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A STUDY OF THE IMPACT OF INFORMATION BLACKOUTS ON THE BULLWHIP EFFECT OF A SUPPLY CHAIN USING DISCRETE-EVENT SIMULATIONS

by

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ABSTRACT

This study adds to the supply chain management literature by introducing and investigating information blackouts, sudden and short-duration failure of the information flow. This study aims to contribute to the literature in following ways: first, to define information blackouts in a supply chain. Second, to investigate the response of supply chains to information blackouts using discrete-event simulation. Prior research has focused more on analyzing systemic disruptions to supply chains from well-known sources. We expect the results of this study to be useful to supply chain managers in disaster prone areas.

Key words: supply chain disruption, discrete-event simulation, information blackout

This dissertation is dedicated to the many people who have contributed to my success in earning this doctoral degree. It is difficult to express my gratitude for the ceaseless patience and support they provided throughout this long and seemingly endless journey.

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CHAPTER 1

1. INTRODUCTION

Hurricane Katrina wrought destruction along the Gulf Coast of the United States on August 25, 2005. Much of the damage presented itself clearly; houses and businesses destroyed, cars flooded, roads and levies failed. People outside the Gulf Region sent help and were grateful they were spared the effect of Katrina. As it turned out, the impact of Katrina extends across the country.

The new house construction market before Hurricane Katrina was on an upswing making demand for drywall high. After Katrina swept through, the domestic of drywall could not keep up with the demand. This forced the import of drywall. “The boom in imported China-made building materials peaked in 2006, driven by domestic shortages created by the nationwide construction boom, as well as a series of Gulf Coast hurricanes. That year, enough wallboard was imported from China to build some 34,000 homes of roughly 2,000 square feet each, according to the AP's analysis and estimates supplied by the nationwide drywall supplier United States Gypsum” (Burdeau, 2009).

The drywall supply chain was functioning at full capacity when an external event caused a temporary shutdown and then an enormous surge in demand. This sequence of events illustrates the problem of temporary blackouts of information in a supply chain. The question that comes to mind is what happens to a supply chain when the information it uses to function is temporarily unavailable, as it is in a hurricane takes out communications for a short period of time.

Hurricane Sandy struck the Northeast coast of the United States in October 2012. Infrastructures were damaged beyond expectations. "Most of us in the path lost power, heat, telephone service, and, in some areas, water. As fiber-optic cables have replaced copper phone lines, landline phones cannot work without electricity. Many cell towers were damaged, so mobile phones did not work either" (Knight, 2012). It took weeks the repair communication systems in many locations. In the meantime, the rest of the country continued the function normally. Sandy caused localized, temporary information blackouts in many supply chains.

These hurricanes produced short-term breaks in supply chain functions. Some of these supply chains were small and completely housed within the effected geographic areas. For these supply chains it was sudden and harsh jolt to their operations. However, as they were all experiencing the same problems, there was not an imbalance between the firms in the supply chain. For supply chains with members effected and others still fully operational, there is pressure for those that are not functioning and impatience from those that are. Anticipating and preparing for these rare events occurrences is difficult. Managers are busy focusing on the daily demands of inventory management.

Inventory management commands the attentions of managers. There are costs associated with carrying too much inventory and running out of inventory. While it has long been studied, there is now heavier reliance on automated inventory control systems. Managers search for inventory control systems that keep inventory levels at a sweet spot where storage costs are minimal and stock-outs are rare. To that end, managers examine inventory flow throughout their entire supply chain. By increasing awareness of up-stream and down-stream inventory movement, managers have more information on which to base inventory decisions.

Christopher defined a supply chain as “the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer” (2016). What happens when supply chains are hit by a disaster like those described above? What are the effects of an interruption in information flow on the nodes of a supply chain? How do supply chain managers mitigate the effect of such disasters on their segment of the supply chain? This research investigates what happens when there are information blackouts between members of a supply chain. An information blackout is a sudden and unexpected, short-duration interruption in the information flow between nodes of a supply chain, usually due to a disaster. The information flow may be disrupted to or from one or more node of the supply chain.

