AN INVESTIGATIVE FRAMEWORK FOR STUDYING THE GROWTH AND EVOLUTION OF COMPLEX SUPPLY NETWORKS

By

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DEDICATION

Dedicated

To

My Parents

Dr. Pabitra Ranjan Pathak

And

Aruna Pathak

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CHAPTER I

OVERVIEW OF THE DISSERTATION

Introduction

A Supply Network (SN) is defined as a collection of firms that maintain local autonomy and decision-making capability, but who interact with other firms to fulfill customer requirements by transforming raw materials into finished products (Simchi-Levi, et al. 2000). In the last five years, SN researchers have focused on the need to understand the reasons behind the diversity in the number and types of supply networks as well as, how these diverse networks interact, change and adapt over time (Choi, et al. 2001, Choi and Hong 2002, Harland, et al. 2002, Lee 2004). Events such as breaking down of SN's (dot-com meltdown (Mandel 2000)), dramatic changes in SN topology (the data mining industry, (Barabâasi 2002)), failure of firms to force topological changes in their SN's (Covisint effort, (Joachim and Moozakis 2001)), exit of established firms from SN's (IBM's exit from the pc industry, (Bulkeley 2004)), inefficiencies and losses between tiers in a SN ($15 billion per year losses between tiers in the construction industry, (NIST 1999)) and effects of uncertainty on the SN (Cohen, et al. 2003) have further justified the need to understand the dynamic forces controlling the growth of these diverse types of SN's (Hendricks and Singhal 2003). This dissertation exclusively focuses on the dynamic growth aspect of SN's. Based on the examples of dynamic effects just presented, the dissertation focuses on two fundamental questions:

1. How do Supply Networks grow and emerge?
2. Are there simple rules and conditions that control the growth and emergence process?

By answering these two questions, the dissertation will contribute towards extending the current state of knowledge of SN's as a dynamic system. The insights drawn from my research can aid managers/decision makers towards a better understanding of their SN's. This in turn will help them in making informed policy decisions while setting up and managing SN's. A classic example that illustrates the effect of policies on future evolution of a SN can be seen in the US Healthcare industry. In 1996 the US Congress passed the Healthcare Insurance Portability and Accountability Act (HIPAA) that mandated adoption of a set of regulations relating to standards and requirements for the electronic submission of health information. HIPAA's intent was to eliminate the wide variety of reporting requirements set by the multitude of healthcare providers and insurance payers. The expectation was that implementation of this act would eliminate the cost of the intermediators clearinghouses, which convert the diverse forms from one structure to another. HIPAA, while projecting significant long-term savings for the total healthcare system, completely ignored the fact that most local providers did not have the resources to implement the changes. Facing a significant danger to their livelihood, clearinghouses stepped in to provide a HIPAA compliant information standard for the healthcare providers. Thus, instead of eliminating the clearinghouses, the position of intermediaries in the supply chain was strengthened. The dissertation focuses on developing a framework that allows policy makers to capture such policy rules and observe their effect on the system evolution.

To answer the research questions and develop a framework, the dissertation takes an inductive approach (Trochim 2001). It starts by making the observation that Supply Networks are dynamic emergent systems (Parunak and Vanderbok 1998) that have both structural and behavioral dynamics. Consistent with the inductive research methodology, the dissertation then proceeds to creating a modeling framework that can help in generating patterns of growth based on a fundamental theoretical framework, which then leads to tentative hypothesis that can be tested.

To facilitate such a process, the dissertation creates a new theory-based unified model of supply network (now onwards called as UMSN) that incorporates four theoretical lenses, namely Industrial growth theory (Utterback 1994), Network growth theory (Barabasi, et al. 2000, Newman 2003), game theory and market structure theory (Osborne and Rubinstein 1994, Shy 1995) and Complex Adaptive Systems theory (Holland 1995, Kauffman 1995, Schuster 2001), to provide a holistic framework for modeling growth and emergence in Supply Networks. A generic rule-based modeling framework and a simulation based computational framework has been developed to operationalize and implement the "unified model". For preliminary validation of the model, the dissertation presents results from simulation using data from the US automobile industry over the last 80 years.

The results and analysis of the simulation experiments (presented in Chapter III, IV) clearly answers the two research questions raised previously. Firstly, we got similar trends in results as compared to empirically published data on the US automobile industry; both from network topology and population dynamics perspectives. The SN system grew and emerged as a Complex Adaptive System. Secondly, the dissertation presents statistically significant results that supply networks grow and emerge based on interactive effects of local decision-making rules and environmental conditions, and that there is an underlying order to the emergence process. This result effectively answers the second research question. The dissertation takes the research, one step forward by presenting novel analysis techniques for possibly predicting the SN system behavior over time and suggesting how such techniques can generate insights for policy makers and managers.

Organization of the dissertation

The dissertation is organized in a format with each chapter written as an essay on one aspect of dynamic SN. Each chapter contributes to the solution of the entire problem.

Chapter II introduces the problem domain and lays the foundation for a new theoretical model by presenting the limitations of the existing models in the Supply Network literature. It then presents the UMSN and explains how each theoretical lens in the unified model plays an important role towards modeling a growth-oriented supply network. The chapter then justifies the need for a computational framework for investigating such a system.

Chapter III presents the details of the generic rule modeling framework and the simulation framework for operationalizing the "unified model". The chapter presents two fundamental entities in a SN system and the respective rule categories for modeling a generic supply network. An industry (US automobile industry) is taken as a sample industry and the rules are instantiated for the industry. The chapter presents simulation results that suggest that the modeling framework produces valid results that matches with the empirically published work of Utterback (with regards to industrial growth) (Utterback 1994), on the automobile industry.

After introducing the theoretical model and the generic rule-modeling framework, Chapter IV presents the detailed simulation results using data from the US automobile industry as an example. The paper formally answers the dissertation questions raised previously, by presenting rigorous statistical analysis of the observed simulation results and explaining the observed interactive effects seen in the system. It draws general conclusions for practicing managers and explains the ramifications of the observed results and analysis. The chapter establishes that SN's are indeed CAS by nature that grow based on simple interaction of local behavioral rules.

Chapter 5 introduces novel analysis techniques for analyzing the stability effects (evolution of SN structures into stable patterns) in the experiments performed using data from the US automobile industry. It draws general conclusions with regards to stability in any supply network and how mangers and decision makers can interpret such results and the potential benefits of doing so. The paper presents a novel analysis technique of predicting the emergence path of the entire supply network by utilizing standard chaos theory tool sets (Williams 1997) such as lag calculations using autocorrelation tests (Makridakis and Wheelwright 1989) and reconstructing the pseudo-phase space (attractors) of the system (Williams 1997). Based on the simulation results, the paper suggests the presence of periodic attractors (limit cycles) in SN systems. The paper also comments on the different values of lag in the system and its importance for practicing managers and decision-makers.

The conclusion chapter summarizes the problem, the solution designed and presented in the dissertation and the important findings of this dissertation. The future work section outlines the direction in which research can be carried out. Specifically this dissertation proposes to further validate the unified model by simulating additional industries, both similar and dissimilar to the US automobile industries. The results from such experiments will eventually lead towards a general theory of Supply Networks. Generic rule-modeling framework needs to be extended to capture and model the growth of already existing networks. This will allow the research framework presented in the dissertation to model wide range of problems in SN's and present robust solutions.

In order to do so, the computational framework needs to be extended. A new agent based framework that allows users to rapidly set up different types of SN's and corresponding rules needs to be developed. Lastly, future research in this area should look into combining chaos theory techniques with statistical techniques for analyzing patterns of growth and providing more complex growth result parameters such as Lyapunov exponents (Williams 1997)for small sample sizes (that are typical in these studies) .

Topic Index

Table 1, provides a list of primary topics in the dissertation and indicates where they appear through out the dissertation.

Table 1: Topic Index

Serial Number	**Topic**	**Chapter**
1.	Theoretical framework for modeling growth oriented SN	2,3,4,5
2.	Generic Rule modeling framework	3,5
3.	Computational framework	2, Appendix (2, 3, and 4)
4.	Detailed rule modeling	5, Appendix 1,2
5.	Instantiation of the generic rule modeling framework: -Simulation of the US automobile Industry	2, 3,4,5
6.	Macro results and analysis	2, 3
7.	Detailed Statistical Analysis of SN growth and emergence	4
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CHAPTER II

GROWTH, EVOLUTION AND EMERGENCE OF SUPPLY NETWORKS

Abstract

Over last two decades, study of emergence has been actively carried out for biological, physical and chemical systems. In more recent times researchers have tried to apply the lessons learned from these studies towards the investigation of non-orthodox systems such as large organizations and management systems. In this chapter attention is drawn towards one such system that forms the backbone of any industry; i.e., Supply Networks (network of firms transforming raw material into finished products). To the best of our knowledge, no comprehensive Supply Network model exists that can model emergence dynamics of Supply Networks. The chapter presents a UMSN using concepts from Complex Adaptive System Theory, Industrial Growth Theory, Game Theory, Industrial Organization Theory and Network Growth Theory of Supply Networks. We suggest how the UMSN can be used for investigating the growth and emergence dynamics of supply networks. Such an understanding of the supply network system behavior would allow policy makers and managers to better understand the evolution of their supply networks.

Introduction

"December 2nd, 2004, IBM Corporation announced its decision to sell its personal computer (PC) business to Lenovo Corporation of China" (Bulkeley 2004). In 1980, when IBM started the US PC industry, no one would have envisioned such an outcome. Yet within a short span of 25 years, technology advancement, falling prices, birth of new firms like Dell Corporation, coupled with IBM's internal policy decision to subcontract to Intel and Microsoft probably resulted in IBM's and exit from the industry. Could this outcome have been predicted?

The IBM example clearly highlights the dynamic, emergent nature of the industrial landscape and the corresponding network of firms (known as Supply Networks) residing in that landscape. A Supply Network (SN) is defined as a collection of firms (or nodes) that maintain local autonomy and decision-making capability, but who interact with other firms to fulfill customer requirements (demand) by transforming raw materials into finished products (Simchi-Levi, et al. 2000). One of the classical properties of emergent systems as has been shown in numerous models, such as the sand cone model (Per Bak, et al. 1988), Eigen's prebiotic evolution model (M.Eigen 1971), and Holland's Genetic algorithm models (Holland 1995), flock of flying birds (Reynolds 1987), gene regulatory network (Kauffman 1971), artificial markets (Arthur 1999) and the Internet (Albert, et al. 1999), is that the emergent behavior is driven by interaction of simple rules and conditions. This interaction results in self-organization, adaptation and evolution in such systems. SN's show these same characteristics (Ashby 2004, Choi, et al. 2001). So possibly IBM's outcome could have been predicted if there was a way to understand the effect of "simple rules" (IBM policies) on the system and identifying the underlying order. How then can we study, investigate and manage such an emergent system, i.e., a SN? And identify any underlying order?

A major difficulty encountered in the study of emergent systems is the non-determinism and non-linear dynamics (Parunak, et al. 1998) present in SN's. The problem is compounded further due to the diversity in the number and types of supply networks and a lack of understanding as to how these diverse networks interact, adapt, and emerge over time (Lee 2004). For example, the automotive industry follows a classic hierarchical supply network formation: a formal set of tiered suppliers, with each sub-tier supplying a higher tier, up to the final assembler, who then distributes the finished vehicles to dealers. Contrast this SN to that found in the construction industry where there is no single assembly facility, rather, every town has a host of contractors, architects, and builders. This heterogeneity of SNs becomes more of a problem when a variety of SN's must be managed simultaneously by a customer, such as in healthcare where a hospital must deal with pharmaceutical suppliers, medical equipment manufacturers, and general medical supplies of medical specialists, each of which has a different SN structure. Thus, in order to answer the questions and issues raised above, we present a systematic research effort in this paper.

We begin by formally raising the following two fundamental questions:

1. How do supply networks emerge?
2. Are there certain simple rules/conditions that drive the growth and emergence process in such systems?

Past efforts in SN research has typically focused on research models, which present centralized static networks (Beamon 1998), with a focus on flow of materials, money or information using a logistical or operational efficiency perspective (Parunak and Vanderbok 1998). They are unable to capture the structural and behavioral dynamics of a SN. Network growth theory and emergent system research (Newman 2003) on the other hand are unable to address the issue of modeling rules for SN.

This paper introduces a Unified Model of Supply Network (UMSN) that borrows from four different theoretical lenses, namely, Industrial growth theory (Utterback 1994), Network growth theory (Newman 2003), market structure theory (Shy 1995), (Tirole 1989), game theory (Osborne and Rubinstein 1994) and complex adaptive systems theory (Schuster 2001), (Kauffman 1995), (Holland 1995), to build a holistic framework. This framework helps in capturing the structural and behavioral dynamics and provides a way to study chaos, complexity, order, and emergence in a supply network. Along with the theoretical model we also argue for the need of a simulation based computational framework that can provide a "what if" analysis platform for performing scenario analysis. Only by taking computational modeling approaches as has been increasingly recommended by social and organizational scientists (Anderson 1999), (Kamps and Masuch 1997) and performing multiple scenario analysis can a knowledge base be created and insights can be gained on how complex supply networks self-organize. Such knowledge in turn will lead to better understanding of how to manage these networks.

Finding a growth oriented Supply Network model: Past and existing Literature

Why develop a new theoretical model of Supply Networks? Because, there is no comprehensive supply network model that allows modelers to model SN rules, policies and investigate the dynamics in SN's.

Past Supply Network modeling approaches

In the past, researchers have employed a variety of modeling techniques for analyzing supply networks. Most of these approaches analyze inventory oscillation issues, demand amplification (bullwhip effect) and other flow (material/money and information) related issues. Table 2 summarizes the past efforts.

Table 2: Past modeling and analysis techniques

Area	Sample Articles	Remarks
System Dynamics and Continuous time differential equation modeling	Forrester (1961), Towill et.al (1991), Simon (1952)	Analyzing flow in supply chains using first order and second order differential equations
Discrete time differential equation modeling	Porter and Taylor (1972), Porter Bradshaw (1974), Bradshaw and Daintith (1976)	Modeling supply chains using discrete time differential equation model
Discrete event simulation	Ho and Cao (1992), Cao (1991)	Event based analysis of supply chain interactions
Operation Research Techniques	Pyke and Cohen (1993), Altiok and Raghav (1995)	Analysis of operational aspects of a supply chain, such as stock levels etc.
Agent Based Techniques	Parunak (1998), Kohn et.al (2000), Lin and Lin (2002)	Analysis and optimization of supply network flow of material money and information using software agents

These approaches typically assume a static supply network structure and focus on optimizing the flow within the network; hence they are unable to model the evolving structural dynamics of a supply network, which is essential for understanding growth phenomenon. This inherent assumption of a static network structure is limiting when studying evolutionary dynamics of supply networks (Parunak and Vanderbok 1998) as, in actual supply networks, the number of firms and the linkages between firms do not remain constant.

Dynamic Supply Network Models

More recently researchers have suggested dynamic models of supply networks (Choi, et al. 2001), (Harland, et al. 2002). These models take a deductive approach to identify the reasons behind the SN dynamics. Since the emergence phenomenon in any system actually is non-deterministic, a deductive approach is limited in its ability to efficiently explore the entire range of possibilities driving the emergence dynamics of SN's.

The dynamic models also do not define growth in a SN. In order to investigate growth and evolutionary dynamics in SN, a clear definition of growth is needed, both from a SN topology perspective and the perspective of an individual firm in the SN. As we define in subsequent sections, this research considers how the population of firms and the corresponding SN topology grows with time as a measure of growth in SN systems.

Emergent System Models

Researchers from such diverse disciplines as physics (Per Bak, et al. 1988), computer science (Holland 1995), network growth theory (Newman 2003), economics (Arthur 1999), and biology (Kauffman 1971), (M.Eigen 1971), (Neumann 1949) have suggested growth models to explain the diverse emergence phenomena in real world systems. These models suggest that real world systems are not static and these systems constantly grow and evolve over time. The growth and emergence process is governed by simple interaction rules between the entities in the system. Unfortunately none of these models can help with the actual rule modeling process in SN's the growth rules are more strategic and Darwinian in nature, being composed of 1) birth and death of firms, 2) growth of capacity and fitness of a firm to play a specific role in the SN, 3) creation and deletion of linkages between firms in the SN, and 4) reconfiguration of the existing linkages as the environment changes. Since the rules in a SN depict behavior of firms and a market, they are multi-dimensional. A fundamental economic theory driven approach is required in conjunction with the basic concepts of network growth theory to capture the growth rules of a SN.

The Theoretical Framework: Unified Model of Supply Network (UMSN)

The unified model of SN (UMSN) (Figure 1) addresses the limitations presented in the previous section and builds a holistic framework for modeling growth oriented SN's. The UMSN starts by defining growth and evolution in SN at a macro level using the Industrial growth theory lens (Utterback 1994). It then highlights what this lens cannot provide and moves over to the next lens, i.e., Network growth theory. Subsequently the model highlights how each of the lenses contributes a missing piece of the whole puzzle to provide a comprehensive platform.

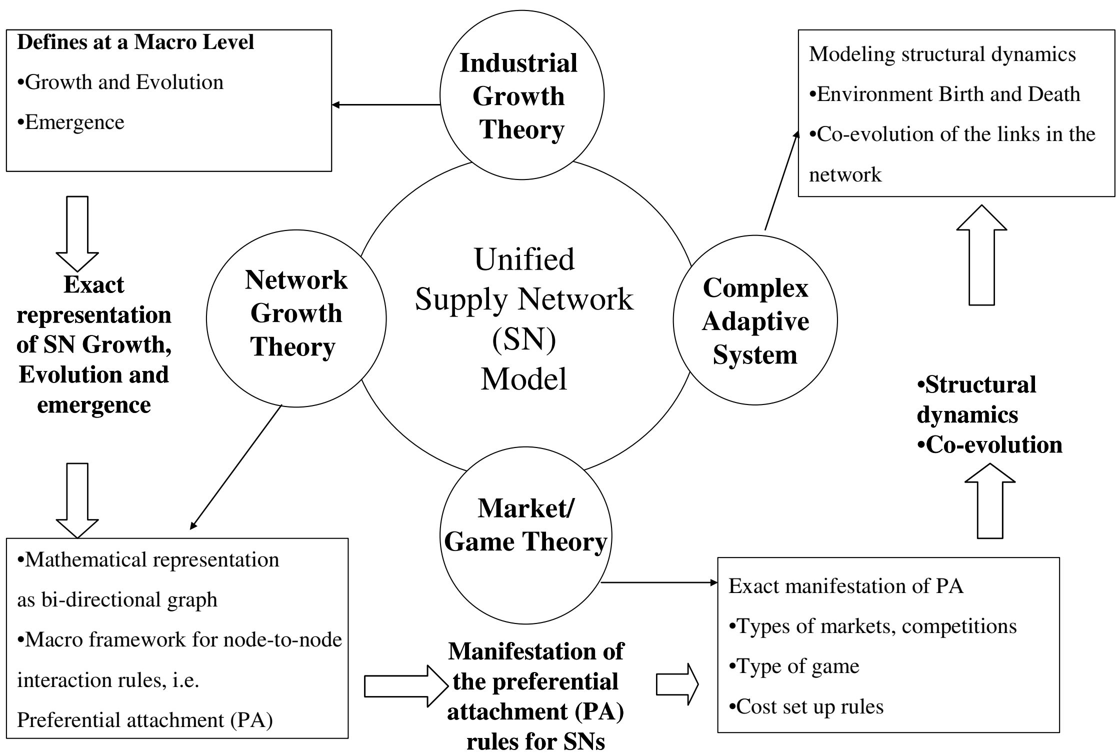

Figure 1: Unified model of supply network (UMSN)

1. Industrial Growth Theory:

Growth and evolution in supply networks involves both the birth and death of firms, and the creation and dissolution of links between these firms. Underlying rules and conditions for defining node-to-node and node-to-market interactions may drive both of these conditions. The industrial growth model (Utterback 1994) provides a theory for modeling growth. According to this model, as new industries emerge; SNs also grow, with new relationships being formed between firms to work collectively to satisfy demand. The Industrial Growth (IG) model considers that at industry inception, entry barriers for firms are low and there is no clearly defined market structure (Utterback and Suarez 1993, Utterback 1994). At this stage there are a number of relatively identical new entrants, with each firm attempting to establish itself as a leader. In this early phase, there are many unsolved issues and unproven assumptions. However, over time, as the problems become solved or proven, growth in the number of firms can become nearly exponential. The next phase in the IG model is of the emergence of a clearly defined market structure with firms focusing on economies of scale and network externalities. Not all firms are successful, and the unsuccessful firms are shaken out of the market. As time progresses and the industry stabilizes, the number of new market entrants rapidly decline as empty market niches become filled. In addition, as the primary market tier becomes saturated, firms learn to play specialized roles in sub-tier levels of the network. Therefore, in the beginning of an industry, most firms are generalists but, as time progresses and a few firms become dominate, other firms must adapt into specialized roles or leave the network.

This behavior is illustrated by the automobile industry. In the early 1900's, "buggy" and "bicycle" makers were making cars. As time progressed only a few "generalist" firms (i.e., assemblers such as Ford and General Motors) remained, and other firms either died (e.g., Deloren and AMC) or they learned to play a "specific" supplier role (e.g., Firestone and AC-Delco). Interesting, this industry has undergone a new revolution in SN, with two of the major domestic automotive firms simultaneously converting their parts divisions into stand-alone supply firms (i.e., GM spinning off Dephi Automotive Systems and Ford spinning off Visteon) and joining together to create virtual supply market (e.g., Covisint).

While the IG model is useful, it captures evolution of an industry only with respect to the number of firms entering or exiting the market (Suarez and Utterback 1995). An additional dimension that must be captured while studying emergent systems is the internal growth of an individual entity in the system (Barabâasi 2002, Barabasi, et al. 2000). We use individual capacity of a firm in a SN as a surrogate for size in this research (rationale is that the quantity a firm can produce is directly proportional to how big the firm is). With this kind of a representation then growth in size can have two possible growth scenarios. In one possible scenario, as market size increases with time, there is differential growth in firms, with some firms expanding capacity to dominate the industry. An alternative scenario is where a subset of firms does not grow to dominate the industry and the resulting market is composed of a large number of limited capacity firms. An example of the first scenario is the automobile industry, and the second the construction industry. Thus, the unified model defines growth in a SN from the perspective of both the number and size of firms.

2. Network Growth Theory

SN's are more than a collection of firms: they are also the linkages among the firms. A graph representation of SNs consists of nodes (representing firms) and edges (representing linkages between firms). Erdos and Renỳi (Erdos and Renyi 1960) suggest a random-graph model of a network in which, the number of nodes is fixed but the interconnections among nodes are dynamic. The random graph model is thus not appropriate for SN, as the number of firms is not fixed. Recently, Barabasi et.al (Albert, et al. 1999, Albert, et al. 2000, Barabasi, et al. 2000) have suggested a network model that specifically addresses the issue of growth and evolution by taking into account dynamic population of nodes and dynamic linkages between nodes. Barabasi and Albert (Barabasi, et al. 2000) found that many real world networks such as, social networks (Scott 2000, Wasserman and Faust 1994) , the citation index network, the World Wide Web, electric power grid network, and biological networks (Kauffman 1971, Newman 2003) are essentially dynamic graphs that grow based on rules such as "preferential attachment" (Barabâasi 2002) where new nodes entering the network link to existing nodes based on the number of links and the fitness of the incumbent nodes.

SN literature clearly shows that nodes in a SN link with each other based on parameters such as price, quantity, etc (Chopra and Meindl 2003, Simchi-Levi, et al. 2000). In other words nodes in a SN seem to follow the idea of preferential attachment (PA). However, the interconnection rules are more strategic in nature, dealing with material, money, and information flow (Parunak and Vanderbok 1998). So an example manifestation of a PA rule would be the decision of a node to subcontract to a supplier, which quotes the lowest price. Another example can be the decision of a supplier node to supply only if the incoming demand is above a certain threshold level, such that it is a profitable deal for the firm.

The existing network growth models (including Barabassi's model) do not consider the dynamic reconfiguration of existing linkages between the edges in the graph. So, while network formation models are a step toward describing growth in supply networks (structural aspect), they are not sufficient to describe other aspects of growth (driving forces); they need to be extended to account for the competitive /cooperative nature of the interaction process or for death of existing nodes.

The mathematical representation of SNs as a graph helps us handle the growth issues that IG model did not address but it raises a new problem in the form of defining node interaction rules. Preferential attachment is a general concept in network growth theory but the exact manifestation of the rules is derived from market structure and game theory as presented next.

3. Market structure theory

Industrial Organization/ microeconomic theory (Shy 1995, Tirole 1989, Varian 1990) and game theory (Osborne and Rubinstein 1994) provide the theoretical base for characterizing behavioral rules that may be used in SNs by nodes. The environment in which firms reside can be characterized based on Market Structure Theory (Shy 1995, Tirole 1989) which is a description of the firm's behavior in a given industry or market. In any industry, there are specifics of firm behavior which include: 1) the actions available to each firm, (e.g., choosing a price, setting production capacity, etc.); 2) a firm's expectation of the actions available to competing firms, and how the competing firms will respond to each firm's action; 3) the number of firms in the industry, and whether this number is fixed or whether free entry of new firms is allowed and 4) a

firm's expectation about the number of potential entrant firms. Using these behaviors specifying a market structure is similar to specifying the rules of the game or rules for interaction between existing and potentially entering new firms (Shy 1995). Two other theories provide a basis for rules in an industry. Game theory literature (Osborne and Rubinstein 1994) provides a strong theoretical base for defining a meaningful set of rules. Microeconomic theory (Varian 1990) contributed towards setting up cost rules for individual firms, as well as rules that aid in defining a firms operational behavior such as production rules, capacity expansion and contraction rules.
The market structure, microeconomic and game theory lens helps characterize behavioral rules for the nodes and the environments, effectively allowing interactions between the respective components.

4. Complex Adaptive Systems (CASs):

If the interaction between firms is driven by simple rules and conditions, this may give rise to non-linear dynamics in SNs (Choi, et al. 2001). Because rule-based interactions and non-linear structural and behavioral dynamics lead to evolution of systems, the fourth lens of UMSN is complex adaptive systems (Holland 1995, Kauffman 1995, Schuster 2001). This approach is well suited for modeling systems with structural and behavioral dynamics such as found in SNs. CAS allow the network emerges over time without any singular entity controlling or managing the global structure or node interactions (Choi, et al. 2001, Choi and Hong 2002). CAS can be characterized by three important components; namely, 1) environment that the network exists within, 2) internal mechanisms (deals with agents schemas (defines rules), connectivity (describes the interaction between agents) and dimensionality (ability of an agent to connect with multiple nodes in a flexible way), and 3) co-evolution (quasi equilibrium and state changes, non-linear changes, and non-random future).

UMSN Summary: The four lenses provide the basic theoretical components of the model. Industrial Growth theorizes the cause of birth and death of nodes in a SN, and for causes of varying roles that emerge in a network. Network theory theorizes that SNs can be represented as bidirectional graphs that grow based on preferential attachment rules, i.e., rich nodes (i.e., those with the largest number of links) get richer (i.e., differentially gain additional links). The actual rules of behavior for firms in a market have been studied in market structure theory and game theory. Finally, complex adaptive systems theory provides a method to model dynamic evolution of locally autonomous nodes into SNs. We integrate these four lenses into a unified modeling framework, which is capable of defining markets and firms in a SN, capturing their behavioral rules, and analyzing the temporal growth and evolution process.

The Computational Framework

The "unified model" by itself can only provide an abstract modeling framework for SN's, but to actually understand how the behavioral rules and conditions interact to drive the emergence process, a computational platform is needed. An ideal computational platform should allow a modeler to specify rules and conditions for a supply network. It should then be able to support a flexible temporal evolution process during which the local entities in the system driven by the behavioral rules interact amongst themselves. Simulation based methods can provide such a platform (Zeigler, et al. 2000). As shown in Figure 2, a simulation-based approach can allow a modeler to capture the interaction process and record the resulting emergent behavior of the supply network system, i.e., the evolution of the SN topology. A causal relationship can be established between the input rules/conditions and the output parameters. This causal relationship increases the modeler's general knowledge about the system, generates insights and helps in policy decisions. Simulation based techniques can allow the modeler to discover and increase general knowledge by allowing him/her to perform repeated multiple scenario analysis. Such a possibility does not exist with analytical techniques for emergent systems, as there is no close form equation for the system that can be analyzed (Parunak, et al. 1998).

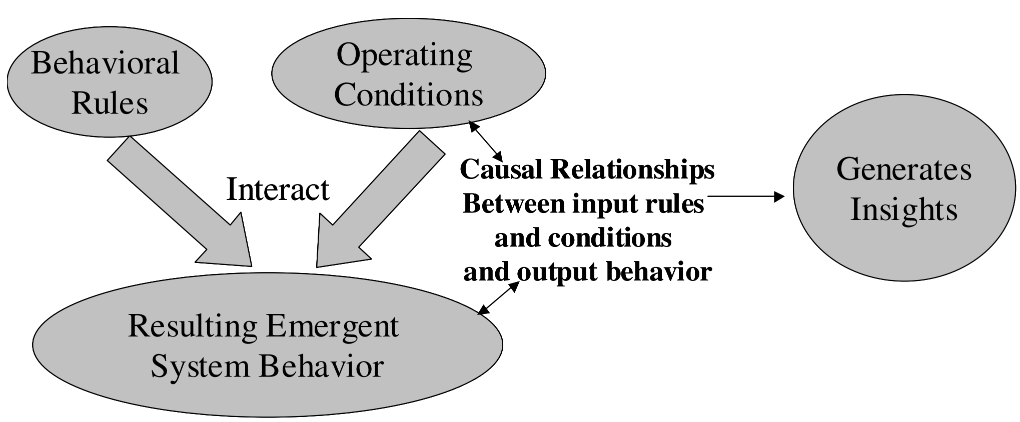

Figure 2: Need for a computational framework

We propose a simulation based computational platform to complement our theoretical model. In a SN system, there are two fundamental entities, i.e., the firms that participate in the network formation process and the environment/market in which the firms operate. We have developed a multi-paradigm discrete-time (Zeigler, et al. 2000), discrete-event (Cassandras 1993) simulation platform to seamlessly capture the hybrid nature of the system. Some of the components, such as the environment, fit a discrete time modeling (DTS) paradigm. On the other hand individual node behavior is both event and time driven, and best captured by a hybrid, discrete event-discrete time formalism (DEVS-DTS).

Furthermore, since firms in a SN display a complex goal directed behavior, software agents (Ferber 1999) are used to implement this feature. Agent based modeling techniques have been successfully used for modeling supply networks in the past (Kohn, et al. 2000, Lin, et al. 2002, Strader, et al. 1998, Swaminathan, et al. 1997). Using a message passing protocol, agents can effectively simulate node-to-node interactions (effectively forming the graph linkages). Also as the software agent architecture supports, group and role modeling, it allows for the development of a range of rich and robust studies, such as studying group behavior of firms in a market, development of specialized roles or role adaptation process of each individual firm.

To implement the advanced multi-paradigm simulator, we have developed a tool suite called CAS-SIM (Complex Adaptive Supply Networks Simulator) (Pathak and Dilts 2004). This suite is built using multi-agent-based techniques discussed earlier to capture dynamic interactions between nodes and the changing configuration of the network for each demand cycle. CAS-SIM uses MadKit (Multi agent development kit) (a Java based agent package) (Ferber 2004) as the agent platform. MadKit provides a bare bone agent infrastructure where the modeler has to write the behavioral description of the agents in Java. MadKit uses a CORBA (Common Object Request Broker Architecture) based platform for implementing a message based communication infrastructure.

Emergence in Supply Networks

This section demonstrates how the unified model in conjunction with the computational framework can model and simulate growth patterns for a real life SN. Subsequently we provide an example on building insights for policy makers and managers based on the simulation results. The simulation also achieves the goal of validating the unified model and computational framework against empirically published results on the chosen industry.

We used data from a very well structured industry (the US automobile industry) for simulation purposes. The industrial growth theory lens and the market structure/game theory lens in the UMSN were used for setting the rules and conditions for the simulation experiments. For example the automobile industry was set up as a free entry market (Shy 1995) where firms play an n-person Bertrand's pricing game (Edgeworth 1925). Based on Utterback's work (Utterback 1994) initial number of firms in the market, individual firms ability to expand/contract its capacity, ability to learn and adapt, and the type of environment (easy to live or harsh) were selected as the input rule parameters. The details of the rule setting and the generic rule-modeling framework are presented in Chapter III and IV. For different combinations of these parameters with respect to type of structures formed (connectivity of the network) and the population dynamics (Survivability), preliminary analysis illustrates classic CAS behavior such as perturbation effects and emergence of various patterns indicated similar the growth trends with respect to population dynamics of the automobile industry.

Emergence of Structural patterns in the Automobile industry

A commonly accepted fact about the US automobile industry supply network is that it has a deeply hierarchical structure with multiple tiers of suppliers (Parunak and Vanderbok 1998). The computational platform successfully grew such a structure using few simple "rules" mentioned earlier. What was more remarkable, and something that is often overlooked was that an hourglass structure is not the only structure that can be formed based on these rules. During the temporal evolution process we observed numerous patterns as shown in Figure 3, such as the star shaped network, linear networks, shallow hierarchical networks apart from the deeply hierarchical structure form over a period of time. These patterns of network topologies observed during the simulation fits the classic definition of emergence (Goldstein 1999) (thus confirming that SN's are indeed CAS that emerge with time). The temporal emergence of these structures was governed by the ordered interaction of the input rules used in the simulation (for detailed statistical analysis, see Chapter IV). For example, hierarchical structures were only formed in a high threshold environment (harsh) were firms were willing to learn specialized roles in order to survive. Thus the simulation not only yielded results that matched the current state of the industry under certain conditions it also suggested the possible path the industry took in order to emerge into its current state.

