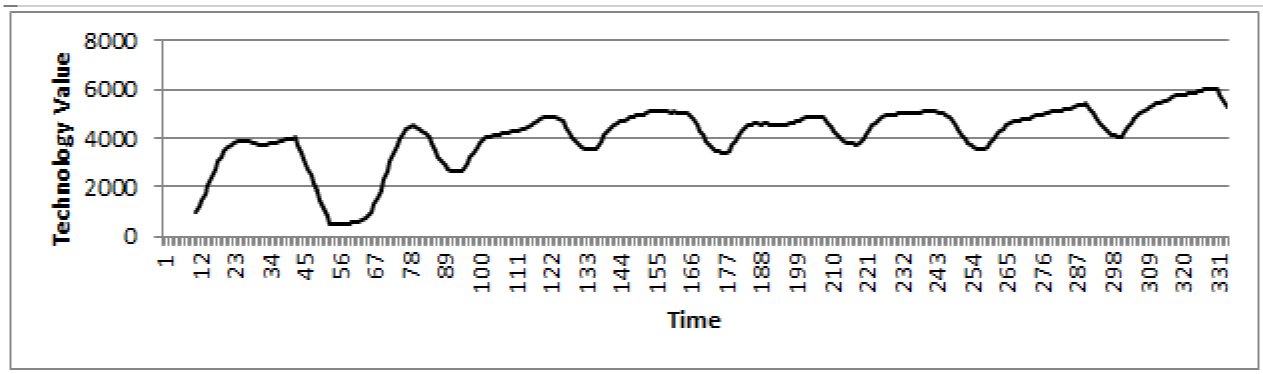
Finally, we devleop a final calculation of TRTR, giving us an estimated simulation resilience threshold of 0.405421, or 40.54%. This threshold represents the the upper stress-bound of the base simulation model after which negative regime change is likely to occur. This can generally be associated with percentage of time D_l when the system is under stress. In a vacuum, this value is relatively unremarkable. However it does provide a baseline for cross-policy comparison in future experimentation and more critically allows model output



(**a**) Average technology value for high frequency, short duration disturbance



(**b**) Average technology value for medium frequency, medium duration disturbance conditions.



(**c**) Average technology value for low frequency, high duration disturbance conditions

Figure 6.14: Overview of disturbance characteristics across various combinations of D_f and D_l.

to be directly compared with empirical studies which utilize *direct regional economic resilience* ($DRER$),*indirect regional economic resilience* ($IRER$), and *total regional economic resilience* ($TRER$) with significantly less transformational work than existing innovation simulations (Rose, 2004).

6.8 Chapter Summary

In this chapter we developed a series of experiments based on our simulation model with the intention of validating our core hypothesis:

"The development and maintenance of innovation economies can be explained on the basis of an ecologically driven agent-based model of the triple-helix model of public-private partnership."

In order to do so we proceeded with the construction of a formal Design of Experiments with the paired goals of quantifying our simulation model's performance with respect to a minimum set of input parameters and establishing a reusable resilience metric for facilitating comparisons between innovation simulations and empirical studies. To accomplish the first goal, we performed a sensitivity analysis and reduced our parameter set to a tractable set of variables that had the broadest impact on the response variables of interest to policy makers.

Further refinement led us to the discovery that number of university's present in our model had the strongest impact on innovation production and industrial productivity of the entire set of input parameters present. However, the impact of increasing this variable resulted in a bifurcation in the response data, with larger university populations exerting significant negative competitive pressure on one another and eventually stifling growth economic and academic growth. This finding suggests that while increasing the number and maturity of academic institutions within an innovation ecosystem leads to robust economic gains, there is a maximum carrying capacity within the novelty production sector of the triple helix that when exceeded turns the system over into negative terrain.

Following the sensitivity analysis we conducted a study of the ecological impact of environmental stress on the resilience of our model with the express aim to develop an output metric that would allow future innovation ecosystem simulations to be directly compared and contrasted with each other and empirical studies. This preliminary experiment introduced several new environmental input factors to simulate system stress through a 'drought' mechanic. The model was tested under a set of independent stress conditions the results were compared linear model of expected system output. This comparison resulted in the computation of total regional technological resilience (TRTR), an adapted variant of a total regional economic resilience (TRER), a metric proposed by Rose (2004) for the study of regional economic system resilience in the face of natural disaster. A TRTR index value was computed from the experimental results that compared favorably with results from empirical studies. Validation of this technique will rely on future studies that perform direct comparisons between real innovation systems and computational models.

Chapter 7

Conclusion & Recommendations for Future Work

In this work we present an agent-based computational model of the triple helix innovation ecosystem supported by formal sensitivity analysis and eclogical experimentation. Our model leverages the ecoogical paradigm and ant-colony optimization toward the development of lightweight agent models, as well as presenting a novel environmental representation of the government grant system. This model supports the contention that ecological modeling is a useful methodology for developing tractable agent-based simulation models of systems whose complexity defies traditional techniques. Our contribution to the field come in three parts. First, we present a holistic model of the regional innovation ecosystem that encompasses all three control regimes of the triple helix and at multiple levels of scale. Second, we introduce the cooperative and competitive activity of individual grant-seeking researchers within a physical environment and connect to innovaiton development and trade network between academia and private industry. Third, we implemented a simulation tool based on model discussed above and demonstrated that the behavior of the system is consistent with both prior simulation efforts as well as empirically-supported relationships between the control regimes of innovation systems.