1.1. STATEMENT OF THE PROBLEM

Supply chain uncertainty is a hot topic for supply chain managers and scholars. Simangunsong et al. (2012) identified fourteen sources of supply chain uncertainty. The last of these are non-deterministic chaos such as earthquake, tsunamis, and hurricanes. Their definition for such an event is a “Natural disaster, e.g. earthquakes, hurricanes, and storms that has a great impact on the supply-chain processes” (Simangunsong et al., 2012). This would also include infrastructure catastrophes due to cascading various failures like the Northeast blackout of 2003. This case started with overgrown plants weighing on powerlines. This should have set off an alarm letting the power company know the lines in that area needed to be attended to, however, a bug in the system program caused the alarm to not be signaled. Transformers adjacent to the effected lines had to re-route the electricity to travel via different transmission lines. Eventually a race condition existed in the system causing the blackout.

In addition to listing the models used in researching the fourteen sources of uncertainty, Simangunsong et al. (2012) also identified gaps in the literature by uncertainty type. They believed uncertainty types with the fewest citations were the areas that needed further research. These areas include decision complexity, organizational/behavorial, order forecast horizon and disasters. This last under-studied source of uncertainty is what this research will explore.

Kleindorfer and Saad (2005) identified "two broad categories of risk affecting supply chain design and management: (1) risks arising from the problems of coordinating supply and demand, and (2) risks arising from disruptions to normal activities". Their research focused on the second type of supply chain risks, disruptions. They explain that these disruptions could range from worker strikes, economic problems, intentional acts, such as terrorism, and natural disasters. Further, Kleindorfer and Saad promote three tasks of disruption risk management: specifying sources of risks, assessment, and mitigation (SAM) (2005). We touch of each of these three tasks in this investigation. First, the risk source, information blackout, is defined. Second, the assessment of this risk is the bullwhip effect, is used to measure the impact of an information blackout on a supply chain. Third, the mitigation when an information blackout occurs will vary based on the level of impact on the supply chain and the manager's risk tolerance. **Table 7** and **Figure 12** illustrate how supply chains react to information blackouts when the blackouts occur in one or more of the stocking points in the supply chain.

Sources of uncertainty in a supply chain and methods for handling interruptions resulting from them have both been identified as areas in supply chain management that need further research. This study focuses on simulating a supply chain before and after an event that will cause order information to no longer be passed down the supply chain. This break in communication could be caused by any number of events that disrupt the supply chain. This research intends to define the term information blackout, model the occurrence of an information blackout in a discrete-event simulation, and provide empirical evidence of an information blackout.

1.2. SIGNIFICANCE OF THE PROBLEM

The significance of the disruptions in supply chains is well-recognized. When a supply chain fails to operate, even for a short period of time, the result is lost production and profit. While many customers within a supply chain are willing to wait for the system to start back up again, many retail customers will not wait. They will purchase from a retailer that can immediately provide the good or service they seek. In some cases, these customers who were once returning customers, have been forever lost to the new provider. This means supply chain failures have the potential to cause both short-term and long-term problems.

As an example of a natural disaster causing losses we can look to the 2011 earthquake in Japan. As Tang et al. (2016) reported the “Toyota Motor Company was forced to stop operations in twelve assembly plants and absorb a production loss of 140,000 vehicles. The main cause of this problem was the disruption of the supply chain supporting the manufacturing subsystem. During disruptive events, supply chains are particularly vulnerable to propagating failure." Assuming a modest price of $15,000, the lost income from those vehicles is over two billion U.S. dollars. This expresses the lost income only, not any of the peripheral losses like the wages of employees and then the losses to the local economy because the employees were short of funds.

To look at a less drastic example, Hendricks and Singhal (2003) investigated changes in stock price due to announcements of supply chain glitches. They listed possible sources of supply chain glitches as

- inaccurate forecast
- poor planning
- part shortages
- quality problems
- production problems
- equipment breakdowns
- capacity shortfall
- operational constraints
- suppliers
- customers
- internal sources

Examples of the glitches Hendricks & Singhal examined include the parts shortage the lead Sony to run short of Playstation 2 units and the internal and supplier production problems that prevented Ericsson from meeting the demand for mobile phones in 2000 (2003). They found that "glitches do affect a firm's short- and long-term profitability, which in turn affects shareholder value" (Hendricks & Singhal, 2003). The results of their studied showed a drop in shareholder value of US $ 251.47 million (US$ 26.29 million) in 2000 dollars. "Clearly, supply chain glitches have significant negative shareholder wealth impacts" (Hendricks & Signhal, 2003).

