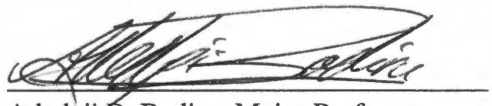
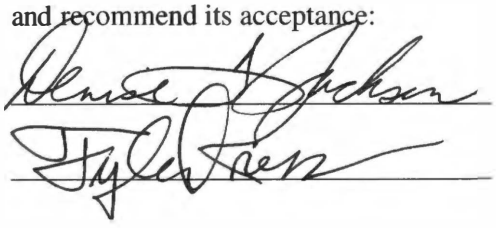
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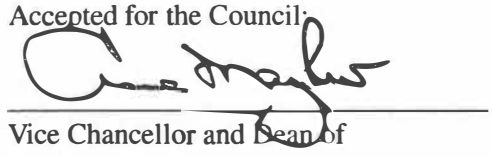


Adedeji B. Badiru, Major Professor

We have read this thesis
and recommend its acceptance:



Accepted for the Council:



Vice Chancellor and Dean of
Graduate Studies

Thesis
2006
.D69

Development of a Transportation Network Model for Complex Economic and Infrastructure Simulations

A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Paula S. Downes
August 2006

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Dedication

This thesis is dedicated to my home family who gave more encouragement and moral support than I thought possible; and to my work family who provided programming support, thought provoking discussions, and more patience than I deserve.

Abstract

The intent of this effort is to add a transport network to an agent-based economic simulation model, thereby increasing the fidelity of the economic results reported. The majority of existing agent-based work regarding transportation infrastructures deals with traffic management and urban planning. However, little work has been done in modeling the transport system as a basic infrastructure dependency for an agent-based representation of the economy. In an agent-based modeling environment the transportation component derives its demand from the activities of the agents as they buy and sell goods which require transportation services. The NetworkShipper agent was added to allow transportation based on the existing U.S. interstate highway system. The agent determines the shortest path between a buyer and seller and estimates a time of arrival. To represent the dynamic nature of a highway system capacity and speed constraints are imposed on the network.

The transportation network was then tested using data for the US milk supply chain. The strongest result of this work is the demonstration that inventory levels in a supply chain must buffer the delivery time uncertainty created when rigorous pursuit of minimum cost supply creates churn in the set of preferred suppliers for a firm. The current geographic distribution of supply and demand, along with variations in the effective time-dependent throughput capacity of the transportation network across the country, creates differential regional sensitivities. In particular, the North Atlantic region is most susceptible to this condition, and as a consequence experiences almost twice the price fluctuation of the South Atlantic region for cheese, despite having half the average supply distance of the south.

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Chapter 1

Background

There are many modeling constructs and associated simulation tools available for the analysis of supply-chain management. All of these constructs can be used to create simulation models that belong to one of four categories: spreadsheet simulation, system dynamics, discrete-event dynamic systems simulation, or business games [1]. Spreadsheet simulation techniques are typically used in statistical process control models and material requirements planning efforts. System dynamic modeling tools are used to simulate and evaluate the interplay between individual components of a supply-chain, however the analysis is typically at an aggregated level of detail, representing total flow of goods through the supply-chain. The discrete-event dynamic system simulation represents the supply-chain as a set of individual events that initiate a response by the chain. As a result, this type of simulation tool is more detailed. Business game type simulations are directed more toward human behavior than the supply-chain itself, and are typically used as training tools.

The foundation of the work herein is a discrete-event dynamic simulation tool developed using an agent-based simulation construct. Agent-based simulations have been customarily used for socio-economic modeling efforts where the simulated systems are modeled such that multiple entities sense and stochastically respond to conditions in their local environments, mimicking complex large-scale system behavior. Sandia National Laboratories,[1] as a member of the National Infrastructure Simulation and Analysis Center (NISAC),[2] uses agent-based simulation techniques to gain understanding of the interdependencies between infrastructures identified to be critical by the Department of Homeland Security (DHS) [2]. Examples are the national economy, telecommunications, transportation, banking/finance, and electric power. The analyses preformed by NISAC consider local, regional, and national-scale infrastructure interdependencies.

N-ABLE™ (NISAC-Agent Based Laboratory for Economics)[3] is the agent-based micro-simulation tool developed by Sandia National Laboratories to simulate complex interdependencies between

[1] Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company for the United States Department of Energys National Nuclear Security Administration under contract DE-AC04-94AL85000.

[2] The National Infrastructure Simulation and Analysis Center (NISAC) is a program under the Department of Homeland Securitys (DHS) Preparedness Directorate. Sandia National Laboratories (SNL) and Los Alamos National Laboratory (LANL) are the prime contractors for NISAC under the programmatic direction of DHSs Infrastructure Protection/Risk Management Division.

[3] patent pending

economic and infrastructure sectors [3]. N-ABLE™ is designed to develop large data-driven simulations quickly while allowing computation to be conducted on Sandia's massively parallel computing clusters. More discussion of N-ABLE™ can be found in Chapter 2. The goal of this thesis is to add to the development of N-ABLE™ by including a highway transportation network to the infrastructure simulation capabilities. The context of N-ABLE™ is economics, and therefore the network will need to meet the requirements of the economic impact modeling for NISAC. The transportation network will represent an infrastructure and therefore must have connectivity to other infrastructures where appropriate, and be disruptable. Disruptable, in this case, implies the ability of the programmer/analyst to specify events that cause the network, or portions thereof, to be unavailable for periods of time.

Chapter 1 contains the background material and introductory matter regarding both agent-based and transportation modeling. A literature review is also included in this chapter. Chapter 2 follows with a description of the chosen network representation, and its applicability within the N-ABLE™ framework. The applicability discussion includes limitations as well as capabilities. Chapter 3 is an hypothetical case study used to exercise the transportation network within N-ABLE™. Chapters 4 and 5 presents results and discussion, respectively.

1.1 Introduction

The development of N-ABLE™ focuses on the economic infrastructure of the U.S. is basically a plethora of supply-chains connected through one or more infrastructures (transportation, banking and finance, etc.) [4]. The working hypothesis for the development herein is that the transportation infrastructure, by altering both supply chain dynamics and components of raw material cost, influences the emergence across a national scale of regions of relatively self-contained economic activity under non-disruption conditions. To test this hypothesis, a multi-step economic value chain is simulated under standard economic assumptions of neglible transportation costs and fixed transit time (the null hypothesis) and under novel assumptions made possible by this work: cost and time are functions of simulated movement across a detailed, data-driven representation of transportation infrastructure (the alternative hypothesis).

1.1.1 Agent-based Modeling

Agent based modeling began in the 1980s with the advent of the personal computer. An agent is a software object that can be programmed to operate proactively to achieve predefined goals. It gathers information about its environment, creates strategies, makes goal-oriented decisions, and performs delegated actions derived from those decisions. The earliest agent models were intended to study societal behaviors. One of the more well-known early developments was a model of the flight pattern of a flock of geese [5]. Reynolds' based his simulation model on some simple rules that govern the interaction of the flock in flight. His model did not actually represent the individual birds or the flock as an entity, but rather the relationship between adjacent birds (distance, and speed). The theory being that each bird in the flight pattern reacts (changes speed or direction) based on the actions of the surrounding birds that it can see. Agent models developed since then have a minimum of four basic characteristics [6].

Agents are autonomous. *The system is not directly modeled as a globally integrated entity. Systemic patterns emerge from the bottom up, coordinated not by centralized authorities or institutions (although these may exist as environmental constraints) but by local interactions among autonomous decision makers. This process is known as "self-organization" (Kaufman 1996). [7]*

Agents are interdependent. *Interdependence may involve processes like persuasion, sanctioning, and imitation, in which agents influence others in response to the influence that they receive. Interdependence may also be indirect, as when agents' behaviors change some aspect of the environment, which in turn affects the behavior of other agents, such that the consequences of each agent's decisions depend in part on the choices of others.*

Agents follow simple rules. *Global complexity does not necessarily reflect the cognitive complexity of individuals. "Human beings," Simon contends (1998, p. 53), [8] "viewed as behaving systems, are quite simple." We follow rules, in the form of norms, conventions, protocols, moral and social habits, and heuristics. Although the rules may be quite simple, they can produce global patterns that may not be at all obvious and are very difficult to understand (like Reynolds' "boids"). Hence, Simon continues, "the apparent complexity of our behavior is largely a reflection of the complexity of the environment." ABMs explore the simplest set of behavioral assumptions required to generate a macro pattern of explanatory interest.*

Agents are adaptive and backward-looking. *When interdependent agents are also adaptive, their interaction can generate a "complex adaptive system" (Holland 1995, p. 10). [9] Agents adapt by moving, imitating, replicating, or learning, but not by calculating the most efficient action (Holland 1995, p. 43). They can adapt at two levels, the individual and the population. Individuals learn through processes like reinforcement, Bayesian updating, or the back-propagation of error in artificial neural networks. Learning alters the probability distribution of behaviors competing for attention within each individual. Populations learn through evolutionary processes of selection, imitation, and social influence. Evolution alters the frequency distribution of agent-types competing for reproduction within a population.*

When applied to supply-chain models, these rules for agent-based modeling still hold. Each firm within the supply-chain is made up of agents: buyer, sellers, and consumers. Each agent makes decisions based on what they know, can predict, and the results of previous decisions. Agent-based modeling is not typically used for determining the optimal solution to a supply-chain problem, but rather to gain an understanding of the implications of an agent choosing among many solutions, and based on the information available, selecting one that is less than optimal. Agents within the supply-chain are affected by the decisions of other agents, either directly or in-directly.

1.1.2 Transportation Modeling

The importance of transportation research to the U.S. became evident with the formation of the Transportation Research Board in 1920. In the beginning, the mission of the Transportation Research Board was to *provide a mechanism for the exchange of information and research results about highway technology* [10]. Its mission has changed little in the years that have followed. What has changed is the ability to create models of the transportation infrastructure. With the advent of *low-cost high-capacity* computing, the limitations of transportation modeling are now human and technical [18]. Modeling the transport system follows the same constructs as supply-chains modeling in that there are several options for the mathematical simulation (spreadsheet, system dynamics, and discrete-event dynamic systems). In simplistic terms, transportation analyses are a special case of the supply-chain with their own characteristics for supply and demand. The main distinction is the fact that transportation is a service, not a good, that is purchased. The supply portion of the transportation problem has two components: mobile resources (e.g. trucks and drivers) and a stationary infrastructure (e.g. roads). The demand portion of transportation analyses is highly dynamic and occurs spatially.

The demand on the infrastructure is actually *derived* from the distribution of activities across locations. Typically, a given geography is divided into zones exhibiting similar characteristics. For example, one might want to specify zones corresponding to urban speed limits and congestion patterns that differ from rural zones. To add further complexity to the transport problem, the demand is also distributed across time: different hours of the day experience varied congestion levels. In N-ABLE™ the transportation component derives its demand from the activities of the agents as they make use of the infrastructure and purchase transportation services.