The development and testing of THESIM-REPAST satisfies both of our initial goals, namely that a computational model of the triple helix innovation system does indeed produce results that are both consistent, dynamical, and sensitive to environmental factors. We find that the productivity triple-helix innovation systems is intrinsically tied to the maturiy and size of its population of universities. This relationship is bounded by the economic resources available to the system as well as inter-firm competition and overall risk-aversity. The result of our sensitivity analysis allowed us to determine an optimal-performance parameter set for use as a benchmark (control) in future experimentation and suggested several interesting sub-model interactions that could spur future research (section 6.6).

With respect to the ecological metaphor, we made several intriguing findings. The most interesting of these findings can be found in section 6.7, where we introduce a new metric for calculating and innovation system's resilience to environmental disturbance; Total Regional Technological Resilience ($TRTR$). Aside from exposing the critical threshold for our simulation model's performance, this metric can be used in future studies to compare findings between other simulation models and emprical data.

As we summarize above, the rigorous effort applied to executing a Repast variant of the simulation model has been significant, and has yielded interesting results that appear to instill confidence in our initial hypothesis that ecological modeling could be applied to the creation of future agent-based simulations of complex, adaptive socio-economic systems. Through this work we have demonstrated an understanding of the problem domain, made the case that ecological concepts are indeed valuable tools which have applications beyond the modeling of biological systems, and provided a novel simulation application with which to test the previous assertions.

From its inception, THESIM was conceived as a long-term project that would start with the development and deployment of the initial simulation tool as a proof-of-concept and would continue to be expanded in scope and detail. Two avenues for future development remain; the refactoring of the simulation to incorporate the testing of specific innovition-supporting policies, and the development of more robust simulation visualization and analysis tools.

The notion of direct policy testing was proposed as part of the model in chapter 4, though only partially implemented (model input parameters set both environmental configuration and agent behavior). To more fully realize this concept we propose the development of explicit policy objects, which consist of a set of environmental and behavior schema which may alter the rules, composition, and activity of agents. These objects would derived from science-of-science liteature and be modifiable by policy makers using an outside tool (or policy builder interface). The simulation model would then be altered to require both environmental parameters (as it currently operates), and a policy (or set of policies) upon instantiation. This expansion would provide a more robust and useful tool to decision-makers, as was the initial goal of the work.

Providing clearer data visualization may help address this, as well as more fully developing the social metrics such as measuring cooperation and innovation contribution through social network graphs. While our model does provide a final graph representation of the system at the end of a simulation run, we did not include any rigourous testing of network composition. Despite this, we have made some preliminary efforts to extend THESIM's data analysis and visualization capabilities in order to provide graph-centric capabilities.

THESiM-DX represents one such effort, and provides a force-directed view of the socio-economic structure which results from individual experimental runs. This secondary tool was developed in python and utilizes a custom mash-up of two software package; NetworkX and D3. NetworkX is a python software package which provides a simple interface for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks. D3 is a javascript library used to build data-driven documents in web interfaces. Additionally, a Java exporter was developed to convert raw graph data from THESIM-REPAST into a format readable in python. This new tool, parses simulation into a NetworkX graph, performs basic network analysis operation, and displays the relational structure of the data in a force-directed graph. The output of THESIMDX is stored in a custom graphml format which is readable by most open-source graph analysis software packages. An example of this file output can be found in the appendix. Sample output of THESIMDX's interactiveforce-directed graph view can be seen in figure 7.1.

The design and development of experimental cases which test configurations, rules, and parameters of relevance to policy makers (or drawn from known data sets related to real-world RSIs) will be critical to determining the value of this model. In addition, we can