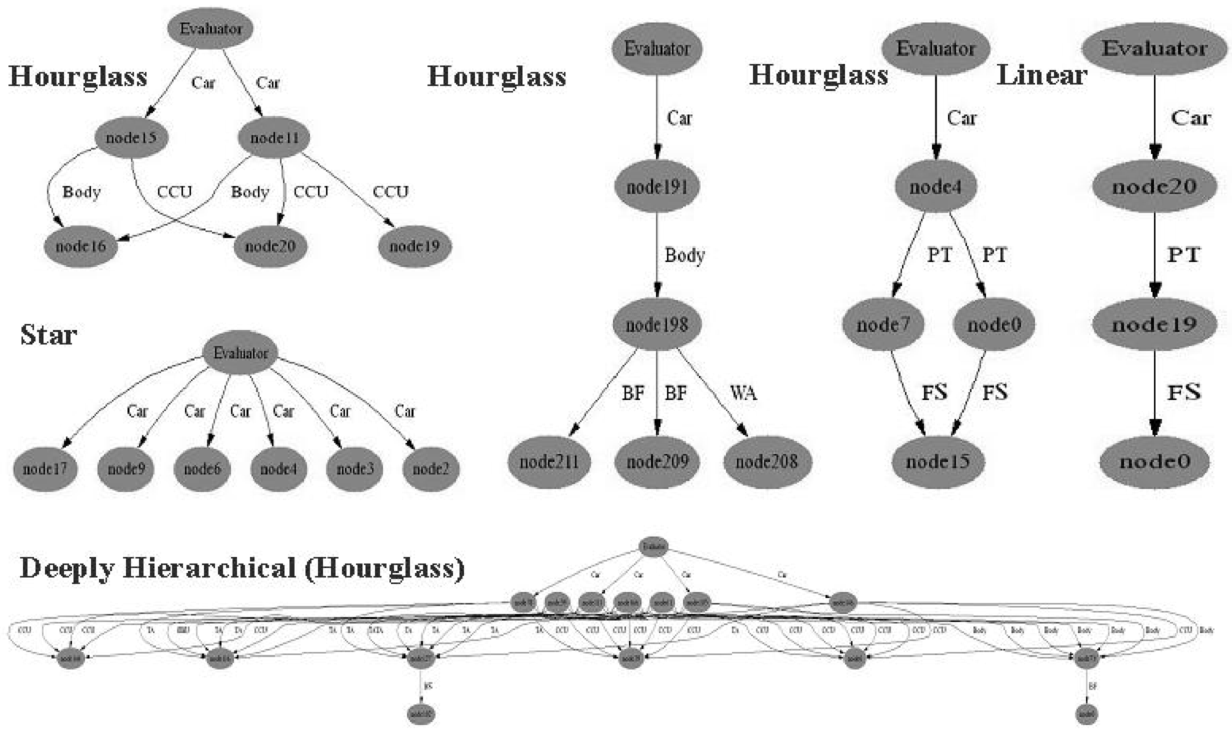

Figure 3: Emergence patterns in supply networks (CCU: central console unit, WA: Wheel assembly, FS: Fuel system, PT: Power Train)

Emergence of SN population in the US Automobile industry

Utterback's work (Utterback 1994) on different industries, clearly identifies the growth of the population of firms in a SN as another outcome parameter that emerges with time. We compared our results on the mortality profile (growth of population dynamics during the simulation) with those of Utterback's (Utterback 1994), empirical work on industrial growth cycle of the automobile industry. It was observed from the experiments that the mortality profile was always a skewed, near bell shaped curve (Utterback's ideal growth curve is bell shaped, but actual data on the auto industry is a skewed bell shape curve), indicating that initially number of firms enter the market, but as the market matures, few firms dominate and the number of entries reduce with time (Figure 4).

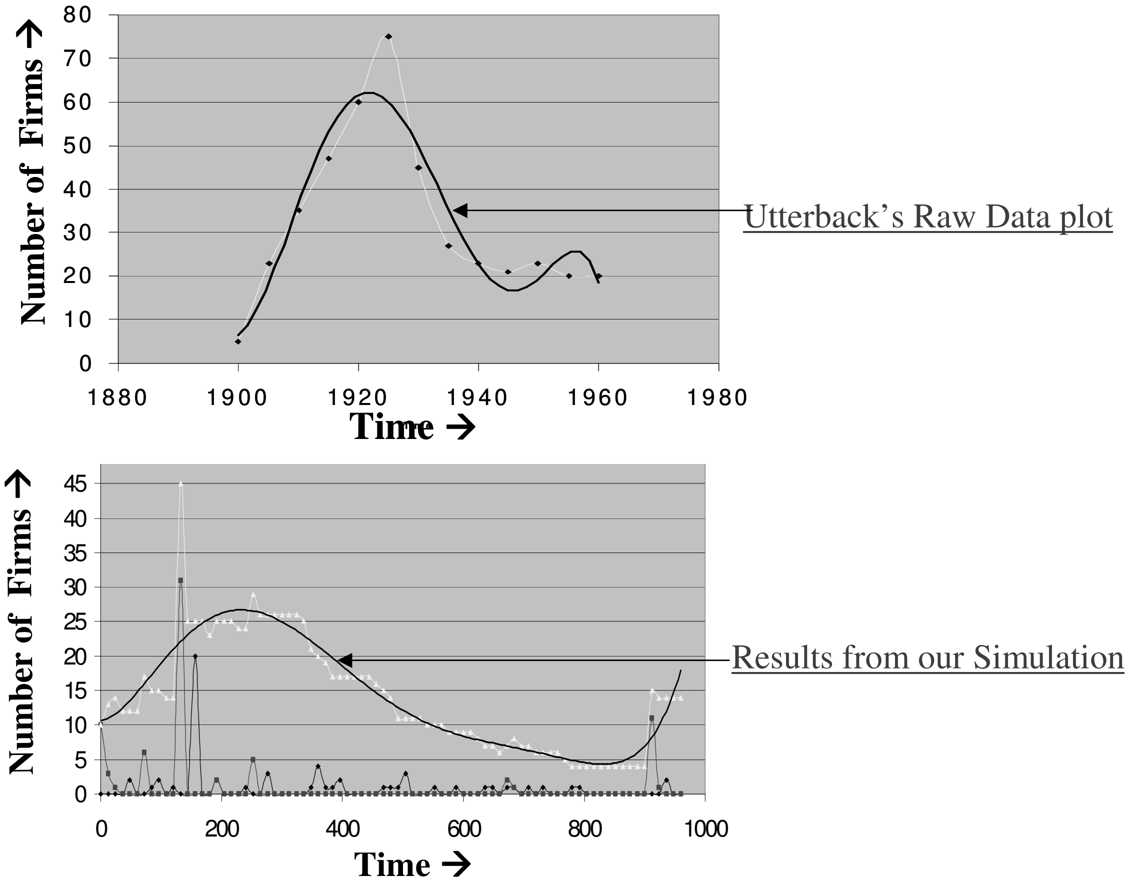

Figure 4: Skewed bell shaped mortality profile for the automobile industry

Thus the macro results with respect to emergence of structures (Figure 3) and emergence of population (Figure 4) showed similar trends with the existing empirical results. Some of the simulation results illustrated the characteristic deep hierarchical SN topology of the current US Automobile industry under certain conditions as well as the bell shaped population dynamics growth curve.

SN's are CAS: Rule based emergence

Next we examine if the emergence process may be driven by simple rules and even slight changes in certain simple rule alters the emergence course for the SN. This is a classic property of a CAS, and would establish and answer the first question: SN's are CAS.

By varying rule setting for an individual node's capacity expansion parameter (for detailed experimental setting, please see chapter III), sensitivity analysis test for the SN system was carried out. Four different settings of capacity expansion (ranging from slow →CE= 6, i.e., fast contraction hence slow expansion (shrink capacity after every 6 negative demand cycles), to fast→ CE= 12, i.e., slow contraction hence fast expansion) were used in the simulation. The resultant population dynamics curve for each setting is shown in Figure 5.

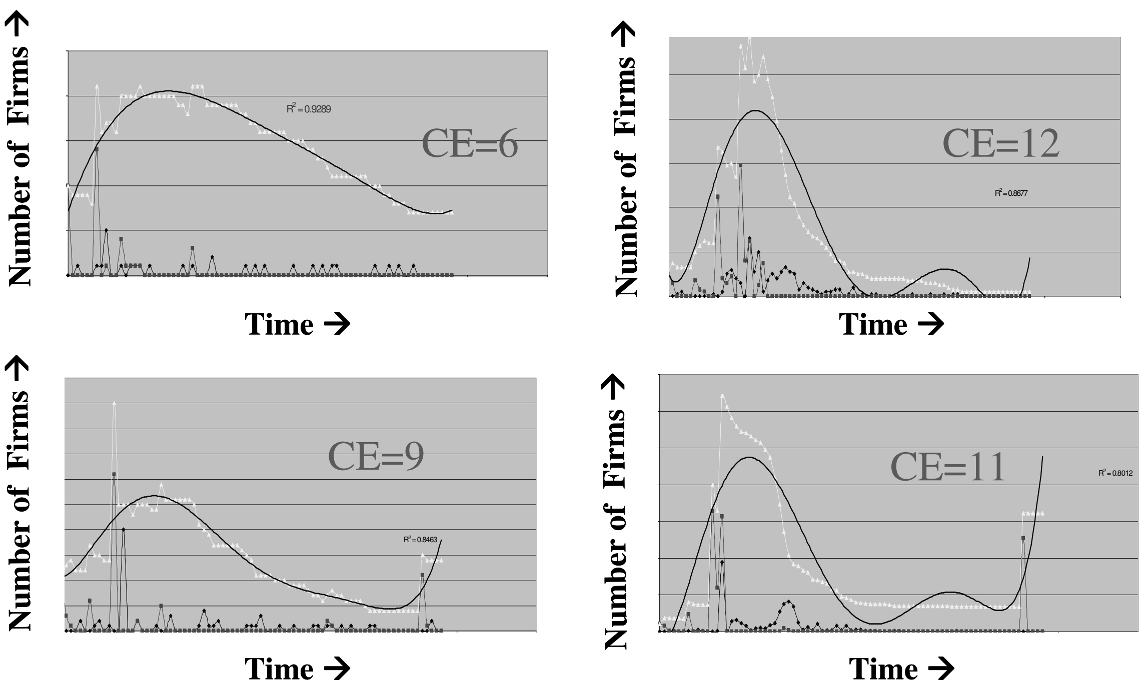

Figure 5: Population dynamics curve for sensitivity analysis

Slight change made to a single parameter in the system (CE in this case), results in the system behavior changing dramatically. The population curve starts showing significant bimodalities. Such kind of behavior truly suggests that SN's are indeed Complex Adaptive by nature.

An example of providing insights from simulation results

Preliminary analysis of the results presented in Figure 5 revealed that a combination of environmental effects such as perturbations in the market and individual node behavior (rate of capacity expansion) contributed towards such dynamic behavior. In a slow capacity expansion condition (CE→6) a single firm does not dominate the market as every node grows their fitness slowly. Hence over time a group of firms grow into a position of strength and share the profits. Unfit nodes are eliminated (explains the bell shaped curve). In such environments even when there are perturbations such as drop in demand (for example drop in demand in the US automobile industry after word war II), the shock is shared equally between all incumbent nodes. But under fast CE conditions (CE→12) typically one or two firms were observed to grow their capacity and fitness at a much faster rate than other firms in the market. Essentially the "rich gets richer" condition was observed (increasing returns to scale). This result in a slow fitness growth for the other incumbents and under perturbations such as drop in demands many incumbent nodes die. This reduces the cumulative capacity of the entire SN, there is unfulfilled demand in the market and newer firms enter the market (such behavior in SN, enforces a limiting constraint on the "rich gets richer" phenomenon).

An important lesson for practicing managers and policy makers: if you don't manage your SN according to the market you are in, it can have disastrous results. If a firm does not expand its capacity fast enough in a market where other firms are responding fast, it can be left behind and new firms can take their spot. Automotive industry is a classic example where only a handful of the initial starters made it big, rest were either eliminated or were reduced to the role of playing bottom tier suppliers. On the other hand if you are in an industry were fast growth is not required, such as the florist industry (having the biggest collection of flowers not necessarily means you are better off) it can result in losses and inefficiencies and eventual bankruptcy. Another example is the "Google Effect". Inktomi corporation dominated the internet search engine market till year 2000. Once Google entered the market, Inktomi failed to adapt to the changing market and was wiped out.

Conclusion

Supply Networks are dynamic networks that grow and evolve over time. Past research has been inadequate in addressing this problem. This paper clearly identifies the need for a new model of supply networks that can capture the structural and behavioral dynamics. A new theory-based unified model: UMSN is presented that provides a platform for modeling growth oriented SN's. The paper justifies the need for a computational framework that can operationalize the unified model of supply network.

A high level simulation using data from the US automobile industry and analysis illustrated that SN's are truly CAS that emerges over time. A high-level sensitivity analysis suggested how such a research framework could be utilized for helping policy or decision makers analyze and build insights. The present version of the model and the framework has established a core set of fundamentals on which we expect to build on. Quoting Choi and Hong (2002), "*if we are to truly practice management of supply networks, we need to understand the structure of supply networks and be able to build theories of supply networks*". In this paper we have taken a step further towards that endeavor.

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CHAPTER III

UNDERSTANDING THE GROWTH AND EVOLUTION OF SUPPLY NETWORKS

Abstract

Little is known about how supply networks grow, evolve and adapt. To study this complex phenomenon we utilize a theory-based modeling framework that combines aspects of industrial growth theory, network theory, market structure, game theory, and complex adaptive systems theory for modeling the growth of supply networks. Specifically a generic rule-modeling framework is introduced in this chapter that specifies categories of rules describing behavior of the fundamental components of a complex adaptive supply networks, i.e., the environment and the firm. The framework is implemented as a multi-paradigm simulation that utilizes software agents and combines discrete time-discrete event formalisms. This allows us to simulate different network structures in order to evaluate the possible causes behind the evolution of different topologies. We have developed a simulation model using data and parameters from the US automobile industry. Our analysis suggests that the generated industrial growth curve is similar to that of published empirical results, validating the generic rule-modeling framework. Interestingly, these results illustrate complex adaptive system properties such as perturbation effects and possible chaos. We discuss the possible use of these results for understanding policy implications for a Supply Network system such as the effect of not increasing a firm's internal capacity fast enough in a dynamic environment.

Introduction

Many different forms of supply networks exist supporting a variety of industries, but there is a dearth of research that provides explanations for the observed diversity in the network structures, and the processes that govern the emergence, growth, and evolution of these over time (Harland, et al. 2002). For example, what were the conditions or "rules" that led to the growth of a flat, shallow florist industry supply network as compared to a deep, structured, hierarchical automobile industry supply network[1]? Policy makers often create laws and regulations with a vision that such rules will lead to the evolution of certain types of stable supply network structures. However, unanticipated changes in market forces faced by most supply networks often negate such intentions. From a policy maker/strategist's point of view, the impact of these dynamic forces on the growth and evolution structure of networks is interesting and challenging (Choi and Hong 2002). Unfortunately it has been extremely difficult to forecast with any degree of certainty the implications of such rules or how industry/supply network structures will evolve given these policies (Choi, et al. 2001).

For example, in 1996 the US Congress passed the Healthcare Insurance Portability and Accountability Act (HIPAA) that mandated adoption of a set of regulations relating to standards and requirements for the electronic submission of health information. One of the intents of HIPAA was to eliminate the wide variety of reporting requirements set by the multitude of healthcare providers and insurance payers. The expectation was that implementation of this act would eliminate the cost of the intermediators clearinghouses, which convert the diverse forms from one structure to another. HIPAA, while projecting significant long-term savings for the total healthcare system, completely ignored the fact that most local providers did not have the resources to implement the changes. Facing a significant danger to their livelihood,

[1] In USA, florist industry has a vast number of retail outlets; each assembling and selling flower arrangements with a correspondingly vast number of suppliers. Their supply network is primarily composed of three tiers: outlet-distributor-grower. The automotive industry, on the other hand, is composed of a few major assembly plants, many direct suppliers, and a multitude of lower-tiered suppliers. Some researchers may argue that the two industries are quite different: one primarily behaving as a distribution industry, and the other more as a provisioning industry dealing with completely different products and conditions surrounding the product. But the issue of interest for our work is not the exact nature of the industries but the "rules" behind why the networks evolved the manners they did.

clearinghouses stepped in to provide a HIPAA compliant information standard for the healthcare providers. Thus, instead of eliminating the clearinghouses, the position of intermediaries in the supply chain was strengthened (WebMD 2004).

There are other examples where tiers in a supply network have dramatically changed the “rules” of the network. The classic example of this is the effect of Microsoft and Intel on the IBM personal computer supply network, where the suppliers went form a low power position to dominating the supply network. A more recent example is the logic products industry (Lewis 2000). It was predicted that given the regulations and state of the industry, logic-products (used for designing circuits) would die out and that the industry would vanish. What has happened is completely the opposite: with the adoption of new strategies to reduce logic device prices to less than 25 cents, the industry has never been healthier. In fact, due to limited supplies, now suppliers control delivery, forcing customers to experience extended lead times, Controlled Order Entry (COE), and higher prices. In other words, a network tier that was written off as “dead” changed a “rule” and, as a result, has dominated the supply network.

The previous examples show the need to understand growth mechanisms in supply network to understand the possible evolutionary path a supply network may take. The fundamental concept of a supply network is that of a group of firms engaged in activities toward a shared goal (Ganeshan 1999, Simchi-Levi, et al. 2000). While such firms may have a shared goal, there may be (and typically are) different levels of rewards allocated to each member in the supply network because each member is an autonomous unit, allowed to make independent decisions. Hence, firm behavior in such a market (Kotler 1997) is driven by individual policies and strategies, while the overall market may be constrained by governmental regulations or industrial norms. Thus any study related to the growth and evolution of supply networks must capture the individual firm’s behavioral dynamics as well as the structural dynamics of the linkages between individual firms, while keeping in mind the influence of the environmental conditions.

While the outcome of every decision cannot be known in advance with certainty, an approach where different policy scenarios can be modeled and simulated over time for different conditions may reveal important characteristics of the dynamics of the network structure. What is needed is a framework to understand the evolutionary mechanisms of an emergent network of firms by: 1) capturing rules (policies, strategies), 2) modeling such rules within a framework that is capable of evolving, and 3) simulating such systems over time to observe what structures evolve for a given set of rules/conditions.

Our paper introduces a generic rule-modeling framework based on a unified model of supply network (UMSN, see Chapter II for details). This framework aids in capturing the structural as well as the behavioral dynamics of supply networks in order to provide a way to study chaos, complexity, order, and emergence (Schuster 2001). We simulate the time variant behavior of supply networks in order to demonstrate that complex networks can emerge from simple rules (policies/strategies). As an investigative example, we simulate SN growth using data and parameters from the US automobile industry over the last 80 years and identify the fundamental set of "rules" that led to the growth and evolution in supply network structures. Through our experiment, we show that the growth and evolution of such networks can be a function of environmental policies and strategies, as well as each firm's individual characteristics. Based on the network evolution patterns we then suggest possible implications for practicing managers.

The remainder of the paper is organized as follows. Section II provides a review of past modeling and analysis techniques and their limitations in addressing the research questions. It then introduces the UMSN. Section III presents the conceptual framework and the corresponding rule-based computational model for supply networks. Section IV presents the research methodology, i.e., a multi-paradigm simulation approach for implementing the framework with an overview of the software agent technology used to operationalize the framework. Section V presents experiments completed on the simulator. Section VI presents the experimental results. Finally, Section VII summarizes results and outlines future research.

Modeling Growth Dynamics of Supply Networks

Supply networks are complex and bi-directional, having parallel and lateral links, loops, bi-directional exchanges of materials, money, and information (Harland, et al. 2002). Historically supply networks have been viewed as centralized static networks (Parunak and Vanderbok

1998), where research has focused on simplified, linear flow of materials, money and information using a more logistical or operational perspective (Choi, et al. 2002, Choi and Liker 2002, Heragu, et al. 2002, Parunak, et al. 1998). In the past, supply network research has employed modeling techniques that analyze inventory oscillation issues, demand amplification (bullwhip effect) and other flow (material/money and information) related issues. Table 3 summarizes the past efforts.

Table 3: Past modeling and analysis techniques (also in Chapter II)

Area	Sample Articles	Remarks
System Dynamics and Continuous time differential equation modeling	Forrester (1961), Towill et.al (1991)	Analyzing flow in supply chains using first order and second order differential equations
Discrete time differential equation modeling	Porter and Taylor (1972), Porter Bradshaw (1974), Porter and Daintith (1976)	Modeling supply chains using discrete time differential equation model
Discrete event simulation	Ho and Cao (1992), Cao (1991)	Event based analysis of supply chain interactions
Operation Research Techniques	Pyke and Cohen (1993), Altiok and Raghav (1995)	Analysis of operational aspects of a supply chain, such as stock levels etc.
Agent Based Techniques	Parunak (1998), Kohn et.al (2000), Lin and Lin (2002)	Analysis and optimization of supply network flow of material money and information using software agents

These approaches typically assume a static supply network structure and focus on optimizing the flow within the network. This inherent assumption of a static network structure is limiting when studying evolutionary dynamics of supply networks, such as growth and evolution phenomenon of both node and network structures (Parunak and Vanderbok 1998). In actual supply networks, the number of firms and the linkages between firms do not remain constant. Our model addresses these limitations.

Unified model of Supply Networks (UMSN)

UMSN takes an inductive approach (See Chapter II) and suggests that growth and evolution in SN's are governed by simple fundamental rules that can give rise to patterns of emergent behavior. The rules are Darwinian in nature (survival of the fittest), with the growth and evolution process being composed of 1) birth and death of firms, that are governed by the capacity and fitness of firms to play specific roles in the SN, 2) creation and deletion of linkages between firms in the SN that are based on environmental conditions and individual node behavioral rules, and 3) node driving dynamic reconfiguration of the existing linkages as the environment changes. The model draws from four existing theoretical frameworks (See Table 4).

Table 4: UMSN Theoretical Lenses

Theory Lenses	Characteristics of the SN model	Issues not addressed	Reference
Industrial growth theory (IG)	Defines at a macro level: • Growth & Evolution • Emergence	• Exact representation of SN growth, evolution and emergence • Individual behavior of nodes	(Utterback and Suarez 1993, Utterback 1994)
Network growth theory	Exact mathematical representation as bi-directional graph Macro framework for node-to-node interaction rules, i.e. Preferential attachment (PA)	• Manifestation of the preferential attachment (PA) rules for SNs	(Barabasi, et al. 2000, Newman 2003)
Market structure, microeconomic and game theory	Exact manifestation of PA Types of markets, competitions Type of game Cost set up rules	• Structural dynamics • Co-evolution	(Osborne and Rubinstein 1994, Shy 1995, Tirole 1989)
Complex Adaptive Systems theory (CAS)	Modeling structural dynamics Environment Birth and Death Co-evolution of the links in the network	• **NA**	(Holland 1995, Kauffman 1995, Schuster 2001)

1. Industrial Growth theory (Utterback and Suarez 1993, Utterback 1994) defines growth at a macro level. It specifically addresses how a population of firms in an evolving Supply Network dynamically changes with time going through periodic birth and death cycles. IG theory also defines how firms evolve their role-playing capability in a SN, but it does not suggest an exact representation that can be used in a computational model.
2. Network Growth theory (Albert, et al. 1999, Albert, et al. 2000, Barabâasi 2002, Barabasi, et al. 2000, Newman 2003), fulfills this void by allowing the representation of a supply network as a bi-directional graph, with vertices representing firms in the graph

and the links representing relationships between firms. Network growth theory also suggests the concept of “preferential attachment rules (PA) (Barabâasi 2002) that governs how nodes in a network link to other nodes. The actual rules differ from domain to domain, and for the SN domain being studied we use market structure and game theory to manifest the concept of preferential attachment.

3. Market Structure and Game theory (Osborne and Rubinstein 1994, Shy 1995, Tirole 1989), defines the type of market, type of competition, internal node behavioral rules, such as bidding rules, subcontracting rules, and cost set up rules.
4. Complex Adaptive System (CAS) theory (Holland 1995, Kauffman 1995, Schuster 2001) theory defines SN as a system comprising of simple entities, driven by the PA rules that evolves and emerges over time. By representing the SN as a CAS we can utilize the vast array of modeling and analysis techniques (Williams 1997) for investigating dynamic network growth.

<u>Research Model: Complex Adaptive Supply Networks</u>

Conceptual Model

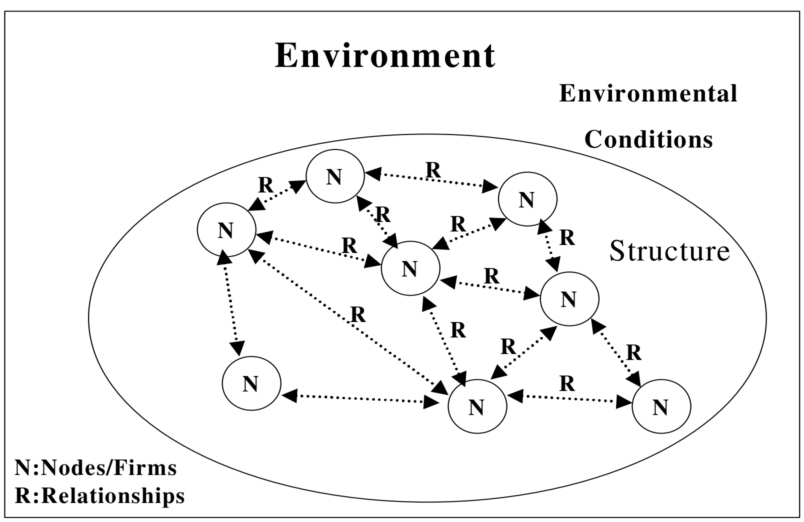

Figure 6: Conceptual Research Model

The unified model provides the conceptual structure (Figure 6) for representing a supply network as a system consisting of an environment i.e., the market or an industry in which firms (nodes) reside and interact to fulfill global market demands. Stochastic environmental conditions, individual node decision-making rules, and differential fitness growth of nodes, all contribute to structural and behavioral dynamics in the resulting SN, ultimately leading to growth and evolution of both nodes and links between nodes.

In order to evolve, nodes must be fit for their environment. Each node in the environment has a notion of fitness, and nodes must be evaluated with regard to their fitness in the environment. In practice, fitness is multi-dimensional and extremely difficult to quantify (Kauffman 1995). In the absence of any agreed upon measure of firm-fitness in supply network literature, we borrow the concept of fitness from CAS and network theory, where researchers consider fitness as the ability of an entity to live and thrive in an environment. Kauffman (1971) has used such an idea in his work on the study of biological networks, where each gene in the genetic network has an associated absolute fitness value that changes over time, influencing the evolution process. Similarly, others (Barabâasi 2002, Barabasi, et al. 2000, Kauffman 1971) have used the notion of absolute fitness of a node to describe the growth behavior in complex real world networks like the Internet.

Generic rule-modeling framework for supply networks

One of the fundamental tenets of the unified model is that supply networks evolve over time driven by intra-firm and government level policies. The conceptual model can then be further expanded into a detailed “rule-based” modeling framework as shown in Figure 7 to formally capture such rules and policies.

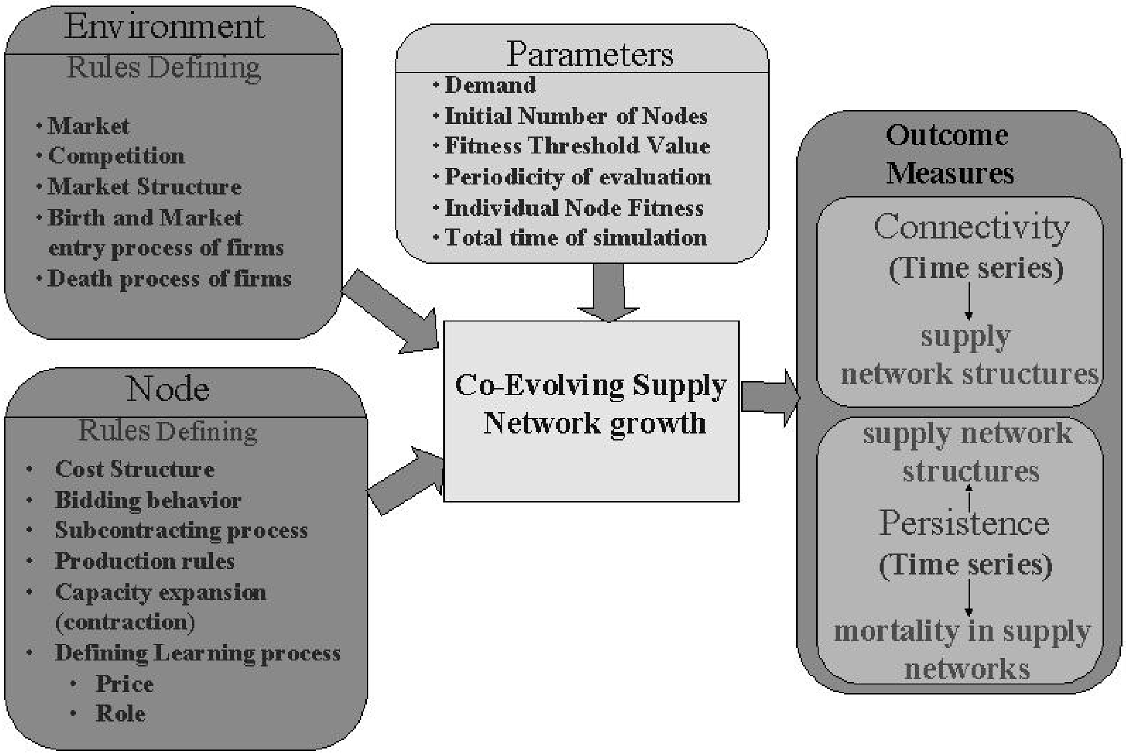

Figure 7: Rule modeling framework

There are three primary constructs: 1) the environment in which the nodes interact, 2) the internal mechanisms used by nodes to make decisions, and 3) the co-evolution of these two constructs into various types of SNs.

Environment: is where the supply network entities (nodes) reside As shown in Figure 2, the environment is characterized by conditions which can be divided into two parts: (i) Parameters, which specify the demand, timing, number of firms and cost related information, and (ii) Operational rules, which specify government regulation and policies, or business rules imposed on the system. Specifically from the UMSN we suggest five basic rule categories (see Figure 7) that help in modeling a wide range of supply network environments.

1. Type of market

Industrial organization theory (Shy 1995) typically considers two types of markets. A market can be regulated, in which case a regulatory body (like the government) decides how many firms enter the market (e.g., Telecommunication Industry). On the other hand a market can have free entry where firms can decide whether they wish to enter the market or not.

2. Type of market structure and competition

Market structures[2] can be classified into two principal categories: competitive and imperfectly competitive. The competitive market structure assumes that each firm set is its production quantity, while taking the market price as given, where the market price is determined by the intersection of the market demand curve and the industry's aggregate supply curve. In imperfect competition, firms follow a price setting behavior and the market can be set up as a monopoly/duopoly/oligopoly (Shy 1995).

3. Birth and entry process of firms

The birth function modeling is done based on classical microeconomic theory, such that whenever there is unfulfilled demand in the market, the market attracts new firms, who can join it and make profit (Mueller 2003, Tirole 1989, Varian 1990). Firms' continue entering the market until unfulfilled demand in the market has been fulfilled and the market is cleared (Mueller 2003). The entry of a firm into the market can either be a "free entry" (firms decide when to enter and whether to enter at all) (Tirole 1989) or a regulated one (entry of firms is regulated by the government, or a regulator body, e.g. the telecommunication market) (Laffont and Tirole 2000). In case of a regulated entry the nodes generated by the evaluator start participating in the supply network. In case of a free market entry, the nodes decide whether to enter the market at all by taking into consideration the entry barrier (Tirole 1989, Weizsacker 1980) of a market.

4. Death of firms

Firms that do not make sufficient profits over time have a steady decrease in their fitness value. If fitness falls below the environmental fitness threshold the nodes exit the environment (dies). The environment sets a global fitness threshold value that is independent of any individual node

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[2] Market structure is not the topology of the supply network. Rather it is the characteristics of the market place or industry the firms compete in.

fitness. It specifies the minimum fitness necessary for a node to survive in the environment. For example, if a firm receives no orders, it will eventually run out of cash and declare bankruptcy, i.e., it "dies".

To summarize, Environment E can be formally defined as the 4-tuple:

$$E = \{V, T, \zeta, \mu\}, E \neq \text{null}$$

where:

V is represented as the 3-tuple:

$$V = \{p, n_1, v \mid p, n_1, v \in R\}$$

p is product price

n_l is number of firms

v is demand volume (v>0)

T is the environmental fitness threshold (evaluation criterion for nodes)

ζ represents the evaluator in the environment (computational component).

μ is a k-tuple $=\{m_1, m_2,.. m_k\}$

$\mathbf{m_k}$ represents environment operational rules.