1.1.3 Literature Review

The purpose of this literature review is to (1) show how agent-based supply-chain modeling coupled with transportation modeling fits into the related research, and (2) identify the fundamental components necessary to adequately represent the transportation function of a supply-chain within a micro-economic simulation tool. The literature review began by searching relevant journals for recent works regarding transportation modeling using the agent-based construct. The initial search revealed 79 journals with titles containing one or more of the following: transportation, modeling, or agent. The original journal list was further modified based on the results of the research itself, resulting in 45 journal titles, and 5 reference texts. The availability of literature regarding multi-layer infrastructure networks is *rather sparse* [11]. This is mainly because the dynamics of interdependency among infrastructures is not yet fully understood.[4] Challenges faced by the researcher in this arena include being able to capture 1) time scale flow dynamics, 2) flow characteristics, 3) performance characteristics, and 4) the complex nature of decision flow across infrastructures.

One of the most helpful journal articles available for guidance in determining where agent-based modeling is leading with regard to the challenges of infrastructure modeling appeared in *Autonomous*

[4] A description of infrastructure interdependencies and associated modeling challenges is described in: S. Rinaldi, J. Peerenboom, and T. Kelly (2001). *Complexities Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies*. IEEE Control Systems Magazine 21(6), 11-25; and,
M. Heller (2001). *Interdependencies in Civil Infrastructure Systems*. The Bridge 31(4).

Agents and Multi-Agent Systems in March 1998. Jennings et al. describe, in detail, the direction of agent simulation research and possible application arenas which includes manufacturing, process control, telecommunication systems, air traffic control, traffic and transportation management, information filtering and gathering, electronic commerce, business process management, entertainment, and medical care [12]. The article is somewhat dated; however, the development trends discussed are in line with works in recent publications. Both manufacturing (supply-chain management) and traffic and transportation management are mentioned in this work as areas of continued development, but there is no reference to the two areas of research being combined.

Agent-based models of manufacturing supply-chains are typically created in order to gain a better understanding of factory operations.[5] Similar to other works found during the literature review, Fung and Chen model transportation across a supply-chain using linear programming techniques [13]. The resulting transportation agent design is a transportation task that contains an origin, a destination, a quantity of goods transported, a window of time for transport, and a price associated with completing the task. The window of transport time is very rigid in this application. The assumption is that deliveries cannot be early or late, and while this meets the challenge of capturing flow characteristics, it does not address the issue of time scale flow dynamics.

Time scale flow dynamics are prevalent in transportation modeling and research. The majority of agent-based work regarding transportation infrastructures deals with traffic management and urban planning. One of the more recent works from the University of Washington is a product called URBANSIM [17]. The relevancy of this work is the use of a dynamic disequilibrium approach whereby there are different time scales for decisions: short-term decisions, mid-term and long-term policy decisions. Waddell et al. present the example of recurring daily traffic disruptions that cause people to make short-term decisions to avoid congestion which lead business owners to make location decisions, that in the long-term, translate into real estate development policies. The parallels between transportation and economy infrastructure interdependencies are easily identified; as disruptions to the transportation infrastructure cause delivery of goods to be consistently behind schedule, do markets adjust, and if so, how?

[5]For examples of recent manufacturing applications see: Vincent A. Cicirello and Stephen F. Smith, *Wasp-like Agents for Distributed Factory Coordination* Autonomous Agents and Multi-Agent Systems, 8, 237-266, 2004; Shaw C. Feng, *Preliminary design and manufacturing planning integration using web-based intelligent agents*, Journal of Intelligent Manufacturing, 16, 423-437, 2005; Weiming Shen, Francisco Maturana and Douglas H. Norrie. *MetaMorph II: an agent-based architecture for distributed intelligent design and manufacturing*, Journal of Intelligent Manufacturing (2000) 11, 237-251.

Chapter 2

The Transportation Model in N-ABLE™

N-ABLE™ is used to evaluate the economic impacts of disruptions to the U.S. critical infrastructures. Given this direction, a transportation network representation within N-ABLE™ must include both traditional characteristics of a transportation network and also those factors that allow for analysis of the interdependencies between the transportation and other infrastructures. Within N-ABLE™ supply-chain modeling is conducted such that each entity is modeled as an independent firm. As is characteristic of supply-chains that have many independent, competing firms that collectively provide a commodity product, individual firms are not aware of the performance of the entire supply-chain; that is, the firm has only local information about supply-chain conditions. In this context, individual firms attempt to maximize profits subject to prices and sales in their market, and the costs and availability of inputs. As a result, they may make decisions that are ultimately sub-optimal for the overall supply-chain. The purpose of adding a specific representation of transportation infrastructure to N-ABLE™ applications, then, is to capture the supply-chain-wide economic dynamics that result from the transport-mediated interactions of these autonomous firms.

2.1 Transportation within N-ABLE™

Transportation within N-ABLE™ occurs through the *ShipperAgent*. The ShipperAgent is called when a buyer and seller have placed a contract for purchase of goods. The Seller calls the ShipperAgent to arrange for transport services. Including the development herein, there are three categories of shipping that can be used within N-ABLE™: simple, constrained, and network. The SimpleShipper schedules an arrival time for a shipment based on a transport time estimate provided in the simulation input file. When specified time has elapsed, the shipment arrives at its destination, the buyer firm. The SimpleShipper allows the user to make an assumption that transportation is not a major component for a specific analysis. The ConstrainedShipper is a modification of the SimpleShipper allowing the analyst to specify a fleet size available for use. If sufficient fleet resources are available, the mechanics of shipment delivery are the same as in the SimpleShipper however, lack of sufficient mobile resources creates an additional delay above in-transit time while the ConstrainedShipper waits until a vehicle is available for transport. The NetworkShipper was developed to bring a geospatial component to N-ABLE™ analyses.

2.2 The New NetworkShipper

N-ABLE™ can now be used to analyze local, regional, and national markets within the same model. The NetworkShipper contains a network of transportation routes read from the simulation input file in a completely data driven sense and logic for traversing the network. The newly developed NetworkShipper was tested in this work with data consisting of a highway transportation network represented by a series of nodes and arcs. The nodes function as location points along the U.S. interstate highway system. The arcs represent distance between nodes. The NetworkShipper receives requests for shipment in the same manner as the Simple and Constrained Shippers. The NetworkShipper, however, calculates a shortest path between the seller and the buyer, and estimates a time of arrival. The shortest path determination uses the classic method developed by Dijsktra. For large networks, it is the method most computationally efficient [20]. After identification of the shortest path, the Seller is quoted a transport cost, which is then passed to the Buyer. Once a shipment departs, its actual travel time as opposed to estimated time is based on the dynamics of the network itself. The network has speed limits that vary by state and urban boundaries. In addition, speed is also modified by the amount of demand (traffic) on the network. The network attributes are more fully described in the next section.

2.3 The Network

The data used to develop the nodes and arcs is a subset of the ESRI©StreetMap Data [21], a geocoded database of U.S. boundaries, landmarks and streets. There are over 245 million arcs in the StreetMap data. In order to reduce the number of nodes and arcs to a manageable number, the subset of arcs is reduced to contain the nodes and associated arcs where 3 or more highways (local, state, and federal) intersect. Additional nodes are added where an interstate crosses a state boundary. These data reducing rules were chosen in order to ensure sufficient detail of the network while retaining runtime efficiency. Figure 2.1 shows the resulting N-ABLE™ network. This network consists of 4,042 nodes and 9,298 arcs. The arcs range in length from 0.001 miles (urban area on and off ramps) to 158 miles (rural highway).

To represent the dynamic nature of highway system capacity and speed, constraints are imposed on the network. Capacity of the network is used as a bounding condition where if reached, flow on the network ceases. If demand on the network is reduced, flow will resume. A maximum capacity of 2000 vehicles per hour per lane is imposed on the network [23]. The speed of each shipment traveling on the network varies across arcs.

Segment speed for the network is dependent on several attributes: the state where it is located, its classification (urban or rural), and the average demand on the arc. The speed across an arc with demand on the arc. Each arc in the network has a posted speed limit based on the actual posted limits per state as of May 2005. As demand on the network increases, the effective speed (Vf) decreases. The effective speed is determined from the demand to capacity ratio, also referred to as percent load L [22]:

$$L = Q/C \tag{2.1}$$



Figure 2.1: Continental U.S. Interstate Highway Network

where :

L is the demand on an arc expressed as a percentage of the maximum capacity,
Q is the current demand on and arc and
C is the maximum capacity.

The value of Q in Equation 2.1 includes ambient traffic as well as the demand on the network from the shipments scheduled by the NetworkShipper. The ambient traffic demand has two components; the average daily traffic demand and the hourly distribution of ambient traffic. The average daily traffic values are derived from the Federal Highway Administration [25]. The average daily traffic demand by state is shown in Table 2.1.[1] The hourly distribution is obtained by using data from the Federal Highway Administrations *RealCost User Manual 2.1* [23].[2] The resulting effective speed is determined as shown in Equation 2.2 [22]:

$$V_f = \begin{cases} U[0.75V_p, V_p] & ; \quad L \leq 0.65 \\ U[0.66V_p, 0.75V_p] & ; \quad 0.65 \leq L \leq 0.85 \\ U[0.50V_p, 0.66V_p] & ; \quad 0.85 \leq L \leq 1 \\ U[0, 0.50V_p] & ; \quad L \geq 1.0 \end{cases} \tag{2.2}$$

where : Vp is the posted speed limit for a given arc

The posted speed limits used in N-ABLE™ are averages delineated by state [24]. As shown in Table 2.2, the posted speed for an arc varies by state and highway classification (rural or urban).[3]

[1]The table in 2.1 shows the daily demand (vehicles per day) by state. This data was taken directly from http://www.fhwa.dot.gov/policy/ohim/hs03/re.htm by choosing table hm62.pdf

[2]The values used in N-ABLE were extrapolated from *Exhibit 8-6*

[3]The table was adapted from the *Maximum Posted Speed Limits for Passenger Vehicles* provided by the Insurance Institute for Highway Safety

Table 2.1: Daily Traffic Demand by State

State	Interstate Rural	Interstate Urban	State	Interstate Rural	Interstate Urban
Alabama	7553	12183	Montana	1368	3126
Alaska	2189	7083	Nebraska	4705	12265
Arizona	5551	17836	Nevada	3133	14432
Arkansas	6585	9491	New Hampshire	6699	11919
California	8685	20563	New Jersey	10876	13178
Colorado	6047	16632	New Mexico	3622	11208
Connecticut	10534	16643	New York	5909	13222
Delaware	0	15566	North Carolina	9003	14322
Dist. of Columbia	0	20768	North Dakota	1736	4475
Florida	8916	17954	Ohio	8513	14964
Georgia	8842	17557	Oklahoma	5161	11220
Hawaii	10046	15089	Oregon	5778	15950
Idaho	2679	8479	Pennsylvania	6277	13839
Illinois	4628	18395	Rhode Island	12305	16537
Indiana	7745	14727	South Carolina	9072	11203
Iowa	4596	9568	South Dakota	2417	4700
Kansas	3508	9926	Tennessee	8868	14653
Kentucky	7594	12895	Texas	6107	15636
Louisiana	6801	12020	Utah	3336	13901
Maine	5607	8379	Vermont	3171	5881
Maryland	9651	18606	Virginia	8997	15887
Massachusetts	9558	16120	Washington	6844	16597
Michigan	6941	14644	West Virginia	6303	10050
Minnesota	5799	17486	Wisconsin	7532	17310
Mississippi	5371	11667	Wyoming	1984	3079
Missouri	6282	14293			