1.3. PURPOSE OF THIS RESEARCH

The purpose of this dissertation is to establish evidence of an information blackout when order information is limited due to a disruption in the information flow of a supply chain. The hypothetical disruptions being considered in this study are intended to represent the short-term disruptions that happen due to disasters like hurricanes. The outages are brief and often limited to a geographic area so the entire supply chain is not shut down, only particular nodes. These disruptions cause losses of money and customers that extend beyond the outage period. For this reason, members of supply chains need to take the most advantageous actions during an information blackout in order to minimize its impact. The intended goal of this investigation is to provide empirical support for the concept of an information blackout.

1.4. METHOD AND PROCEDURE

The method that will be used for this dissertation is a discrete-event simulation using Rockwell's Arena® software. Computer simulations has been used by many previous studies including Datta and Christopher (2011), Chatfield (2013), and Chatfield and Pritchard (2013). A discrete-event simulation analysis begins with creating a conceptual model of the problem. The system that will be model needs to be thoroughly understood and described. It should contain details that may be left out of simulated system because they are deemed unnecessary to represent the part of the system being studied. Then the simulation is created in the software. For a discrete-event simulation, the entities, resources, and queues must be identified along with system processes. Once the model seems to be running properly, it is validated and verified against other models, computational and computerized. Then the experimental parameters can be run and the resulting data collected.

1.5. ORGANIZATION OF THIS DISSERTATION

The dissertation is organized into five chapters. The first chapter has been an introduction to this study. Some of the relevant literature has been introduced and an initial discussion of the usefulness of such a study has been given.

The second chapter provides the background of this study. There is a review of supply chain analysis literature. The gap being addressed by this research is identified in this analysis of the supply chain literature. This leads to the key performance measure being considered in this study, the bullwhip effect (BWE). We will look at how BWE studies have been conducted in the past. Two of these previous studies are used to comparison with the results of this research.

The third chapter explores the methodology used in this dissertation, computer simulation. The conceptual model and the simulation design and specifications are given. Measurement variables are described. The parameters for the verified models and the experimental models are given. The model validation and verification against prior studies is detailed. The simulation tool, Arena© by Rockwell, is described and its selection justified by prior studies.

The fourth chapter discusses the results of the experimental simulation. The results of the control model and the experimental models are compared to each other in order to illustrate the impact of information blackouts on a supply chain. The validation process is explained. This section closes with conclusions and a discussion.

The fifth chapter gives the conclusions and discussion for the entire study. The major findings are summarized. Implications for other studies of the supply chains are given. Future studies and recommendations are also included in this section. The last chapter is followed by the reference section, the appendices, and vitae.

CHAPTER 2

2. BACKGROUND OF THE STUDY: METHODS AND MODELS

In this section, we will discuss the relevant literature on supply chain disruptions and beer game studies. First part of the literature review identifies types of supply chain disruptions and their effects. This is followed by a discussion of the bullwhip effect, one of the most common types of supply chain studies. The second section opens with a description of the beer game, a method for studying the bullwhip effect in a supply chain developed by Sterman (1989) at MIT. The subsections are discussions of the use of simulations to study the bullwhip effect in supply chains and the use of discrete-event analysis.

2.1. LITERATURE REVIEW: SUPPLY CHAIN ANALYSIS

Systems dynamics was one of the earliest approaches for investigating supply chains. Forrester (1958) stated "Beyond these achievements, there will be improvements in company organization resulting from a sounder basis for effective decentralization, from altering the relationships between line and staff tasks in the company, from the more effective utilization of scientific manpower, and from reducing the routine duties and enhancing the creativity of managers. And executives will gain in 'clairvoyance.' For example, they will be able to anticipate clearly (as will be illustrated later in this dissertation):

- How small changes in retail sales can lead to large swings in factory production.

- How reducing clerical delays may fail to improve management decisions significantly.
- How a factory manager may find himself unable to fill orders although at all times able to produce more goods than are being sold to consumers.
- How an advertising policy can have a magnifying effect on production variations."