Node Internal Mechanisms: Nodes (*agents/firms/entities*) represent goal-driven firms in an environment. Every node has a pool of strategies it can use in making decisions to achieve their individual goals. Rules, which operationalize these strategies, are driven by objectives and constraints. An example of a simple objective and constraint for a node is to be a low cost producer while interacting with only one higher-level node. Generally, nodes make two types of decisions, (i) whom to communicate with in the environment (also partly driven by market rules) and (ii) how to strategically decide node specific factors, such as capacity and product price. For example, in the automobile industry assemblers and their suppliers have learned to communicate, and they are driven by internal strategies/policies such as just-in-time or lean manufacturing. These policies dictate the firm's behavior in the supply network and result in connectivity between nodes. Nodes have a fair degree of autonomy in selecting strategies. Decision-making rules used in our research are based on previously described market structure (Shy 1995, Tirole 1989) and Game Theory literature (Osborne and Rubinstein 1994).

Thus an individual node n_i can be represented by a four-tuple

n_i = <O, C, S, F>

where:

O = $\{O_1, O_2, \ldots O_k\}$ represents a finite set of node objectives

C = $\{C_1, C_2, \ldots C_k\}$ represents a finite set of node constraints

S = $\{S_1, S_2, \ldots S_k\}$ represents a finite set of node strategies

f = ~N [μ_f,0.8] represents the node fitness value (μ_f represents average fitness of incumbent nodes).

f is initialized to a random value selected from a Normal distribution with mean value set to the average fitness of the incumbent nodes and a standard deviation (arbitrarily set to 0.8), thus accounting for the birth of both strong and weak firms. Individual node fitness is subsequently updated over time based on a fitness-updating rule built into each node (described later).

In our model, each firm starts with a random selection of fitness value. While this may seem strange, as Utterback (Utterback 1994) points out, in a newly developing industry there is little certainty in determining what is fit and what is not. Hence, we use the surrogate of a random beginning fitness value.

A node is born with an initial fitness and capacity as described by the environment birth rules. The following set of generic rules helps define the behavior of a node (Figure 2).

1. Cost setting rule

According to Industrial Organization theory (Shy 1995), when a node (firm) enters a market, it enters with a certain production capacity (marginal capacity Q) and an associated internal cost structure (marginal cost of production). It has an associated sunk cost (Tirole 1989) (an amount a firm has to invest so as to set up its production capability). The marginal cost of production is typically modeled such that a firm has a certain cost up to its initial plant capacity and if it has to expand beyond that then it incurs a short-term expansion fixed cost (Tirole 1989).

The cost curves can be of different shapes and some examples are shown in Figure 8 below. The curve on the left hand side for example indicates that, up to the marginal capacity Q the firm's marginal cost of production decreases with increased demand (the marginal cost is for fulfilling an incoming demand). But if the incoming demand is greater than Q, then the firm faces a monotonically increasing expansion cost. The right hand side cost structure on the other hand indicates that beyond the marginal capacity Q a firm faces an infinite increase in its expansion cost.

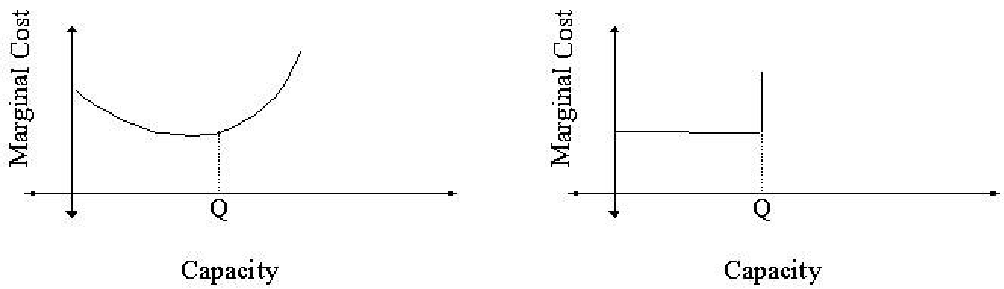


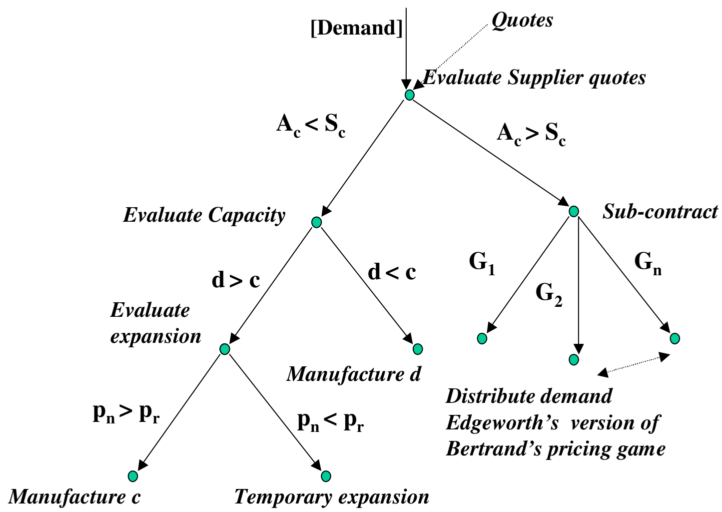
Figure 8: Possible Marginal Cost Structures of a node

2. Bidding Rule

How a node bids depends on two aspects, namely, what role it is playing in the network at that time and the underlying game. As mentioned by Utterback (Utterback 1994), firms in a market develop specialized roles over time. Thus when a node receives a request for proposal (RFP), it only responds to it if it is currently playing that role. A node potentially may play more than one role. The bidding strategy depends on what type of game the node is participating in. For example if, a node is playing a Edgeworth's version of Bertrand's pricing game (Edgeworth 1925), it will try to bid with a price such that it is the lowest bid amongst all supplier bids.

3. Production Rule

As a node receives a demand it decides how much to produce. If the incoming demand is less than a node's capacity, then it poses no problem and the demand is fulfilled. If the demand is greater than the node's capacity then a node can either 1) expand on a short-term basis (it has some fixed costs associated with expansion) subcontract or it can 2) choose to partially fulfill a demand and face the unfulfilled demand penalty (set heuristically in our simulation). The firm, depending on whichever decision leads to greater profits/lower losses, makes the choice. The decision tree representation as shown in Figure 9 depicts a node's response to an incoming demand.



p_n	Penalty of not completing an order
p_r	Expected profit after fulfilling the demand
A_C	Assembly cost
S_C	Subcontracting cost
D	Demand
C	Current Capacity

Figure 9: Decision tree representation of a node's production rule

4. Subcontracting Rule

The sub-contracting rule a node follows depends on the market structure setting. The characteristic of the underlying game is used for defining the node's subcontracting rules. The actual subcontracting rules will vary from industry to industry, depending on the market type, type of competition, and the type of product. Figure 10, shows the decision tree representation for this rule. As a firm gets an incoming demand it sends out a request for proposal (RFP). The exact nature of the RFP is decided by the underlying game and market. For example, in a perfectly completive market structure with n-player cournot oligopoly, a node can request for quantity bids and subcontract to the bidder (single supplier subcontracting) who quotes the highest quantity (at a price fixed by the sub contracting node).

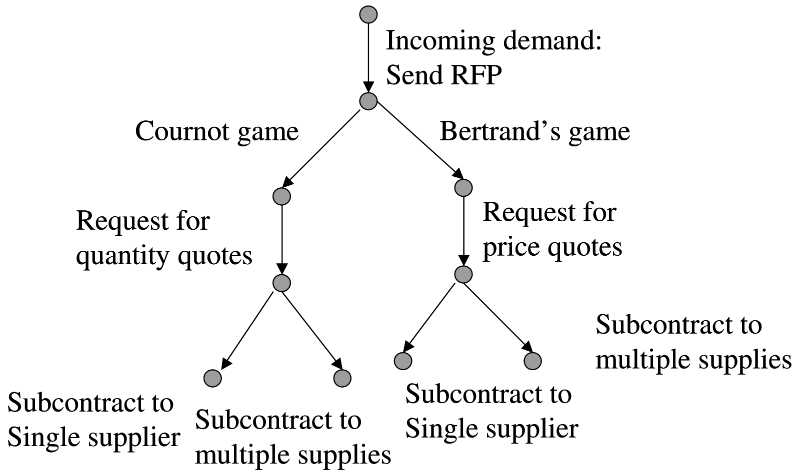


Figure 10: Decision tree for subcontracting rule

5. Capacity expansion/contraction Rule

A unique aspect of the research model is the notion of firm growing in size. This occurs through the process of expansion and contraction of a firm's production capacity (akin to increasing plant size or constructing a new plant). As a firm improves its fitness over time and/or has been doing consecutive short-term expansion, then it may decide to expand its current capacity permanently. To do so it has to make a capital investment that results in a sunk cost. If a node has over capacity (or unused capacity) for successive periods, then it makes loses due to the presence of fixed asset costs such as maintaining an inventory, rent, labor etc. Under such circumstances, a node may want to downsize its current capacity. All capacity decisions impact node fitness.

6. Learning Rules

Firms learn as they interact in a supply network and adapt to the dynamism of the system all the time (Utterback 1994). For adapting to their environments and evolving, firms learn from their interactions with the environment and other firms. To capture such ideas, learning mechanisms are embedded in the behavioral description of each node. Firms in a supply network generally learn from:

1. Changes taking place in the supply network environment (environmental conditions)
2. Effectiveness of the strategies used for supplier selection, bidding etc (node decisions).

A variety of learning models have been suggested, from the fields of artificial intelligence (Mitchell, 1997), computer science (Narendra and Thatcher 1995) and economics literature (Karandikar, et al. 1998, Roth and Erev 1995, Selten 1991). Depending on the industry and the supply network environment, particular learning models can be implemented for defining node behavior. For example, in a growing industry where firms are attempting to establish themselves, firms' start off with generalized roles, typically making everything with internal capacity. Over a period of time, firms' learn the roles they are good at playing and a Roth-Erev reinforcement-learning model (Roth and Erev 1995) can adequately capture such a behavior, where the node associates a propensity with each role it can play. These propensity values then lead to a probability of playing a particular role. As a node grows in fitness while playing a particular role the propensity, and in turn the probability of playing that role, increases. Correspondingly the probability of playing other role diminishes over time.

Fitness

Over time, the fitness value of each node is evaluated and updated based on a fitness function defined for each node. If a node's fitness value falls below the environmental fitness threshold, it dies, and it is removed from the environment. The initial fitness function created is based on simple profit and loss functions, i.e., in a given period; demand unfulfilled by a node is multiplied with a penalty margin (represents the penalty cost) and is subtracted from any profit the node made (demand fulfilled *profit margin). The fitness function also takes into account any inventory and other fixed costs incurred (such as rent, electricity), which is deduced from revenues. Thus,

$F_t = F_{t-1} + \delta_f$, where δ_f is change in fitness in every demand cycle.

$\delta_f = D_f * (P_r - M_b) - (D_u * M_p) - M_f$

where:

D_f is the amount of demand fulfilled

P_r is the price for each unit of demand filled

M_b is the cost per unit

D_u is the amount of unfulfilled demand

M_p is the penalty cost per of unfulfilled demand

M_f is fixed cost (is directly proportional to the inventory capacity)

Due to the lack of any existing fitness model, we use a systematic approach by first considering a fixed fitness threshold for the entire duration of the study. In the future, the evolution of the fitness threshold itself should be studied.

Co-evolution: is the result of the interaction of the other two constructs in the model; it is the network that forms as a result of the interaction between the environment and the internal mechanisms used by the nodes to adapt in this environment over time. The result of such co-evolution, the SN structure, can be viewed as a bi-directional graph, *G,* with nodes representing the vertices and the edges defining the relationships between nodes.

G can be defined as a two-tuple {n, R} such that:

$$n = \{n_1, n_2, \ldots n_k\} \wedge n_i = \{nodes\}, n_i \neq null$$

$$R \subseteq n \times n = \{r_1, r_2, \ldots, r_j\} \wedge r_s = <n_x, n_y>$$

$$\text{Such that, } (n_x, n_y \in n) \wedge n_x \neq n_y$$

R (relationship set) in the graph representation of a supply network captures the pair-wise links between all nodes. It begins as a null set, i.e., no supply network. As linkages between firms in the supply network emerge over time, thus populating the set R. R may also change due to reconfiguration of existing links between nodes. In every demand cycle a new configuration of the network is possible. We do not consider historical relationships between nodes but this should be studied in future research projects.

Based on Utterback's work on industrial growth parameters we are primarily interested in two network growth parameters for commenting on growth phenomenon of SN's. As shown in Figure 4, connectivity in the network provides the information on supply network topologies formed during the growth process. We are interested in both period specific topologies and a time series of the evolution path of the connectivity patterns.

The other macro output parameter we are interested is persistence of individual nodes during the network formation process. By knowing the birth and death time series for node's in an environment we can derive a total mortality profile similar to Utterback's industrial growth curves (Utterback 1994).

Research Methodology

To study the factors affecting the origin, growth and time dependent emergence of supply network structures we have created a simulation model to operationalize the rule framework. Simulation is a widely accepted methodology for studying time varying properties of a system (Zeigler, et al. 2000) and we use simulation to capture node interactions in the supply network over extended periods of time. Output parameters, such as connectivity (network structure) and persistence (population dynamics) computed over time, can then be analyzed in terms of the chosen input parameters.

Structure of simulation algorithm

Figure 11 illustrates the process flow of the simulation. The simulation begins with the environment initializing itself and setting the external system parameters such as the start time of the simulation clock, creating a demand function, activating the evaluator component, and assigning values to all other operational conditions. After this initialization period, an initial number of nodes is generated (birth). The environment then starts a new demand cycle and the evaluator distributes the demand between all the nodes based on node decisions and the market structure settings specified in the environment.

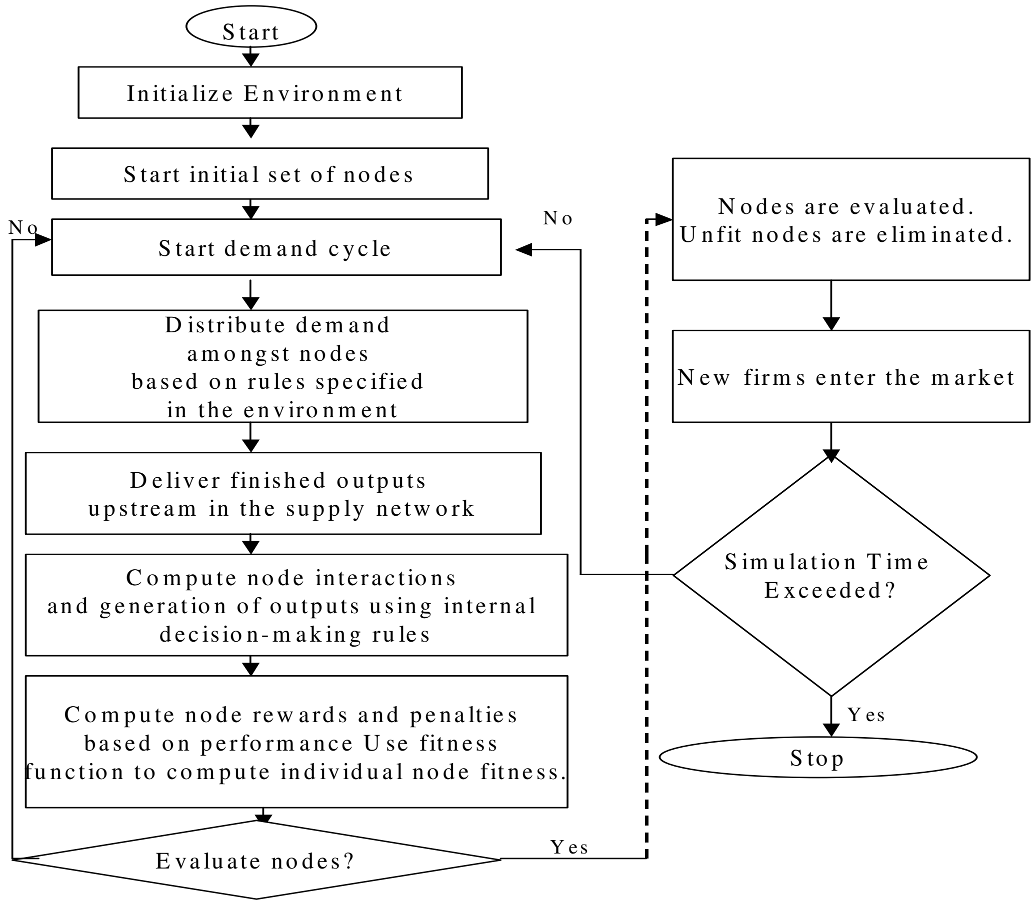


Figure 11: Typical simulation run

The nodes interact amongst themselves driven by their internal mechanisms to fulfill the period's demand. Finished goods are delivered upstream from subcontracting nodes. After profits and losses are calculated for individual nodes, each node updates its fitness value based on its specific fitness function. The evaluator periodically checks the fitness of all nodes in the current population and removes the unfit ones, i.e., those that have fallen below the environmental fitness threshold. Depending on the birth function, new nodes are inducted into the environment. The number of simulation demand cycles is set during the environment initialization process. If the current demand cycle is less than the specified number of demand cycles for the simulation run, the environment continues generating demand.

Since we wish to study the long-term temporal behavior of a system that has both continuous (e.g., demand) and discrete (e.g., node interactions) features, building a multi-paradigm discrete-time (Zeigler, et al. 2000), discrete-event (Cassandras 1993) simulation platform was a logical choice.

The environment generates demand at regular time intervals of 1 demand cycle (discrete unit of time). It also carries out evaluation of existing nodes in the network at a periodic time interval (of say 12 demand cycles). Thus the environment is modeled as a discrete time component. Nodes have a hybrid nature and exhibit both discrete time and discrete event behavior. Inter-node interactions are event driven while fulfilling a demand order; but nodes periodically respond to environmental triggers, such as reporting their fitness (evaluation), or responding to periodic demands.

Operationalization: The CAS-SIM tool suite

To implement the multi-paradigm simulator, we have developed a tool suite called CAS-SIM (Complex Adaptive Supply Networks Simulator) (Pathak and Dilts 2004, Pathak, et al. 2004). This suite adopts an agent-based approach (Ferber 1999) to generate and capture dynamic interactions between nodes and the changing configuration of the network for each demand cycle. Parunak (Parunak, et al. 1998), Kohn et.al (Kohn, et al. 2000), Tesfatsion et.al (McFadzean and Tesfatsion 1999) and some other researchers (Lin, et al. 2002, Zhao and Jin 2000) have successfully used such techniques for other problems. Each node in the model displays a goal directed behavior, and software agents (Ferber 1999) are used to implement this feature. Using a message passing protocol, agents can effectively simulate node-to-node interactions (effectively forming the graph linkages). Also, the software agent architecture supports, group and role modeling. This allows for the development of a range of rich and robust studies, such as studying group behavior of firms in a market, development of specialized roles or role adaptation process of individual firms. The implementation details of CAS-SIM have been discussed in details in (Pathak and Dilts 2004, Pathak, et al. 2004).

Simulating SN growth using data and parameters from the US automobile industry

To demonstrate the capability of the model in aiding decision makers/managers understand supply network growth dynamics, we present the simulation of an actual industry. Utterback (Utterback 1994) has recorded the growth phenomenon of numerous 20th century industries in the US such as the automobile, television, and typewriter industry. For investigating the growth phenomenon in supply networks we have selected the well-documented US automobile industry in the 20th century. In the beginning of the century there were about 5-10 automobile manufacturers (Utterback 1994). The entry barrier to the car market was low and the market itself was not clearly defined. Over time, certain firms developed special roles in the form of assemblers (GM, Ford) and some developed supplier roles (Firestone, Delphi). Today there are few major domestic automobile manufacturers in US, but a large number of supplier firms organized in a multi-level tiered supply network structure. The automobile market grew into a deep hierarchical structure over time.

By illustrating that the simulation results can match reality, the basic validity of the research model will be established. The rule framework can then be used for studying supply networks of different industries. By investigating the effect of different types of "rules" on supply network structures, we hope to shed light on reasons behind the diversity in structure of different real world supply networks around us.

We will test if the origin, growth and emergence of supply networks are due to an interactive effect between environmental conditions and individual node's decision-making rules.

Environment Rules and Conditions for the Automobile Industry

To simulate this industry we need to first identify the basic rules and conditions that drives this industry.

1. Product setting

We use the simplified product architecture for a passenger car shown in Figure 12. The information has been derived from Ford motor company's website. We assume that the three raw materials combine in a fixed proportion to give rise to various parts of a car. Associated with each part is a marginal cost (that includes the assembly cost). Raw material cost is set up as a uniform distribution, thus each firm has a different raw material price and hence marginal costs (see Appendix 7 for actual settings for cost).

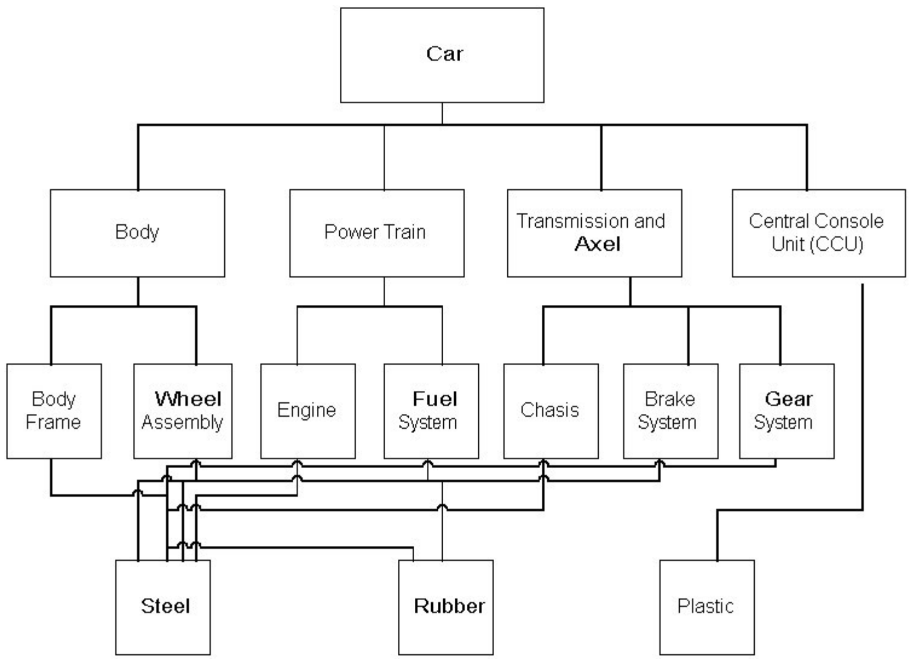


Figure 12: Product Architecture used in the simulation

2. Defining Rules

The rule instantiation for the automobile industry based on the framework is presented in Table 5, Table 6, Table 7 below.

Table 5: Automobile Industry experiment, rule set up

Rule Set Up	
Environment	*Node*

• Free Entry Market
• Imperfect Competition
• Oligopoly
	• Non-linear Cost Structure
	• Role based Bidding
	• Bertrand's pricing game
	• Production (based on sunk cost and penalty)
	• Fitness based capacity expansion and contraction
	• Learning
	    • Aspiration based Price learning
	    • Propensity based Role Learning

Table 6: Automobile Industry experiment, parameter settings

Parameter Settings			
Factors	*Levels*	*Values*	*Remarks*
Initial Number of Nodes (N)	2	5,10	Based on Utterback's work, the US Automobile industry started with firms between the numbers 5, 10
Environmental Fitness Threshold (T)	2 (Low, High)	0.25, 3.0	Due to the lack of an established measure we are assuming a low and high fitness threshold
Capacity Expansion (CE)	2 (Slow, Fast)	6 demand cycles (expansion rate)/6 demand cycles (contraction rate), 6 demand cycles (expansion rate)/12 demand cycles (contraction rate)	Firms expand their capacity based on their performance in successive demand cycles. Thus 6/6 indicates, that a firm will expand its current capacity by a fixed margin if it had made profits in previous 6 demand cycles and so on. Again the values are essentially heuristics.
Role Learning (R)	2 (Low, High)	0.40, 0.15	Again we use heuristics for selecting low and High values. We essentially use a Roth-Erev propensity based learning model for modeling Role learning in individual firms and closely spaced propensity values for different roles result in High role learning.
Demand	NA	Normal distribution with increasing mean (Ward's automotive report, 2002)	We use actual demand data from last 80 years in the US automobile industry.
Periodicity of evaluation	NA	Every 12 demand cycles	Annual evaluations, each demand cycle corresponds to a month
Individual Node Fitness	NA	To begin with mean is set to 0.5 with a arbitrarily high standard deviation of 0.8	Sampled from a Normal distribution with average fitness of incumbent nodes as the mean.
Total time of simulation	NA	960 demand cycles	Corresponds to 80 years (12 months *80 years= 960 demand cycles)

Table 7: Automobile Industry experiment, List of experiments

List of Experiments		
1.	a. Initial number of nodes N=10 b. Environmental threshold (T)=0.25 (Low), 3.0 (High), c. Capacity Expansion (CE) Slow (expansion after 6 positive growth cycle and contraction of capacity after 7 negative growth cycles) Fast (expansion after 6 positive growth cycle and contraction of capacity after 12 negative growth cycles) d. Role learning propensity (R) Low (difference between manufacturer role propensity and supplier role propensity initially set to 0.15: heuristics) High (difference between manufacturer role propensity and supplier role propensity initially set to 0.4: heuristics)	Full Factorial Design: 8 experiments (30 samples each)
2.	a. Initial number of nodes N=10 b. Environmental threshold (T)=0.25 (Low) c. Capacity Expansion (CE) Uniformly vary from Slow to Fast: 6/6, 6/9, 6/11, 6/12 d. Role learning propensity (R) High (difference between manufacturer role propensity and supplier role propensity initially set to 0.4: heuristics)	Sensitivity analysis

3. <u>Output Parameters</u>

The primary parameters that will be recorded during the simulation experiments are node mortality, the demand profile and the node capacities over time (persistence parameters) along with structural growth of the SN (connectivity time series).

4. <u>Experiments</u>

Based on Utterback's work on the automobile industry (Utterback 1994) we selected four factors: two environmental settings (initial number of nodes, Environmental threshold) and two node behavioral rules (Capacity expansion of individual nodes, Role learning) that are assumed to have affected the growth process in the automobile industry significantly. As shown in Table 5, Table 6, Table 7 each factor has two levels thus giving rise to 16 possible experiments. Initial experimentations with initial number of nodes (5/10) did not yield any significantly different system behavior. In subsequent experiments we started with 10 initial nodes. This reduced the number of experiments to 8 (collecting 30 samples for each experiment). In this paper we present results from these set of experiments (240 samples in total) (shown in Table 5). We further experimented with the sensitivity of the capacity expansion (CE) parameter on the overall system behavior.

Results and discussion

We observed similar growth trends in our SN simulations as Utterback's empirical results on the automobile industry. We observed the following results:

Connectivity Patterns (Supply Network Topologies)

We use a novel categorization scheme based on network theory, graph theory and SN literature to come up with a classification scheme for SN structures as shown in Table 8.

Table 8: Categories of SN structure

SN Structure category	Graph Theory classification	SN Structure description
0- No Structure	No edges are formed in the graph	No SN is formed as no firms are willing to play the role of a manufacturer
1- Star	Maximum depth of 1	No tiers exist, every firm is a manufacturer (Dell)
2- Linear	Maximum in and out degree of 1 for any node in the graph	Multiple tiers exist but every firm has exactly one supplier below it (Petroleum Industry).
3- Heterogeneous	Tree/ directed acyclic graphs (DAG), with max depth of 1	Multiple manufacturers multiple supplier SN, with depth of 1 (Florist)
4- Hierarchical	Tree/ directed acyclic graphs (DAG)	Manufacturers and multiple tiers assembling one common product (Automotive Industry)
5- Federated	Ring topology	Every firm plays a dual role of manufacturer and supplier (Hoteling SN)
6- Starburst	Tree/ directed acyclic graphs (DAG)	Same as hierarchical except usually such a network deals with a very dissimilar set of products usually a group of them (Film Production)

We observed the three types of structure for the supply network that is so widely accepted in the literature. But along with the hierarchical structure we also observed two different types of network topologies; namely, star shaped (One single manufacturer/consumer and a single tier of suppliers) and linear supply network topologies (multiple tiers in the network but maximum out degree of the graph is 1) (See Figure 3 in Chapter II).

We went a step further and plotted a categorical time series that illustrates the evolution of the topologies for different values of capacity expansion parameters (sensitivity analysis). We observed that the capacity expansion and contraction rate changed for individual firms the topology evolution pattern changed (Figure 13). When firms were allowed to expand fast and contract slowly, the network quickly settled into a star shaped structure and remained there (time series in Figure 13 with CE =6). This made sense because as the market demand grew, existing firms matched demand resulting in a stable supply network. But as the expansion rate slowed, some firms could not grow their capacity (time series in Figure 13 with CE =9, 11 and 12), which in turn reduced their fitness in the role of a manufacturer and finally forced them to start adapting to other roles (due to the role learning effect). This resulted in the formation of both linear and hierarchical topologies. Linear and hierarchical networks were more prone to market demand which leads to the topology changing with time as shown by the oscillatory patterns (Figure 13).

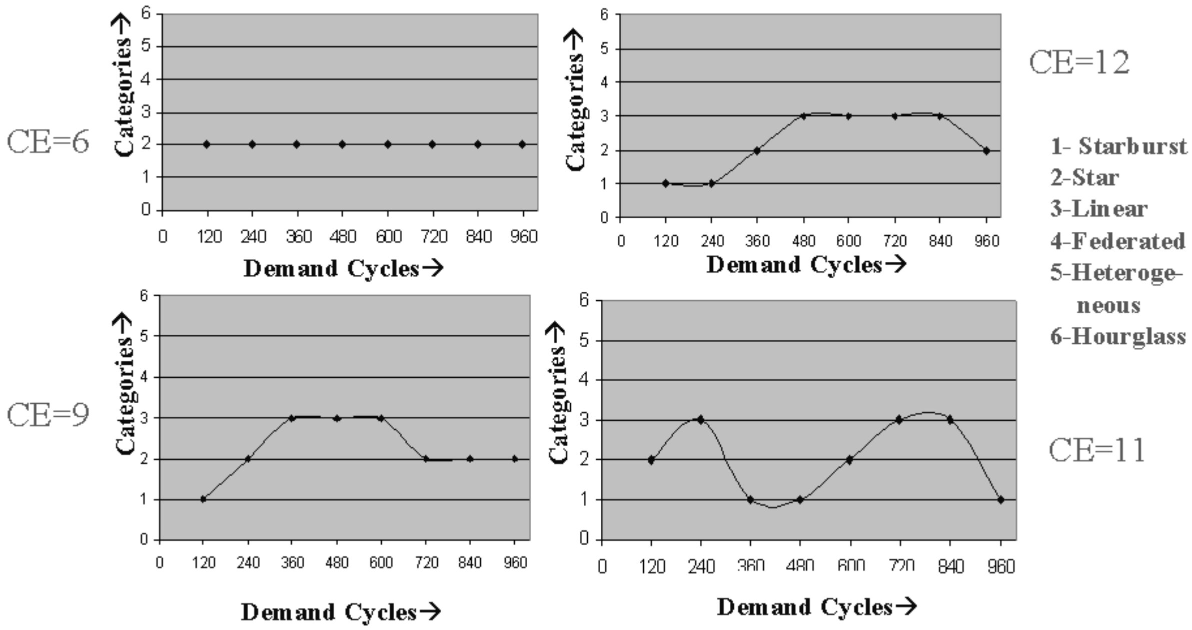


Figure 13: Connectivity Time series (Network Topology evolution)

The research implications of these results definitely suggest that Supply Networks are Complex Adaptive Systems (CAS) as the network evolves based on underlying interaction of rules and conditions. The evolution path changes according to changing conditions (for example the varying of capacity expansion parameter) in a non-deterministic yet ordered manner. As a manager, having such information about the sensitive dependence of your network on underlying parameters can be important. For example, by knowing the effect of changing capacity expansion/contraction on the network topology a manager can choose whether to expand or contract, and if so how fast or slow should the firm proceed.

The other interesting aspect of the topology evolution results are that it shows which kind of SN structure is suited for a particular set of conditions. Such kind of knowledge can be immensely beneficial as has been shown by companies like Dell Computers (Dell operates on a star topology) (Simchi-Levi, et al. 2000). Before Dell came in the market the PC industry was much more hierarchical. Dell came in with a star topology and the change worked very well. On the other hand some topologies may be best suited for the current conditions and that it should not be changed. The US automotive industries (COVISINT) effort of changing from a hierarchical to star like topology is a classic example of a failed design effort (Joachim and Moozakis 2001).

Analysis of the 240 samples with respect to the type of structures formed yielded some interesting observations. Figure 14 clearly suggests the effects of the three independent variables. For example, under low environmental threshold conditions, 48% of network topologies formed are star shaped networks. The same number drops down to a mere 2.5% when the environmental threshold is high. The explanation for this observation is intuitive as low environmental thresholds create an easier environment for firms to survive and establish themselves. In the process, they can achieve higher profits by in-house development and, hence use less subcontracting.

When the environment threshold is higher (indicating a tougher environment to survive in), firms are willing to experiment with newer roles, and, in the process, subcontracting occurs and tiers in the network are formed. This is the reason for 53% of the structures formed under higher environmental threshold condition having hierarchal topologies.