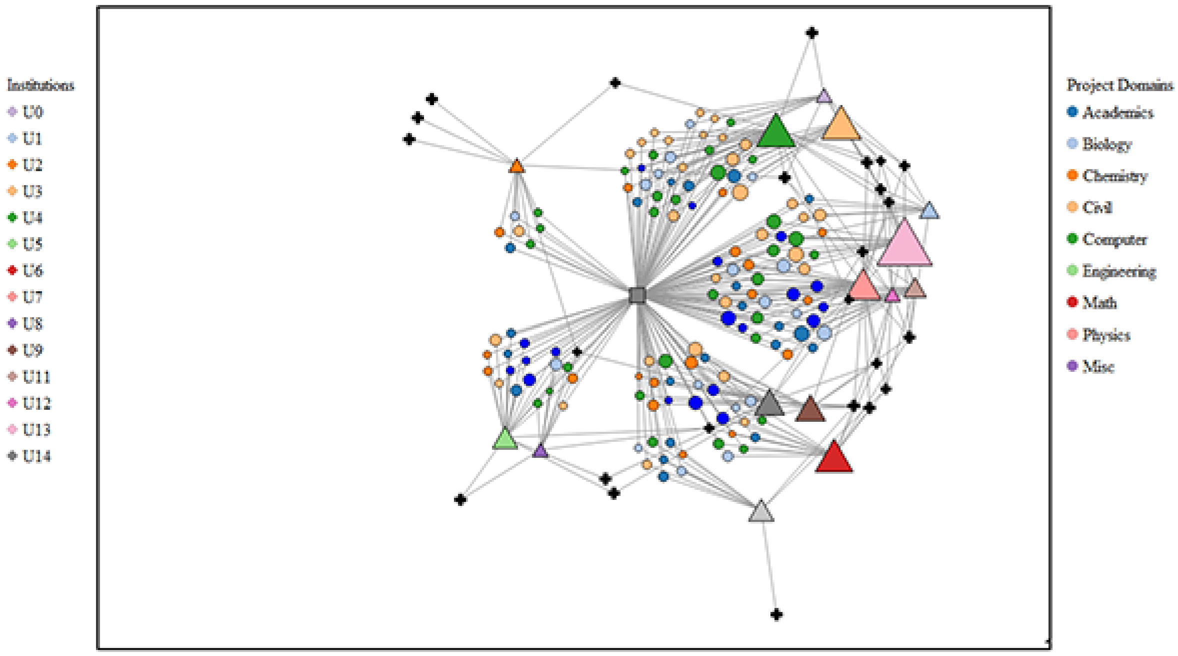


Figure 7.1: Sample output of THESIMDX's force-directed graph running in a web browser.

use well-defined experiments to answer questions of reproducibility and consistency across sub-models as well as better identify incongruence between our assumptions and actual simulation behavior. Many of the sub-models are relatively abstract interpretation of complex systems whose validity should be individually confirmed before broader assumptions about correctness can be made about the simulation model. Experiments should be designed which target critical parameters relevant to these systems to determine the model's sensitivity.

The advantage of the agent-based approach is the capability to implement sub-models at varying scales of complexity. It might become useful to implement more robust market models, social interaction mechanisms, or environmental features. Refining or expanding these sub-models could be useful for more closely integrating the simulation tool to a particular problem or set of explicit experimental conditions. For example, implementing a cooperation model between industrial firms which allows them to form private research consortiums, or introducing work-force dynamics into the productivity of private firms.

Introducing concepts from cognitive science, risk assessment, or game theory might prove to be both fruitful and interesting expansions to the model. Though we have selected species diversity and richness as metrics for substantiating our claim that innovation ecosystems display the same markers of ecological resilience as are found in natural ecologies, it is possible to further expand this analogy in our model by borrowing concepts of evolutionary biology and predation rules. It is also the intention of this project to pursue reproducibility standards in both model specification and data-collection. To this end, providing an online resource where the source code and sample data sets generated by the simulation could also be useful extensions of the project. In all, we believe that this project will not only yield scientifically significant data, but also provide context for further exploration of the agent-based ecological modeling paradigm.

In addition, the original problem of creating a tool useful to policy investigators remains. While the current Repast model is certainly a useful starting point for future development, it is critical to obtain the input of public-policy makers, academics, and professionals involved in the domain of innovation and technology to determine what capabilities would be most useful for generating data relevant to addressing real-world problems. This objective will likely prove difficult to achieve, namely because the field itself is relatively immature and there is little agreement in literature regarding the specific capabilities desired in future tools. For the moment, future model development will focus on broad-level interpretations of systems, mechanisms, and parameters. In all, we believe that the THESIM project offers a strong contribution to the domains of computational modeling, agent simulation, economics, and innovation science.

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Appendices

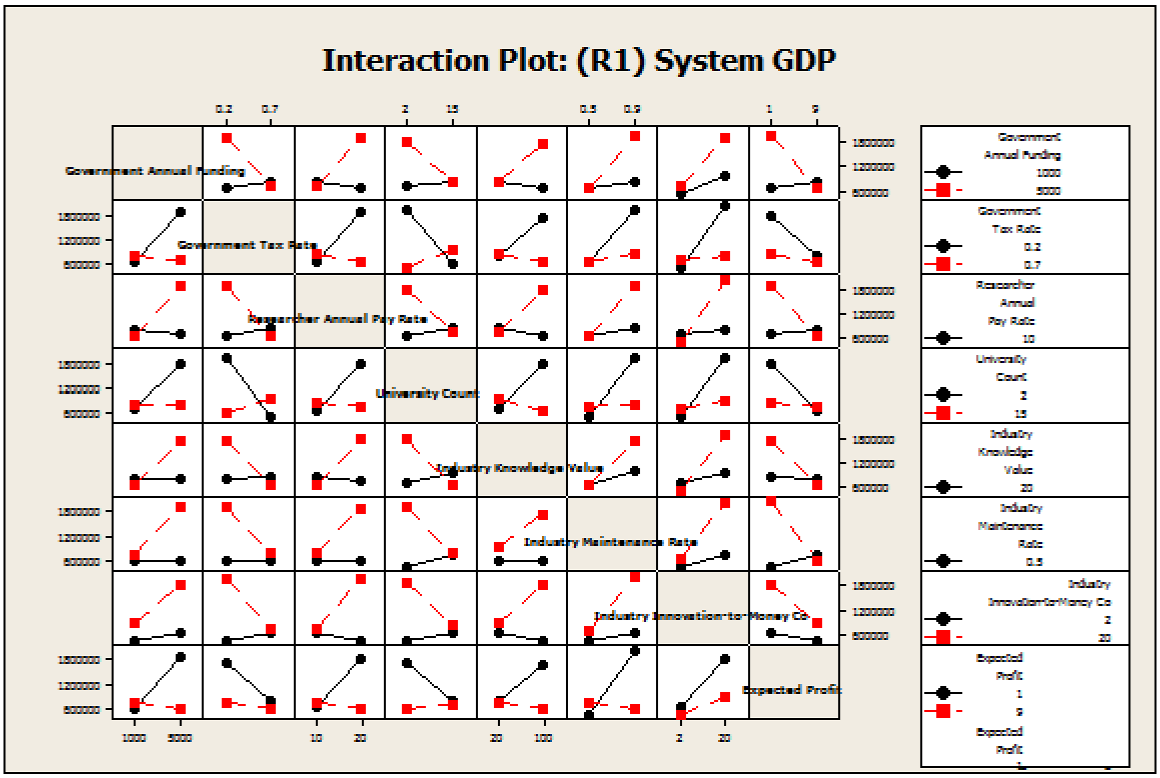

Figure 2: Interaction Effects on R_1 for THESIM Sub-DOE first-iteration.