Table 2.2: Posted Speed Limits by State: 2005

State	Rural mph	Urban mph	State	Rural mph	Urban mph
Alabama	70	65	Montana	65	65
Alaska	65	55	Nebraska	75	65
Arizona	75	55	Nevada	75	65
Arkansas	70	55	New Hampshire	65	65
California	70	65	New Jersey	65	55
Colorado	75	65	New Mexico	75	75
Connecticut	65	55	New York	65	65
Delaware	65	55	North Carolina	70	70
Dist. of Columbia	N/A	55	North Dakota	75	75
Florida	70	65	Ohio	55	65
Georgia	70	65	Oklahoma	55	55
Hawaii	60	50	Oregon	55	55
Idaho	65	75	Pennsylvania	65	55
Illinois	55	55	Rhode Island	65	55
Indiana	65	55	South Carolina	70	70
Iowa	70	55	South Dakota	75	75
Kansas	70	70	Tennessee	70	70
Kentucky	65	65	Texas	65	70
Louisiana	70	70	Utah	75	65
Maine	65	65	Vermont	65	55
Maryland	65	65	Virginia	65	65
Massachusetts	65	65	Washington	60	60
Michigan	55	65	West Virginia	70	55
Minnesota	70	65	Wisconsin	65	65
Mississippi	70	70	Wyoming	75	60
Missouri	70	60			

Chapter 3

The Milk Supply-Chain

The supply-chain used to exercise the network-based transportation infrastructure representation within N-ABLE™ and illustrate the consequent economic dynamics is the national distribution of milk and selected subsequent milk-based products. supply-chain information was drawn from three main sources of data for the basic: the United States Census Bureau, the United States Department of Agriculture, and the National Dairy Association.

3.1 Industry Description

The United States produces 170 billion pounds of milk (19.7 billion gallons) per year [26]. The top five production states (by volume of milk produced) are California, Wisconsin, New York, Pennsylvania, and Idaho. Milk demand by other industries is dominated by the cheese and bottled milk industries, which consume 80 percent of the annual U.S. milk production. The U.S. Agricultural Statistics Board groups the production of dairy goods into 6 geographical regions (see Figure 3.1).[1]

The Agricultural Act of 1949 was structured so that, nationally, there will always be a sufficient supply of each milk-based commodity to meet demand. The supply-demand ratios for the milk-based commodities are 1.23, 1.09, 1.11, 1.21, and 1.34 for bottled milk, butter, cheese, dry-milk, and frozen milk goods, respectively. Regionally however, the supply is not always sufficient for the given demand[2] as shown in Figure 3.2.

The majority of bottled milk, and frozen milk goods are produced in the West region, while the East-North Central region produces the majority of the butter, cheese and dry milk. The West-North Central region produces sufficient quantities of all the milk commodities to meet its demands. The North Atlantic region produces sufficient quantities to meet its demands with the exception of the cheese and dry milk commodities. Neither the South Atlantic nor the South Central regions produce enough of any of the commodities to meet their respective regional demands. Therefore, the assumption that each region contains a self-sustaining supply-chain is not valid.

[1] Figure taken directly from *Dairy Products* Released May 5, 2004, by the National Agricultural Statistics Service (NASS), Agricultural Statistics Board, U.S. Department of Agriculture.

[2] Demand is based on annual per capita consumption of each commodity.

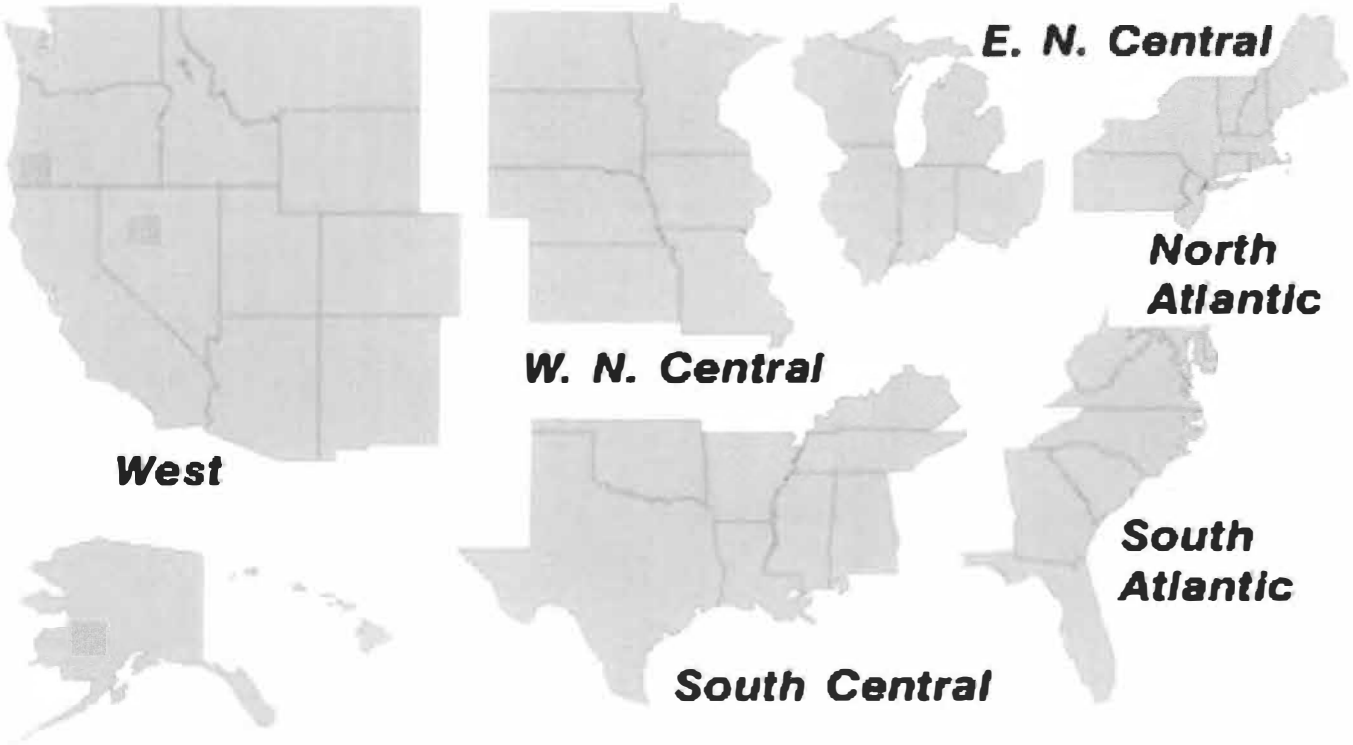


Figure 3.1: Dairy Production Regions

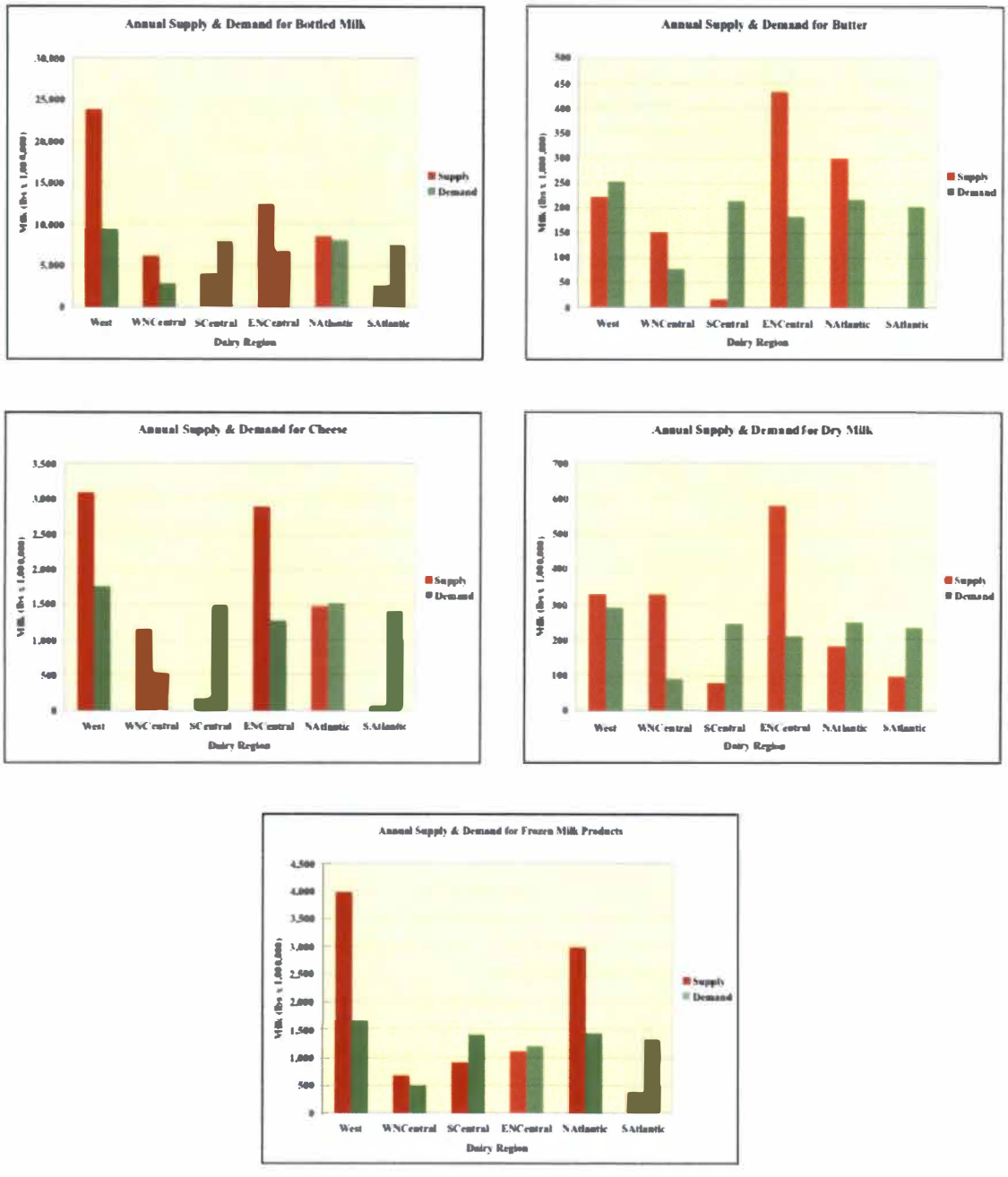


Figure 3.2: Dairy Product Supply and Demand by Region

The bulk-milk portion of the supply-chain is regionalized. Based on supply-demand ratios of 1.83, 1.58, 2.12, 1.47, 1.47, 2.28 for the West, West-North Central, South Central, East-North Central, North Atlantic, and South Atlantic regions respectively, there is excess supply of bulk-milk in each of the dairy production regions. Figure 3.3 shows the consumption of milk by all industries, and the quantity of bulk-milk required to produce each of the milk-based commodities is shown in Table 3.1.