We also observed that in some simulations no supply networks were formed, as no single firm was willing to play the role of an assembler. This usually resulted in many firms playing the suppliers role in the environment but no one actually getting the incoming demand, which is for cars and not for sub-parts. While one may argue that such a condition may never happen in the real world, as some firm will always step in to play the role of an assembler, a simulation environment illustrates the dynamic landscape through which a supply network evolves. From a policy makers perspective, having such knowledge that the current conditions in the environment may lead to periods with no clearly defined leader may be beneficial information for establishing dominance and capturing the market.

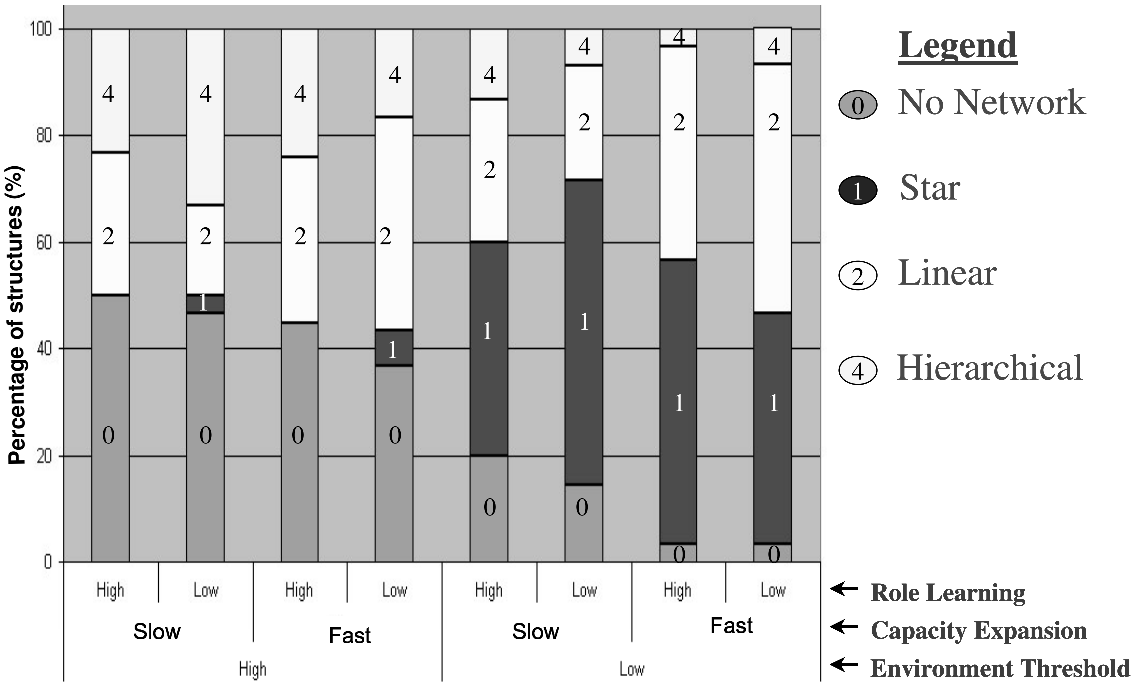


Figure 14: Types of topologies observed for all the 240 samples [3]

Persistence Patterns (Total mortality)

We plotted the total number of nodes present in the network over the entire duration of the simulation. The resulting plot was similar to the skewed bell shaped curve as predicted by Utterback (Figure 15). Thus we observed the classical pattern of entry of numerous firms during the initial growth phase of the market, but as the market stabilized, firms that did not adapt their roles and increase their fitness, were eliminated. As time passed, existing firms grew their capacities to meet the market demand and fewer firms entered the market to become part of the supplier network.

[3] There were no category 3 (heterogeneous) structures were observed, hence the figure has category o, 1, 2 and 4

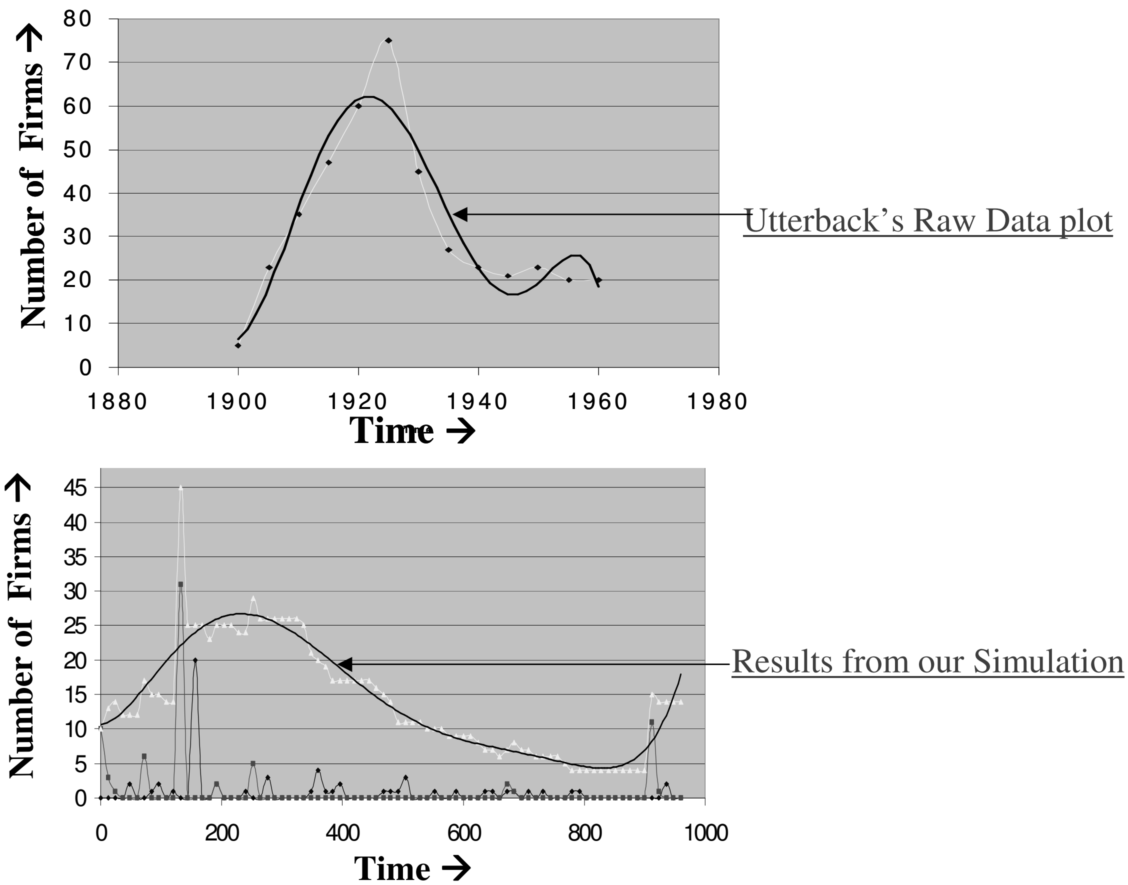


Figure 15: Supply Network Growth Curve comparison with Utterback's ideal growth curve

Bimodality of SN growth curve

Surprisingly, the sensitivity analysis experiments (see Table 5) showed that SN's are very sensitive systems as seen from the resultant plot of the population dynamic curves (Figure 16). As the Capacity Expansion (CE) parameter was systematically changed the population dynamic curve (shown by the black line) significantly showed different evolving pattern and modes. Unimodality of the growth curve was no more a foregone conclusion; there were multi-modalities.

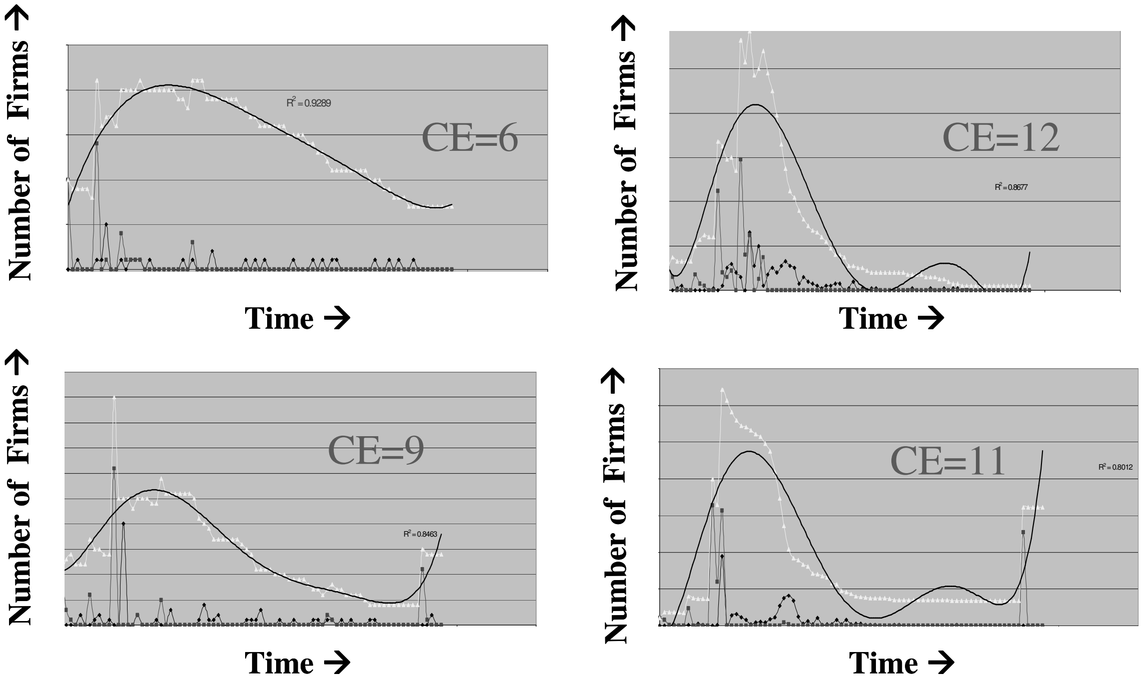


Figure 16: Node Mortality Profiles (also presented in Chapter II)

Looking at Utterback's data (Figure 15) confirmed that multi-modalities were not an artifact of the simulation. Utterback's raw data actually shows a mode at around the year 1950 right after the World War II period. We further investigated our simulation results paying close attention to the actual growth process. The answer lay in the capacity expansion/contraction of individual firms. We found out that if an existing incumbent in the market dies and the remaining incumbent firms do not expand fast enough to fulfill that demand, then new firms join the market, giving rise to multiple modes over periods of time. This is akin to saying that if Daimler Chrysler went broke today and GM and FORD do not step in to fulfill the demand then newer, smaller firms would enter the US automotive markets to capture the demand.

The managerial implications of this result are significant. Utterback presents his data for a period of about 60 years. We have simulated SN growth using data and parameters from the US automobile industry for an 80-year simulation time frame. Some of the dramatic increase in the number of firms towards the end of the simulation as shown in Figure 16 (Capacity Expansion factor CE=11), implies that long-term behavior of supply network systems can be dramatic and very sensitive to parameter changes. Assuming static network structures without understanding the effects of individual factors and their combined effect on the resulting supply network, can lead to misleading results.

Predicting system evolution trajectory

One of the benefits of the unified model is the possibility of using established analysis tool sets from CAS and Network theory for analyzing and predicting growth behavior of supply networks. One such analysis technique is the reconstruction of attractors (Schuster 2001) in a system. Attractors can be reconstructed (Williams 1997) by plotting the number of nodes present in one time cycle with respect to number of nodes present in the next time cycle. We reconstructed the attractors for the four sensitivity analysis experiments (see Table 5). Figure 17 clearly shows an attractor for all the cases, as the plots seem to follow an oscillatory and cyclic pattern. For example with CE =11, it is clearly visible that the system trajectory oscillates around a fixed attractor. Such kind of analysis can show a manager the possible evolutionary path of the supply network system. A manager can utilize such knowledge to make strategic long-term decisions as to whether to enter a new market or exit a market.

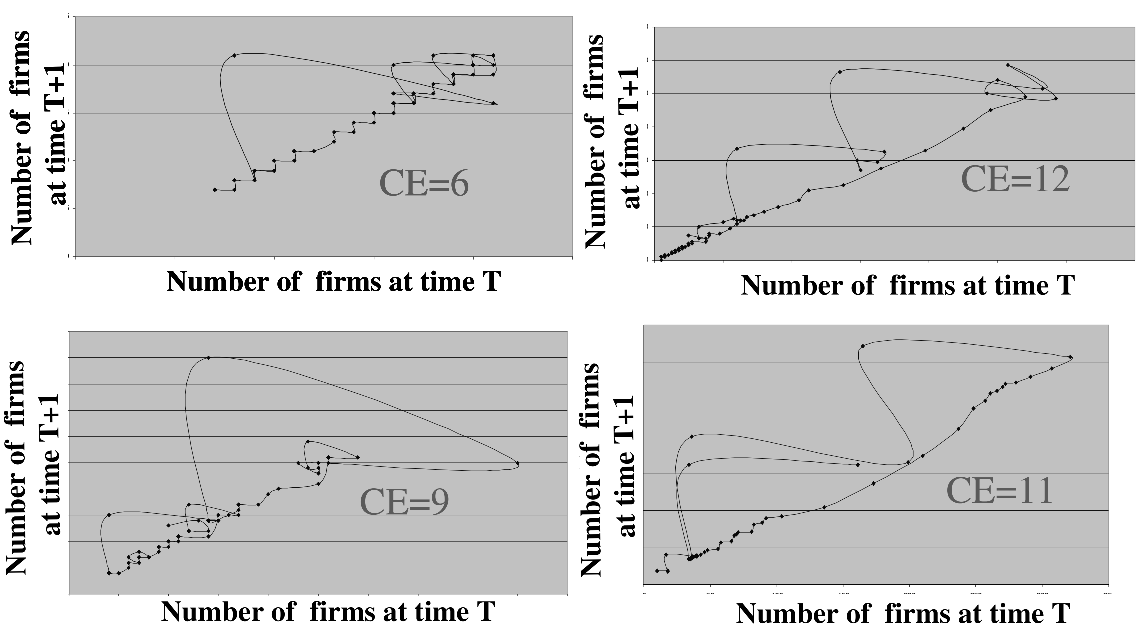


Figure 17: Attractor reconstruction as a predictive tool aiding in policy decisions

Getting back to our original research question, we have been able to show that growth in SN is not due to just environmental factors or the decision making process of individual nodes alone; both combine and thus growth is a co-evolving process.

Conclusion and Future Work

In this new era of fast changing technology and complex market dynamics, it is becoming more and more evident that managers are not adequately informed about the systems (SN) they manage (Lee 2004). We have taken a novel approach of looking at SN's from a growth perspective and use UMSN. We present a rule based implementation framework based on the unified model that can capture real life supply networks. We use an agent based simulation model to capture the growth dynamics and helps in creating an investigative framework that will allow decision makers/policy makers to capture rules governing their system and study the impact of these various rules and conditions over an extended period of time. We have not only been able to match the existing industry structure and growth characteristic but also been able to provide insight on how these systems grow based on the co-evolution process of both environmental factors as well as local decision-making rules.

In future, we will be characterizing multiple industries. We are currently in the process of statistical characterization of the full factorial design experiment on the automobile industry experiment data and hope to add formal chaos theory analysis so as to make our model predictive.

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CHAPTER IV

ANALYZING THE EMERGENCE OF COMPLEX ADAPTIVE SUPPLY NETWORKS

Abstract

Lately researchers have acknowledged the need to research supply networks in order to find out how they grow and evolve as a complex adaptive network with time. This paper uses the unified model of supply network in conjunction with the generic rule-modeling framework (see Chapters II, III) for investigating the growth dynamics in SN's using data and parameters from the US automobile industry over the last 80 years. The approach taken is inductive in nature where in we use a simulation-based environment to grow supply networks over time, observing patterns of emergence. Using rigorous statistical analysis on the simulation result data, we show how an industrial supply network grows and emerges. The paper reports our simulation findings presenting evidence for SN's complex adaptive system nature. Significant ordered interactions between local behavioral rules and conditions were observed to be present in supply networks, which seem to control the growth in such system. Especially parameters such as capacity expansion of individual firms, the type of environment (easy to live/harsh) and ability of a node to learn new roles, showed significant ordered interactive effects, while affecting the type of SN structure formed as well as the population dynamics over time. The paper discusses the ramifications of the simulation results in the general context of managing a supply network and provides insights for managers and decision makers.

Introduction

The recent rise of firms like Google (Barabâasi 2002) and Dell (Simchi-Levi, et al. 2000) in the last decade, the dotcom meltdown (Joachim and Moozakis 2001), and the most recent exit of IBM from the PC industry (Bulkeley 2004) all hint at underlying dynamics of an ever-changing industrial environment. Supply Networks (SN) form the backbone of any industry (Simchi-Levi, et al. 2000) and hence are equally affected by the dynamic events occurring in the environment. In this paper we address one of the most important questions with regards to SN dynamics and emergence that has been focused on lately in the Supply Network (SN) literature, i.e., how do supply networks grow with time? We present detailed simulation based computational experiments and analysis that helps in identifying the factors controlling the growth process in supply networks. We discovered that SN's grow based on an ordered interaction of a very few local behavioral rules in the system. There are clear benefits of having information on what these rules are and in what order do they combine, from a practicing managers/decision maker's point of view; such information would allow them to manage critical parameters and be more efficient while managing their Supply Networks, (Harland, et al. 2002).

Past research in the area of supply network has largely focused on issues of supply chain design, purchasing, buyer-supplier relationship, and use of information technology for inter-firm dyadic relationships (See (Choi and Liker 2002) for an overview of these areas). More recently, researchers have acknowledged the need for investigating supply network as a system (Choi, et al. 2001, Choi and Hong 2002) comprising of complex bi-directed networks, having parallel and lateral links, loops, bi-directional exchanges of materials money and information. A system level view of supply networks encompasses a "broad strategic view of resource acquisition, development, management and transformation" (Harland, et al. 2002) and helps in understanding how these different components interact to give rise to an overall SN system behavior.

Our previous research developed a unified model of supply networks (see Chapter II) that borrows from four different theoretical lenses, namely, Industrial growth theory (Utterback 1994), classical network theory (Newman 2003), market structure theory (Shy 1995), (Tirole 1989), game theory (Osborne and Rubinstein 1994) and complex adaptive systems theory (Schuster 2001), (Kauffman 1995), (Holland 1995). The model encompasses a system view, and provides a framework for investigating and understanding the structural and behavioral dynamics of SN systems.

The focus of this paper is to present the analysis of the dynamic emergence process that can be observed during the simulation of an industry such as the US automobile industry (presented in Chapter II). We use statistical techniques such as linear multivariate analysis, and multivariate analysis for categorical data (Agresti 2002) to look for interactive effects and factors controlling growth and emergence in the SN systems. We draw general conclusions from these analysis results and show how SN's emerge.

Background

We start this section by presenting the general research approaches that have been used for investigating dynamics in SN's arguing for the need to take a different research approach to study growth in SN's. Based on this discussion we highlight the limitations of existing SN models and motivate the need for a new theoretically grounded model of growth oriented SN's.

Deductive versus Inductive research methodology

Most of the recent research in the area of dynamic SN models, have taken a deductive approach (Choi, et al. 2001, Choi and Hong 2002, Harland, et al. 2002). Usually this approach starts by suggesting a theory, building hypotheses, making observations and confirming the observations by various statistical and logical analyses (Trochim 2001). For example, Choi et.al (Choi, et al. 2001), use Complex Adaptive System theory (Schuster 2001) to represent SN as a dynamically emergent system. They then suggest propositions on how individual firm's behave based on this theoretical framework. Subsequently they follow up with an empirical study in the automobile industry and try to confirm their hypothesis. One of the fundamental issues with such an approach is that the hypothesis building is meaningful only when the underlying domain is well known. Since the emergence (dynamic growth of patterns) phenomenon in any system is actually non-deterministic, we feel a deductive approach is limited in its ability to efficiently explore the entire range of possibilities driving the emergence dynamics of SN's.

We suggest an inductive approach towards finding a solution to the research questions (Trochim 2001). We start by making observations and identifying patterns of system behavior (in this case the dynamic emergence process of SN). We then build tentative hypothesis, which can lead toward theory development. For example, in this paper we present our simulation results (observations and patterns) using data from the US automobile industry. We then suggest possible propositions based on these results and build logical inferences to explain possible system behavior. Such an approach is inherently well suited for a problem of this class, where the underlying information about the domain is sparse. This inductive approach allows for the systematic investigation of the actual process driving growth in SN's.

Existing SN Models

Static models

Historically supply networks have been viewed as centralized static networks (Parunak, 1998) and most work done in this area (Burns and Sivazlian 1978, Forrester 1961, Ho and Cao 1991, Pyke and Cohen 1993, Riddalls, et al. 2000, Towill 1991) has focused on simplified, linear flow models of material, money and information (Harland, et al. 2002). These approaches typically assume a static supply network structure and concentrate on optimizing the flow within the network; hence they are unable to model the evolving structural dynamics of a supply network, which are essential for understanding the growth and evolution phenomenon. More recent approaches using agent-based modeling of SN's also make this same assumption (Kohn, et al. 2000, Lin, et al. 2002, Swaminathan, et al. 1997, Zee and Vorst 2005). This inherent assumption of a static network structure is limiting when studying evolutionary dynamics of supply networks, when the number of firms and the linkages between firms do not remain constant over time.

Dynamic Models

More recently Choi, Dooley and Rungtusanatham (2001) suggested a conceptual model of supply network as a complex adaptive system. Their model of supply network as a CAS considers firms in a supply network as agents driven by simple operating rules and fitness criterion. The agents interact between themselves to co-evolve into emerging supply network structures.

The Choi model, though a right step forward towards developing a system-oriented model of supply networks is a very high level model, as it does not specify how the behavioral rules for the agents can be modeled. It is not clear how to exactly characterize different environments for a wide range of supply networks.

Follow up studies by Choi and Hong (Choi and Hong 2002) and Harland et.al (Harland, et al. 2002) have taken the deductive approach to identify key factors driving the dynamics of SN's in the US automobile industry and the telecommunication industry in UK. These studies have essentially suggested that there are interactive effects in a SN environment that affects the growth process. But these studies suffer from the same problem that any deductive approach may have: Since the information about the underlying domain is sparse to begin with, results obtained from these models may not be representative for a general SN. Yet we think that the fundamental concept behind these models (considering a completely dynamic system) is a sound approach and we later suggest an alternate way of solving the problem.

Emergent System Models

A third body of research that does not directly deals with SN's yet is important to consider is the emergent system research. Researchers from diverse disciplines as physics (Per Bak, Tang et al. 1988), computer science (Holland 1995), network growth theory ((Newman 2003), for an excellent review), economics (Arthur 1999), and biology (Kauffman 1971), (M.Eigen 1971), (Neumann 1949) have suggested growth models to explain the diverse emergence phenomena in real world systems. These models suggest that real world systems are non-static, constantly growing and evolving over time. The growth and emergence process is governed by simple interaction rules between the entities in the system. Unfortunately none of these models can help with the actual rule modeling process in SN's. The primary difference between these emergent systems and SN's are that the SN rules are much more strategic and Darwinian in nature, with the growth and evolution process being composed of 1) birth and death of firms, 2) growth of capacity and fitness of a firm to play a specific role in the SN, 3) creation and deletion of linkages between firms in the SN, and 4) reconfiguration of the existing linkages as the environment changes.

So briefly summarizing, we observe that past SN modeling approaches are limited due to their static or their deductive nature, whereas the emergent system models cannot help with modeling rules and conditions associated with SN's. The next section thus discusses the, unified model of supply network that borrows from some of these past works and presents a holistic and comprehensive platform that can help us in addressing the research questions.

Modeling Emergence in Complex Adaptive Supply Networks

The unified model of supply network (UMSN) suggests that growth and evolution in SNs, are governed by simple fundamental rules, that can give rise to patterns of emergent behavior. The UMSN combines four existing theory bases to provide a theory-based platform for modeling growth oriented supply networks (see Chapter II for detailed description). Industrial growth (IG) theory (Utterback 1994) helps in defining growth by specifying how firms are born and how they die in an evolving industrial landscape. The IG theory does not suggest an exact representation such that it can be used in a computational model. Network growth theory, fulfills this void by representing a supply network as a bi-directional graph, with vertices representing firms in the graph and the links representing relationships between firms. Network growth theory also suggests the general concept of preferential attachment rules (PA) (Barabâasi 2002), by which nodes in a dynamic network link to other nodes. For the SN domain we use a market structure theory and game theory lens to manifest PA. Market structure and game theory (Osborne and Rubinstein 1994, Shy 1995), defines the type of market, type of competition, internal node behavioral rules such as bidding rules, subcontracting rules and cost set up rules. But this lens does not specify how the SN as a system evolves and emerges with time. Complex Adaptive System (CAS) theory (Holland 1995, Kauffman 1995, Schuster 2001) lens defines SN as a system comprising of simple entities, driven by the PA rules. By representing SN as a CAS we can utilize the vast array of modeling and analysis techniques in chaos theory and other emergent systems research (Williams 1997) for investigating dynamic network growth.

Conceptual Model

Conceptually (Figure 6) we model a supply network as a system consisting of two fundamental components: (1) an environment or a market in which (2) a group of firms (nodes) reside and interact to fulfill global demand. Stochastic environmental conditions such as a variable demand pattern, firm decision-making (subcontracting, bidding), and differential growth of firms (growth in capacity, fitness of firms etc), all contribute towards structural as well as behavioral dynamics in the resulting supply network (see Chapter III for detailed description).

In addition to this, we model the notion of "fitness". Firm fitness is similar to the idea of fitness of genes in a gene pool as suggested by Kauffman (Kauffman 1971). Fitness of a firm can be a multi-dimensional parameter. We model initial fitness as a uniform random value that a node in our model starts with and subsequently the change in fitness is a two dimensional function of profit and capacity. A firm in our model can increase its fitness by making more profit and can lose fitness by either suffering a financial loss or due to short term/long term expansion in their current capacity (akin to sunk cost). The fitness value of a node is evaluated and updated based on a fitness function defined for each node. The fitness function is based on simple profit and loss functions. In a given period, demand unfulfilled by a node is multiplied with a penalty margin (represents the penalty cost) and is subtracted from any profit the node made (demand fulfilled *profit margin). The fitness function also takes into account any inventory and other fixed costs incurred (such as rent, labor) and subtracts it from the overall profit. The fixed cost in the current model is operationalized by making it directly proportional to a node's current inventory level.

Thus,

$F_t = F_{t-1} + \delta_f$, where δ_f is change in fitness in every demand cycle (can be negative).

$\delta_f = D_f * (P_r - M_b) - (D_u * M_p) - M_f$

where:

D_f is the amount of demand fulfilled

P_r is the price for each unit of demand filled

M_b is the cost per unit

D_u is the amount of unfulfilled demand

M_p is the penalty cost per of unfulfilled demand

Mf is fixed cost (directly proportional to a node's inventory level)

Due to the lack of an existing fitness model, we take a systematic approach by first considering a fixed fitness threshold for the entire duration of the study. In the future, the evolution of the fitness threshold itself should be studied. If a node's fitness value falls below the environmental fitness threshold, it is removed from the environment; it dies just like in an actual supply network where, if a supplier cannot meet financial obligations, they cease to exist.

Generic Rule Modeling Framework

The fundamental approach of any CAS based research is to identify the simple set of rules and conditions that interact to give rise to dynamic system behavior (Kauffman 1995). The UMSN builds around two fundamental entities; i.e., environment and the firm. We have developed a generic rule-modeling framework that can be used for characterizing the behavior of these two entities in a generic SN system. We provide a brief outline of the fundamental rule categories for these two entities in this paper. For details on the definition and implementation please see Chapter III and Appendix A.

Environment: is where firms in a supply network reside. Based on Industrial growth theory ((Utterback 1994) and market structure, game theory (Osborne and Rubinstein 1994, Shy 1995, Tirole 1989), there are five basic rule categories that help us to model a wide range of supply network environments:

Rule 1-- Type of market: - Whether a firm's entry into the market is controlled by a regulatory body (regulated market) or is an internal decision of the firm (free market).

Rule 2-- Type of competition: - Whether firms compete on quantity (perfectly competitive market) or price (imperfectly competitive market).

Rule 3-- Type of market structure: - Whether the market is set up as a monopoly, duopoly or a oligopoly. In case of an oligopoly, whether the market is a cooperative or non-cooperative one.

Rule 4-- Birth/Entry of firms into market: - How new nodes are born over time? Driven by fundamental microeconomic theory, if there is unfulfilled demand in the market new firms enter the market.

Rule 5-- Death of incumbent firms: - How incumbent nodes die? Driven by CAS theory, if node's fitness falls below environmental threshold then it is eliminated from the SN.

Firms: Firms are goal-driven entities in a SN environment. Every firm has a pool of strategies to use in making decisions to achieve their individual goals. Rules, operationalize these strategies. Behavioral rules for individual firms are based on previously described market structure (Shy 1995, Tirole 1989) and Game Theory lens (Osborne and Rubinstein 1994). There are six fundamental rule categories for firms (for details see Chapter III, V and Appendix 1):

Rule 1-- Internal cost set up: - This rule sets the internal cost structure of a firm. A firm has a marginal cost of production and a fixed cost for expansion.

Rule 2-- Bidding: - This rule defines how a node bids. For example, if a node is in a perfectly competitive market playing a n person cournot oligopoly, then it bids with the highest quantity (based on Cournot's quantity setting game), it can produce.

Rule 3-- Production: - This rule defines how a node behaves when faced with an incoming demand. An example of a production rule can be, that a firm produces upto its marginal capacity and subcontracts the rest to a supplier.

Rule 4-- Subcontracting: - This rule defines how a node subcontracts an incoming demand to its suppliers. Subcontracting rule is again driven by the underlying game being played by the node. For example, in the cournot oligopoly mentioned above, a subcontracting node can subcontract the demand to a supplier and set a price depending on the quantity being supplied.

Rule 5-- Capacity growth: - This rule defines how a node increases its internal capacity. We implement a simple "sense and respond" mechanism. A node monitors its fitness growth over time. If the node increases its fitness for a predetermined number of demand cycles then it expands the current capacity. Conversely, if the node does poorly for a predetermined number of demand cycles it contracts its capacity in order to reduce fitness loss due to fixed costs.

Rule 6-- Learning Rules: - This rule defines how nodes in our model learn and adapt over time. Nodes learn primarily on two fundamental aspects (as identified by Utterback's work) currently. They learn how to adaptively price their product and they learn which role to play in the current environment. We use an aspiration satisficing based price learning mechanism (Karandikar, et al. 1998) and a reinforcement learning mechanism (Roth and Erev 1995) for learning roles (see chapter III for a detailed discussion on why these learning models are suitable for this purpose).

Research Methodology

While it would have been ideal to actually observe a SN grow and emerge over time such a live testing is not possible due to limitations in terms of cost, and time. Simulation is a widely accepted methodology for studying such systems (Anderson 1999, Kamps and Masuch 1997, Zeigler, et al. 2000). Simulation provides insight, focuses efforts, eliminates large areas of the possible solution space, and helps in analyzing the system behavior.

Since we wish to study the long-term temporal behavior of a system that has both continuous (e.g. demand) and discrete (e.g. node interactions) features, building a multi-paradigm discrete-time (Zeigler, et al. 2000), discrete-event (Cassandras 1993) simulation platform was a logical choice. In the multi-paradigm architecture, some of the components of the model, such as the environment, fit a discrete time modeling (DTS) paradigm since the environment generates demand at regular time intervals of 1 demand cycle (discrete unit of time). The environment also carries out evaluation of existing nodes in the network at a periodic time interval (of say 12 demand cycles). Thus environment is modeled as a discrete time component. Nodes have a hybrid nature and exhibit both discrete time and discrete event behavior. Inter-node interactions are event driven while fulfilling a demand order; but firms periodically respond to environmental triggers, such as reporting their fitness (evaluation), or responding to periodic demands.

Furthermore, because each node in the operational model displays a complex goal directed behavior, software agents (Ferber 1999) are used to implement this feature. Agent based modeling techniques have been successfully used for modeling supply networks in the past (Kohn, et al. 2000, Lin, et al. 2002, Swaminathan, et al. 1997). To implement the advanced multi-paradigm simulator, we have developed a tool suite called CAS-SIM (Complex Adaptive Supply Networks Simulator) (Pathak and Dilts 2004).

Simulating Emergent Behavior

For investigating the interactive effects of local node and environmental rules on the growth of supply networks we use data and parameters from the US automobile industry in the 20th century. The primary reason for selecting this industry was its very well known emergence pattern over the last 80 years (Utterback 1994).

In the beginning of the century there were about 5-10 automobile manufacturers (Utterback, 1994). The entry barrier to the car market was low and the market itself was not clearly defined. Over time some firms developed special roles in the form of assemblers (GM, Ford) and some developed supplier roles (Firestone, Delphi). Today there are few major domestic automobile manufacturers in US, but a large number of supplier firms organized in a multi-level tiered supply network structure (Parunak and Vanderbok 1998). The automobile market grew into a very deeply hierarchical structure over time.

We used a simplified product architecture (see Figure 12 in Chapter III) for a passenger car with information derived from Ford motor company's website. For details on the product architecture design and associated marginal cost settings, please see Chapter III and Appendix G.

Instantiating the Rule Framework for the US Automobile Industry

Table 9 and Table 10 summarize the rule instantiation of the generic rule-modeling framework. We use the same basic rule categories described in the previous section. The settings are derived from Utterback's empirical research on the US automobile industry in the 20th century (Utterback and Suarez 1993, Utterback 1994).