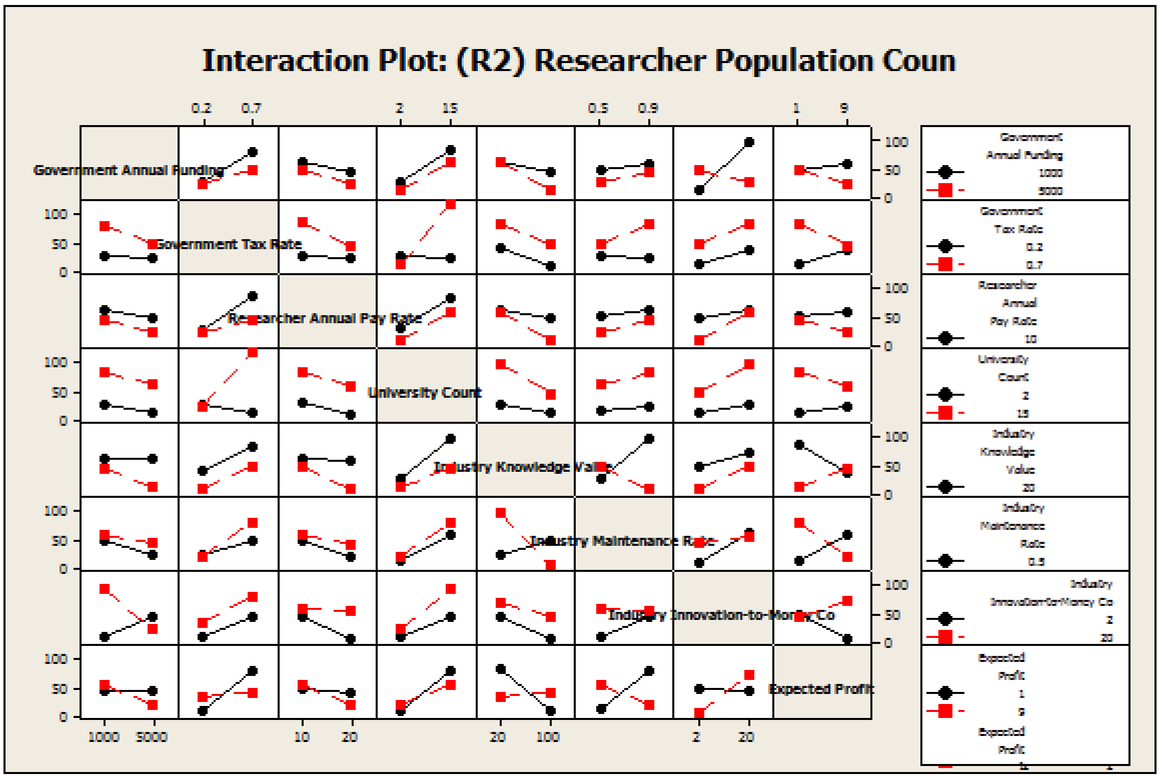

Figure 3: Interaction Effects on R_2 for THESIM Sub-DOE first-iteration.