3.2 The Milk supply-chain within N-ABLE™

Because N-ABLE™ is a stochastic model, model behavior does not always reach steady-state. Random components create localized fluctuations in purchasing, production, and inventory management. The local fluctuations can amplify and propagate up and down the supply-chain, creating swings in demand for raw, intermediate, and finished products and most importantly for this effort, transportation services.

These fluctuations can be divided into intra-firm and inter-firm fluctuations. Intra-firm fluctuations are caused by random changes in internal firm operations; examples include buyer ordering pattern variations coupled with production levels that are modified by changes in sales. Intra-firm fluctuations are caused by a lack of global knowledge by all supply-chain participants about what total demand is and what share of it they are ultimately producing toward. Inter-firm fluctuations are caused by external interactions among firms. These intra-firm and inter-firm dynamics are significantly impacted by the location, number, types, and sizes of firms in the supply-chain.

The milk supply-chain implemented within N-ABLE™ for this research includes bulk-milk production, milk-based product manufacturing (bottled milk, butter, cheese, dry-milk goods, frozen-milk goods) and retail consumption of milk-based products. In simple terms, bulk-milk is sold to industries which in turn sell product to supermarkets. Supermarket demand for goods is used to represent public consumption. Product is moved from supplier to customer by truck along the interstate road network.

Each firm included in the supply-chain uses an extensible N-ABLE architecture for modeling the internal productive operations of firms. As illustrated in Figure 3.4, firms purchase materials to produce goods that are sold in markets. The blue line encompasses the functions that take place within a firm. Each of the functions within the firm have a responsible agent. For example, the function responsible for purchasing raw stock to produce finished goods is called the Buyer agent. The entire collection of functions within the firms comprises the EconomicAgent. The set of actions (decisions) made by each component agent generates a response for the entire EconomicAgent. Figures 3.5, 3.6,[3] and 3.7 present the structure of the EconomicAgent for bulk-milk production firms, milk-based product manufacturing firms, and supermarkets.

[3]The example shown in Figure 3.6 displays an N-ABLE™ Butter firm. This diagram would be similar for bottled milk, cheese, dry-milk, or frozen milk product industries.

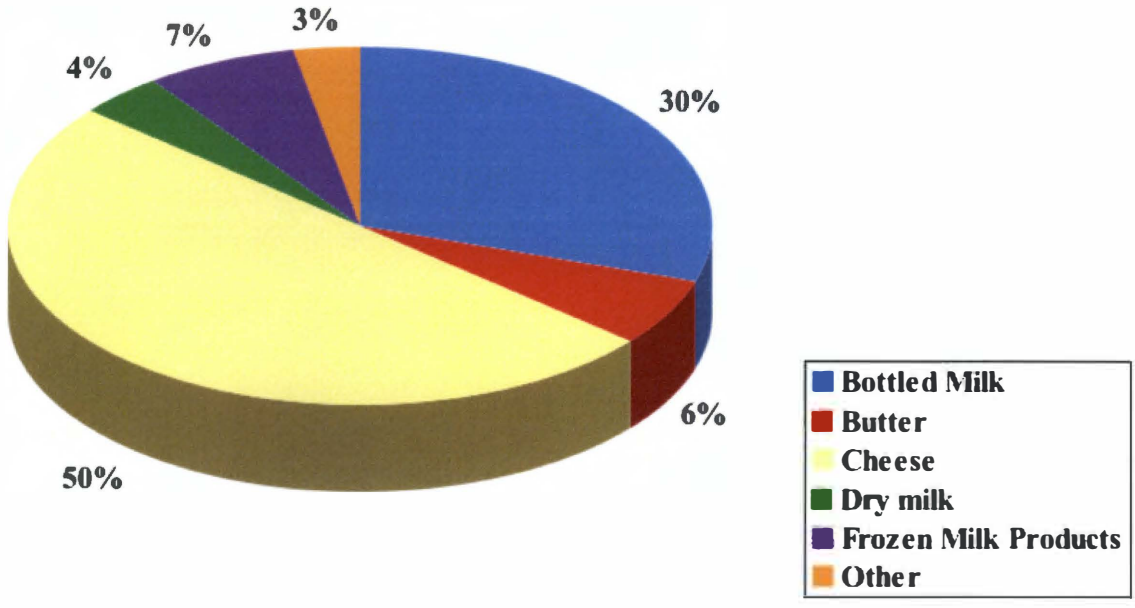


Figure 3.3: Milk Consumption by Industry

Table 3.1: Bulk Milk Requirements, by Milk Product

Milk-based Product	Production Ratio (lbs) Milk:(lbs) Product
Bottled milk	1:1
Butter	9:1
Cheese	10:1
Dry Milk	7:1
Frozen Milk Products	3:1

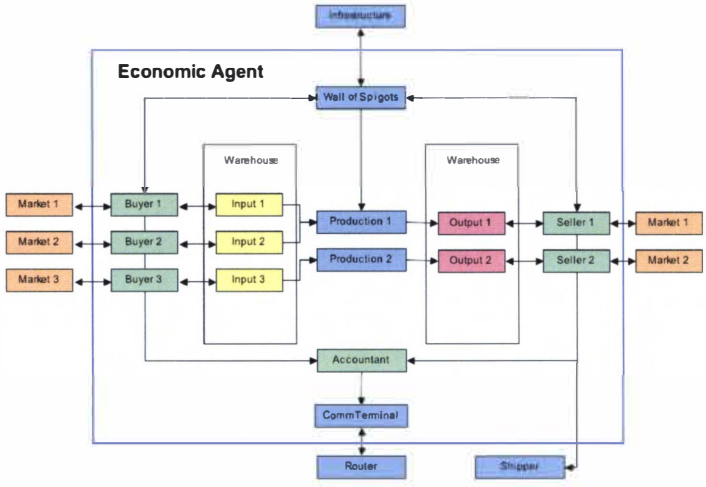


Figure 3.4: Generic Economic Agent Structure

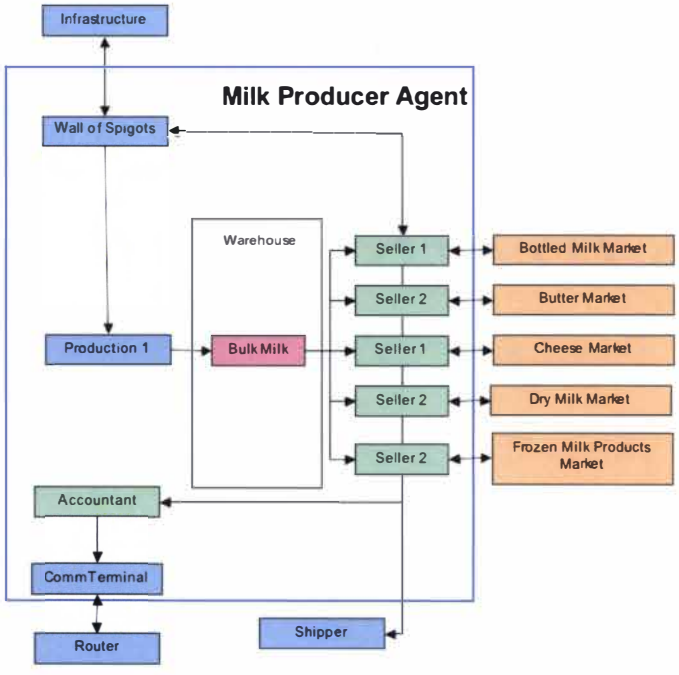


Figure 3.5: Bulk Milk Production Agent Structure

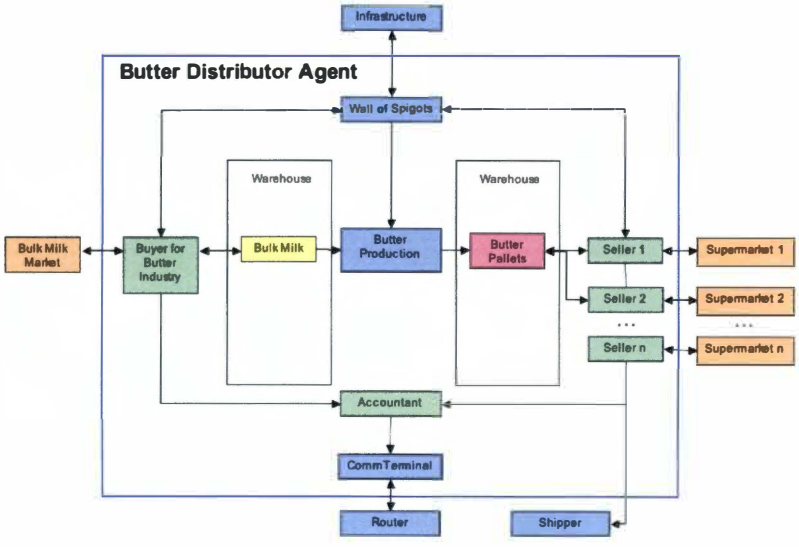


Figure 3.6: Distribution Agent Structure

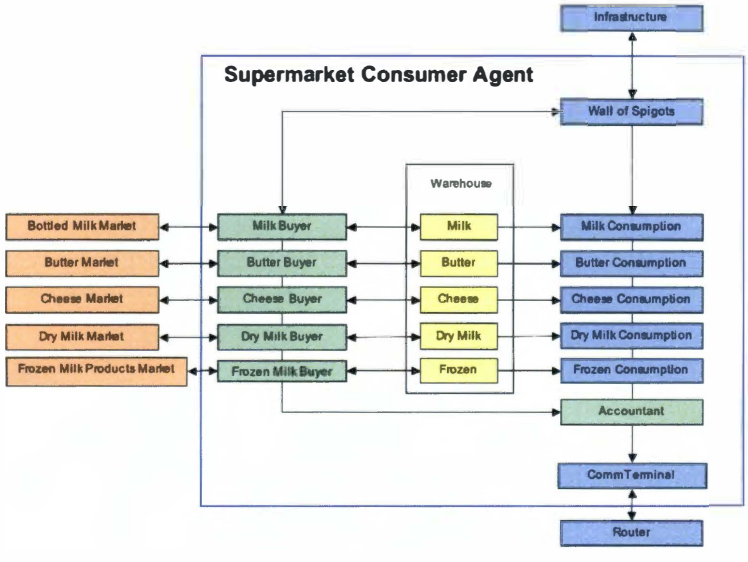


Figure 3.7: Supermarket Agent Structure

The individual agents of an N-ABLE™ firm use the information they have to try and optimize the operations of the firm. The Buyer estimates his daily target order of inputs goods based on the volume of goods in the inventory, the estimated delivery time, the average production schedule, and the predicted amount of sales. The actual order may deviate from the target under two conditions: 1) there are no supplies to be had, or 2) the price of the supplies is more than he is willing to pay. The ProductionAgent adjusts production of goods based on available supplies, and output good warehouse availability. The Seller adjusts the advertised price of the output goods based on the production costs and desired markup. As agents make decisions, they are striving to meet customer demand at the lowest cost so that profits are maximized to the extent possible.