Forrester's work introduced the bullwhip effect (BWE). The bullwhip effect, also called demand variance amplification or order variance amplification, is the tendency of replenishment orders to increase in variability as it moves up the supply chain. In common parlance, at each echelon of the supply chain, more inventory is ordered for replenishment than was sold. The difference between the quantity sold and the quantity ordered, is greater at each level of the supply chain. This every widening variance is where the idea of a bullwhip in motion originated.

There have been several approaches used in supply chain studies of the BWE. These start with Forrester (1958, 1961) using a system dynamics approach. Since then methods such as discrete-event analysis, agent-based modeling and difference equations have been employed.

Forrester discovered the bullwhip effect, also known as the Forrester Effect. His identification of the variance in order sizes provided supply chain scholars and managers with a mechanism for measuring supply chain efficiency. Now, supply chain managers had a standard measure for operations effectiveness that could be used on any supply chain. Product or type of supply chain did not matter in terms of how well its operations are functioning. The discovery of the bullwhip effect coincided with a beginning of the modern retail supply chain. This helped spread the use of Forrester’s efficiency measure very quickly.

As the bullwhip effect began to grow as a measure of supply chain effectiveness, the need to educate supply chain managers on what the bullwhip effect is and how to minimize it became important. Sterman, at MIT, created the beer game to be able to explain the bullwhip effect to his business students. He created a live simulation of a supply chain intended to replicate the path taken by beer on its way to the local bar. His students were keenly interested in making sure the supply chain leading to the beer supply at the local bar was working smoothly. This simplified representation of a supply chain is what much of the supply chain literature uses. In this representation, there is a customer that order from a retailer that orders from wholesaler that orders from a distributor that orders from a factory. It is this simple structure that is used through most of the supply chain literature.

Within the supply chain literature, the many reasons for problems and inefficiencies within are examined from several perspectives. These include topics like management decisions, physical structure of a supply chain, the flow and quality of information between the stages of a supply chain, and disruptions to operations. This is by no means a comprehensive list of the concerns of supply chain managers and scholars. The discussion that follows highlights some of the literature on supply chain management topics related to the research in this dissertation.

Simangunsong et al. (2012) detail the theories prior literature has used to address uncertainty from the possibility of disasters. As mentioned previous, they identified different types of uncertainty and listed the literature that examined each. Many of the sources of uncertainty have been well studied. Rare events, such as hurricanes and earthquakes, have not been.

Christopher and Peck (2004) employed the Risk Sources model in their study. Their standpoint that with greater globalization and the drive to trim down operations, supply chains are more vulnerable. They suggest the solution to this is resilience of supply chains. Their definition for resilience has to do with the speed of a system's recovery after a disruption. They clearly differentiate between robustness and resilience even though they are often used interchangeably.

Tang (2006) also looked into the resilience of supply chains. He observed that some supply chains managed to continue normal operations after a major disruption. Tang noted two strategies for supply chain differentiation, cost-effectiveness and time-efficiency, in the study of supply chain robustness and resilience. He found the practice of these differences along with supply chain robustness and resilience measures helped gain and keep risk-adverse customers before and after major disasters.

Smith et al. (2007) used the IT Vulnerability model to explore the threats that result from interconnecting components of a supply chain. Integrating information technology systems and sharing inventory information help provide better service to customers. They also increase the risk of disruption because the barriers that previous separated stages of the supply chain no longer exist. This means problems that happen at one stage can now move freely to the adjacent stages.

Prater (2005) identified four types of uncertainty in supply chains. They are general uncertainty, foreseen uncertainty, unforeseen uncertainty and chaotic uncertainty. The general and foreseen uncertainty occur most often and managing them are standard parts of daily operations. While they cannot be controlled, they can be prepared for s that managing them takes little effort. Unforeseen uncertainty cannot be planned for based on its nature. These occur less often and the response must be aimed to handle each specific event as they occur. The only preparation that can be undertaken for chaotic uncertainty is the development and practice of a disaster response plan. The circumstances that produce chaotic uncertainty are rare and therefore difficult to plan for or study. This chaotic uncertainty is the type of supply chain disruption being examined in this research.