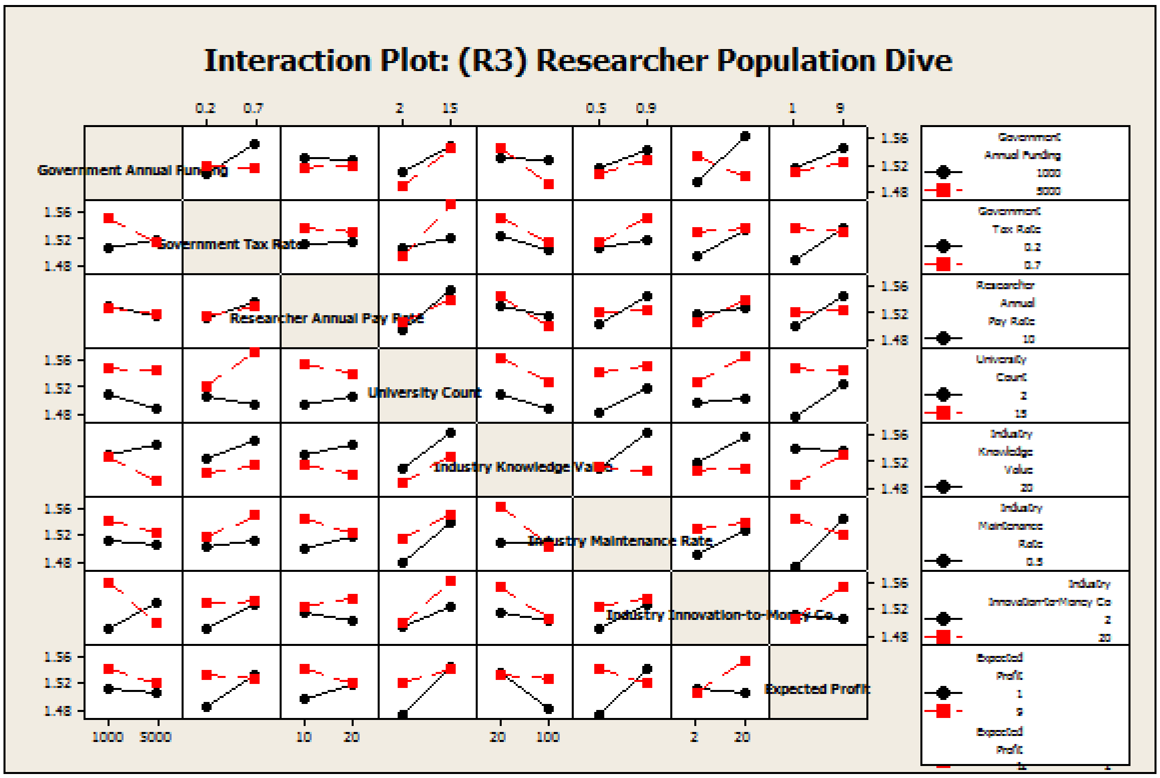

Figure 4: Interaction Effects on R_3 for THESIM Sub-DOE first-iteration.

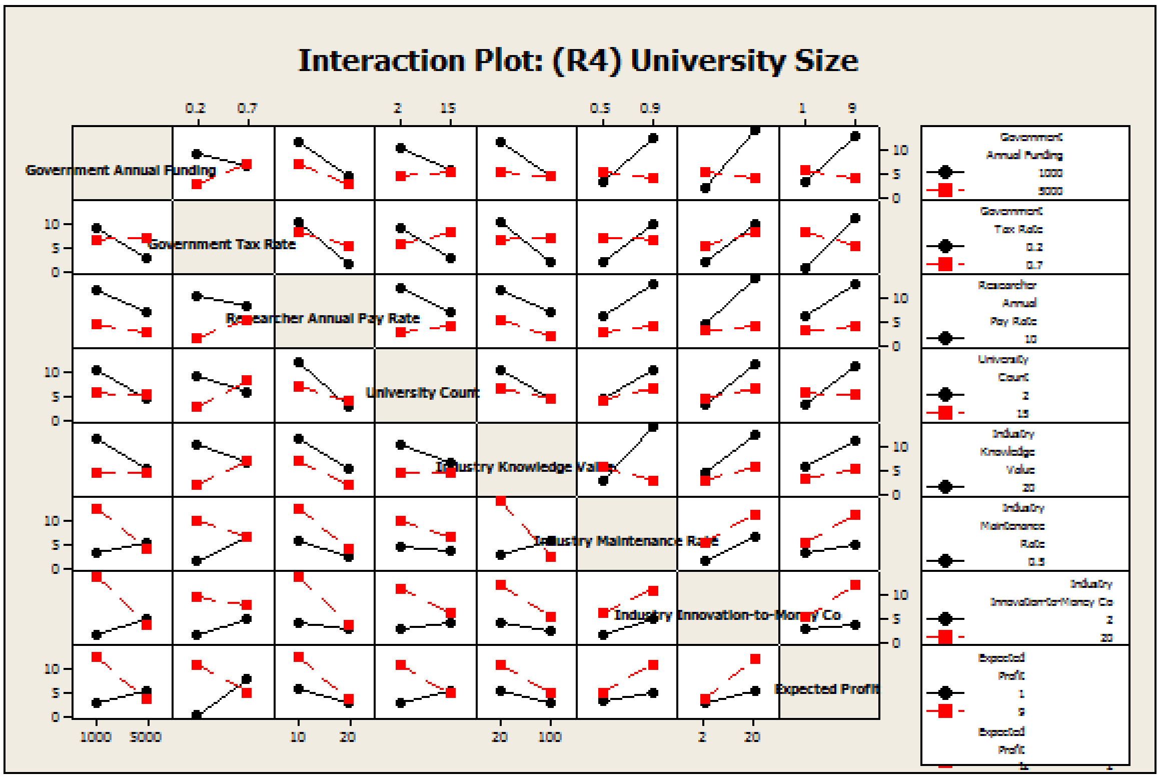

Figure 5: Interaction Effects on R_4 for THESIM Sub-DOE first-iteration.