Table 9: Rules/condition Instantiation for Environment

Environment rules	Rule Setting
Type of market	• Free Entry
Type of Competition	• Imperfect competition
Type of market structure	• Non-cooperative simultaneous Bertrand's pricing game (Edgeworth's version, with capacitated firms)
Birth/Entry into market	• If there is unfulfilled demand in the environment, new firms are born. Firms enter the market if they have a higher fitness than the weakest incumbent node after initial sunk cost adjustments (see Chapter V for details on this rule).
Death/Exit from market	• Firms die if over a period of time they cannot grow their fitness above the required environmental threshold. We use two different settings for threshold. High threshold (Harsh environment) and low threshold (easy to live environment).

Table 10: Rule Instantiation for firm's behavior

Firm rule categories	Rule Settings
Cost Set up	• Marginal cost of production + fixed cost for expansion (step function). • The marginal cost of production is drawn form a uniform distribution and hence is different for each firm within a certain range. (See Appendix 7 for actual values used in the simulation)
Bidding	• Firms bid with their lowest cost they are willing to fulfill the demand for. This is the marginal cost of production and a profit margin that a firm charges on top of that.
Production	• If a firm cannot fulfill the entire demand then it incurs a penalty cost. Where as if a firm has to stretch beyond its marginal capacity, then it incurs a short-term expansion cost. A firm decides how much to produce depending on which of the two (penalty or the expansion) cost brings a higher return on investment (fitness growth)
Subcontracting	• Firms request for quotes for all the sub-parts from suppliers in the environment. • They then compare the in-house assembly cost with the in-house manufacturing cost. Whichever is less, decides whether they produce in-house or subcontract it. • The lowest price bidder is selected and awarded the demand. Subcontracting firm awards only up to the quantity a supplier firm bid for. If a single supplier cannot fulfill the demand, the subcontracting firm awards the remaining demand to other suppliers (based on their bid price).
Capacity growth	• Firm expands its capacity if it has a predetermined number of positive fitness growth cycles. • Firm similarly contracts its capacity if it has it has a predetermined number of negative fitness growth cycles.
Learning	• Price Learning: - Aspiration-satisficing based. If the actual fitness growth by playing a pricing strategy exceeds the expected growth level then the probability of playing that strategy is increased. Conversely if a pricing strategy fails to get a positive fitness growth, then its probability is reduced. • Role Learning: - Each role has an associated propensity. The Assemblers/manufacturers role (Car) has the highest propensity to begin with (consistent with Utterback's observation of the automobile industry). As a firm increases its fitness while playing a role it increases the propensity value. Conversely if a firm loses fitness while playing a certain role it decreases its propensity to play that role. A firm always plays a role with the highest propensity value. Thus if a firm reaches a stage where the propensity value of a suppliers role is higher than of a assemblers role, then it switches roles.

Design of Experiments

Based on Utterback's work (Utterback and Suarez 1993, Utterback 1994) we picked three independent variables that affected the growth in the US automobile industry. We use the ability of a node to learn (R), the rate at which a firm grows in capacity (CE) and the nature of the environment (Th) as the independent variables.

Operationalizing Role Learning (R)

As described earlier, role learning is implemented as a propensity based learning model (Roth and Erev 1995) in every firm's behavioral description. Associated with every role is a propensity to play that role. As a firm successfully plays a role the propensity to play that role increases. Conversely if a firm loses fitness while playing a certain role it decreases its propensity to play that role. Every firm can play an assemblers role (starts of as generalist) and if the propensity of that role decrease and other roles (suppliers) increases, role switching may occur. How fast this switching occurs depends on the difference between the propensity value of an assembler's role and supplier's role. Role learning was set as a bi-level parameter (assumption) with a low and high setting. For low role learning setting we use a difference value of 0.4 (simulation assumptions) between the initial starting propensities of playing an assembler's role and suppliers role. For high role learning this difference between the propensities of playing an assembler's role and suppliers role is reduced to 0.15. Reduced difference indicates that the role switch over will happen faster.

Operationalizing Capacity Expansion (CE)

CE is operationalized as a ratio of number of positive fitness growth cycle (represented by the variable m) required for expansion to number of negative fitness growth cycle required for contraction (represented by variable n). For these simulations, we again select CE as a bi-level parameter (assumption). The m value is kept constant and the setting of n decides whether CE is set to fast or slow setting. So for example m=6, n=7, indicates that a firm is contracting much faster as compared to m=6, n=12. Thus fast contraction equates to slow capacity expansion and slow contraction equates to fast capacity expansion.

Operationalizing Environment Threshold

Environment threshold was also assumed to be a bi-level parameter. Essentially, a low environmental threshold (0.25) indicated an easy to survive environment. Conversely a high threshold environment (3.0) indicated a harsh environment.

For the three independent variables just discussed, we were interested in observing two dependent variables, namely, the patterns of emergence in the SN structures (connectivity of the network) over time and the survivability. These were the two most important parameters highlighted by Utterback (Utterback and Suarez 1993, Utterback 1994) and also in Choi and Hong's study of the automotive industry (Choi and Hong 2002).

Dependent Variable: - Type of Structure at end of simulation (EndStruc)

Four basic topologies of Supply Network structures were used for categorizing the end result of the simulation. They are:

- Hourglass Structure (Category 4): With a central assembler and multiple tiers of suppliers (the current automobile industry structure).
- Linear Structure (Category 2): Vertically integrated structure (IBM's SN before 1980)
- Star (Category 1): This is the classic hub and spoke structure. It has a central node that acts a s a hub and a single tier of suppliers (spokes) (Dell Computers SN)
- No Structure (Category 0): This is a unique case when no existing node is willing to play the assemblers role resulting in a unique situation were there are lot of suppliers but no one to initiate the demand flow between the tiers (essentially a assemblers job). Hence no SN is formed.

Dependent Variable: - Survivability (Surv)

Survivability is operationalized as the ratio of total number of nodes alive at the end of the simulation to the total number of births that took place during the entire simulation.
Rest of the attributes of the model such as demand, cost structure, price learning were all set as static parameter settings for the simulation experiments (same through out all experiments). Table 11 shows the settings.

Table 11: Important parameter settings for the Automobile Industry Simulation

Parameter	Setting	Based On
Demand (passenger cars)	Normal distribution with increasing mean	(Ward 2002)
Initial number of nodes	10	(Utterback 1994)
Periodicity of Evaluation	Every 12 demand cycles (annual evaluations, each demand cycle corresponds to a month)	(Timmons 1999)
Firm's starting fitness	Sampled from a Normal distribution with average fitness of incumbent nodes as the mean and 0.8 std deviation. To begin with mean is set to 0.5	(Utterback 1994)
Total simulation time	960 demand cycles (corresponds to 80 years)	(Utterback 1994, Ward 2002)

We hoped to see interactive effects between the independent variables with respect to the dependant variables, which in turn would allow us to draw logical inferences on the emergence process and answer the two fundamental questions raised previously. In total, there were (2*2*2=8) possible full factorial design experiments.

The simulations were completed on a high performance parallel computing cluster (ACCRE 2005). The ACCRE grid is a heterogeneous Beowulf cluster, with 600 computing nodes, each of which is a dual processor based system. Significantly enhanced computing power on the grid allowed us to increase the scalability of our computational model. The high performance grid infrastructure also allowed us to replicate our results and increase our throughput. Each experiment on the grid ran for 8 hrs. 30 samples per experimental condition (240 samples in total) were collected.

Results

As illustrated in our previous work (see Chapter II and Chapter III), the modeling framework was able to generate industrial growth results using the Automobile industry data indicating that the observed structures and population dynamics follows growth trends similar to empirically published results. We successfully grew a deep hierarchical structure under high environmental threshold conditions. Interestingly it was also observed that during the temporal evolution process we observed numerous patterns (Figure 3 in Chapter II), such as the star, linear, shallow hierarchical topologies apart from the deeply hierarchical structure form over a period of time (emerge). This evolving behavior in the network topology fits the classic definition of emergence (Goldstein 1999), thus confirming further that SN's are indeed emergent networks. We also observed that the population dynamics growth curve was a skewed bell shaped curve (same as Utterback's, see Figure 18), indicating that initially number of firms enter the market, but as the market matures, few firms dominate and the number of entries reduce with time.

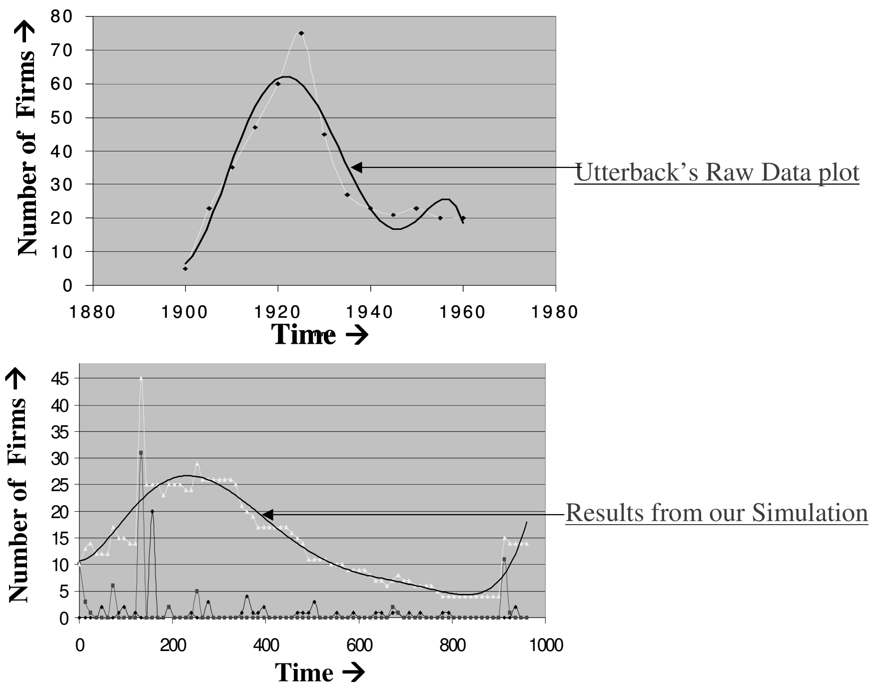

Figure 18: Population Dynamics

Thus we were able to answer the first research question raised previously: Supply network patterns emerge due to the complex adaptive nature of such systems. In order to specifically answer the second research question, we performed a rigorous statistical analysis testing for interactive effects in the system behavior.

Possible Interactive effects in the system

Figure 19, shows an overall picture of the different types of structures (refer to Table 8, in Chapter III for a detailed categorization) formed under different experimental conditions. For example, for a low environmental threshold, fast capacity expansion and low role learning experimental condition, most of the structures formed and the end of the simulation were either star or linear structures (~ 90%). Negligibly small number of hierarchal structures (category 4) was formed (<7%).

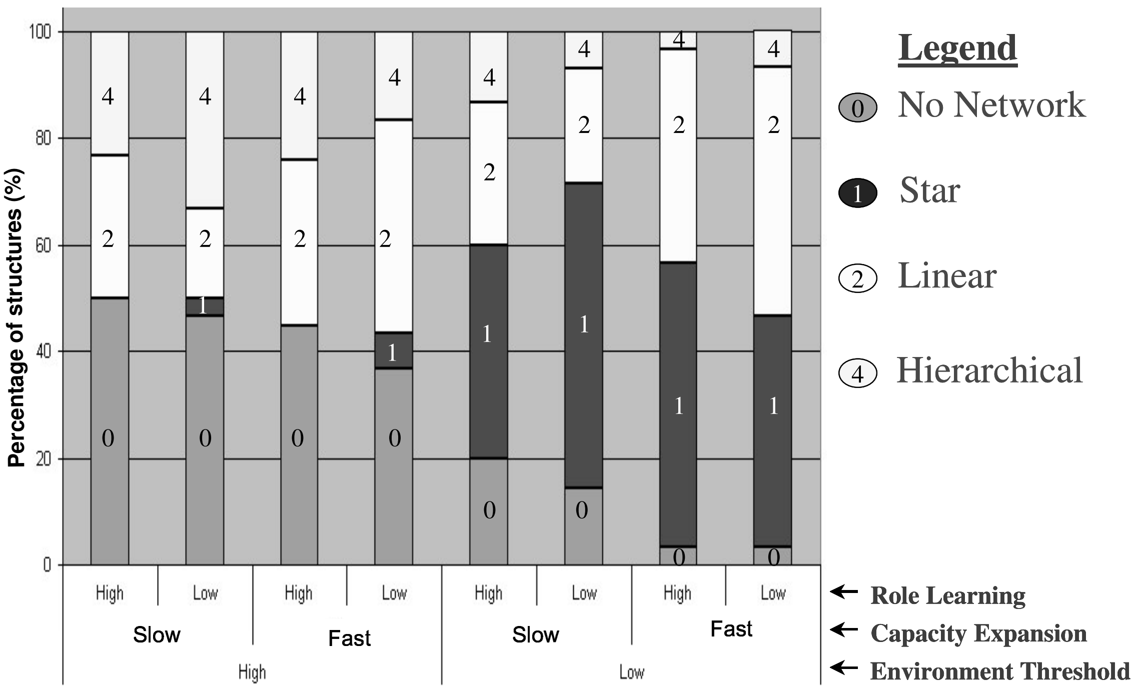

Figure 19: Types of structures observed across all experiments (Same as Figure 14)[4]

Summarizing the Figure 19, the following observations could be made. Low environmental thresholds promote the growth of more star shaped and linear shaped network topologies. Higher environmental thresholds promote more hierarchies. Linear structures are prevalent under all conditions. But on an average faster CE seems to be driving more linear topology formation. And "No structure" conditions are observed under higher threshold conditions (harsher environments). "No structure" indicates that none of the firms in the market were willing to play the role of an assembler.

[4] There were no category 3 (heterogeneous) structures were observed, hence the figure has category o, 1, 2 and 4

The summary results definitely indicate that there are interactive effects between the independent variables with regards to the emergence of SN structure. The next section presents the detailed statistical analysis that confirmed the proposition made in this section

Statistical Analysis

To confirm presence of interactions in the SN system, a detailed statistical analysis was performed on the data from the 240 samples collected.

Categorical Data Analysis for Type of Structures Observed

EndStruc variable (Types of structure) is a nominal variable with 4 different categories (the categories were compiled from the SN examples in the literature). We used categorical data analysis (Agresti 2002) and $\chi 2$ testing (Kotz, et al. 2000) in SPSS (Statistical package for Social Sciences, version 14) for testing for significant interactions between the independent variables. The first step in the analysis was to build a contingency table (Agresti 2002) for all three independent variables taken together and recording the observed count of EndStruc for each of the combinations. Next the expected counts (marginal) were calculated from the individual bin frequencies. A $\chi 2$ test for all single, two way and three way interaction conditions using the observed and expected value was performed. The underlying distribution for $\chi 2$ testing was selected to be a Poisson distribution (consistent with the outcome variable). An α value of 0.05 was used (as is usual in traditional statistical analysis).
, summarizes the results from the $\chi 2$ tests.

We also ran a linear multivariate analysis for survivability (a scale variable) with respect to the independent variables to test for possible interaction effects. The results are summarized in Table 12.

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Table 12: Chi-square test results for interactive effects

Explanatory Variables	**Response Variable Type of Structure (p value)**		**Response Variable Survivability (p value)**
Capacity Expansion	**0.013**		**0.008**
Environmental Threshold	**0.000**		0.087
Role Learning	0.932		0.427
Capacity Expansion * Environmental Threshold	Th (high) 0.230	Th (low) 0.022	0.174
Environmental Threshold * Capacity Expansion	CE (Fast) **0.000**	CE (Slow) **0.000**	
Capacity Expansion * Role Learning	R (high) 0.375	R (low) **0.018**	0.949
Role Learning * Capacity Expansion	CE (Fast) 0.855	CE (Slow) 0.524	
Role Learning * Environmental Threshold	Th (high) 0.372	Th (low) 0.924	0.189
Environmental Threshold * Role Learning	R (high) **0.000**	R (low) **0.000**	

Thus, the statistical analysis shows that rules (independent variables) interact in an ordered way in a SN to affect the emergence of SN topologies. In the Discussion section, we next attempt to explain the results presented in Figure 13, using the interactive effects analysis results.

Discussion

Low Th, Fast CE experiments

The results in Figure 14 clearly show that majority of the structures are either Star shaped networks (48.33 %) or linear networks (43.335 %). There are almost no hierarchical structures (5 %). Fast Capacity expansion in these experiments ensured that the initial firms that the simulation started with grew their fitness fast. Since it was a low threshold easy to live environment, individual firms persisted longer. Fewer firms died and hence fewer numbers of new firms were born. As explained in the role learning model, since firms were growing their fitness under the current role of an assembler (every firm starts of as generalist) their propensity for playing that role became so high that none of the firms switched roles and became a supplier.

Reduced role switching, in turn resulted in almost no hierarchical structures, and mostly Star shaped networks or linear networks with maximum depth of 1 were formed. Hence Role learning did not seem to have any effect for the two experiments due to the fast build up of propensity, low propensity decay (slow reduction in propensity value for a role) and low mortality of nodes. Whether the end structure was linear with depth 1 (essentially a monopoly) or Star with a high degree distribution (order of 5-7, still with a single tier) depended on initial growth in fitness and capacity of nodes. If a single node started growing much faster than the other nodes then the outcome was a linear structure. Where as uniform growth of all incumbent firms resulted in star structures.

Thus the interaction of the capacity expansion (CE) parameter and the environmental threshold seem to strongly control the structure formation in these experiments. The primary effect of CE on Survivability also makes sense. How fast a firm grows actually decides how well it survives in an environment? The faster is the capacity growth, faster is the fitness growth as a firm can produce more, and longer the firm survives. And this precisely leads to the propensity build up which in turn makes the role learning parameter insignificant in these experiments. This result then explains, why there are no primary effects of Role Learning on type of structure or survivability.

Low Th, Slow CE experiments

The results in this also show that majority of the structures are either star shaped networks (48.57 %) or linear networks (24 %). There were a few hierarchical structures 10 %) and some “no structure” situations (17%). Slow Capacity expansion results in slow fitness growth of firms. Because of a low threshold easy to live environment, individual firms persisted longer but mortality increased as compared to the previous experimental conditions (Fast CE). Hence more new firms enter the market place. Due to slower fitness growth, the propensity build up effect is not fast enough as compared to the previous experiments (Fast CE), especially for the new entrant nodes. Hence some amount of role switching occurs, which in turn resulted in few hierarchical (10%) and no structures (13%). Still mostly star shaped networks or linear networks with maximum depth of 1 are formed as the low threshold environment makes it easier for nodes to survive tough times and eventually grow their fitness and propensity to play an assemblers role (a role the nodes started with).

Same as in the explanation of the previous group of experiments, the primary effect of CE and Th on the dependent variables makes sense. CE seems to control the fitness growth, which in turn directly affects survivability. The low threshold clearly results in nodes surviving longer, leading to the propensity build up and formation of star or linear structures.

High Th, Fast CE Learning experiments

The results (Figure 14) clearly show that there are more hierarchies (21%) as compared to the previous experiments. Almost no star shaped topologies were observed (3.33 %). Again fast CE ensured that the initial firms that we started the simulation with grew their fitness fast. But since the environment was harsher, nodes persisted for lesser periods of time. Only a few firms did well and build up their fitness and grew their propensities to play the role of a manufacturer. New firms entering the market, now did not have the fast propensity build up effect due to the less time the nodes got to settle down in a harsh environment. Thus role switching occurred at a much more frequent rate than the previous four experiments. This resulted in increased hierarchies in the SN topology (from 5 % to 21 %). It also resulted in No structure situations, as incumbent nodes sometimes also switched roles, especially under high role learning conditions (40 %). Almost no Star shaped networks are observed probably due to the role learning effect (3.33 %) (Since nodes switch roles, tiers are formed in the SN, essentially eliminating the possibility of a star network). Linear networks are still observed but now with maximum depth of 2 or 3 (35 %).

The explanation for primary effects, are exactly same as before. Clearly, for example Environmental threshold (Th) seems to be affecting type of structure formed as observed in the statistical analysis. Exactly what structure is formed is then governed by the interactive effect between Environmental threshold (Th) and the remaining two independent variables, i.e., Role Learning (R) and Capacity Expansion (CE).

High Th, Slow CE experiments

These experimental conditions represent the harshest conditions out of all the experiments due to slow capacity expansion and high environmental thresholds. Surprisingly this results in the most number of hierarchical structures at the end of the simulation (30 %). Slow Capacity expansion in these experiments resulted in slow fitness growth for individual nodes. This resulted in shorter persistence of firms and hence even lesser propensity build up effect as compared to all other experiments. Thus both incumbent nodes and new entrants switched roles resulting in maximum number of hierarchical topologies observed across all the experiments (30 %). The No structure condition was highest (45 %) probably due to the harsh environment coupled with role learning effects (firms constantly try to improve their fitness by trying new ventures).

The role learning (R) seems to have an effect on the type of structure formed under the high environmental threshold (Th) and slow capacity expansion (CE) conditions. The role learning (R) parameter seems to moderate the effect of capacity expansion (CE) and environmental threshold (Th) on the type of structure formed.

Process of Emergence in SN

From our results, analysis and discussion so far, we can definitely say that Supply Networks, emerge with time into different types of structures. The temporal evolution process of the entire network topologies was visible. The interactive effects we observed in our simulation clearly highlight that such emergence dynamics in SN systems are governed by interaction between local behavioral rules and conditions driving the fundamental entities of the SN system. We clearly have been able to answer both the questions we raised in the beginning of the chapter.

We would like to discuss what these results mean to a decision maker managing such a system. The directional 2-way interactive affects in the system highlight the fact that the interactions in SN systems are not random or chaotic. There is an underlying order. This is one of the fundamental tenets of a CAS. This also supports the propositions of Choi et.al (Choi, et al. 2001), that in SN systems it is important for managers to know which parameters to control and which parameters should not be controlled for efficient management.

For example in our simulation using the automotive industry data, it was clear that a firm's capacity is the most valuable asset and should be looked into carefully under all circumstances. Yet on the other hand depending on the type of environment a firm may be operating in, switching roles may or may not be a good option, or in fact may not have any effect at all. This was observed clearly for the low environmental threshold and high environmental threshold environments. Under low environmental threshold, role learning did not have an effect where as role learning significantly affected the hierarchical topology formations in conjunction with the high threshold environments.

Bottom line from the above discussion is that a practicing manager utilizing the wrong strategy, i.e., focusing excessively on creating a niche space in the market (trying to learn a specialized role) while competing in a generalist market can actually lead the company towards inefficiencies and losses. On the other hand the same strategy can be a life saving in a harsh environment, where it is all about creating niches. Looking at the US automobile industry itself can confirm such happenings in the past. Companies such as Deloren and Magna International, in a harsh environment learned that they needed to find a niche, as they were unable to compete at the assemblers tier. On the other hand if we look at a low threshold environment industry such as the florist business in US, one hardly sees florists that just deal in roses. Usually flowers are treated as a general commodity (a generalist market).

Conclusion and Future Work

The paper focused on discussing how Supply Networks (SN) grow and emerge using the unified supply network as a modeling framework. The simulation results and the statistical analysis using the US automobile industry data indicates that the three behavior rules in this industry interacted in an ordered way to directly affect the dynamics with respect to survivability and the type of structure formed Figure 20.

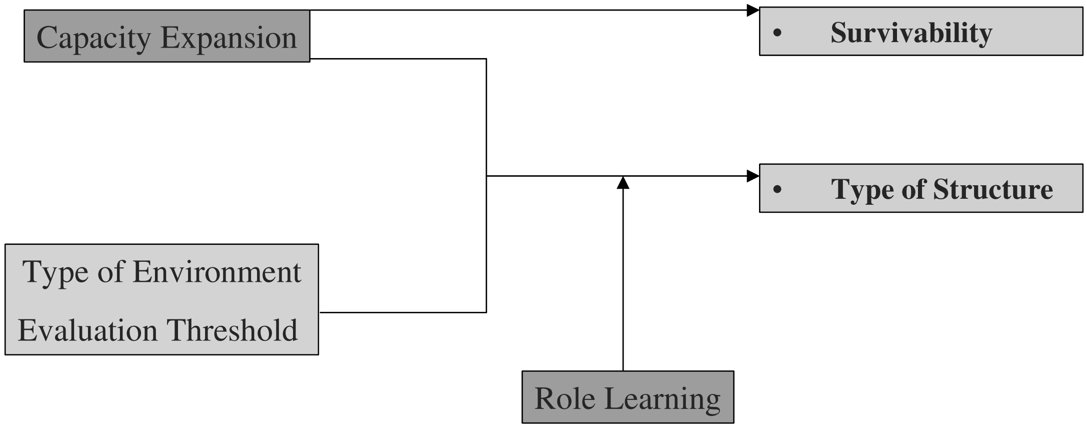

Figure 20: Interaction effects observed in the system

The important contribution in the domain of SN is at multiple levels. The generic rule-modeling framework suggests a basic set of rules that can model different types of supply network systems. We instantiated this framework with the US automobile industry example and showed through statistical analysis that we were able to generate differing behavior using the modeling framework. The same framework can be applied to other industries. The generic rule categories would need to be reconfigured and the simulation framework can then simulate the dynamics of the new SN's.

At another level, we would expect that if we use another industry, which has similar characteristics to the automotive industry, we should see similar results. This in turn would not only validate our model further but it will help in establishing the generality of the entire framework. Also lessons learned from one industry can then be applied in similar domains, saving time and money.

The future of this work looks promising. Now that we have answered the fundamental research question on how supply networks grow and emerge, our immediate task is to use the same modeling framework on another well structured industry and increase the validity of the research. Also we intend to take a different kind of SN industry such as the healthcare industry, and simulate the growth dynamics. By doing so, we would be able to discover and build a general knowledge base about SN dynamics and eventually move towards a general theory of Supply Network.

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CHAPTER V

PREDICTING SUPPLY NETWORKS DYNAMICS

Abstract

Our recent research has illustrated that supply networks (SN) may be complex adaptive systems that grow and emerge due to an ordered interaction of local behavioral rules and conditions. This paper builds on our previous research presenting a novel set of analysis techniques that can investigate the effects of these behavioral rules on stability and emergence of SN topologies. Specifically the result data from the US automobile industry simulation (see chapter IV) are used for analysis in this chapter. Proportional analysis of time series data (using SAS) is utilized to identify statistically significant patterns of instability during the entire simulation time period. The analysis shows that certain parameters like the "type of environment" plays an important role in affecting the stability of the entire SN topology. We utilize chaos theory analysis tools for predicting the SN system's path of emergence. The results from attractor reconstruction analysis suggest presence of periodic attractors in SN environment, which in turn indicates that meaningful trends can be generated for managers with regards to issue of dynamism in the environment. The paper builds such insights from the analysis results and discusses how such insights may help managers/policy makers make better-informed decisions.

Introduction

Before the year 2000, the Internet search engine supply network looked as shown in Figure 21 (Barabâasi 2002). Inktomi Corporation provided the web search engine for all the major players (Yahoo and Microsoft). Inktomi was in a very comfortable position within a stable environment. The company had no idea that all that was about to change with the advent of a new firm: Google. Google came in the year 2000 with its superior data sources and web services in turn single-handedly eliminating Inktomi Corporation from the market while taking its position in the Supply Network.

How could such an event occur in a stable environment? Could Inktomi have prevented this by having a prior knowledge of the dynamic properties of a stable supply network environment? Switching focus to Google, the company has continued its meteoric rise. Infact Google has become a first tier provider (as opposed to a second tier in year 2000) forcing a topological change. This in turn has forced incumbent nodes such as Yahoo and Microsoft to switch gears and the underlying rules of the game have changed. Do any of these firms know how the search engine market will emerge over time?

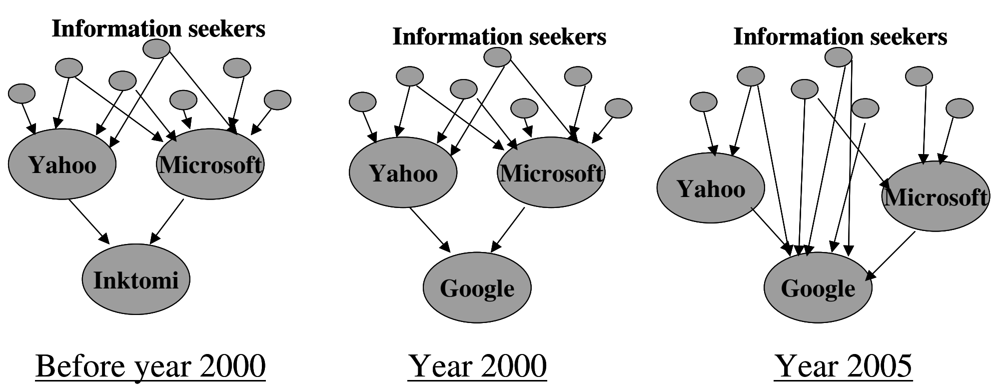


Figure 21: Internet Search Engine Supply Network

This paper presents a novel set of analysis techniques for analyzing stability patterns and future emergence path of Supply Network topologies. Stability of a SN topology and the evolutionary path have been identified as the key parameters that can help managers and practitioners make long term strategic decisions (Choi, et al. 2001, Choi and Hong 2002).

Recent studies have clearly emphasized the need for studying supply network dynamics from a network topology perspective (Choi and Hong 2002, Randall and Ulrich 2001, Zhang and Dilts 2004). We consider evolution of entire network topologies and look for stability and emergence patterns over time. One of the primary difficulties in investigating SN dynamics is the lack of knowledge regarding how SN's grow and adapt (Forrester 2003, Lee 2004). Recent research (see Chapter III and Chapter IV) has illustrated that supply networks (SN) may be complex adaptive systems that grow due to the ordered interaction of local behavioral rules of participating firms and the environment. Utilizing results from this research, statistically significant inferences are drawn with respect to stability and emergence of SN topologies over time.

Previous result (see Chapter IV) from simulating SN growth using the US automobile industry data over the last 80 years is used for analysis in this paper. Proportional time series analysis (Log linear modeling) is carried out using the SAS package (version 9) for evaluating stability of network topology evolution with time. χ^2 tests (Kotz, et al. 2000) are used to investigate which system parameters (independent variables/local rules) affect the stability of SN evolution.

Next, attractor reconstruction techniques are used (Williams 1997) to recreate the pseudo-phase space (signature of the system behavior with time) (Williams 1997) and identifying trends. Specifically autocorrelation tests (Makridakis and Wheelwright 1989) are used to calculate system lag and drawing inferences about the dynamic nature of the entire SN system. We then combine our findings from these analyses with our previous findings on interactive effects in SN (see Chapter IV) and suggest insights for policy-makers/managers.

Background

The simulation platform used for simulating SN growth is built on the unified model of supply network (UMSN, see Chapter II). Based on the unified model, we conceptually (see Figure 6 in Chapter II) model a supply network as a system consisting of two fundamental components: (1) an environment or a market in which (2) a group of firms (nodes) reside and interact to fulfill global demand. Stochastic environmental conditions such as a variable demand pattern, firm decision-making (subcontracting, bidding), and differential growth of firms (growth in capacity, fitness of firms etc), all contribute towards structural as well as behavioral dynamics in the resulting supply network. The same fitness model as introduced in Chapter III is used.

Generic Rule Modeling Framework and the Computational Framework

A generic rule-modeling framework has been developed in our prior work (see Chapter III and IV) that can be used for characterizing the behavior of the two fundamental entities of the UMSN, namely, environment and the node. We used the same framework for our SN growth simulations using data and parameters from the US automobile industry. Analysis was presented in Chapter IV that showed capacity of a firm as the primary driving force in the simulations. Thus in this paper we focus in details on the Environment and Node rules, where capacity of a firm plays an important role. We present example implementation of two such rules.

Birth/market entry rule for inducting new firms in the market

The birth function modeling is done based on classical microeconomics (Varian 1990) and industrial organization theory (Shy 1995). According to classical microeconomics theory, whenever there is unfulfilled demand in the market, the market attracts new firms, who can join it and make profit (Mueller 2003, Tirole 1989, Varian 1990). Firms' keep entering the market till the unfulfilled demand in the market has been fulfilled and the market is cleared (Mueller 2003). Figure 22 present's flowchart of actions that represent the birth function algorithm.

1. At simulation start if there is unfulfilled demand, the environment generates a new firm (node). The new node is born with a fitness value that is calculated as follows:
   i. The average fitness of incumbent nodes are taken (f_{avg})
   ii. The initial fitness (f_i) of the new node is then sampled from a N~(f_{avg} , 0.8).
   iii. Entering firms in a market can be both large and small firms.

2. The initial capacity Q is set for the new node as follows:

   A node's start up capacity is proportional to the ratio of its starting fitness and the average incumbent node fitness. Thus the fitter a node is as compared to the average incumbent population; higher will be its starting capacity.

$$Q = \eta * \left(\frac{1}{k} \sum_{j=1}^{k} Q_j \right), \quad (1)$$

where k is the number of incumbent nodes in the environment

and $\eta = \frac{f_i}{f_{avg}}$,

where average fitness f_{avg} of the incumbent nodes is represented as

$$f_{avg} = \frac{1}{k} \sum_{j=1}^{k} f_j$$

This ensures that a new entering firm has capacity proportional to its starting fitness. The fitter the firm is, higher is the starting capacity. Based on fundamental microeconomic theory principle of unfulfilled demand attracting new firms, the environment keeps on generating nodes till it has cleared the market. Depending on whether it's a free or regulated market, a firm may/may not decide to enter (based on market entry rule).