Tomlin (2006) took a unique viewpoint for looking into supply chain disruptions. He used a supply chain model with two suppliers. One of the suppliers was more reliable, but more expensive than the less reliable supplier. The key finding was “that a supplier’s percentage uptime and the nature of the disruptions (frequent but short versus rare but long) are key determinants of the optimal strategy” (Tomlin, 2006).

The complexity of supply chains is a limitation to experimenting with operational supply chains. While the name supply chains does express the interconnectedness of the members, it implies a simple linear structure. This is rarely the case. Supply chains are more accurately described as networks of customers and suppliers. In many, suppliers buy from and sell to each other, making a study of them even more complex. It is this complexity of supply chains that leads to most researchers to use simplified models of supply chains.

Table 1 lists many, but not all, of the literature that studies supply chains. There are many themes and techniques mention in the titles themselves. Uncertainty is one of the most common themes studied in supply chains and it is what this dissertation studies. Simulating supply chains is a method frequently employed to study them.

There are two primary limitations to experimenting with operational supply chains. The first is the cost involved and the second is the complexity. Changing how a supply chain functions can incur expenses and runs the risk of lost production or delivery of goods and services. The costs of altering a supply chain may include the expenses of physically changing some facilities, longer production or delivery times, and the need for more resources.

2.2. LITERATURE REVIEW: BULLWHIP EFFECT MODELS

The bullwhip effect is a phenomenon that occurs in supply chains due to variations between inventory that is sold and inventory that is ordered by each stage in a supply chain. The difference between the two inventory quantities becomes large further up the chain. This progressively larger variation was observed and described by Forrester and is sometimes referred to as the Forrester Effect. In depth examinations for the bullwhip effect are provided by Baganha and Chen (1995), Kahn (1987), and Metters (1996).

The bullwhip effect is measured via a ratio the variance of the orders to the variance of the demand. Referred to as the total variance amplification of the supply chain, it expresses the efficiency of the inventory management policies and the application of them by the supply chain managers.

$$\text{Bullwhip} = \frac{\text{Variance of orders}}{\text{Variance of demand}} = \frac{\sigma^2_{\text{orders}}}{\sigma^2_{\text{demand}}}$$

As Chen et al. (2000) explains “most of the previous research in the bullwhip effect has focused on demonstrating its existence, identifying its possible causes, and providing methods for reducing its impact. In particular, Lee, Padmanabhan and Whang (1997a, b) identify five main causes if the bullwhip effect: the use of demand forecasting, supply shortages, lead times, batch ordering, and price variations. This previous work has also let to a number of approaches and suggestions for reducing the impact of the bullwhip effect. For instance, one of the most frequent suggestions is the centralization of demand information, which is, providing each stage of the supply chain with the complete information on customer demand."

AUTHORS	YEAR	TITLE
Ancarani, Di Mauro, D'Urso	2013	A human experiment on inventory decision under supply uncertainty
Beamon	1998	Supply chain design and analysis: Models and methods
Boyle	1977	Options: A Monte Carlo Approach
Cantor, Katok	2012	Production smoothing in a serial supply chain: a laboratory investigation
Chatfield	2013	Underestimating the bullwhip effect: a simulation study of the decomposition assumption
Chatfield, Harrison, Hayya	2006	SISCO: An object-oriented supply chain simulation system
Chatfield, Hayya, Cook	2013	Stock-out propagation and amplification in supply chain inventory systems
Chatfield, Hayya, Harrison	2007	A multi-formalism architecture for agent-based, order-centric supply chain simulation
Chatfield, Kim, Harrison, Hayya	2004	The bullwhip effect - impact of stochastic lead time, information quality, and information sharing: a simulation study
Chatfield, Pritchard	2013	Returns and the Bullwhip Effect
Chen	1998	Echelon reorder points, installation reorder points, and the value of centralized demand information
Chen (1999 a)	1999	94%-effective policies for a two-stage serial inventory system with stochastic demand
Chen (1999 b)	1999	Decentralized supply chains subject to information delays
Chen, Drezner, Ryan, Simchi-Levi	2000	Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information