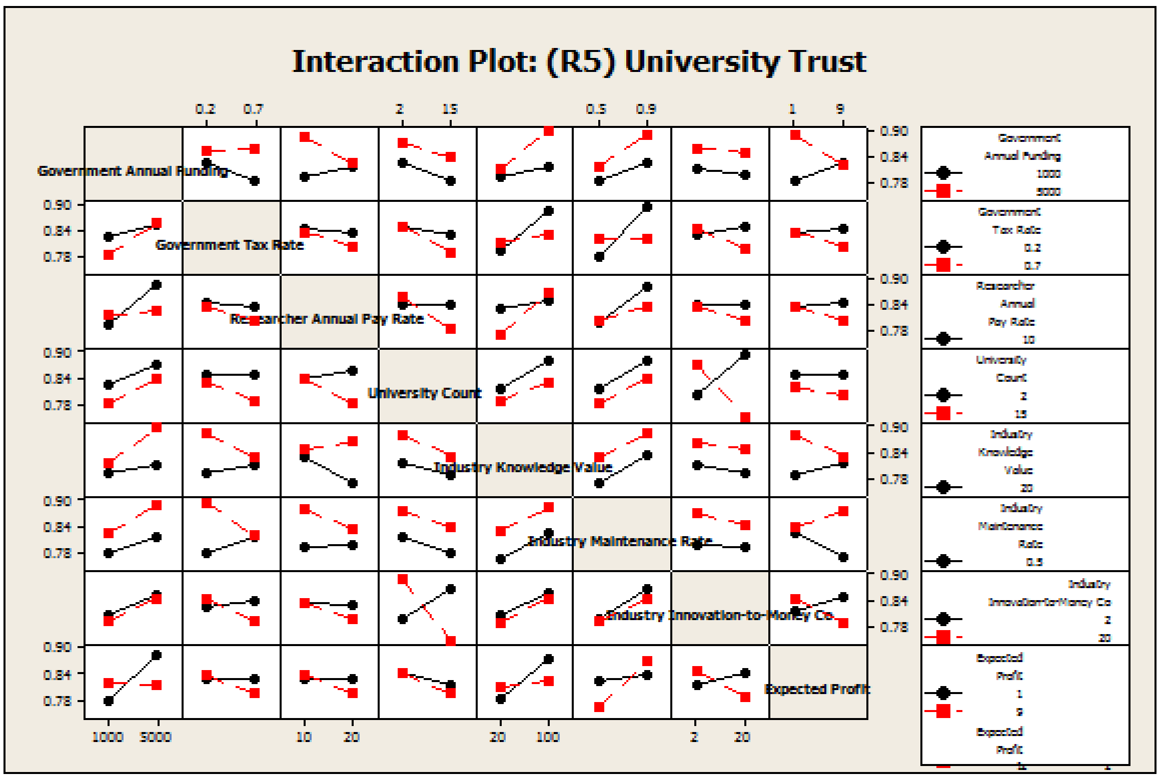

Figure 6: Interaction Effects on R_5 for THESIM Sub-DOE first-iteration.

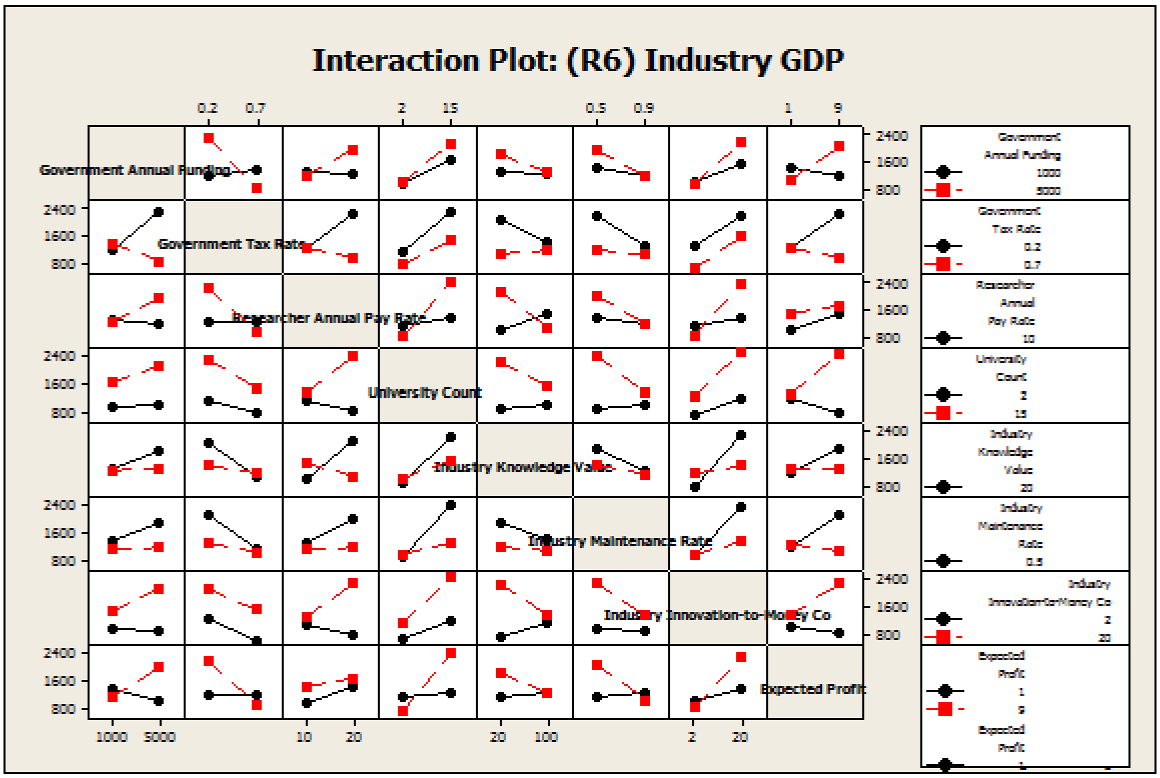

Figure 7: Interaction Effects on R_6 for THESIM Sub-DOE first-iteration.