The milk supply-chain within N-ABLE™ is composed of 5,443 agent firms. The production firm locations were obtained from U.S. Census Bureau by querying County Business Pattern data, which contains the number of businesses and associated employees by U.S. county by industry category. The industry categories are grouped according to the North American Industry Classification System (NAICS) [27]. The five codes corresponding to the production milk and milk-derived products are: 311511, 311512, 311513, 311514, and 311520 [28]. These NAICS codes correspond to the production of liquid milk, butter, cheese, dry-milk goods, and frozen-milk goods production, respectively. The agent firms are sized relative to the number of employees reported in the data. Supermarkets are used to represent daily consumption of the milk-based products by assigning each county a supermarket. The supermarket consumes milk-based goods on a daily basis at rates relative to the population of the given county. In order to represent the dynamic nature of the demand, the daily average demand varies randomly by 10 percent each day for each supermarket.

3.2.1 Firm-Level Input Data

N-ABLE™ is a data driven model. The data used in the milk supply-chain is publicly available industry-wide data. Firm-level characteristics were estimated using the employee size information from the County Business Pattern database. The initial production rate of a firm for a given commodity was derived from Equation 3.1. Production rates change over the course of an N-ABLE™ simulation based on the available supply of raw material, in this case bulk-milk, and demand for the finished goods experienced by the firm. In order to provide a production cap, a maximum production rate of 1.1 times the daily average (production) is employed for the milk supply-chain.[4]

$$P_i = (E_{fi}/E_i) * MP_i * MP) \tag{3.1}$$

where

P_i is the initial firm production rate for milk-based industry i,
E_{fi} is the number of employees for a firm f in milk-based industry i,
E_i is the number of employees for the milk-based industry i,
MP_i is the percentage of milk consumed annually for milk-based industry i, and
MP is the annual milk production for the U.S.

[4]The implicit assumption in this cap is that firms have only invested in production capital to met current demand levels because the entire industry is already operating with surplus capacity.

The consumption of goods at the end of the milk supply-chain is conceptually straight forward: each supermarket consumes all five commodities (bottled-milk, butter, cheese, dry-milk, and frozen-milk products). Equation 3.2 is used to estimate the daily need of each milk-based commodity.

$$C_{ci} = (P_c / P_{U.S.}) * PCD_i \tag{3.2}$$

where :

C_{ci} is the daily consumption rate in county $c$for milk-based industry i,
P_c is population in county c,
$P_{U.S.}$ is the total U.S. population, and
PCD_i is the annual per capital demand for milk-based industry i.

The per capita demand values used in this equation are presented in Table 3.2[5] [29].

3.2.2 N-ABLE™ Milk Markets

The final link in the N-ABLE™ supply-chain model development is the establishment of the firm-to-firm relationships, or markets. Markets have participants and structure; market participants are entities that buy and sell like goods within the market, and the market structure defines the behavior of the participants as they compete for customers. There are four main idealized market structures that have been used in trade theory: perfect competition, monopoly, oligopoly, and monopolistic competition. Perfect competition implies a large numbers of both buyers and sellers, all of them small, such that any single market participant cannot influence prices. Perfect competition assumes homogeneous products and complete information whereby all buyers and sellers have all the information they need to make optimal decisions. A monopoly contains only one seller or supplier. An oligopoly has a small number of suppliers that are unequal in terms of price influence, i.e., decisions and actions of a few influence the entire market price. Monopolistic competition implies that a market has many sellers, each producing a differentiated product. Each can set its own price and quantity, but is too small (relative to the whole) for individual decisions to influence prices and quantities of other producers in the industry.

Table 3.2: National Per Capita Demand for Milk-Based Products

Milk-based Product Industry	Daily Per Capita Demand (lbs per day)
Bottled milk	0.40
Butter	0.01
Cheese	0.09
Dry Milk	0.20
Frozen Milk Products	0.08

[5]Bottled-milk demand was adjusted from 0.6 to 0.4 in order to account for discrepancies between bulk-milk production as reported by the National Milk Producers Federation and the liquid-milk demand reported by the U.S.D.A.

There are six markets within the N-ABLE™ milk supply-chain model, one for each class of dairy product. The 5,443 firms in the milk supply-chain are segregated into markets as shown in Table 3.3.[6] The supermarkets listed in the table function as end use consumers in the bottled milk, butter, cheese, dry milk, and frozen milk product markets. The structure of the U. S. dairy markets is driven by the Agricultural Marketing Agreement Act of 1937, subsequently updated by the Agricultural Adjustment Act of 1949 [31]. The intent of these Acts is to increase and stabilize farm income while ensuring an adequate supply of milk for the population of the United States. This is accomplished by price discrimination at the farm level with minimum prices paid to farmers for milk sold to processors, coupled with government purchases of butter, cheese, and powdered milk from processors at specified prices.[7]

An outcome of the Agricultural Adjustment Act is inelasticity in the dairy market [30]. Demand elasticity measures the change in the quantity demanded of a good caused by a change in one of its determinants, when all other things are held equal. To maximize the ability to compare across various goods, it is defined as a percentage change. In economics there are three demand elasticities that can be calculated: price elasticity (also know as own-price elasticity of demand), income elasticity, and cross-price elasticity. Income and cross-price elasticity are not currently components of N-ABLE™ due to how Buyers operate. The price elasticity of demand can be included in NABLE™ and would reflect both the base cost of the commodity and the cost transportation. Meadows suggests however, that *for commodity users, the commodity price is only a small fraction of the final product cost. Consumption is relatively price inelastic* [32]. Therefore, this model of the dairy supply-chain does not allow the price of the commodity to change other than to respond to increases in transportation costs which are passed on to the end-use customer.

Commodity prices used in the model are based on 2004 wholesale prices where available, otherwise the latest available year is used[8] [33]. Table 3.4 lists the wholesale prices used in the model. Transportation costs are based on a loaded rate of $1.60 per mile and an average load weight of 44,000 pounds [34].

[6] CBP data does not distinguish between milk production and milk bottling firms. Herein, it is assumed that each milk production firm is producing to sell commercially and therefore has an associated bottling plant.

[7] Governmental purchase of these commodities is not represented in this model.

[8] The wholesale price of frozen goods is estimated based on the consumer price index of ice cream.

Table 3.3: Bulk Milk Requirements by Industry

National Milk-Based Industry Markets	Number of Firms
Milk Production Firms	573
Milk Bottling Firms	573
Butter Manufacturing Firms	35
Cheese Manufacturing Firms	533
Dry Milk Products Manufacturing Firms	214
Frozen Milk Products Manufacturing Firms	407
Supermarkets	3018

Table 3.4: Wholesale Dairy Prices

Dairy Commodity	Wholesale Price (per lbs)
Bulk-Milk	$0.11
Bottled-Milk	$0.28
Butter	$1.47
Cheese	$1.93
Dry-Milk	$1.31
Frozen Desserts	$0.50

Chapter 4

Simulation Results

Economic models traditionally focus on reaching static-equilibrium where supply and demand reach a market-clearing price and quantity; the price at which supply equilibrates with demand. However in a national market sense, it can be argued that true equilibrium is never reached. Market participants continually attempt to find the next level of cost optimization in an effort to gain more of the market share than they currently have. As discussed in Chapter 3, the dairy product markets are price inelastic, and therefore net quantities demanded are not responsive to commodity price changes. However changes in transportation costs will have impacts on where these quantities are obtained for every milk-based product in the supply chain even though the commodity price is fairly stable. In doing so, local, regional and national economic interdependencies are created.

4.1 Statistical Analysis

Analyzing the results of agent-based simulations is challenging for two reasons (1) the volume of data produced by a simulation is large, and (2) gross steady-state behavior may or may not exist. Large-scale agent models such as N-ABLE can generate extremely large quantities of output data. The typical milk simulation reporting output data for all 5,443 firms for a model duration of one year creates a compressed data file greater than 2.4 Gigabytes in size. The uncompressed files size is well over 500 Gigabytes in size.

Depending on the placement of the firm within the milk supply chain (bulk-milk producer, intermediate goods manufacturer, or end use customer, each firm can have from 41 to 118 output variables. The simulation also tracks firm to firm order information which creates an a subsequent data set with a potential size of:

$$Size = O(N^2 * T/t) \tag{4.1}$$

where :

N is the total number of firms in the simulation

T is the simulation duration

and

t is time required to transact one order

In addition, geographic regions also report regional averages of the output variables. With 5,443 firms in the simulation, the data generated requires a significant amount of analysis. To make this more manageable, the output data from N-ABLE is read into SAS9.0© *Statistical Analysis Software* where the full data set is segregated into data analysis tables. Using these data analysis tables statistical analyses and plots are created. The results reported herein are at the regional level, with the exception of a few individual firm results used as examples.

The geographic regions in the milk supply chain model correspond to the regions in Figure 3.1. Each region reports results 116 variables in the output file. The variables used in this analysis concern inventory levels, distance transported, production volumes production costs, variable input costs, met demand, and unmet demand. In the typical simulation analysis, it is desired to find the point in the model where steady-state is reached and perform comparisons from that point forward. Given the academic focus of this thesis research, however, the desire is to study how the model uses the transportation infrastructure as a mechanism for reaching a state of quasi- equilibrium. The approach is similar to what one would do to determine a baseline where the definition of *normal* variation is determined. However in this case, we are more concerned with wether the representation of transportation infrastructure and economic accounting for transportation costs provide enough capability to allow firms search for their quasi-equilibrium state.

4.2 Presentation of Results

In order to determine when the agents of the firm are struggling to find their place in the market, the indicators of met demand and unmet demand are used. Met demand, within this simulation, is the measure of what supplies were needed (also known as target order). Unmet demand, for this study, is the amount of supplies that weren't available for purchase. Met and unmet demand provides a measure of the ability of the firm to find and purchase supplies. If demand for a firm's finished goods continually increases, the market as a whole has not reached a stable state. Once the unmet demand is consistently reduced to a small percentage of the total demand, the supply is said to be adequate to meet demand needs; quasi-equilibrium is reached.