Market Entry Rule for potential firms

The entry into the market can either be a "free entry" (firms decide when to enter and whether to enter at all) (Tirole 1989) or a regulated one (entry of firms is regulated by the government, or a regulator body, e.g. the telecommunication market) (Laffont and Tirole 2000). In case of a regulated entry the nodes generated by the evaluator start participating in the supply network. In case of a free market entry, the nodes decide whether to enter the market at all by taking into consideration the *"entry barrier"* of a market. There are two primary definitions of *"entry barrier"* that are used in the marketing and economic literature (Bain 1956, Weizsacker 1980). We use the Weizsacker's definition that defines "*barrier to entry as the cost of producing that has to be born by entrant firms but not the incumbents"*. This definition also ties up with (Tirole 1989) definition of sunk cost. The marketing literature has also identified sunk cost and capital investment requirements as a credible entry barrier (Karakaya and Stahl 1989). Thus sunk cost is used in the model as an "entry barrier decision parameter" by the entering firms.

The sunk cost in the supply network model is made proportional to the initial node fitness.

d_f (Loss in initial fitness due to sunk cost)= $r*f_i$, (2) Where $r = \dfrac{Q_i}{\frac{1}{k}\sum_{j=1}^{k} Q_j}$

Here k is the number of incumbent nodes in the environment

Thus, adjusted initial fitness $f_i^{'}$ is,

$$f_i^{'} = f_i * \left(\frac{\left(\frac{1}{k}\sum_{j=1}^{k} Q_j\right) - Q_i}{\left(\frac{1}{k}\sum_{j=1}^{k} Q_j\right)} \right)$$

Thus higher the nodes initial capacity and fitness, higher are its sunk cost. If the adjusted node fitness value is greater than the weakest incumbent node, then it decides to enter the market. The rational here is that a new entrant firm has to be atleast as strong as the weakest incumbent to have a chance of surviving.

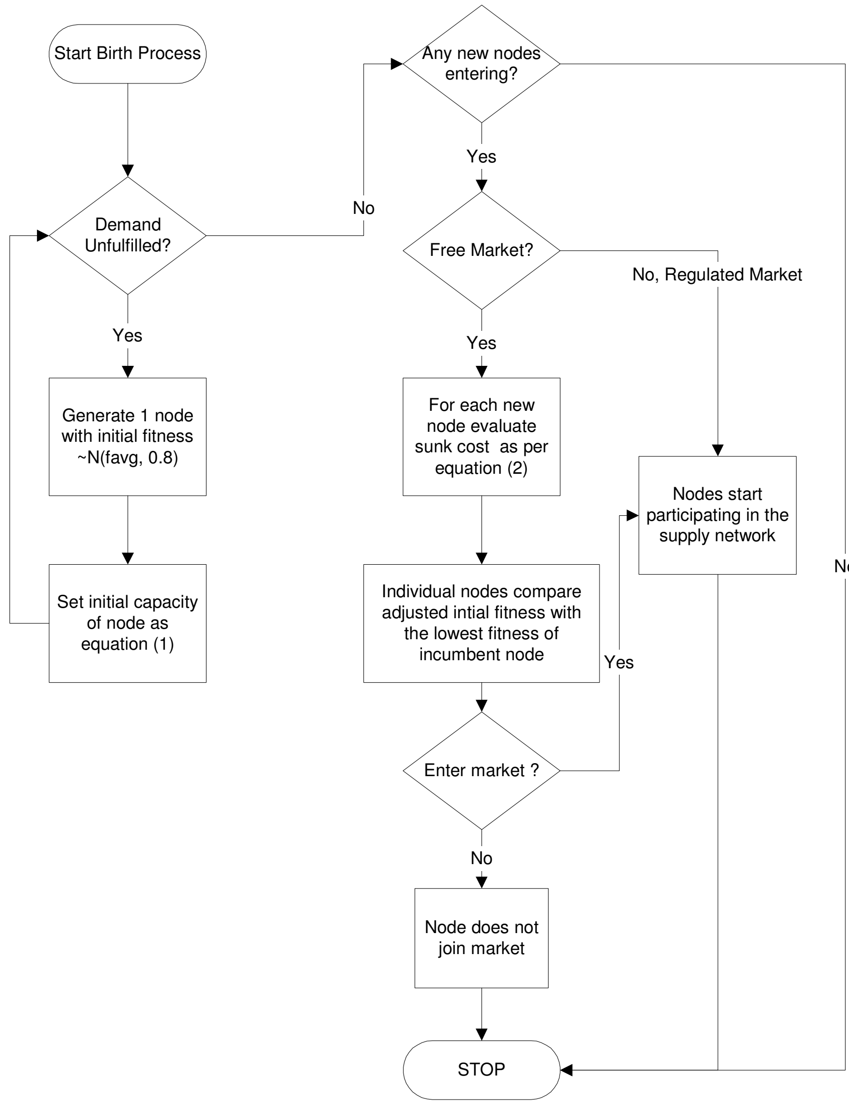


Figure 22: Birth function modeling flowchart

Production Rule for an individual node

As a node receives a demand it has certain decisions to make and the decision path is shown in the flowchart in Figure 23.

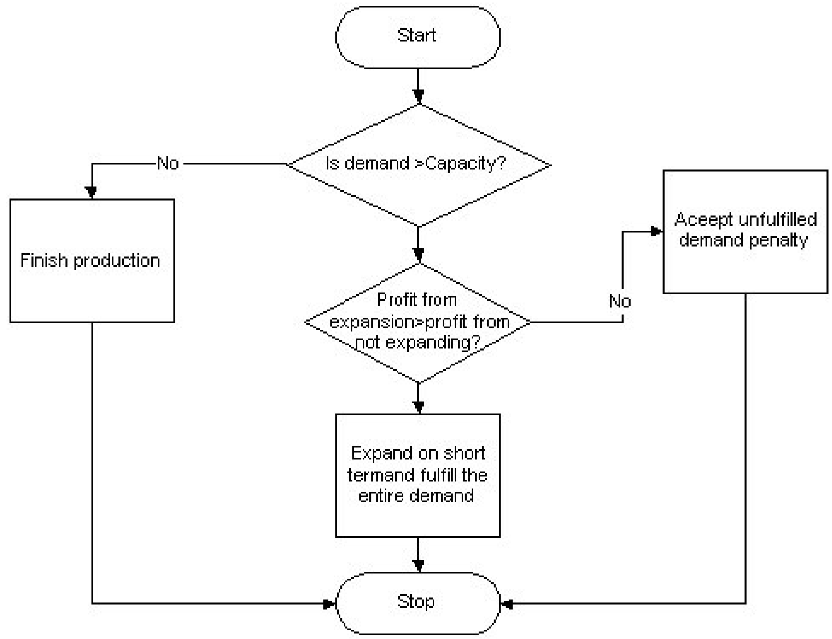


Figure 23: Expansion/Contraction rule

If the incoming demand is less than its capacity, then it poses no problem and the demand is fulfilled. If the demand is greater than the node's capacity then a node has two options. It can either expand on a short-term basis (it has some fixed costs associated with expansion as shown in Figure 24) or it can choose to partially fulfill a demand and face the unfulfilled demand penalty. The marginal cost structure (Figure 24) indicates that the firm faces a cost of α_i upto its marginal production capacity Q. Subsequently if it has to expand then the cost increases to a fixed amount α_j where $\alpha_i < \alpha_j$.

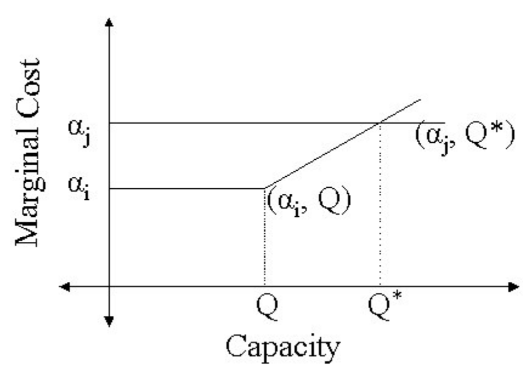


Figure 24: An example of a marginal cost structure used in the production rule of a node

The firm, depending on whichever decision leads to greater profits/lower losses, makes the choice. The penalty function can differ from supply network to supply network and can be a function of numerous parameters such as importance of that unfulfilled demand, relationship between two firms etc. The above process can be represented in a quantitative form as follows:

Let π_1 be the profit earned if expansion is carried out
Let π_2 be the profit earned if expansion is not carried out
According to the marginal cost structure shown in Figure 6

$$\pi_1 = (\alpha_i + p_i) * Q^* - (\alpha_j - \alpha_i) * (Q^* - Q)$$

$$\pi_2 = (\alpha_i + p_i) * Q - \text{penalty} * (Q^* - Q)$$

Q^* is the demand
p_i is the markup profit that a firm charges over the marginal cost α_i
α_j is the fixed cost (Tirole, 1989) for the expansion, driven by the firms underlying cost strucutre
If $\pi_1 \geq \pi_2$ then expand and fulfill the entire demand
If $\pi_2 \geq \pi_1$ then do not expand and face the unfulfilled demand penalty

In order to operationalize the generic rule-modeling platform, an agent based discrete event discrete time simulation methodology is utilized. Firms and the environment are represented as software agents that interact amongst themselves while facing a demand, driven by simple behavioral rules discussed earlier (see Chapter III and Appendix 2, 3, 4, 5 for details on simulation platform).

Simulation

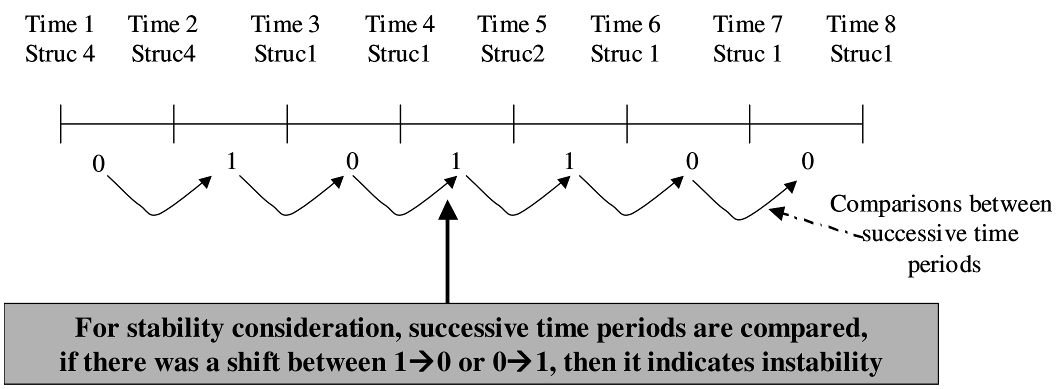
For demonstrating stability and emergence analysis of supply networks results data from our previous simulation of a well-structured industry, using data and parameters from the US automobile industry (see Chapter III and Chapter IV). The simulation used simplified product architecture for a passenger car as shown in the architecture diagram (see Figure 12 in Chapter III and Appendix 7). The information has been derived from Ford motor company's website. Table 9 (Chapter IV), and Table 10 (Chapter IV) summarize the rule instantiation of the generic rule-modeling framework, for the simulation experiments. Based on Utterback's work (Utterback and Suarez 1993, Utterback 1994) three independent variables that were thought to affect the growth in the US automobile industry over the last 80 years were picked as independent variables. We used the ability of a node to learn (R) (High/Low), the rate at which a firm grows in capacity (CE) (Fast/Slow) and the nature of the environment (High threshold/low threshold environment) (Th) as the independent variables. We were primarily interested in two dependent variables, namely, the patterns of emergence in the SN structures (connectivity of the network) over time and correspondingly how the population dynamics evolved (survivability/persistence of firms). In total, (2*2*2=8) possible full factorial design experiments were run on a high performance parallel computing cluster (ACCRE 2005). Each experiment ran for 8 hrs. 30 samples per experimental condition (240 samples in total) were collected.

Results and Analysis

Our previous work (see Chapter IV) has illustrated that SN's may be CAS. They are driven by local behavioral rules of participating entities, and emerge based on ordered interaction between the rules and conditions of the environment. In this section we discuss the results of our stability analysis and predictive analysis for emergent system behavior with regards to the population dynamics.

Investigating the stability patterns

We operationalize stability as the phenomenon of the SN structure not changing its topology between successive time periods during the simulation process. The stability evolution process is encoded with a simple binary mechanism. '0' represents stability and '1' represents instability. Entire time series (960 simulation cycles or 80 years) is divided into 8 time points (driven by data collection limitations during the simulation process) (each representing 120 simulation cycles or 10 years). Each time point is encoded as Time 1, Time 2 and so on up to Time 8. Successive time points are compared for structural changes. For example in Figure 25, between Time 1 and Time 2, the SN structure was a category 4 (we use the same 4 categories for describing the SN topologies as used in Chapter IV) hence it was encoded as '0', indicating between time 1 and time 2 the topology evolution was stable. But as we move from Time 2 to Time 3 the structure changes from a category 4 to category 1, and hence we encode it as ‘1’, indicating the topology changed and there was instability. The overall picture of the 0’s and 1’s then give a broad picture of stability for each type of experimental condition. From a decision-maker’s perspective, it would be important to know, that given the current conditions and rules, are there any particular portions on the time series where there is instability (presence of 1’s indicating topological changes).



0→ Represents no change in network topology between successive time periods
1→ Represents change in network topology between successive time periods
Time #→ Corresponds to every 10th year of simulation time
Struc→ Corresponds to Supply Networks topology (structure) category

Figure 25: Stability analysis results

Next we performed a complete statistical analysis (all the 8 experiments, 240 samples) looking for any significant interaction effects between the explanatory variables (Capacity Expansion→ CE, Role Learning→ R, Environmental Threshold→ Th) and the response variable (patterns of 1’s between successive time periods. We are interested in instability; stability is mutually exclusive and exhaustive and hence only one response variable is sufficient). We used proportional time series analysis and Chi square testing (Kotz, et al. 2000) using the SAS package (version 9) for checking for interactive effects between the independent variables in conjunction with Time (the entire time series data for all the 240 samples→ operationalized as the variable Time) with respect to instability patterns on the time series. Summary of the results are provided in Table 13.

Table 13: Statistically significance interactive effects for stability in SN's

Interactions	**Statistical Significance (α < 0.05)**
Time	**.0001**
Role Learning*Time	.6886
Environmental Threshold*Time	**.0001**
Capacity Expansion*Time	.7859
Role Learning * Capacity Expansion *Time	.9610
Role Learning * Environmental Threshold *Time	.5213
Environmental Threshold * Capacity Expansion *Time	.3281
Role Learning * Environmental Threshold * Capacity Expansion *Time	.3031

We observe that only environmental threshold has a significant effect in conjunction with the Time variable on the overall instability. The 'type of environment (easy to live or harsh)' affected whether the topologies changed frequently or not between successive time points. This result was consistent with the interaction effects result presented in Chapter IV. There we observed that the type of structures formed under high and low threshold condition was significantly affected by the type of environment (low thresholds resulted in more star topologies and high thresholds resulted in hierarchical). We next drilled even deeper, by checking for each level of Environmental threshold, Th (high and low) with respect to instability between successive pairs of time points (Table 14). For example there was instability between Time point1 and 2 and Time point 2 and 3.

Table 14: Statistical effect of Environmental Threshold (Th) on time periods

Successive Time Period Comparisons	**Statistical Significance (α < 0.05) Th = Low**	**Statistical Significance (α < 0.05) Th = High**
Time 1-Time 2 ←→ Time 2-Time 3	.0699	**.0001**
Time 2-Time 3 ←→ Time 3-Time 4	.4328	.6407
Time 3-Time 4 ←→ Time 4-Time 5	**.0001**	**.0497**
Time 4-Time 5 ←→ Time 5-Time 6	.1506	.2687
Time 5-Time 6 ←→ Time 6-Time 7	**.0001**	.3722
Time 6-Time 7 ←→ Time 7-Time 8	**.0001**	.2386

Table 14 shows the portion of the time series where there was statistically significant instability present with respect to each level of Th (Environmental threshold). For example, for Th=low, time point pair (3,4) and (4,5) show significant instability. In other words for low threshold conditions between time period 30-50 years seem to show instability. It was surprising to find out that under both the conditions a completely different portion of the time series was significantly affected for different levels of Environmental thresholds. Under high thresholds the instability was observed early on the evolution process where as low threshold environments showed instability towards the end of the simulation. We discuss the ramifications of this finding in the next section.

Predicting the emergence path of SN system: - Population dynamics analysis

The other important aspect presented in this paper is the prediction of the emergence path for an SN, especially with respect to the population growth over time and the dynamic nature of the environment. From our previous results in Chapter IV, we have seen that having knowledge about the nature of the market (type of environment) can dictate how you should manage your system.

We use time series analysis and attractor reconstruction techniques for predicting the growth path of an SN. The growth of population (of firms) during the simulation is essentially a time series with 80 time points. For each experimental condition 30 samples were collected, essentially providing with 30 different time series. The population dynamics analysis was started by first plotting an average time series curve for each of the experimental plots as shown in Figure 26.

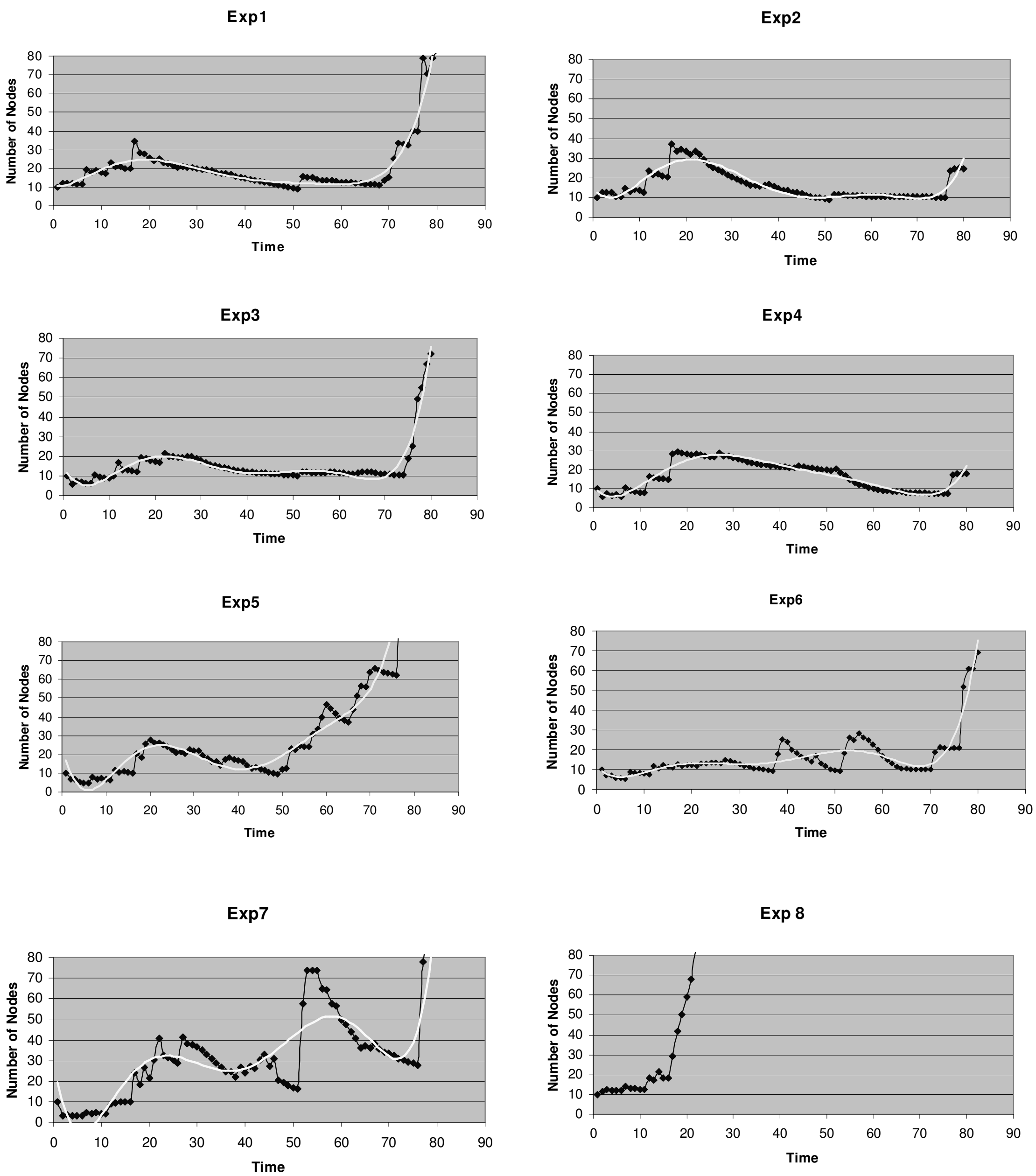


Figure 26: Average Industrial growth curves (average time series plot for all 240 experiments)

It was observed that Experiment 8 did not show the same trend as the rest of the experiments and we wanted to test if it was ok to further test the time series for other emergence properties. We compared all the 30 samples for each experiment within the group at each time period (for all the 80 data points), by comparing the standard deviation at each time point on the time series. Essentially this involved comparing each point on the 30 curves with each other (e.g., at time t1 compare all the 30 points and so on). We took a logarithmic transform of the standard deviation to eliminate outliers and plotted the group wise results for each experiment for all the 80 data points as shown in Figure 27.

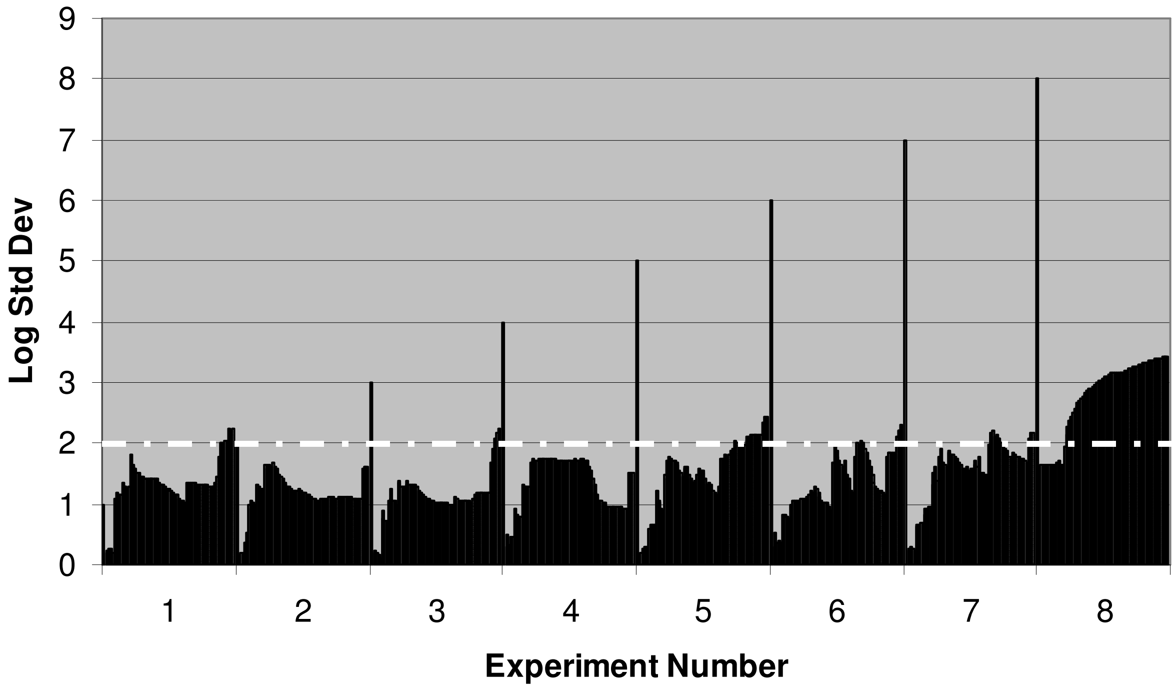


Figure 27: Standard deviation plot for each time point on the entire time series across all the experiments

The standard deviation comparisons (using a threshold of 2) also confirmed our previous observation. Experiment 8 did not follow the same trend as rest of the experiments (much higher standard deviation as compared to the rest). Experiment 8 was discarded for rest of the population dynamics analysis. For the remaining 7 experiments, a formal time series analysis was carried out, looking for trends, patterns and attractors (Williams 1997).

For each experiment, we took the average time series data of the population (total number of firms at each time step during the entire simulation). The standard practice in chaos theory time series analysis is to check for autocorrelation in the time series (Williams 1997). Autocorrelation is defined as the ratio of auto covariance and variance given by (Salas, et al. 1980) (Chapter V) for a given lag value (Makridakis and Wheelwright 1989). The lag value essentially compares the main time series to its own sub-series to see if there is a correlation between them. The autocorrelations are calculated for up to lag values, where the autocorrelation factor drops to 0, or up to N/4 (standard practice, (Williams 1997), (Salas, et al. 1980)), where N is the total number of time steps (in our case 20).

$$\text{Autocorelation} = \frac{\sum_{i=1}^{N-m} (x_t - x_{mean}) * (x_{t+m} - x_{mean})}{\sum_{i=1}^{N} (x_t - x_{mean})^2} \tag{1}$$

where N is the total number of time steps

m is the lag for which time series is being compared for autocorelation

Then the lag values for each experiment are plotted with the corresponding correlations factors yielding the correlograms (Williams 1997) as shown in Figure 28. The correlograms indicate any trends if present in the data. If there is a regular pattern such as a sinusoidal wave, then it means that the data needs to be uncorrelated before any further analysis. Also if the correlograms never approaches zero even after N/4 plots the no judgments can be made on such time series and data from these experiments are unusable for reconstructing attractors in the system.

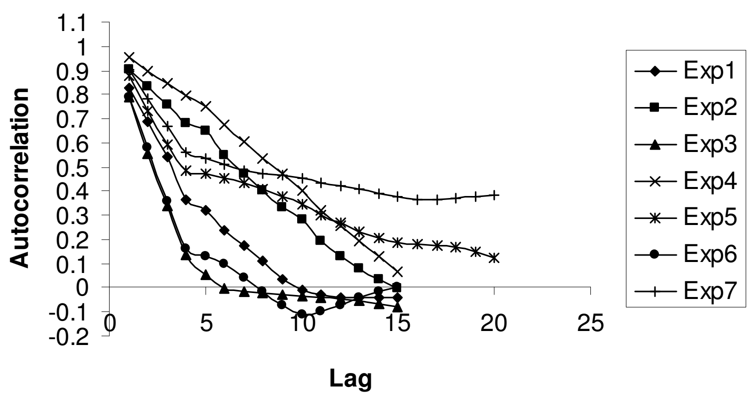


Figure 28: Correlogram plots for Experiments 1 to7

Table 15 summarizes the lag values for each experiment where the correlograms approaches near 0. The correlogram plot of Figure 28, clearly shows that Experiment 5 and Experiment 7 never approach zero even after 20 lag plots. Thus experiment 5 and experiment 7 data cannot be used for reconstructing possible attractor’s in the system. We are thus in the end left with five experiments that we attempt to reconstruct the attractors for.

Table 15: Lag values at which the time series data is uncorrelated for each experiment

Experiment Number	Lag at which correlogram goes to zero
1	10
2	15
3	6
4	15
5	NA
6	8
7	NA

An attractor in a CAS is defined as a point on the system phase space (Williams 1997) where the system behavior returns again and again, over a period of time (Schuster 2001). The previous steps are essential for attractor reconstruction, in order to eliminate any in built trends and repetitions in the data (Williams 1997). After that the attractors can be visually constructed by plotting the pseudo phase space plots (plot of $X_t \rightarrow X_{t+m}$ where X represents number of firms) (Williams 1997) where m is the lag value at which the correlogram approaches 0. The pseudo phase space plots for each experiment is shown in Figure 29.

All five plots clearly illustrate a cyclic pattern, where the number of firms over time passes through a cyclic variation. Such kind of an attractor is called as a periodic attractor or a limit cycle (Williams 1997). For example as shown in Figure 29, for experiment 1 the firm population in the SN evolution process starts with 10 firms increases up to 85 and returns back to around 10 to trace a complete cycle in the clockwise direction. All the other pseudo phase space plots can be explained on similar lines. This concludes the last step in the emergence analysis of population data.

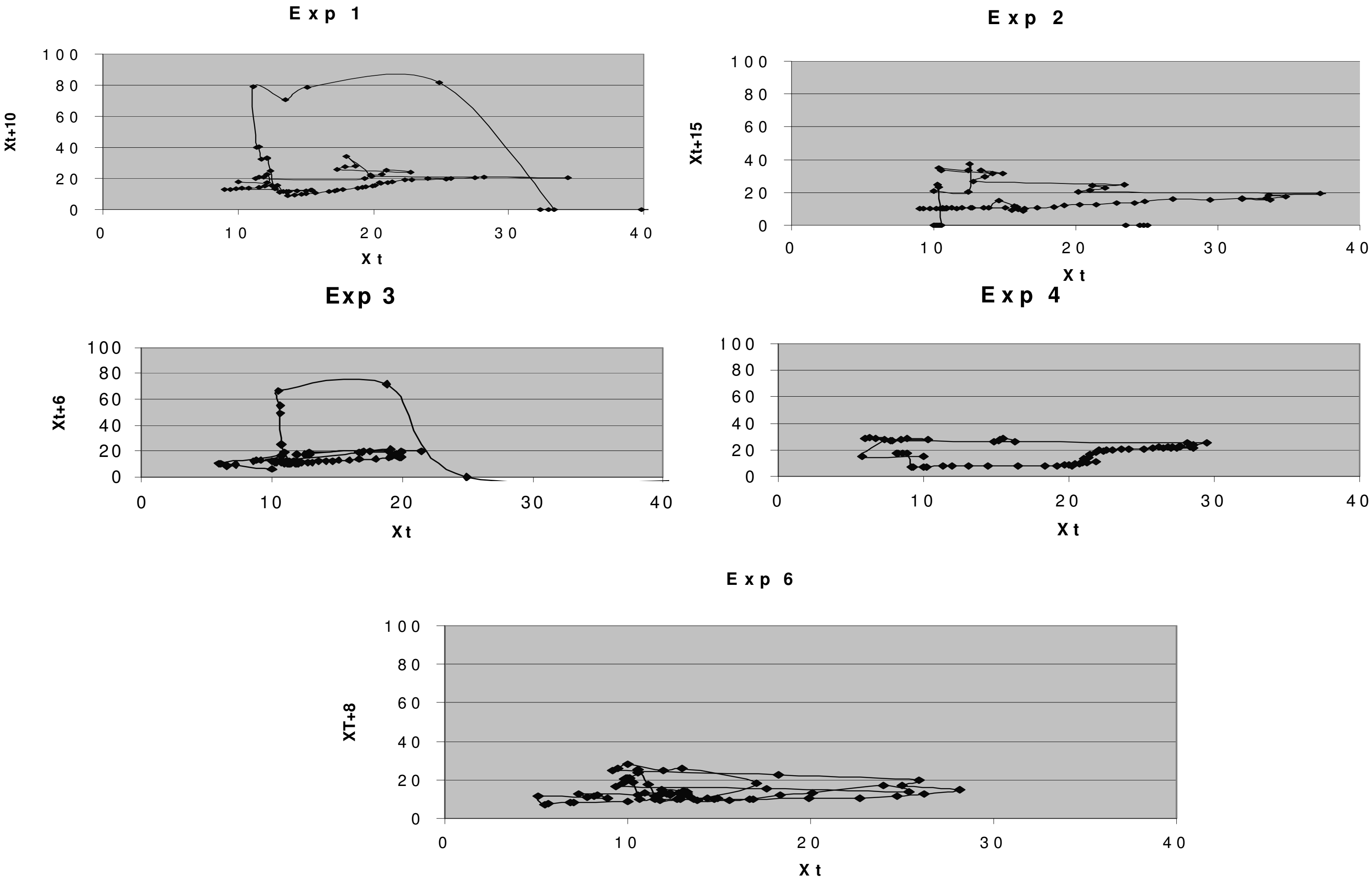


Figure 29: Reconstructing attractors by drawing the Pseudo phase space signature

Discussion

The growth and evolution patterns observed during the simulation clearly indicate that SN's can be CAS that emerges based on ordered interaction of local rules and conditions. One of the key ramifications of such a finding is that policy makers and decision makers should know which parameter/aspect of their SN is important and should be controlled and which ones should be left alone. For example in our previous work (Chapter III and IV), simulation results using automobile industry data has implied that role learning by itself is not an important factor that controls structural emergence. Rather more attention should be paid to what type of environment is the firm operating in and how fast should it grow?

Switching our focus on to population emergence, we observed the familiar bell shaped curve that Utterback's model suggests under specific conditions. But the interesting aspect that we observed was the presence of multiple modes in the growth time series. Utterback's ideal model suggests a unimodal bell shaped curve (Utterback 1994). But the raw data plot for the US automobile industry shows a small mode near the year 1950. Also Utterback shows data for only 60 years (Utterback 1994). We simulated it for 20 years longer and especially for low threshold environments the mode start forming towards the end of the simulation frame.

We feel that multiple modes in a SN population growth curve are not artifacts and should not be smoothed out. In fact they may be appearing because of the periodic attractors (limit cycles) present in the system (as seen from the attractor reconstruction analysis results, see Figure 29). One of the classical properties of a CAS with a periodic attractor is that, when such a system is perturbed, it returns to its original behavior in as soon as possible due to presence of a limit cycle (periodic attractor) (Williams 1997). A perturbation in a SN may be an event like sudden drop in demand. In fact 1950 was right after World War II and the demand data shows a dramatic drop. Such an event may have caused a number of firms to die and new firms entering the market. This shows up as second mode growth on the time series. In fact in all our simulations wherever we observed multi-modality, the cause was due to the death of firms, causing a void in the cumulative capacity of the entire system, which in turn attracts newer firms to enter the market. In other words, if Ford motor company goes out of business today, and General Motors doesn't step into fulfill the demand then it will attract other firms to step in and grab a share of the pie.