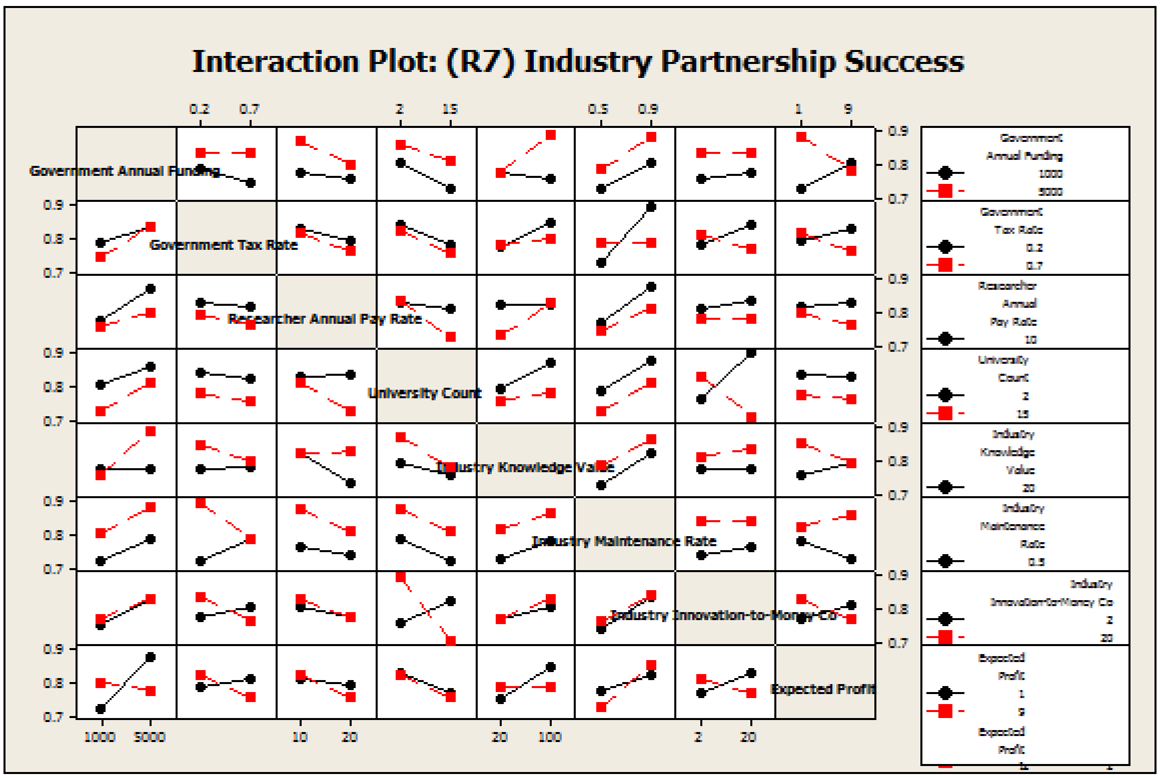

Figure 8: Interaction Effects on R_7 for THESIM Sub-DOE first-iteration.

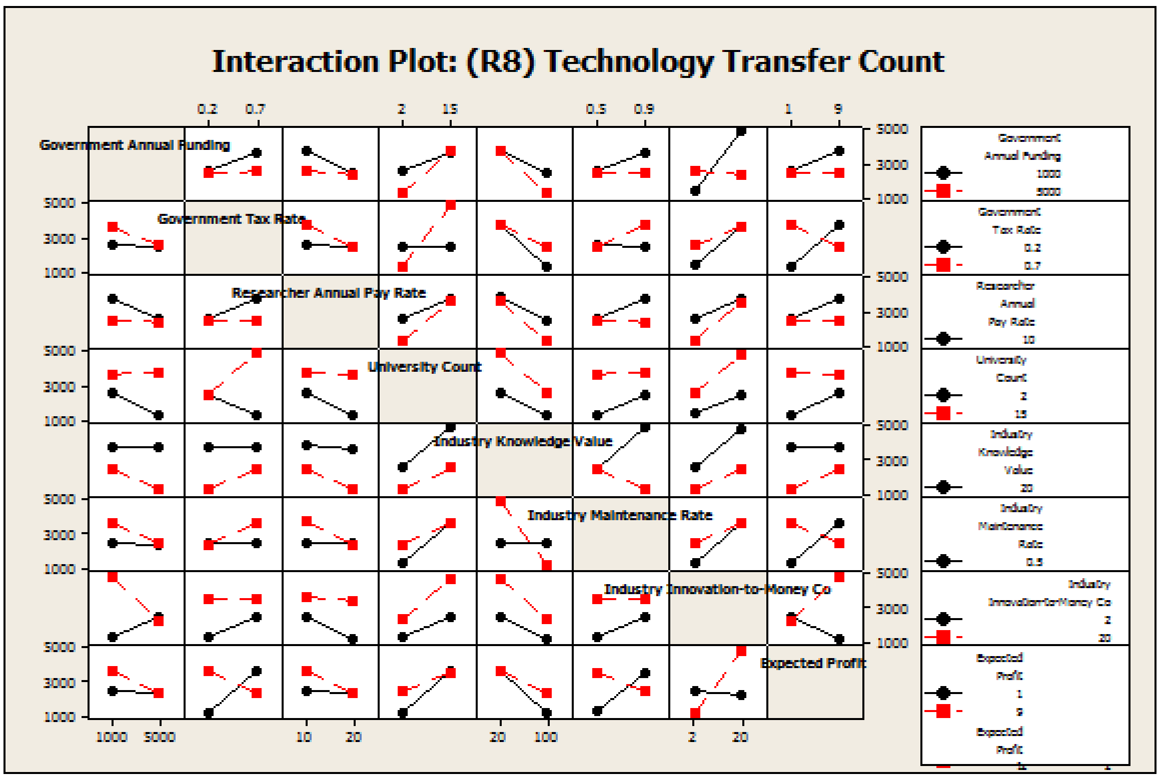

Figure 9: Interaction Effects on R_8 for THESIM Sub-DOE first-iteration.