Figures 4.1 through 4.3 show the fraction of unmet demand for each commodity supplied to the supermarkets, by region. Figures 4.4 through 4.6 show the fraction of unmet demand for bulk-milk used in intermediate milk-products manufacturing. Beginning with the supermarkets, we see that the butter and dry-milk demand by the supermarkets is met for all regions. Frozen good demand has little problems as well with only a temporary shortage condition around day 40 in the East-North Central region[1]. The unmet demand for bottled-milk requires more time to be satisfied, and occurs in two high-demand regions (East-North Central and South Atlantic). The unmet demand for cheese oscillates for the duration of the simulation. The only region with with low or no unmet cheese demand at the supermarkets is West, due to the availability of cheese available within the region. The unmet demand ranges for bulk-milk by the cheese industry is shown in Figures 4.4 through 4.6.

[1]Such occasional shortages are typical given the stochastic nature of the simulation

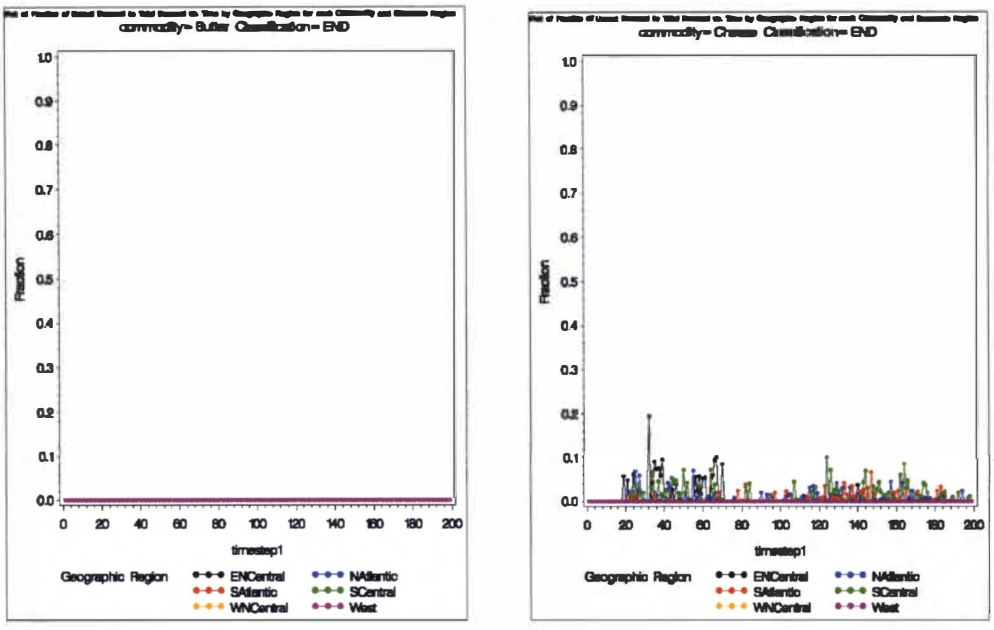


Figure 4.1: Unmet Demand for Butter and Cheese at the Supermarkets

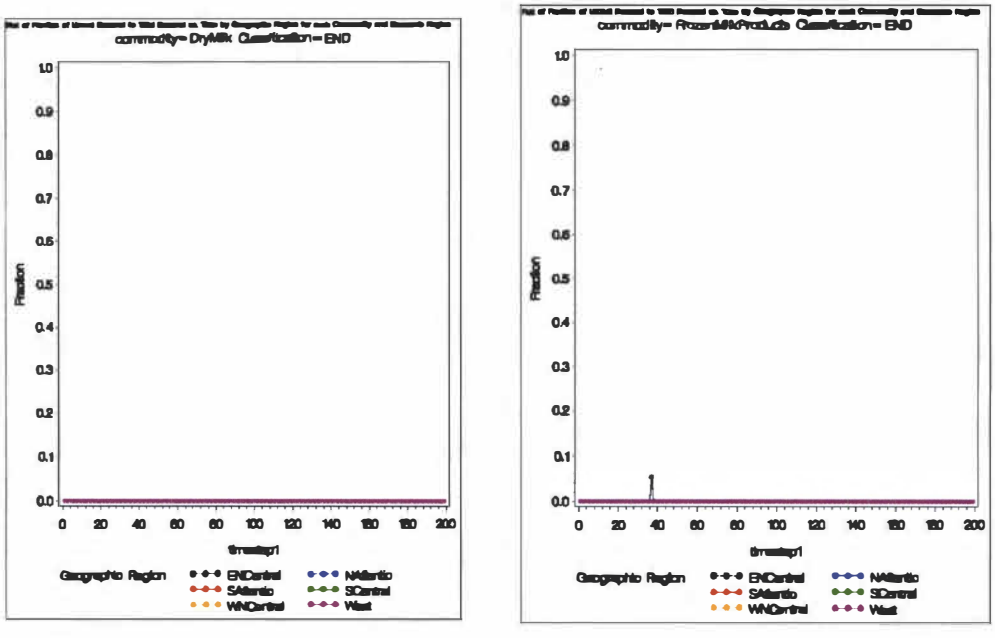


Figure 4.2: Unmet Demand for Dry Milk and Frozen Goods at the Supermarkets

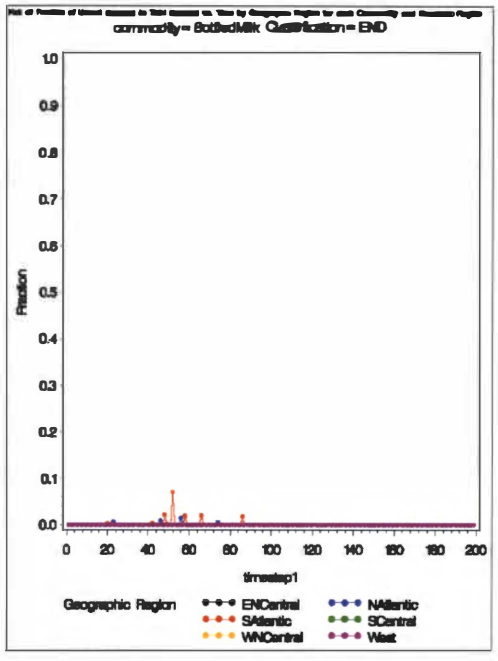


Figure 4.3: Unmet Demand for Bottled Milk for the Supermarkets

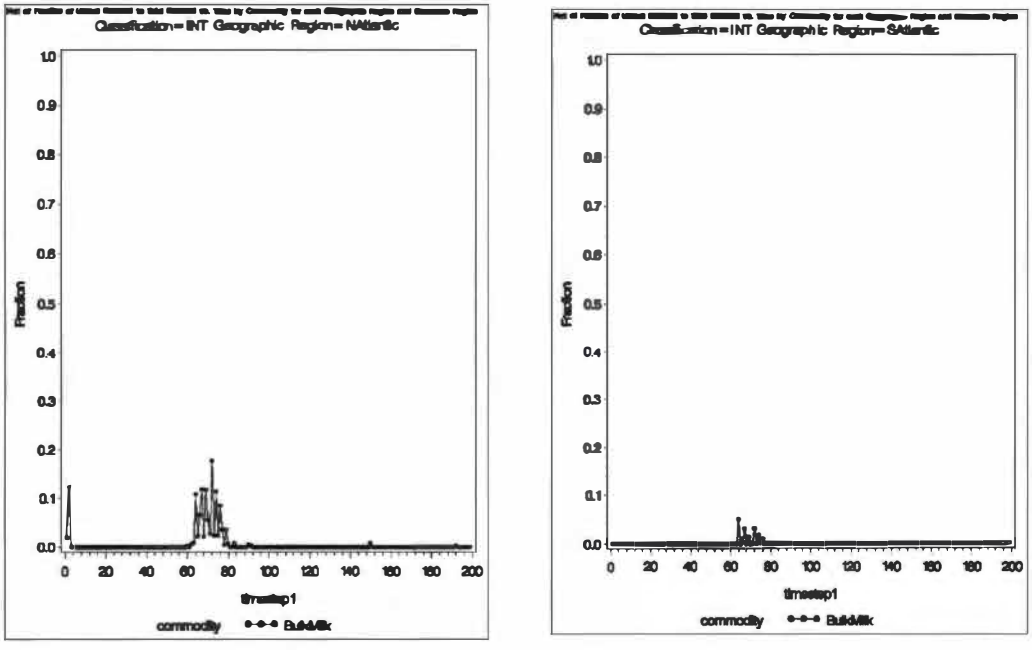


Figure 4.4: Unmet Demand for Bulk Milk in the North and South Atlantic Regions

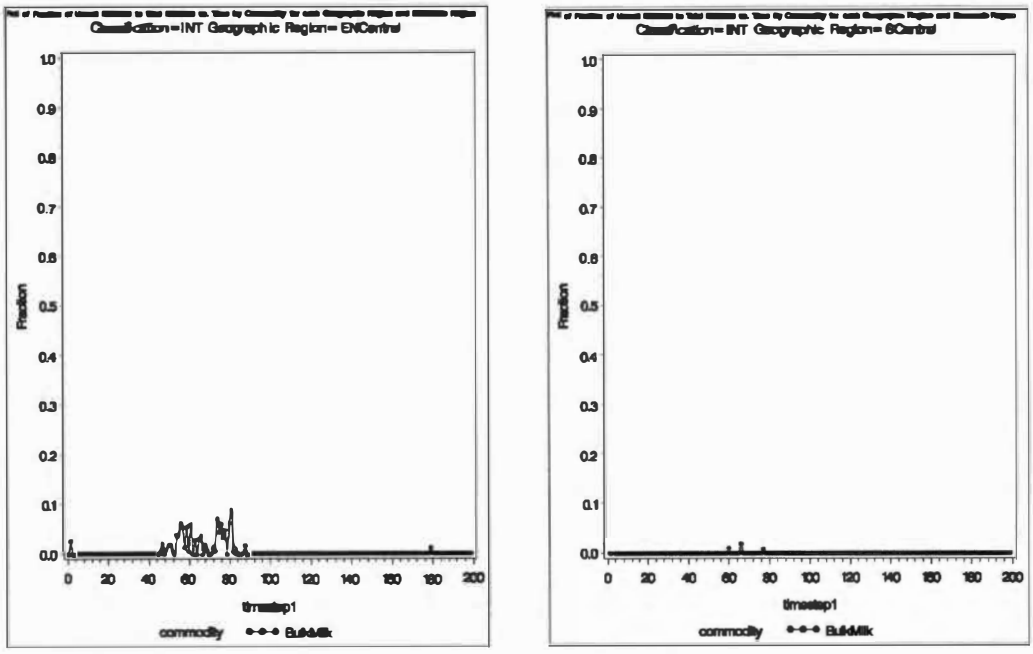


Figure 4.5: Unmet Demand for Bulk Milk in the East-North Central and the South Central Regions