From a manager/decision-makers perspective, this is important information to have as it highlights the dynamic nature of the SN system. If not monitored properly, it may result in a firm's exit from the market. IBM's recent exit from the PC industry (Bulkeley 2004) suggests a similar story line. IBM did set up the PC market in US in the year 1980 but could not capture the market fast enough. That gave an opening to firms like Dell computers, which then has emerged as the market leader.

Stability of SN

Low threshold environments (easy to live environment) seem to develop instability later in the growth life cycle. That makes sense as the firms get a chance to build up their fitness and grow for a longer time due to low survival threshold. It takes the environment a long time to weed out the unfit firms. But once unfit firms are eliminated, room is created for newer firms to possibly join the market. Under such conditions if new firms are able to establish dominance, the SN dynamics changes and there is a possibility of structural evolution and growth dynamics. An example of this was the entry of Google in the Internet search engine market. Before Google, the search engine market was completely different, with Inktomi being the leader in the market (Barabâasi 2002). The search engine market was a low threshold environment. With the entry of Google in the fray, things changed. Google grew very fast and practically drove Inktomi out. Now the market is no more a low threshold environment, the increasing service based fierce competition between firms like Google and Yahoo is a standing proof of such an environment change.

In case of a higher threshold environment (harsher environment), the instability is in the beginning of the life cycle and early mid life cycle (fitting very well with Utterback's description of firms entering market). Early on, unfit firms are quickly weeded out; new firms keep entering until equilibrium is reached. By that time, incumbent firms establish themselves strongly in their respective roles and newer firms find it hard to enter the market, unless there is a major perturbation in the system and the cumulative capacity of the system reduces drastically (observed in Experiments 5, 6, 7). The automobile industry is a very good representative example.

From a manager's perspective what should you do with such information? The answer depends on whether you are an incumbent firm or you are a new entrant. The strategies will significantly differ. We suggest a few scenarios and insights: -

Easy environment (low threshold): - Results illustrate that expanding the capacity may be the best way to go in such a situation. Grow as fast as you can, keeping overheads low, and try to capture as much of the market as possible. Experimental results have shown that role learning and other factors may not matter. If you are new entrant, then you will have a tough time, and the only solution may be to grow faster than the incumbents. Though we did not test this, we feel that looking at the Google example, the growth may not be just in size but also in the quality of service and issues like that.

Harsh environment (high threshold): - Here if you are an incumbent firm, you should try to capitalize on the initial instability present in any harsh environment. You should grow to a position of security (again the automobile example is a classic one). On the other hand if you are a new entrant, then strategy is completely different. A firm should then try to find a niche in the market and establish it there. Simulation results show that in harsh environment, role learning becomes an important moderating variable.

Dynamism of a SN environment

How do policy-maker's decide on what time frame is important to consider while taking long-term decisions? Or in other words, how dynamic is the SN environment? Is the environment extremely dynamic such that, the actions of this year will affect the growth and emergence process next year or is the environment a long-term one, where decisions taken today will only affect the system behavior over a longer time range (like 10-15 years). Use of chaos theory analysis tools allows us the freedom to develop novel operationalization for measuring such kind of dynamism in a SN environment. We use the system lag value at which the population dynamic time series is uncorrelated. The logic is, that the lag represents dependency between successive time-period under a particular set of conditions (experiments in our case), for which the system behavior changes significantly (in our experiments it was the number of firms existing at any given time). So for example, a firm in experiment 2 should consider strategic planning from a long-term perspective (lag value of 15), as compared to a firm in experiment 3 (lag value of 6). Such kind of analysis information has strong policy implications for large firms like IBM Corporation, or the US Government planning on healthcare issues.

Conclusion and Future work

This paper addresses a very important problem: Can the dynamics in a SN with respect to stability and emergence of firm population, be predicted? We present novel analysis of structural and population emergence in SN using statistical and time series analysis, with respect to stability and evolution of system behavior. The key findings, suggest that its is extremely important to know what type of a SN system a firm is operating in from a managers perspective, in order to make meaningful decisions, that would keep costs down and allow for efficient management. Insights are presented on how having knowledge of ordered interaction of rules in a SN environment can help managers/policy makers decide accordingly. With the help of chaos theory toolsets, possible emergence paths are reconstructed for an SN system. We suggest how properties such as limit cycle attractors may account for dynamic behavior and multiple modes observed in the industrial growth curve. We also suggest that, having a prior knowledge of such possibilities can help firms strategize appropriately by taking corrective measures.

The results and insights presented in this paper though based on the simulation of a well-structured industry are relatively generic. The research uses a generic rule-modeling framework and a theory base to derive “rules for the system”. Other industries and environment can be easily instantiated with this framework. Also, analysis techniques presented are very generic and we should be able to apply for any other industry. Hence, the contributions from this paper are at three different levels; it suggests how to use a novel SN modeling framework, to investigate growth and dynamism, it suggests how to analyze such dynamic behavior and make logical inferences and present insights and thirdly, it highlights the classic scenario analysis benefits that decision makers can benefit from.

We have laid a foundation for investigating growth oriented SN's. In future we are planning to model other industries within our framework. We are in the process of developing the capability of modeling existing networks (whose growth and dynamism we want to study) rather than always start from scratch. Also, from an analysis point of view, we are working on setting up formal experiments to test the effect of attractors on the number of modes of an industrial growth curve. Our ultimate goal is inline with the current focus of the research community: to move towards a general theory of Supply Network's.

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CHAPTER VI

SUMMARY, CONCLUSION AND FUTRE WORK

Dynamism in today's industrial landscape has directly affected the way Supply Networks (SNs) grow, evolve, and are managed. Recently there were numerous cases were an ineffective strategy led to failures and losses (IBM, Inktomi) and effective supply network management led towards success (Dell, Google). What drives this kind of dynamism and growth in Supply Networks?

The focus of this dissertation was to answer the two fundamental research questions of Supply Networks: -

1. *How do Supply Networks grow and emerge?*
2. *Are there simple rules and conditions that control the growth and emergence process?*

The dissertation explored existing SN literature and the emergent system literature for an appropriate model for modeling growth oriented Supply Network's. One of the limitations of the existing models in SN literature was that they only investigated at static structures (see Chapter II and III for a detailed discussion). The ones that viewed dynamic structures took a deductive empirical approach, which limited the scope of the models with respect to generality. Emergent system models characterized growth in dynamic networks with a graph representation, but were found lacking in suggesting how the exact manifestation of fundamental growth principle occurs in Supply Networks.

This dissertation took an inductive approach towards answering the research questions. The dissertation presented a new unified model of supply network (UMSN), which formed the basis for development of a platform for observing growth patterns in SN. Specifically, the dissertation contributed a generic rule-modeling framework and an agent based simulation (computational) framework that can be used for modeling Supply Network dynamics. The simulation using data and parameters from the US automobile industry over the last 80 years served as a investigation basis for the research.

Results and analysis from the simulation experiments revealed that the SN's in our setting are Complex Adaptive Systems by nature. They grow and emerge based on certain simple rules and conditions. These rules and conditions drive the local behavior of individual firms and the market. The rules interact in an ordered way (non-chaotic) to give rise to emergence patterns. The presence of such a phenomenon in SN systems in fact can possibly explain the presence of diverse types of SN's around us.

The dissertation takes the research one step forward by suggesting novel analysis techniques for predicting the SN system behavior over time and showing how such techniques can generate strategic insights for policy makers and managers.

Contributions

There are two fundamental contributions of this dissertation. First, the dissertation presents a new scientific approach towards solving a complex interdisciplinary problem of investigating growth phenomenon in Supply Networks. Specifically, UMSN, a new theory based framework for modeling growth rules was developed for the first time. UMSN takes a holistic approach and combines four diverse disciplines to solve the growth and evolution problem of SN's. Based on the UMSN, the dissertation proposes a fundamental subset of rules that can model a multitude of growth oriented supply networks across multiple industries. Both the UMSN and the rule-modeling framework extend the current SN literature. In order to operationalize the UMSN a corresponding computational framework was developed for observing growth phenomenon. Using software agents and learning models the dissertation presents a simulation framework that can simulate real life SN's. The simulation outcome that was analyzed in this dissertation was essentially evolving network topologies. The dissertation then suggests the use of novel analysis tools such as chaos theory analysis and statistical analysis for generating inferences and insights for policy makers. Such kind of analysis has never been done before in the SN literature for investigating SN dynamics.

The contribution of this dissertation exists in another dimension also. The modeling platform, the computational framework and the analysis toolsets developed in this dissertation can also be applied for investigating network growth problems in other domains that have characteristics similar to the supply network domain. Once the underlying rules are fed into the framework, similar kind of computation and analysis can yield domain specific results that can help researchers understand how their system grows. Example domains include creation of dynamic wi-fi networks, development of computational grid networks and cellular networks (biology).

Future Work

Specifically this dissertation breaks up the future work in terms of five fundamental categories as follows: -

1. "Unified Supply Network model" validation and towards a general theory of Supply Networks

Model validation is the key issue that needs to be addressed in future work. The dissertation illustrated an instance of how rules can be modeled for using a real life industry (automotive industry). The results from the simulation illustrate general trends matching the current state of the industry. Yet results such as formation of no SN structures and a lower percentage of Hierarchical structures, indicates additional research must be conducted. It may be a possibility for example that the simple bi-level parameter settings for role learning, capacity expansion and environmental threshold may not be adequate. A detailed and careful investigation of the generic rule framework and the model parameters is required. In order to do so, more industries need to be simulated and analyzed. Specifically, I plan to investigate three industries in the near future; i.e., the healthcare industry in US, the pharmaceutical industry, the florist industry and the aircraft industry. Only by doing so, can an underlying pattern that has a strong statistical significance can be "un-earthed" which then will eventually lead towards a "General Theory of Supply Networks".

2. Generic rule-modeling framework

The existing computational framework supports the simulation of SNs from the inception of the industry. The behavioral architecture of the fundamental components of the simulation model, i.e., environment, evaluator and node implements this in the form of hard coded rules. To be able to model both pre-existing networks and networks from their inception, a new node modeling and network structure modeling framework needs to be added to the computational platform.

3. Node modeling framework.

Simulation of pre-existing networks will require some fundamental changes in the existing computational framework. In a pre-existing network, there may be a number of different types of nodes that play different roles. For example to simulate the current automobile industry, there will be assembler nodes, tier one supplier nodes, tier-two, and tier-three nodes. Currently, only generic node definitions are available, i.e., all nodes start with a randomly generated fitness value, no existing linkages, and a set of other node attributes defined at the outset of the simulation. For a pre-existing network a modeler would need to define specialized nodes with predefined roles, fitness values, capacities, cost structure etc. I will extend the current node component by providing two types of nodes a modeler can capture: generic nodes (as currently implemented) and specialized nodes (to be implemented in future).

   a. Network Structure modeling framework.

Apart from the capability of defining specialized node in the network, a modeler would need to specify the existing structure by specifying the pair-wise linkages between all the nodes in the network. I plan to develop a network structure-modeling framework as shown in Figure 4.

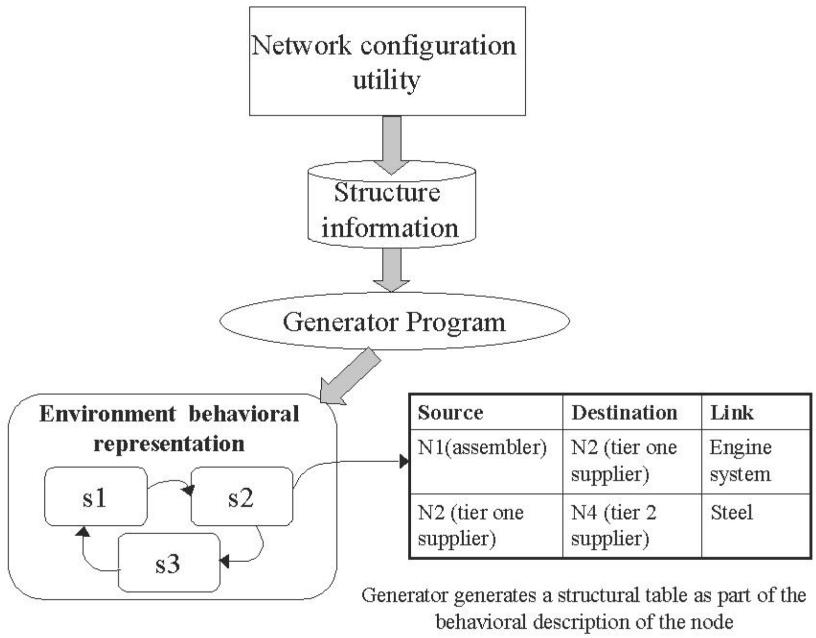

Figure 4: Network Structure Modeling Framework

While specifying a pre-existing network, a modeler will first describe all the specialized nodes in the network. The modeler then uses the configuration utility to specify the pair-wise linkages, with the links describing the role of the supplier. The information is then transformed into the environment's behavioral representation code by a generator program. The environment utilizes the source and destination information to distribute the demand initiating at the upstream of the supply network. I believe that this framework will seamlessly integrate with the existing one, as it would still allow the birth of generic nodes if demand remains unfulfilled. The only difference would be that the list of firms who remain in contention for getting the demand would have both the pre-existing firms specified by the modeler and any new firms born over time.

4. Simulation based computational framework

The current computational framework is limited in its capability to capture such a wide range of rules. In this study the rules were hard coded into the node, environment and the evaluator components. To be able to efficiently simulate multiple industries a generic rule-modeling environment must be developed. The rule modeler will contain generic methods to specify market and node configurations. As currently envisioned, once a modeler selects a set of rules for the current simulation, a rule translator will transform these rule specifications into behavioral states for the nodes and the environment. Figure 30 shows the corresponding Statechart (Harel and Politi 1998) representation of the node behavior as translated by the rule translator. While implementing a code generator will generate java code to represent the Statechart.

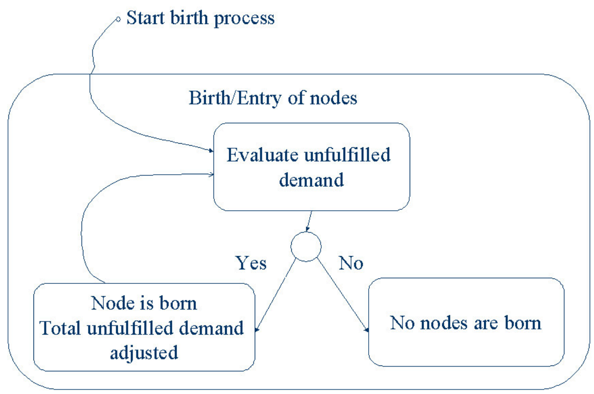

Figure 30: State Chart Translation

5. Analysis of emergence dynamics

The dissertation presented some initial stability analysis techniques from a very macro perspective of the entire system. Using stability criterion analysis from classical cellular automata theory (Cassandras 1993) and chaos theory (Schuster 2001) can extend the stability analysis and a formal analysis framework can be developed for determining whether the network structure is stable/marginally stable or unstable (Williams 1997). I further plan to establish a grading scale for the type of stability based on the five levels of stability as described in cellular automata theory (Zeigler, et al. 2000).

Recently network theorists have shown that the degree distribution of some networks can follow a power law. Such networks are called scale-free networks (Barabasi, et al. 2000). I propose to develop a tool that will determine the degree distribution of a stable supply network. Knowing the degree distribution can be of immense use to a policy maker as a scale free network has some very robust and interesting properties. For example, a scale free network is highly robust and does not break down easily even if some nodes die out.

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APPENDIX A

Fundamental Rule categories

<table>
<tr><th>Rule Number</th><th>Environment rules/condition</th><th>Description</th></tr>
<tr><td>Rule1</td><td>Type of market</td><td>This condition defines what type of market it is.
Regulated: - regulatory body (like the government) decides how many firms enter the market (Telecommunication Industry).
Free Entry: - firms can decide whether they want to enter the market or not.</td></tr>
<tr><td>Rule 2</td><td>Type of Competition</td><td>This condition defines what type of competition it is.
Competitive market: - Each firm set is its production quantity, while taking the market price as given, where the market price is determined by the intersection of the market demand curve and the industry's aggregate supply curve.
Imperfect competition: - Firms follow a price setting behavior. A sub-contracting body (may be a manufacturer or some regulatory body) decides the quantity that each firm will produce. Various types of market structures such as Monopoly, duopoly and oligopolies may exist for an imperfectly competitive market.</td></tr>
<tr><td>Rule 3</td><td>Type of market structure</td><td>This condition defines what type of market structure it is.
Monopoly market structures.
The duopoly (two sellers) and the oligopoly (more than two sellers) market structures can be classified as cooperative and non-cooperative.

1. “Cooperative behavior is defined by firm’s colluding by agreeing to produce in total the monopoly's profit-maximizing output level, or to charge the monopoly's price.

2. A non-cooperative behavior can be modeled either using simultaneous games where all firms choose their strategic variables (quantity produced or price) once and at the same time, or dynamically, where the firms move in sequence”. Finally, repeated interaction of a simultaneous-move oligopoly game is such that in each period, each firm chooses its action from the same action set after observing what actions have been chosen in earlier periods.</td></tr>
<tr><td>Rule 4</td><td>Birth/Entry into market</td><td>This rule defines how new firms are born in the SN environment.
If there is unfulfilled demand in the environment, new firms are born. Firms enter the market depending on the type of market and the sunk cost involved for entering the market (with respect to initial start up capacity and fitness).</td></tr>
<tr><td>Rule 5</td><td>Death/Exit from market</td><td>This rule defines how incumbent firm’s die/exit the SN environment.
Firms die if over a period of time they cannot grow their fitness above the required environmental threshold.</td></tr>
</table>

Rule Number	Firm rule categories	Description
Rule 1	Cost Set up	This rule category sets up the internal cost structure of a firm • Marginal cost of production + fixed cost for expansion. • The cost set up curves can be of different shapes, both linear and non-linear depending on the type of environment
Rule 2	Bidding	This rule category defines how a firm bids. • Depends on the type of market structure and competition. For example in an oligopolistic market with imperfect competition (firms playing essentially a Bertrand's pricing game), bidding rules will involve bidding the lowest price to win the contract.
Rule 3	Subcontracting	This rule category defines how a firm subcontracts. • Depends on the market structure setting. The characteristic of the underlying game is used for defining the node's subcontracting rules. The actual subcontracting rules will be varying for industry to industry, depending on the market type, type of competition, and the type of product.
Rule 4	Production	This rule category defines how a firm handles an incoming demand. • The final strategy for production depends from environment to environment. For example one strategy can be to produce only up to the marginal capacity and subcontract the rest to a supplier.
Rule 5	Capacity growth	This rule category defines how a firm grows its capacity with time. • Depending on the fitness growth, or its need to expand on short time basis (and incurring higher fixed costs) firms can expand their capacities over the time. The capacity expansion is made proportional to the fitness growth (assuming that positive fitness growth means availability of more capital for investment purposes). The same reason holds true in the other direction for contracting existing capacities (if losses due to fixed asset costs are too high).
Rule 6	Learning	This rule category defines how a firm learns and adapts with time. • Firms learn on various aspects through out their lifetime. They learn about how to price optimally, how much capacity to expand, and what role to play in the supply network. • The actual learning process is dependent on the underlying industry we simulate. For example for the US automobile industry, we use a aspiration satisficing based price learning model (Karandikar, Mookherjee, Ray, & Vega-Redondo, 1998) for each firm and a reinforcement learning (Roth & Erev, 1995) based role learning model for learning which role to play (assembler, tier 1 supplier, tier 2 supplier etc).

APPENDIX B

Simulation model architecture

Figure 31 shows the multi-paradigm simulation architecture used in the research framework. The Environment agent acts as the root coordinator and is a coupled model. Evaluator, Visual Manager and Timekeeper are children, which the environment launches and controls. The environment runs on a simulated clock. **Evaluator** acts as a coupled DEVS coordinator as it owns all the nodes and communicates with them using a message passing protocol. The evaluator launches all the nodes and sends them demand information and other messages. At the end of a fixed number of demand cycles it also evaluates all the nodes and kills the unfit ones. **Nodes** are atomic DEVS models and are owned and coordinated by the evaluator.

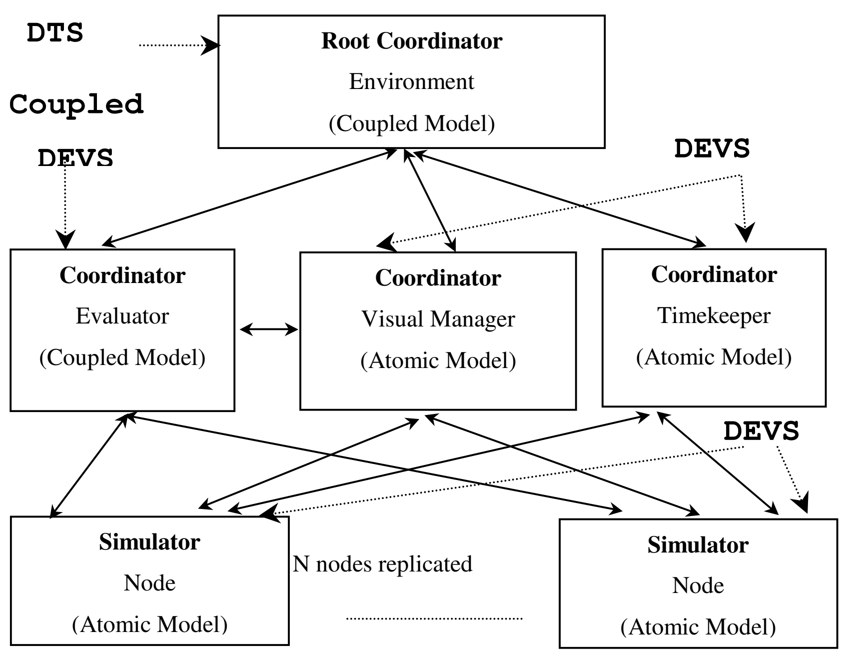

Figure 31: Multi-paradigm Simulator Architecture

APPENDIX C

Agent Based Simulation of Supply Networks

To capture the dynamic notion of the simulator components, agent-based technique (Ferber, 1999) was used for implementation purposes. Parunak (1998), Kohn et.al (2000), Tesfatsion et.al, (1999) and others (Lin Fu-Ren et.al, 1998; Zhao and Jin, 2000) have successfully used agent-based techniques for similar work.

The research framework uses Ferber's (1999) definition of an agent: "*a physical or virtual entity, which is capable of acting in an environment. It can communicate directly with other agents, which is driven by a set of tendencies (goals). It also possesses resources of its own and is capable of perceiving its environment"*.

Node Architecture

Based on this definition of an agent,

Figure 32 shows the node architecture used in the research framework. Each node consists of sensors, a decision-making unit (DMU), an information processor unit, and an external interface. The node utilizes the sensors to monitor the external world and receive signals from the environment and other nodes. For example, nodes pick up demand information, product information etc, which the information processor unit processes all the incoming signals and handles the routine tasks such as reporting its fitness to the environment etc, and requests the DMU to perform the decision-making tasks such as supplier selection. Then, the DMU takes the processed information and evaluates the information based on the strategies encoded within the node and provides the best response selection. There is "to and fro" communication between the DMU and the processor unit. Once agreement is reached, the processor unit responds to the incoming signals by sending responses with the help of the node external interface.

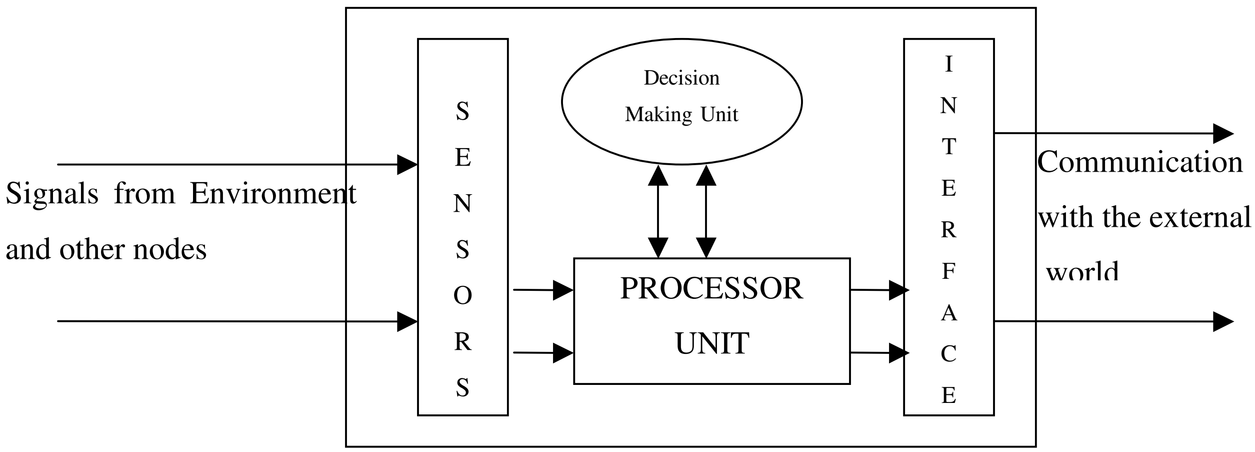

Figure 32: Node Architecture

Node Intelligence

The node architecture allows us to consider two different types of nodes within the research framework: non-intelligent and intelligent. Non-Intelligent nodes do not utilize strategic decision making rules. Their DMU lies dormant and the entire behavior is dictated by the encoded rules in the processor unit. Their sensory capabilities are also limited, as they cannot differentiate between what is good and what is bad for them. For example, every node has a capacity constraint and before accepting a contract, a node should check on its internal capacity and decide on its ability to satisfy the demand based on their current fitness level. Non-Intelligent nodes do not perform such a check and, hence they can suffer in an environment of demand munificence but capacity limitations, because they may repeatedly underprice bids and accept orders they cannot fulfill, which results in a reduction in their fitness values.

Realistically, firms participating in an a supply network should act more "intelligently" by evaluating the "goodness" of their actions based on the payoffs they receive from the environment. Intelligent adaptive nodes have active DMU's, scan for feedback information from the environment and other nodes, learn from their previous interactions, and continuously adapt to the dynamism of the system over time. To capture the notion of learning and adaptation by firms in the research model, learning mechanisms have to be embedded in the behavioral description of each node. Firms in a supply network generally learn about the following occurring in the system:

- Changes taking place in the supply network environment (environmental conditions)
- Effectiveness of the strategies used for supplier selection, bidding etc.

Variety of learning models have been suggested in the literature, from the fields of computer science (machine learning), artificial intelligence (Mitchell, 1997) to psychology and economics literature (Roth and Erev, 1995, Simon, 1957, Selten, 1991, Karandikar et.al 1998). Since decision makers in a supply network are humans, we use human interaction-based learning models described in the psychology literature to structure the learning models. There are principally two classes; forward-looking learning models (when subjects have a reasonably good idea of the underlying situation and the corresponding payoffs at stake) and backward looking learning models (when subjects learn based on their previous interactions and results of those interactions) (Shor 2003). Forward-looking models generally forecast based on present conditions what would be the best solution, given conditions remain more or less same within the forecasting period. Since nodes in the research framework do not have a good idea about the environment or the corresponding payoffs while responding with bids, forward-looking models are not suitable. In the category of backward looking models, there are a number of well-studied heuristic approaches, such as the single parameter reinforcement learning Roth and Erev model (Roth, Erev, 1995), aspiration models (Selten, 1991) such as satisficing (Karandikar et.al, 1998) and evolving aspirations (Borgers and Sarin, 2000). Additionally, there are other models, such as reinforcement learning with reference points, world resetting and responsive learning automata; all these models have been described and dealt with in great detail in Shor (2003).

The supply network scenario presented in this paper has a high degree of uncertainty with regards to the information about the environment that is available to each node. Aspiration models are well suited for such scenarios, where what is a good and what is a bad strategy is not known with certainty; hence they are the models selected for CAS-SIM

Aspiration Models

In light of the little information about the environment and its attainable payoffs (by playing a particular strategy), people/firms may develop aspirations. A strategy is played more often if the resulting payoff from an interaction exceeds the aspiration level and less often otherwise (Shor, 2003). Karandikar, et al. (1998) proposed a model in which players repeat a strategy as long as payoffs exceed aspirations. If payoffs fall below the aspiration level, the probability of repeating the strategy decreases in proportion to the difference between the aspiration and received payoff.

When a realized payoff falls short of the aspiration level, probability updating is governed by equation 2 below (if strategy *i* played at time *t*, *p* is the probability of playing each strategy and *β* is the factor that determines speed of learning):

α_t represents the aspiration level and π_t be the received payoff

For $\alpha_t > \pi_t$

$$p_{t+1}(i) = \frac{p_t(i)}{1+\beta(\alpha_t - \pi_t)}$$

$$p_{t+1}(j) = \frac{p_t(j)}{1-p_t(i)} * \left(1 - \frac{p_t(i)}{1+\beta(\alpha_t - \pi_t)}\right) \text{ where } j \neq i \qquad \text{...2}$$

Thus, the probability of the unsuccessful strategy (represented by *i*) is reduced by a factor governed by the denominator in 2. On the other hand, probability of all other strategies in the strategy space is increased proportionately.

When the learner is satisfied, having received a payoff exceeding his/her aspiration level, the satisficing model is used.

Satisficing

Karandikar, et al. (1998), suggested the revising of probabilities only in the case of disappointment. If payoffs are above aspirations, one simply repeats the previous action that the player is said to be "*satisficed*" with the outcome of the interaction. Equation 3 below governs the probability updating mechanism of each strategy in the strategy space.

α_t represents the aspiration level and π_t be the received payoff

For $\pi_t \geq \alpha_t$

$p_{t+1}(i) = 1$

$p_{t+1}(j) = 0 \qquad \text{where } j \neq i \qquad ...3$

Now that the research model (Figure 1 and Figure 2) has been introduced and the theoretical foundations have been laid down, the next section introduces CAS-SIM as a multi-paradigm agent based simulation tool that incorporates all the features of the research model.

APPENDIX D

CAS-SIM (Complex Adaptive Supply Network Simulation)

To implement the multi-paradigm simulator described above, we have developed a tool suite called CAS-SIM (<u>C</u>omplex <u>A</u>daptive <u>S</u>upply Networks <u>Sim</u>ulato<u>r</u>).

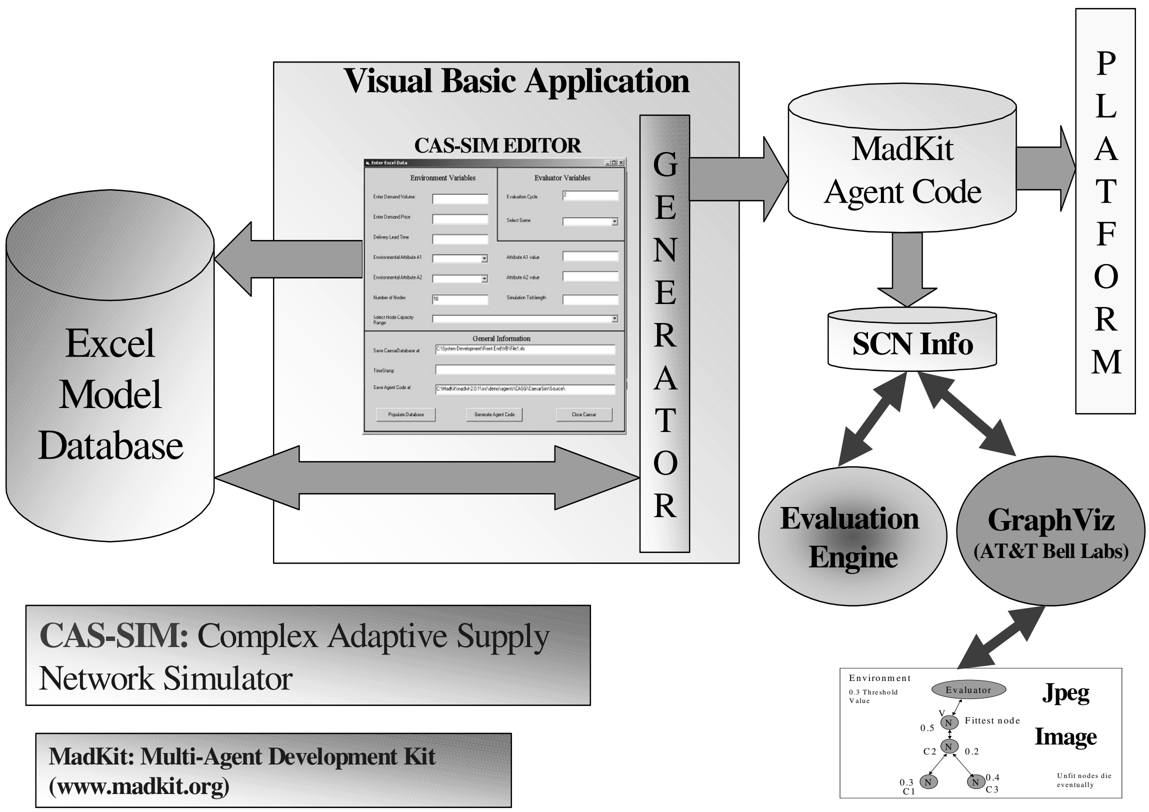

Figure 33: CAS-SIM Architecture

The CAS-SIM architecture is shown above in Figure 33. It consists of a Graphical front-end called the configuration manager. The configuration manager allows a modeler to configure the simulation parameters such as demand range, number of nodes etc. The parameters are then stored in a persistent database. A code generator program then reads from the database and generates the agent code. The agent code is run on the agent platform and simulations output in the form of Supply Networks are stored in another persistent database. Evaluation and

Visualization Engines then read from these databases and analyzes and reports the results of the simulation.