Chen, Ryan, Simchi-Levi	1999	The impact of exponential smoothing forecasts on the bullwhip effect
Chen, Samroengraja	2000	The stationary beer game
Cho, Lee	2012	Bullwhip effect measure in a seasonal supply chain
Croom, Romano, & Giannakis	2000	Supply chain management: an analytical framework for critical literature review.
Croson, Donohue	2002	Experimental economics and supply-chain management
Croson, Donohue	2005	Upstream versus downstream information and its impact on the bullwhip effect
Dejonckheere, Disney, Lambrecht, Towill	2003	Measuring and avoiding the bullwhip effect: a control theoretic approach
Denolf, Trienekens, Wognum, van der Vorst, & Omta	2015	Towards a framework of critical success factors for implementing supply chain information systems.
Duc, Luong, Kim	2008	A measure of the bullwhip effect in supply chains with stochastic lead time
Forrester	1992	Policies, decisions, and information sources for modeling
Forrester	1958	Industrial dynamics - a major breakthrough for decisions makers
Forrester	1961	Industrial dynamics
Fransoo, Wouters	2000	Measuring the bullwhip effect in the supply chain
Helmuth, Craighead, Connelly, Collier, Hanna	2014	Supply chain management research: Key elements of study design and statistical testing
Hollocks	2006	Forty years of discrete-event simulation - a personal reflection

Iannone, Miranda, Riemma	2007	Supply chain distribution simulation: An efficient architecture for multi-model synchronization
Katok	2011	Laboratory experiments in operations management
Khalifehzadeh, Seifbarghy, & Naderi	2015	A four-echelon supply chain network design with shortage: Mathematical modeling and solution methods.
Kim, Chatfield, Harrison, Hayya	2006	Quantifying the bullwhip effect in a supply chain with stochastic lead time
Kim	2007	Organizational structures and the performance of supply chain management.
Kumar, Chandra, Seppanen	2007	Demonstrating supply chain parameter optimization through beer game simulation
Lambert & Cooper	2000	Issues in supply chain management.
Lee, Cho, Kim, Kim	2002	Supply chain simulation with discrete-continuous combined modeling
Lee, Padmanabhan & Whang	2004	Information distortion in a supply chain: the bullwhip effect.
Lee, Padmanabhan, Whang	1997	The bullwhip effect in supply chains.
Leuschner, Rogers, & Charvet	2013	A Meta-Analysis of Supply Chain Integration and Firm Performance.
Li	2002	Information sharing in a supply chain with horizontal competition.
Li, Ragu-Nathan, Ragu-Nathan, & Rao	2006	The impact of supply chain management practices on competitive advantage and organizational performance.

Ma, Wang, Che, Huang, & Xu	2013	The bullwhip effect under different information-sharing settings: a perspective on price-sensitive demand that incorporate price dynamics
Macy, Willer	2002	From factors to actors: computational sociology and agent-based modeling
Madenas, Tiwari, Turner, & Woodward	2014	Information flow in supply chain management: A review across the product lifecycle.
Manuj, Mentzer, Bowers	2009	Improving the rigor of discrete-event simulation in logistics and supply chain research
Marchena	2010	Measuring and implementing the bullwhip effect under a generalized demand process
Metters	1997	Quantifying the bullwhip effect in supply chains
Mula, Campuzano-Bloarin, Diaz-Mandronero, & Carpio	2013	A system dynamics model for the supply chain procurement transport problem: comparing spreadsheets, fuzzy programming and simulation approaches
Parlar, Wang, Gerchak	1995	A periodic review inventory model with Markovian supply availability
Persson, Olhager	2002	Performance simulations of supply chain designs
Rahmandad, Sterman	2008	Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models
Ranganathan, Teo, & Dhaliwal	2011	Web-enabled supply chain management: Key antecedents and performance impacts
Rong, Shen, Snyder	2008	The impact of ordering behavior on order-quantity variability: a study of forward and reverse bullwhip effects
Silver	1981	Operations Research in Inventory Management: A Review and Critique