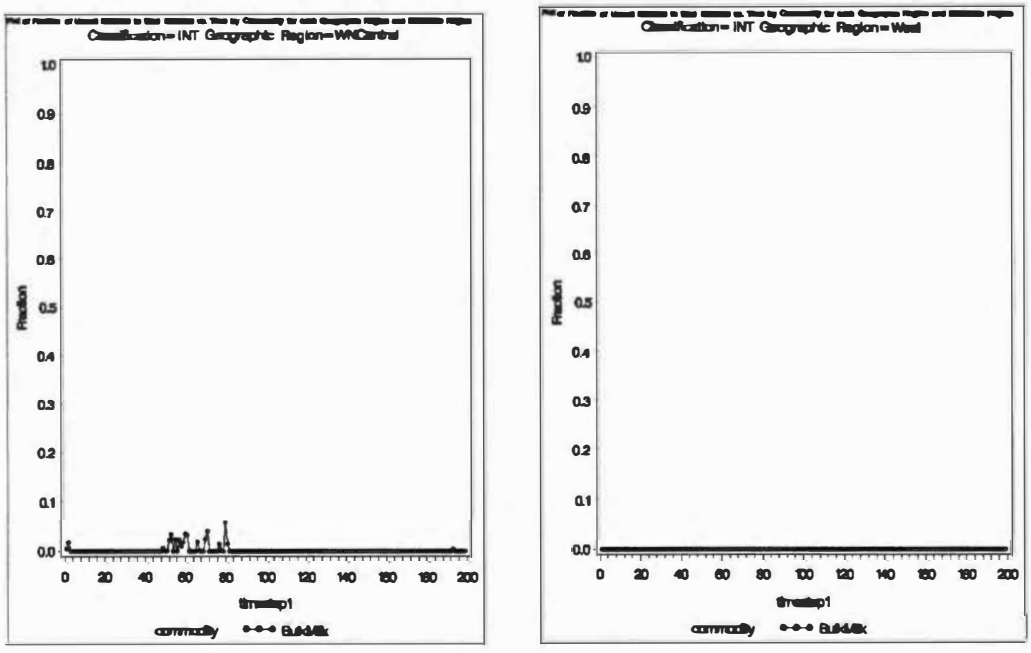


Figure 4.6: Unmet Demand for Bulk Milk in the West-North Central and the West Regions

Based on the results of the unmet demand, the remainder of the analysis focusses on the cheese to supermarket portion of the supply chain. On-site and in-transit inventory variations are the results of decisions made by the agents in the model. For example, a buyer for a cheese manufacturing firm buys bulk-milk as an input to his manufacturing process. The cost of the milk is proportional to the distance the bulk-milk travels to arrive at the cheese manufacturer. Variations in the cost of the milk cause the per-unit production cost of the cheese to fluctuate, which in turn are passed on to the price offered to the supermarket. The supermarket responds by trying to find suppliers with lower prices. As the dynamics unfold, so do regional interdependencies.

4.2.1 Dynamics of the Supermarket Quest for Cheese

Regional supermarket inventories of cheese are shown in Figure 4.7 and reported in Table 4.1. Low coefficients of variation indicate small changes relative to the mean value. The variance in cheese inventory at supermarkets under these non-disrupted conditions is a direct result of supermarkets searching for cheaper supplies. Figure 4.8 shows a single supermarket and its supplier connections for a given day. Notice that most are fairly close, however, for one order the supermarket had to buy from far away to get needed supply.

The statistics for average distance are shown in Table 4.2. The coefficients of variation for inventory and distance are not 1:1 correlated (although the ordinal ranking of variation by region for inventory and average distance match very well). The reason there is not a direct correlation is because inventory consumption is inherently time-based, whereas time to traverse a given network distance is not a fixed quantity. The time portion of variation is dependent on speed of the network and the number of vehicles on the network. Consider, the locations shown in Figure 4.8. Most of the orders are nearby, but these orders are traveling through large metropolitan areas where the attributes of the network are more constraining; the posted speed is slower and as network usage increases effective speed decreases (Veffective from Equation 2.2). These network constraints mean that past experience of transit times in heavily populated regions of the country is not necessarily an accurate predictor of future transit times, especially when generalized to new suppliers in new geographic locations. The net result of these temporal variations (uncertainty in arrival time), is variation in the firm inventory levels. Inventory levels buffer the uncertainty inherent in switching to new suppliers based on the current lowest ask price for the commodity.

Figure 4.9 shows the total and the average distances cheese travels to reach regional supermarkets. Table 4.3 provides the statistics for the total distance traveled. Comparing Table 4.2 and Table 4.3 we notice the ordinal ranking between the two variations is different. The S. Atlantic and S. Central region supermarkets experience relatively large coefficients of variation for total distance traveled at 0.14 as compared to the variance using the average distance per cheese order. This is, in fact, a characteristic of the supply demand attributes of these regions. From Figure 3.2, we know that the supply-demand ratio for bulk-milk entering into cheese manufacturing approaches 0 for both the S. Atlantic and S. Central regions, indicating a large demand with little regional supply. The total distance traveled is influenced greatly by drastically shorter regional purchases, however, the average distance is not highly sensitive due to their infrequent nature. The S. Atlantic and S. Central regions almost always purchase outside their own region with very few regional purchases.

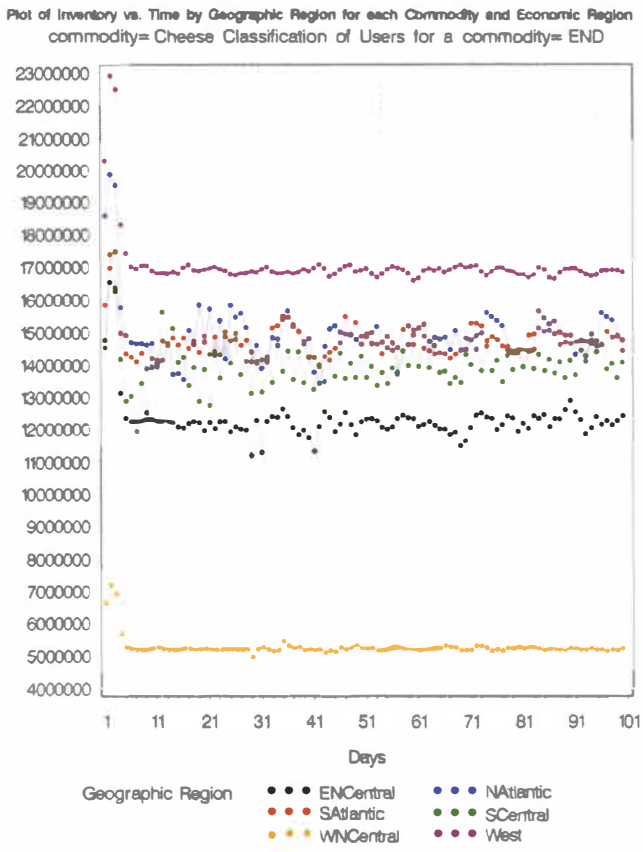


Figure 4.7: Regional Supermarket Cheese Inventories

Table 4.1: Warehouse Cheese Inventory Statistics for Supermarkets by Region

Region	Mean (lbs)	Standard Deviation	Coefficient of Variation
E-NC	12,335,128	535,842	0.043
N-ATL	14,911,729	707,115	0.047
S-ATL	14,721,472	424,097	0.029
SC	13,959,259	543,876	0.039
WNC	5,247,447	214,464	0.041
WEST	1,697,3724	643,721	0.038

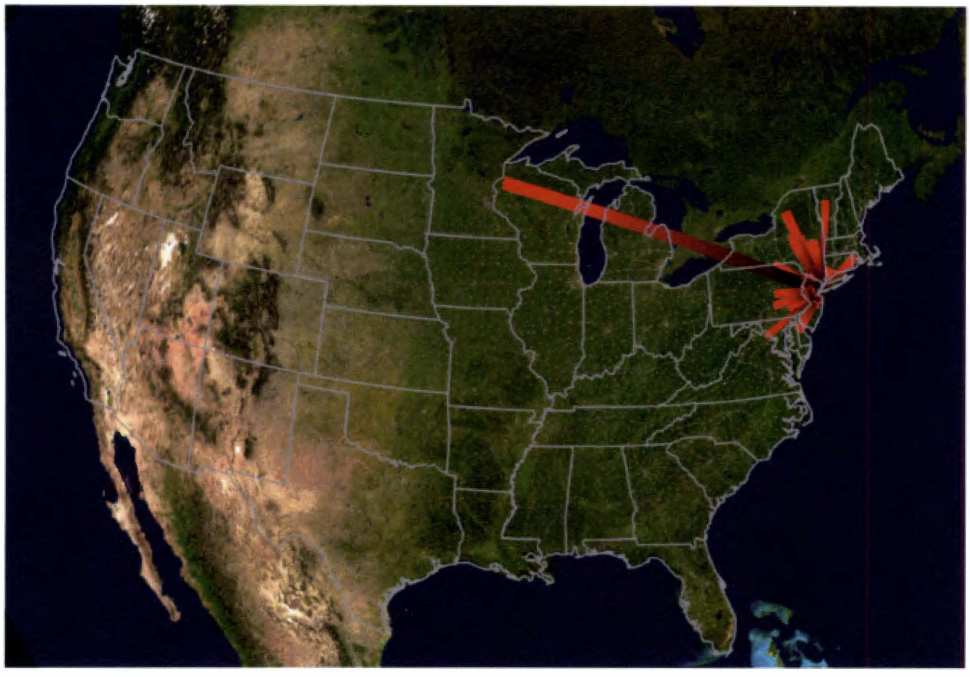


Figure 4.8: Cheese Orders from a Single Supermarket

Table 4.2: Average Distance for Cheese Supply to Supermarkets by Region

Region	Mean (miles)	Standard Deviation	Coefficient of Variation
E-NC	268.96	24.0841	0.09
N-ATL	457.7256	99.00277	0.22
S-ATL	987.3143	45.70242	0.05
SC	673.6378	41.55776	0.06
WNC	280.3461	19.89268	0.07
WEST	322.8855	22.98756	0.07

Table 4.3: Total Distance for Cheese Supply to Supermarkets by Region

Region	Mean (miles)	Standard Deviation	Coefficient of Variation
E-NC	152386.5	22360	0.15
N-ATL	203141.2	68397	0.34
S-ATL	466360.6	66941	0.144
SC	596681	80863	0.14
WEST	146241.1	16770	0.11
WNC	184830.4	21649	0.12