The CAS-SIM simulation toolkit has been developed by integrating a number of tool suites into a single framework. The heart of the framework is the MadKit platform (2003). MadKit (Multi-agent Development Kit) is a versatile; java based agent development platform that can be used for cross-platform multi-agent system development. MadKit platform allows us to model the nodes and the environment as java agents, thus capturing all the nuances described in the simulation model. It uses the node architecture described in the background section and each of the components in the architecture is implemented as java code. The configuration manager is implemented using a Visual Basic front end that captures all the relevant information from the modeler and stores it in a excel database. This allows the storing of initial conditions used in the simulation for future analysis. A code generator written in Visual Basic then reads the startup simulation parameters from the excel database and generates the java agent code for MadKit kernel. An evaluation engine and visualization engine has been developed so that the growth structures that are generated during the simulation can be recorded and analyzed as well as observed. Table 16 provides a summary of the various tools used in CAS-SIM.

Table 16: Tool Selection for CAS-SIM architecture

Components	**Tools**
Configuration Manager	Visual Basic
Model Database	Microsoft Excel
Code Generator	Visual Basic
Agent Platform	MadKit, Java
SCN Info Database	Microsoft Excel
Evaluation Engine	Visual Basic
Visualization Engine	GraphViz (AT&T), Visual Basic

APPENDIX E

Behavioral Modeling of key simulation components

The detailed behavior of some of the components in the simulation model can be shown using a state chart representation. The environment in the model is used for defining the market settings and generating demand patterns and hence has a simple state chart representation as shown in Figure 34.

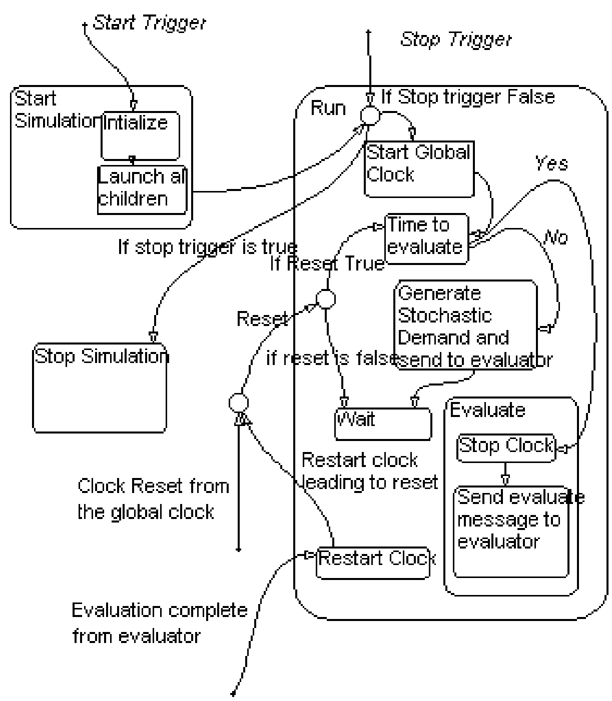

Figure 34: State chart representation of environment

The environment is the first to start in the simulation and initializes itself. It then launches the evaluator, the support agents (visual manager and timekeeper) and goes to its run state. In its run state it first starts the global clock and transitions to the next state to check if it is time to evaluate for unfit nodes. In the first run, the flag is not set and the environment generates a stochastic demand and sends it to the evaluator. The environment keeps generating these demands asynchronously. The evaluator and the nodes have a multi-threaded implementation to enable parallel processing of these demands. This corrects the earlier problems the earlier model had with synchronization and inefficient simulations due to tying up of the nodes to the global clock. When the "time to evaluate" flag is set, the environment stops the global clock and requests the evaluator to evaluate all the unfit nodes.

Figure 35 shows the state chart representation for the evaluator. The evaluator, upon receiving the launch message, goes into the Start state, initializes it, and launches the initial number of nodes set in the environment. It then waits for a demand from the environment. Once it gets the first demand it goes into the run state and distributes demand based on the game theoretic and market structure rules. It then returns and waits for further demand messages from the environment. When it receives a evaluate message from the environment, it first broadcasts a pause message to all nodes so that it can flag all the unfit nodes that are below the environmental threshold level, such that they cannot get any new orders. It then removes all the nodes from the simulation that have been previously flagged. The evaluator also responds to other messages from nodes, such as the node fitness report, and so on.

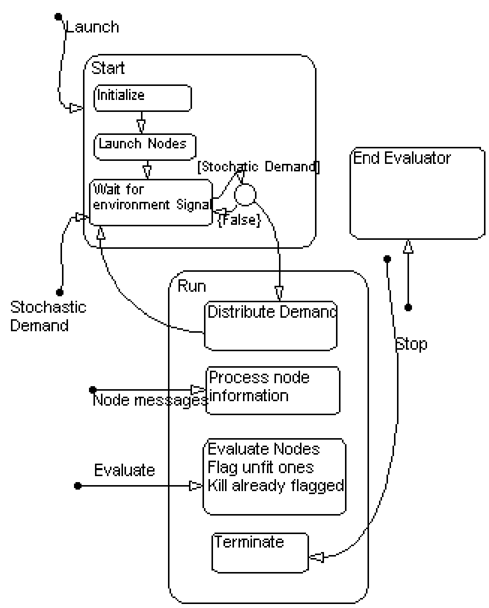

Figure 35: State chart representation of evaluator

Figure 36 represents a high-level state chart representation for node behavior. A node is completely event driven. When the evaluator first launches it, start state is entered and the node initializes itself. It then transitions to its run state. In its run state it waits for incoming messages.

A node fundamentally responds to seven basic messages or events. We use decision tree diagrams to illustrate node behavior in response to some of the important messages.

Pause

After every 12 demand cycles (equivalent to a "month" in simulated time), the evaluator evaluates the nodes. During this time no transactions take place in the environment and to facilitate this the evaluator sends a "Pause" message to all nodes. Upon receiving this message a node suspends all its activities.

Report

Node responds to this message by sending back its current fitness value to the evaluator.

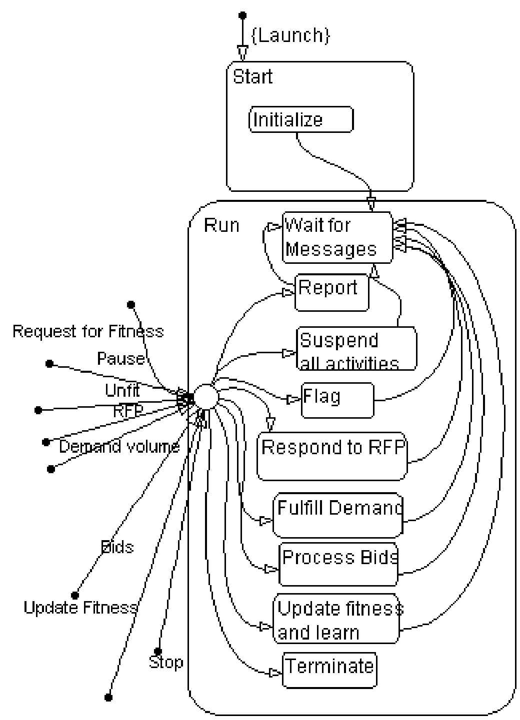

Figure 36: State chart representation of nodes

Flag

This message sets the death flag in a node. This tells the node that it will be removed from the environment in the next cycle and it does not get any new orders. The node cannot control this flag.

Demand

Figure 37 describes the decision tree representing the behavior of the Fulfill demand state that is triggered due to this event. Once a node is awarded an order, it sends out a RFP (Request for Proposal) and waits for a fixed amount of time for the bids to arrive. It then compares its internal assembly cost with respect to the sub-contracting cost. If the internal cost is lower and the demand is less than the current capacity then the entire demand is manufactured and shipped. If the demand is greater then node capacity, it can either decide to accept the penalty of not meeting the demand and produce up to capacity or else undergo a temporary expansion, especially if it improves the profit margin. If the node sub-contracts, then as described in case of the evaluator it follows Edgeworth’s version of Bertrand’s pricing game (1925) and distributes the demand between the responding bidders.

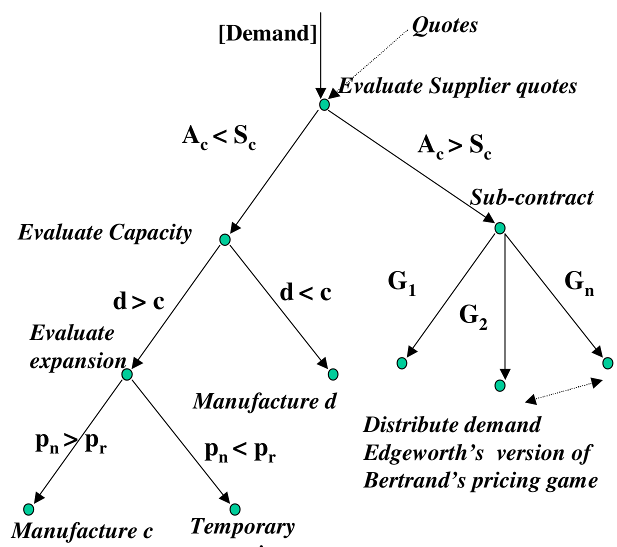

Figure 37: Decision tree embedded in the fulfill demand state

Request for Proposal (RFP)

When a node receives a request for proposal, it responds based on its role propensities. Every role a node can play has an associated propensity value. Every node also has an associated “available to promise” (ATP) capacity by role. Bidding is based partially on role propensity and role ATP. If a node receives a RFP (due to a new demand in the environment) while it is still processing a current demand, it uses the ATP capacity to bid on the new demand and thus tries to ensure that it doesn't remain idle in the near future (see Figure 38).

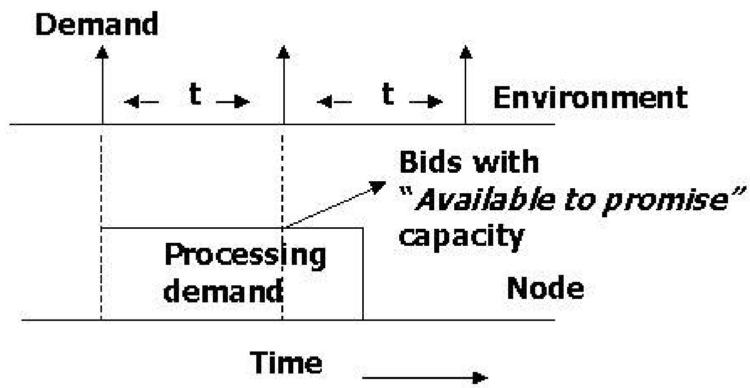

Figure 38: Parallel response to multiple demands

Time

A node requests a separate timekeeper agent for waiting on bids. When time is up the node receives this message.

Update Fitness

Figure 39 represents the Learn state behavior. Upon receiving this message, a node activates its learning module and adapts its behavior according to its performance in the current demand cycle. If it results in a positive change in fitness then it updates the propensity of playing that role. It then checks if the immediate history of demand cycles (number of demand cycles are heuristically fixed) has yielded a positive growth. If yes, then it expands its current capacity under that role, else it stays at the current capacity. If it experienced a negative fitness growth then it decreases the propensity of playing the role and checks if the immediate history of demand cycles has yielded negative growth. If yes then it shrinks its current capacity associated with that role, else it remains at its current level. At the end of both of these growth cycles a node updates the probability of playing its current pricing strategy once again. If the change in fitness (δf) is greater than the aspiration level (a), then it increases the probability, else decreases it. The aspiration level indicates what a node thinks is a successful outcome. From time to time a node excites (modifies) the aspiration level, so as to experiment around the strategy space (Karandikar et al. 1998).

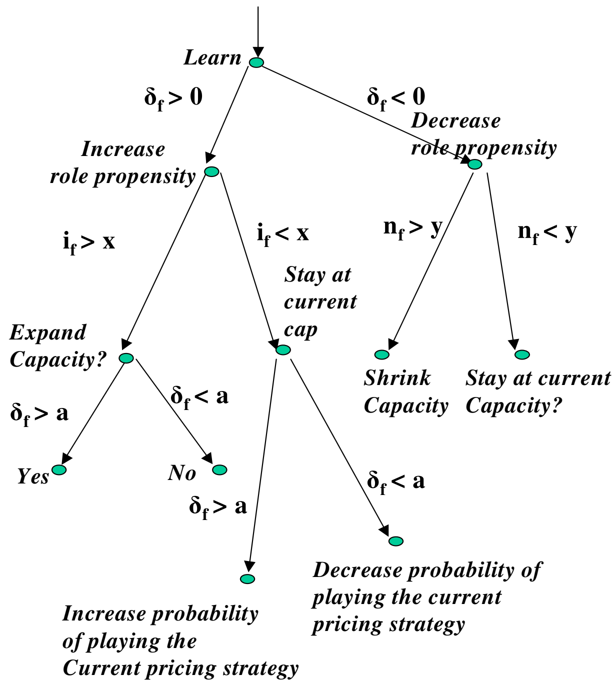

Figure 39: Decision tree embedded in the learning state

APPENDIX F

Details of statistical Analysis

Capacity Expansion

Crosstab

			EndStruc				Total
			0	1	2	4	
CE	Fast	Count	39	29	26	24	118
		Expected Count	32.4	29.9	36.3	19.4	118.0
		% within CE	33.1%	24.6%	22.0%	20.3%	100.0%
		% within EndStruc	60.0%	48.3%	35.6%	61.5%	49.8%
		Std. Residual	1.2	-.2	-1.7	1.0	
	Slow	Count	26	31	47	15	119
		Expected Count	32.6	30.1	36.7	19.6	119.0
		% within CE	21.8%	26.1%	39.5%	12.6%	100.0%
		% within EndStruc	40.0%	51.7%	64.4%	38.5%	50.2%
		Std. Residual	-1.2	.2	1.7	-1.0	
Total		Count	65	60	73	39	237
		Expected Count	65.0	60.0	73.0	39.0	237.0
		% within CE	27.4%	25.3%	30.8%	16.5%	100.0%
		% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	10.781[a]	3	.013
Likelihood Ratio	10.903	3	.012
N of Valid Cases	237		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 19.42.

Role Learning

Crosstab

			EndStruc				Total
			0	1	2	4	
R	High	Count	34	28	37	20	119
		Expected Count	32.6	30.1	36.7	19.6	119.0
		% within R	28.6%	23.5%	31.1%	16.8%	100.0%
		% within EndStruc	52.3%	46.7%	50.7%	51.3%	50.2%
		Std. Residual	.2	-.4	.1	.1	
	Low	Count	31	32	36	19	118
		Expected Count	32.4	29.9	36.3	19.4	118.0
		% within R	26.3%	27.1%	30.5%	16.1%	100.0%
		% within EndStruc	47.7%	53.3%	49.3%	48.7%	49.8%
		Std. Residual	-.2	.4	-.1	-.1	
Total		Count	65	60	73	39	237
		Expected Count	65.0	60.0	73.0	39.0	237.0
		% within R	27.4%	25.3%	30.8%	16.5%	100.0%
		% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	.440[a]	3	.932
Likelihood Ratio	.440	3	.932
N of Valid Cases	237		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 19.42.

Environmental Threshold

Crosstab

			EndStruc				
			0	1	2	4	Total
Th	High	Count	54	3	33	29	119
		Expected Count	32.6	30.1	36.7	19.6	119.0
		% within Th	45.4%	2.5%	27.7%	24.4%	100.0%
		% within EndStruc	83.1%	5.0%	45.2%	74.4%	50.2%
		Std. Residual	3.7	-4.9	-.6	2.1	
	Low	Count	11	57	40	10	118
		Expected Count	32.4	29.9	36.3	19.4	118.0
		% within Th	9.3%	48.3%	33.9%	8.5%	100.0%
		% within EndStruc	16.9%	95.0%	54.8%	25.6%	49.8%
		Std. Residual	-3.8	5.0	.6	-2.1	
Total		Count	65	60	73	39	237
		Expected Count	65.0	60.0	73.0	39.0	237.0
		% within Th	27.4%	25.3%	30.8%	16.5%	100.0%
		% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	86.971[a]	3	.000
Likelihood Ratio	100.689	3	.000
N of Valid Cases	237		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 19.42.

Capacity Expansion Versus Role Learning

CE * EndStruc * R Crosstabulation

R				EndStruc 0	1	2	4	Total
High	CE	Fast	Count	20	12	16	12	60
			Expected Count	17.1	14.1	18.7	10.1	60.0
			% within CE	33.3%	20.0%	26.7%	20.0%	100.0%
			% within EndStruc	58.8%	42.9%	43.2%	60.0%	50.4%
			Std. Residual	.7	-.6	-.6	.6	
		Slow	Count	14	16	21	8	59
			Expected Count	16.9	13.9	18.3	9.9	59.0
			% within CE	23.7%	27.1%	35.6%	13.6%	100.0%
			% within EndStruc	41.2%	57.1%	56.8%	40.0%	49.6%
			Std. Residual	-.7	.6	.6	-.6	
	Total		Count	34	28	37	20	119
			Expected Count	34.0	28.0	37.0	20.0	119.0
			% within CE	28.6%	23.5%	31.1%	16.8%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%
Low	CE	Fast	Count	19	17	10	12	58
			Expected Count	15.2	15.7	17.7	9.3	58.0
			% within CE	32.8%	29.3%	17.2%	20.7%	100.0%
			% within EndStruc	61.3%	53.1%	27.8%	63.2%	49.2%
			Std. Residual	1.0	.3	-1.8	.9	
		Slow	Count	12	15	26	7	60
			Expected Count	15.8	16.3	18.3	9.7	60.0
			% within CE	20.0%	25.0%	43.3%	11.7%	100.0%
			% within EndStruc	38.7%	46.9%	72.2%	36.8%	50.8%
			Std. Residual	-.9	-.3	1.8	-.9	
	Total		Count	31	32	36	19	118
			Expected Count	31.0	32.0	36.0	19.0	118.0
			% within CE	26.3%	27.1%	30.5%	16.1%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

R		Value	df	Asymp. Sig. (2-sided)
High	Pearson Chi-Square	3.098[a]	3	.377
	Likelihood Ratio	3.113	3	.375
	N of Valid Cases	119		
Low	Pearson Chi-Square	10.102[b]	3	.018
	Likelihood Ratio	10.383	3	.016
	N of Valid Cases	118		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.92.

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.34.

Role Learning Versus Capacity Expansion

R * EndStruc * CE Crosstabulation

CE				EndStruc 0	1	2	4	Total
Fast	R	High	Count	20	12	16	12	60
			Expected Count	19.8	14.7	13.2	12.2	60.0
			% within R	33.3%	20.0%	26.7%	20.0%	100.0%
			% within EndStruc	51.3%	41.4%	61.5%	50.0%	50.8%
			Std. Residual	.0	-.7	.8	-.1	
		Low	Count	19	17	10	12	58
			Expected Count	19.2	14.3	12.8	11.8	58.0
			% within R	32.8%	29.3%	17.2%	20.7%	100.0%
			% within EndStruc	48.7%	58.6%	38.5%	50.0%	49.2%
			Std. Residual	.0	.7	-.8	.1	
	Total		Count	39	29	26	24	118
			Expected Count	39.0	29.0	26.0	24.0	118.0
			% within R	33.1%	24.6%	22.0%	20.3%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%
Slow	R	High	Count	14	16	21	8	59
			Expected Count	12.9	15.4	23.3	7.4	59.0
			% within R	23.7%	27.1%	35.6%	13.6%	100.0%
			% within EndStruc	53.8%	51.6%	44.7%	53.3%	49.6%
			Std. Residual	.3	.2	-.5	.2	
		Low	Count	12	15	26	7	60
			Expected Count	13.1	15.6	23.7	7.6	60.0
			% within R	20.0%	25.0%	43.3%	11.7%	100.0%
			% within EndStruc	46.2%	48.4%	55.3%	46.7%	50.4%
			Std. Residual	-.3	-.2	.5	-.2	
	Total		Count	26	31	47	15	119
			Expected Count	26.0	31.0	47.0	15.0	119.0
			% within R	21.8%	26.1%	39.5%	12.6%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

CE		Value	df	Asymp. Sig. (2-sided)
Fast	Pearson Chi-Square	2.239[a]	3	.524
	Likelihood Ratio	2.255	3	.521
	N of Valid Cases	118		
Slow	Pearson Chi-Square	.776[b]	3	.855
	Likelihood Ratio	.777	3	.855
	N of Valid Cases	119		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.80.

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.44.

Capacity Expansion Versus Environmental threshold

CE * EndStruc * Th Crosstabulation

Th				EndStruc 0	1	2	4	Total
High	CE	Fast	Count	30	1	12	17	60
			Expected Count	27.2	1.5	16.6	14.6	60.0
			% within CE	50.0%	1.7%	20.0%	28.3%	100.0%
			% within EndStruc	55.6%	33.3%	36.4%	58.6%	50.4%
			Std. Residual	.5	-.4	-1.1	.6	
		Slow	Count	24	2	21	12	59
			Expected Count	26.8	1.5	16.4	14.4	59.0
			% within CE	40.7%	3.4%	35.6%	20.3%	100.0%
			% within EndStruc	44.4%	66.7%	63.6%	41.4%	49.6%
			Std. Residual	-.5	.4	1.1	-.6	
	Total		Count	54	3	33	29	119
			Expected Count	54.0	3.0	33.0	29.0	119.0
			% within CE	45.4%	2.5%	27.7%	24.4%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%
Low	CE	Fast	Count	9	28	14	7	58
			Expected Count	5.4	28.0	19.7	4.9	58.0
			% within CE	15.5%	48.3%	24.1%	12.1%	100.0%
			% within EndStruc	81.8%	49.1%	35.0%	70.0%	49.2%
			Std. Residual	1.5	.0	-1.3	.9	
		Slow	Count	2	29	26	3	60
			Expected Count	5.6	29.0	20.3	5.1	60.0
			% within CE	3.3%	48.3%	43.3%	5.0%	100.0%
			% within EndStruc	18.2%	50.9%	65.0%	30.0%	50.8%
			Std. Residual	-1.5	.0	1.3	-.9	
	Total		Count	11	57	40	10	118
			Expected Count	11.0	57.0	40.0	10.0	118.0
			% within CE	9.3%	48.3%	33.9%	8.5%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

Th		Value	df	Asymp. Sig. (2-sided)
High	Pearson Chi-Square	4.309[a]	3	.230
	Likelihood Ratio	4.352	3	.226
	N of Valid Cases	119		
Low	Pearson Chi-Square	9.641[b]	3	.022
	Likelihood Ratio	10.104	3	.018
	N of Valid Cases	118		

a. 2 cells (25.0%) have expected count less than 5. The minimum expected count is 1.49.

b. 1 cells (12.5%) have expected count less than 5. The minimum expected count is 4.92.

Environmental threshold Versus Capacity Expansion

Th * EndStruc * CE Crosstabulation

CE				EndStruc 0	1	2	4	Total
Fast	Th	High	Count	30	1	12	17	60
			Expected Count	19.8	14.7	13.2	12.2	60.0
			% within Th	50.0%	1.7%	20.0%	28.3%	100.0%
			% within EndStruc	76.9%	3.4%	46.2%	70.8%	50.8%
			Std. Residual	2.3	-3.6	-.3	1.4	
		Low	Count	9	28	14	7	58
			Expected Count	19.2	14.3	12.8	11.8	58.0
			% within Th	15.5%	48.3%	24.1%	12.1%	100.0%
			% within EndStruc	23.1%	96.6%	53.8%	29.2%	49.2%
			Std. Residual	-2.3	3.6	.3	-1.4	
	Total		Count	39	29	26	24	118
			Expected Count	39.0	29.0	26.0	24.0	118.0
			% within Th	33.1%	24.6%	22.0%	20.3%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%
Slow	Th	High	Count	24	2	21	12	59
			Expected Count	12.9	15.4	23.3	7.4	59.0
			% within Th	40.7%	3.4%	35.6%	20.3%	100.0%
			% within EndStruc	92.3%	6.5%	44.7%	80.0%	49.6%
			Std. Residual	3.1	-3.4	-.5	1.7	
		Low	Count	2	29	26	3	60
			Expected Count	13.1	15.6	23.7	7.6	60.0
			% within Th	3.3%	48.3%	43.3%	5.0%	100.0%
			% within EndStruc	7.7%	93.5%	55.3%	20.0%	50.4%
			Std. Residual	-3.1	3.4	.5	-1.7	
	Total		Count	26	31	47	15	119
			Expected Count	26.0	31.0	47.0	15.0	119.0
			% within Th	21.8%	26.1%	39.5%	12.6%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

CE		Value	df	Asymp. Sig. (2-sided)
Fast	Pearson Chi-Square	40.744[a]	3	.000
	Likelihood Ratio	47.849	3	.000
	N of Valid Cases	118		
Slow	Pearson Chi-Square	48.058[b]	3	.000
	Likelihood Ratio	56.392	3	.000
	N of Valid Cases	119		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.80.

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.44.

Environmental threshold Versus Role Learning

Th * EndStruc * R Crosstabulation

R				EndStruc 0	1	2	4	Total
High	Th	High	Count	28	0	17	14	59
			Expected Count	16.9	13.9	18.3	9.9	59.0
			% within Th	47.5%	.0%	28.8%	23.7%	100.0%
			% within EndStruc	82.4%	.0%	45.9%	70.0%	49.6%
			Std. Residual	2.7	-3.7	-.3	1.3	
		Low	Count	6	28	20	6	60
			Expected Count	17.1	14.1	18.7	10.1	60.0
			% within Th	10.0%	46.7%	33.3%	10.0%	100.0%
			% within EndStruc	17.6%	100.0%	54.1%	30.0%	50.4%
			Std. Residual	-2.7	3.7	.3	-1.3	
	Total		Count	34	28	37	20	119
			Expected Count	34.0	28.0	37.0	20.0	119.0
			% within Th	28.6%	23.5%	31.1%	16.8%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%
Low	Th	High	Count	26	3	16	15	60
			Expected Count	15.8	16.3	18.3	9.7	60.0
			% within Th	43.3%	5.0%	26.7%	25.0%	100.0%
			% within EndStruc	83.9%	9.4%	44.4%	78.9%	50.8%
			Std. Residual	2.6	-3.3	-.5	1.7	
		Low	Count	5	29	20	4	58
			Expected Count	15.2	15.7	17.7	9.3	58.0
			% within Th	8.6%	50.0%	34.5%	6.9%	100.0%
			% within EndStruc	16.1%	90.6%	55.6%	21.1%	49.2%
			Std. Residual	-2.6	3.3	.5	-1.7	
	Total		Count	31	32	36	19	118
			Expected Count	31.0	32.0	36.0	19.0	118.0
			% within Th	26.3%	27.1%	30.5%	16.1%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

R		Value	df	Asymp. Sig. (2-sided)
High	Pearson Chi-Square	45.673[a]	3	.000
	Likelihood Ratio	57.789	3	.000
	N of Valid Cases	119		
Low	Pearson Chi-Square	42.142[b]	3	.000
	Likelihood Ratio	47.227	3	.000
	N of Valid Cases	118		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.92.

b. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.34.

Role Learning Versus Environmental threshold

R * EndStruc * Th Crosstabulation

Th				EndStruc 0	1	2	4	Total
High	R	High	Count	28	0	17	14	59
			Expected Count	26.8	1.5	16.4	14.4	59.0
			% within R	47.5%	.0%	28.8%	23.7%	100.0%
			% within EndStruc	51.9%	.0%	51.5%	48.3%	49.6%
			Std. Residual	.2	-1.2	.2	-.1	
		Low	Count	26	3	16	15	60
			Expected Count	27.2	1.5	16.6	14.6	60.0
			% within R	43.3%	5.0%	26.7%	25.0%	100.0%
			% within EndStruc	48.1%	100.0%	48.5%	51.7%	50.4%
			Std. Residual	-.2	1.2	-.2	.1	
	Total		Count	54	3	33	29	119
			Expected Count	54.0	3.0	33.0	29.0	119.0
			% within R	45.4%	2.5%	27.7%	24.4%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%
Low	R	High	Count	6	28	20	6	60
			Expected Count	5.6	29.0	20.3	5.1	60.0
			% within R	10.0%	46.7%	33.3%	10.0%	100.0%
			% within EndStruc	54.5%	49.1%	50.0%	60.0%	50.8%
			Std. Residual	.2	-.2	-.1	.4	
		Low	Count	5	29	20	4	58
			Expected Count	5.4	28.0	19.7	4.9	58.0
			% within R	8.6%	50.0%	34.5%	6.9%	100.0%
			% within EndStruc	45.5%	50.9%	50.0%	40.0%	49.2%
			Std. Residual	-.2	.2	.1	-.4	
	Total		Count	11	57	40	10	118
			Expected Count	11.0	57.0	40.0	10.0	118.0
			% within R	9.3%	48.3%	33.9%	8.5%	100.0%
			% within EndStruc	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

Th		Value	df	Asymp. Sig. (2-sided)
High	Pearson Chi-Square	3.131[a]	3	.372
	Likelihood Ratio	4.289	3	.232
	N of Valid Cases	119		
Low	Pearson Chi-Square	.475[b]	3	.924
	Likelihood Ratio	.477	3	.924
	N of Valid Cases	118		

a. 2 cells (25.0%) have expected count less than 5. The minimum expected count is 1.49.

b. 1 cells (12.5%) have expected count less than 5. The minimum expected count is 4.92.

Linear multivariate analysis results for Survivability

Tests of Between-Subjects Effects

Dependent Variable: Surv

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	.593[a]	7	.085	2.063	.048	.059
Intercept	21.105	1	21.105	514.018	.000	.692
CE	.295	1	.295	7.194	.008	.030
R	.121	1	.121	2.952	.087	.013
Th	.026	1	.026	.632	.427	.003
CE * R	.000	1	.000	.004	.949	.000
CE * Th	.076	1	.076	1.863	.174	.008
R * Th	.071	1	.071	1.736	.189	.008
CE * R * Th	.001	1	.001	.025	.875	.000
Error	9.402	229	.041			
Total	31.082	237				
Corrected Total	9.995	236				

a. R Squared = .059 (Adjusted R Squared = .031)

Stability results from SAS

The CATMOD Procedure

Analysis of Weighted Least Squares Estimates

Effect	Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	0.6364	0.0131	2356.94	<.0001
TIME	2	-0.1314	0.0283	21.57	<.0001
	3	-0.00548	0.0267	0.04	0.8375
	4	0.1204	0.0269	20.06	<.0001
	5	-0.00578	0.0271	0.05	0.8312
	6	-0.0656	0.0279	5.53	0.0187
	7	0.1284	0.0238	29.10	<.0001
R_NUM	8	-0.00523	0.0131	0.16	0.6900
R_NUM*TIME	9	-0.0147	0.0283	0.27	0.6030
	10	0.0362	0.0267	1.83	0.1761
	11	-0.00459	0.0269	0.03	0.8644
	12	-0.0224	0.0271	0.69	0.4079
	13	0.00940	0.0279	0.11	0.7363
	14	-0.0216	0.0238	0.82	0.3653
TH_NUM	15	-0.00404	0.0131	0.09	0.7580
TH_NUM*TIME	16	0.0591	0.0283	4.36	0.0367
	17	-0.0233	0.0267	0.76	0.3828
	18	0.0442	0.0269	2.71	0.1000
	19	-0.0486	0.0271	3.22	0.0729
	20	-0.1001	0.0279	12.88	0.0003
	21	0.0856	0.0238	12.92	0.0003
R_NUM*TH_NUM	22	0.0186	0.0131	2.01	0.1564
R_NUM*TH_NUM*TIME	23	0.0281	0.0283	0.99	0.3197
	24	0.00404	0.0267	0.02	0.8800
	25	0.0216	0.0269	0.65	0.4217
	26	0.0204	0.0271	0.57	0.4518
	27	-0.00608	0.0279	0.05	0.8275
	28	-0.0120	0.0238	0.26	0.6133
CE_NUM	29	0.0124	0.0131	0.89	0.3453
CE_NUM*TIME	30	-0.00910	0.0283	0.10	0.7477
	31	0.00668	0.0267	0.06	0.8029
	32	-0.00255	0.0269	0.01	0.9244
	33	-0.0347	0.0271	1.64	0.2009
	34	0.000128	0.0279	0.00	0.9964
	35	0.0311	0.0238	1.70	0.1918
R_NUM*CE_NUM	36	-0.00072	0.0131	0.00	0.9560
R_NUM*CE_NUM*TIME	37	-0.0210	0.0283	0.55	0.4578
	38	0.00310	0.0267	0.01	0.9076
	39	0.0105	0.0269	0.15	0.6949
	40	-0.0133	0.0271	0.24	0.6248
	41	-0.00344	0.0279	0.02	0.9018
	42	0.0192	0.0238	0.65	0.4206

TH_NUM*CE_NUM	43	-0.0138	0.0131	1.11	0.2919
TH_NUM*CE_NUM*TIME	44	0.0171	0.0283	0.37	0.5457
	45	-0.0588	0.0267	4.83	0.0279

APPENDIX G

Cost set up for Automobile