Frequency	Duration	D_t	Y	Y_{le}	DRTR	%ΔTQ
High	Low	150	4481	5025.03	0.40436	0.108264
High	Med	160	5888	4972.172	0.217334	-0.18419
High	High	253	5731	4480.593	0.238203	-0.27907
Med	Low	75	5814	5421.465	0.22717	-0.0724
Med	Med	150	5441	5025.03	0.276751	-0.08278
Med	High	190	4581	4813.598	0.391067	0.048321
Low	Low	50	5802	5553.61	0.228765	-0.04473
Low	Med	130	5657	5130.746	0.248039	-0.10257
Low	High	130	5004	5130.746	0.33484	0.024703
High	Low	150	5241	5025.03	0.303336	-0.04298
High	Med	160	3992	4972.172	0.469361	0.197132
High	High	253	4622	4480.593	0.385617	-0.03156
Med	Low	75	5387	5421.465	0.283929	0.006357
Med	Med	150	4527	5025.03	0.398245	0.09911
Med	High	190	4904	4813.598	0.348132	-0.01878
Low	Low	50	5693	5553.61	0.243254	-0.0251
Low	Med	130	4573	5130.746	0.392131	0.108707
Low	High	130	5109	5130.746	0.320883	0.004238
High	Low	150	5361	5025.03	0.287385	-0.06686
High	Med	160	5437	4972.172	0.277283	-0.09349
High	High	253	4669	4480.593	0.37937	-0.04205
Med	Low	75	4799	5421.465	0.36209	0.114815
Med	Med	150	4503	5025.03	0.401436	0.103886
Med	High	190	5088	4813.598	0.323674	-0.05701
Low	Low	50	6047	5553.61	0.196198	-0.08884
Low	Med	130	4352	5130.746	0.421507	0.15178
Low	High	130	5334	5130.746	0.290974	-0.03961

Figure 10: Full data table for THESIM-ER Including all values for DRTR and the Linear Model Y_{le}.

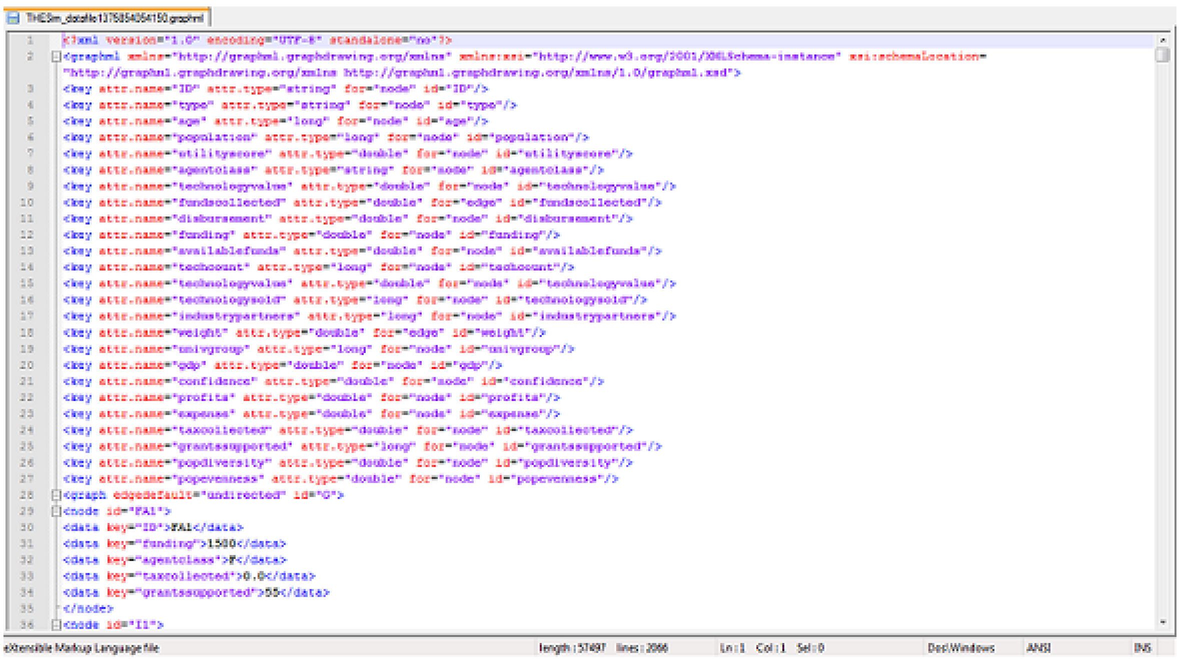


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Figure 11: Sample THESIMDX graphml output from a single-simulation trial. Note the node and edge schema as well as the govenrment node representation ($FA1$)