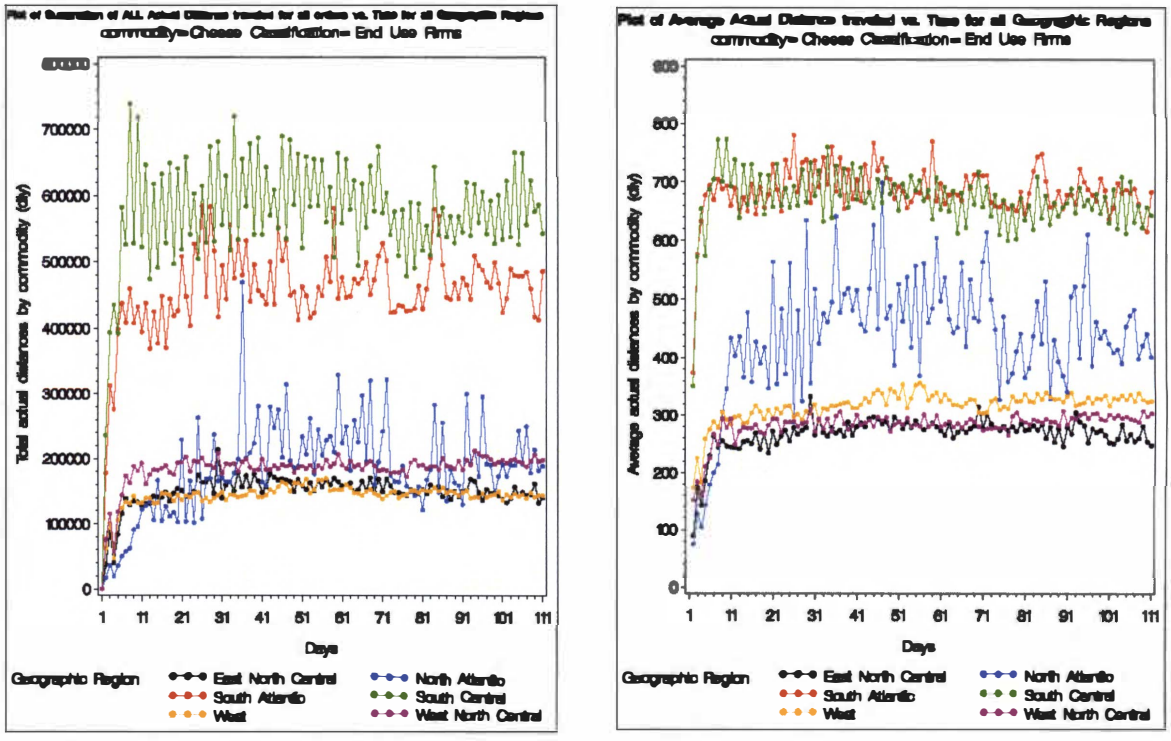


Figure 4.9: Total and Average Distance Cheese Travels to Supermarket

These same dynamics flow through to the price the supermarket pays for the cheese. The coefficient of variation for the price of cheese in the North-Atlantic Region is approximately twice that experienced by the South-Atlantic and South Central Regions. The average price of cheese for each region is presented in Figure 4.10. The trend of the price is downward, indicating that the agents are learning over time how to achieve their lowest cost.

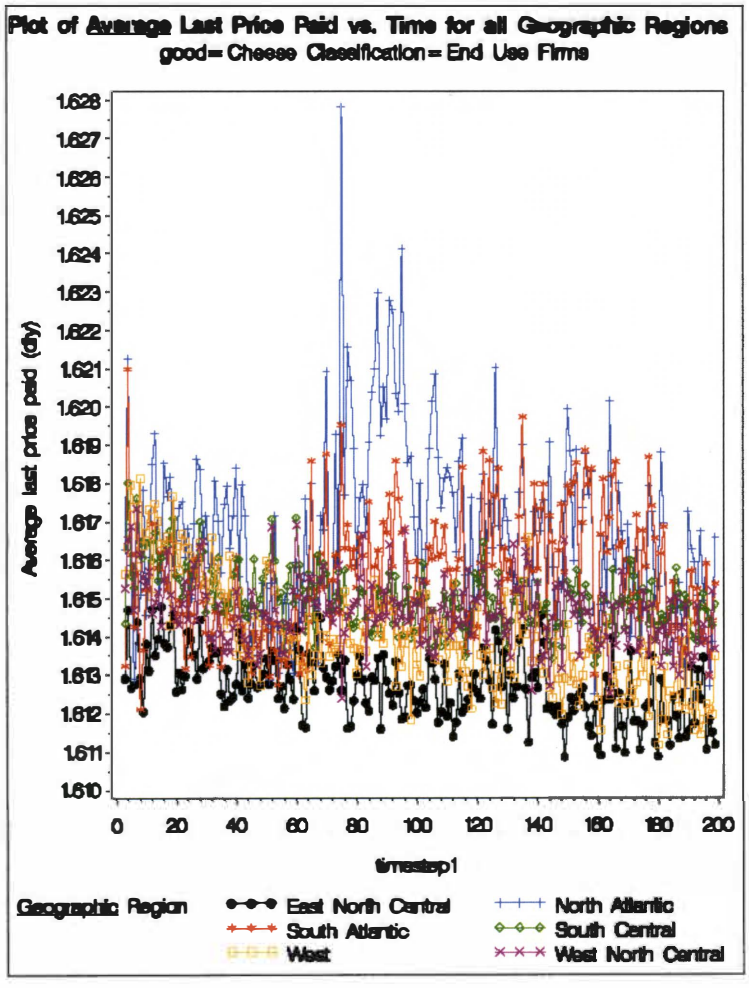


Figure 4.10: Regional Price of Cheese

Chapter 5

Discussion

The intent of this effort is to add a transport network to the N-ABLE™ model, thereby increasing the fidelity of the economic results reported. The strongest result of this work is the demonstration that inventory levels in a supply chain must buffer the delivery time uncertainty created when rigorous pursuit of minimum cost supply creates churn in the set of preferred suppliers for a firm. The current geographic distribution of supply and demand, along with variations in the effective time-dependent throughput capacity of the transportation network across the country, create differential regional sensitivities to this basic reality. In particular, the North Atlantic region is most susceptible to this condition, and as a consequence experiences almost twice the price fluctuation of the South Atlantic region for cheese, despite having half the average supply distance of the south.

Although the fundamental tenets of economics suggest that such cost minimization behavior is appropriate for commodity markets such as the dairy product market, knowledge of the risk-averse nature of firm buyers and supply chain management personnel suggests an alternate strategy of managing preferred supplier lists based on prior business experience may be appropriate. Such a strategy would seek to reduce uncertainty in a firm's estimation of both its raw material cost and its available inventory level by minimizing switching between suppliers. The open question is whether the lower operating costs possible by running with lower levels of safety stock and better knowledge of margins in making pricing decisions in the long run is more cost effective than maintaining brutally competitive supplier relations.

5.1 Value of Contribution

This work was motivated by the need to provide to the Department of Homeland Security detailed, predictive estimates of the economic impacts of transportation disruptions. Until this work, there were no tools capable of capturing the local, regional, and national economic effects when the initiating event is highly localized (losing a bridge, for example) and/or short term (shipment interruptions of a few days or weeks). Figure 5.1 illustrates typical results from an N-ABLE™ simulation prior to this work, under conditions of the standard economic theory treatment of transportation, that is, fixed time transportation duration and negligible cost. Note that the economic interactions

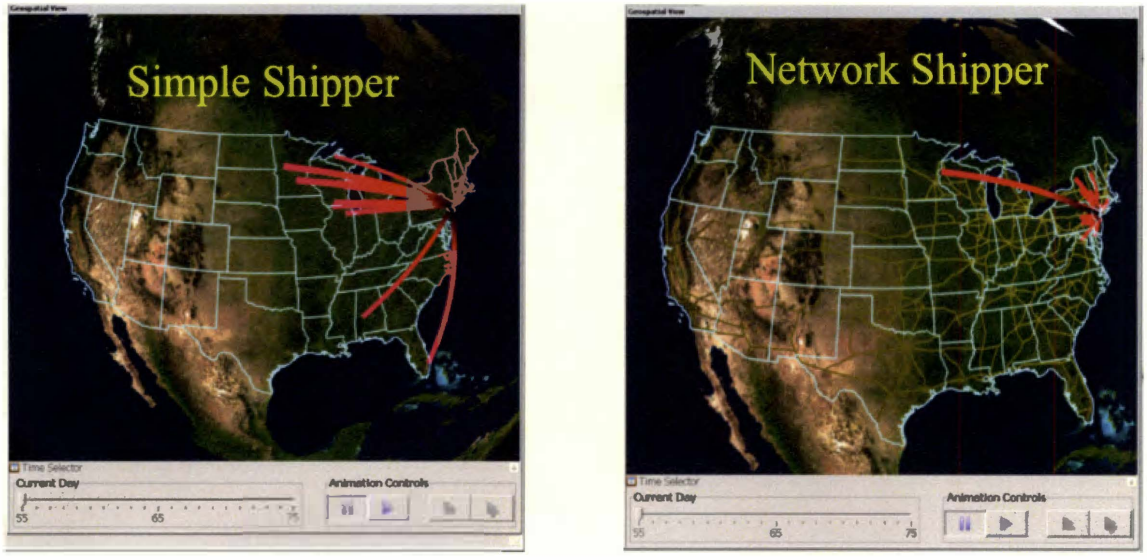


Figure 5.1: N-ABLE™ Results with and without Transportation Network

shown by arcs in the figure cover an unrealistically large geographic region. These results are representative in that regional markets do not emerge endogenously from this formulation. Furthermore, since there is no fundamental representation of the components of the transportation infrastructure (bridges, highways, and secondary roads), it is not possible to impose a transportation disruption on this formulation. The model presented in this thesis allows the National Infrastructure Simulation and Analysis Center to analyze potential impacts to an individual firm, an industry, a supply-chain, a localized area, a region, a state, or the national economy by explicit consideration of transportation as both a constraint on and an enabler of economic activity. Using N-ABLE™, NISAC can represent, at a firm level, value-add activity dependencies on a flexibly specified transport network, which, when simulated on massively parallel hardware, allows the regional and local economic activity engendered by that mode of transportation infrastructure to emerge endogenously. The patterns of these emergent economic activities, arising in co-dependence with the characteristics of the transportation layer described here, drive the responses of businesses during disruptions, and lead to a direct, decomposable, and defensible impact estimate.

For further work, we would like to introduce price elasticity at the consumer level, so that the quantity of the commodity purchased is strongly dependent on the price asked for the commodity. This will increase the amount of 'noise' in the system, as net demand will no longer be a fixed quantity. We are keenly interested in how the detailed, high-fidelity representation discussed here will respond to, and possibly amplify, the dynamics of this new supply chain boundary condition.

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Vita

Paula Sue Downes was born in Phoenix Arizona on May 4, 1968 to James Irl Downes and Lillian Kay Downes. Paula graduated high school in 1986 from Socorro High School, in Socorro County New Mexico. After taking a few years to determine what and where to study, Paula went back to Socorro, New Mexico to attend the New Mexico Institute of Mining and Technology. She received a Bachelor's of Science in Environmental Engineering in 1994. From there, she went to work for the Environmental Evaluation Group at the Waste Isolation Pilot Plant in Carlsbad New Mexico. In 1995, she went to work for Sandia National Laboratories as a programming analyst and remains there today. She still hasn't figured out what she wants to be when she grows up, but she is definitely having fun testing out all the options.

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