Speier, Mollenkopf, Stank	2008	The Role of Information Integration in Facilitating 21st Century Supply Chains: A Theory-Based Perspective
Sterman	1989	Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment
Sucky	2009	The bullwhip effect in supply chains - an overestimated problem?
Tan	2001	A framework of supply chain management literature.
Terzi, Cavalieri	2004	Simulation in the supply chain context: a survey
Wadhwa, Mishra, Chan, Ducq	2010	Effects if information transparency and cooperation on supply chain performance: a simulation study
Wang, Jia	2013	Impact of echelon ration for bullwhip effect in three-echelon supply chain based on multi-agent simulation
Wi, Oh, Mun, Jung	2009	A team formation model based on knowledge and collaboration
Wu, Katok	2006	Learning, communication, and the bullwhip effect
Zamarripa, Hjaila, Silvente, & Espuña	2014	Tactical management for coordinated supply chains
Zarandi, Avazbeigi	2012	A multi-agent solution for reduction of bullwhip effect in fuzzy supply chains
Zhang, Zhang	2004	Design and Simulation of demand information sharing in a supply chain

Table 1: Relevant Literature

2.3. CONCLUSION AND DISCUSSION

After this review of the supply chain literature, it is clear that there is a need for more research in the area of the impacts of rare-event disasters on supply chains. Several previous studies have identified this as an area that needs to be researched further. This research is an attempt to help fill this gap in the field of disaster caused disruptions to supply chains. While this research is far from comprehensive, it is a solid first step toward a better understanding of how to manage disruptions in supply chains.

CHAPTER 3

3. METHODOLOGY: DISCRETE-EVENT MODELING

This section explains the research approach and the methodology that is followed in the study. There are three main parts in the section. First part provides two example of discrete-event models of supply chains. The second section is the conceptual model for this study. The third section gives the model assumptions followed by operationalizing the conceptual model in Arena.

3.1. LITERATURE REVIEW: A DISCRETE-EVENT APPROACH TO SUPPLY CHAINS

Discrete-event models have been used to study many different aspects of supply chains. Chatfield (2013) used a discrete-event analysis to investigate the impact of information quality in supply chains. This work supports previous work that indicates the advantage of using actual lead times instead of approximations. While this study was of a multi-echelon supply chain, it was decomposed into node pairs instead creating each stage of the supply chain.

Cigolini, Pero, Rossi, & Sianesi (2014) used a discrete-event analysis to examine how the configurations of supply chains inform their performance. They noted that increasing the number of suppliers actually degrades the performance of the distributors and manufacturers.

3.2. DISCRETE-EVENT MODEL

This sections provides the traditional conceptual model that is part of a simulation study. It details the parts and actions within the system being represented. The flow of the systems is expressed so the directionality understood. Key measures are identified.

Conceptual Model

R, S Inventory System Conceptual Model

Description & Objectives:

This model represents an inventory system with an order-up-to-level of S and an order frequency of every period, R. The parts in the supply chain being modeled include customer, retailer, wholesaler, distributor, and factory.

Metrics:

- Number of retailer information blackouts
- Number of wholesaler information blackouts
- Number of distributor information blackouts
- Number of factory blackouts
- Variance of customer demand orders
- Variance of retailer demand orders
- Variance of wholesaler demand orders
- Variance of distributor demand orders
- Variance of factory demand orders

Assumptions:

- There is one order placed per day at each stage of the supply chain

- A replenishment order quantity is for the difference between S, the order-up-to-level, and the inventory position
- All inventory counts are accurate
- The factory is always stocked and fully operational.

System Description:

Customer orders are created and assigned a demand quantity. Each order is filled by the retailer immediately on a first-come, first-served (FIFO) basis.

The retailer receives the customer demand order for that day. The order is filled immediately. If the retailer does not have enough stock on-hand, a backorder for the needed quantity is created. Each day the retailer places a replenishment order with the wholesaler. The quantity of the retailer replenishment order is based on the inventory position and the order-up-to-level, S. If the position is less than S, then the order is placed for a quantity that will bring the position back up to S.

The wholesaler completely fills the retailer replenishment orders on a FIFO basis. Inventory is received by the retailer after a lead time following a gamma distribution of 4, 1. This increases the on-hand, decreases on-order. The wholesaler and distributor follow these same operation. The factory completely fills distributor orders as they are received and then produces more inventory.

Input Data Source:

Customer orders enter the system at rate of 1 per day representing the cumulative quantity of all individual orders by customers for that day.

Customer order demand is normally distributed in the verification and experimental models. The distribution for the Chen et al. (2000) model verification was (50, 20) and for the Chatfield (2013) model verification was (50, 10).

Diagram:

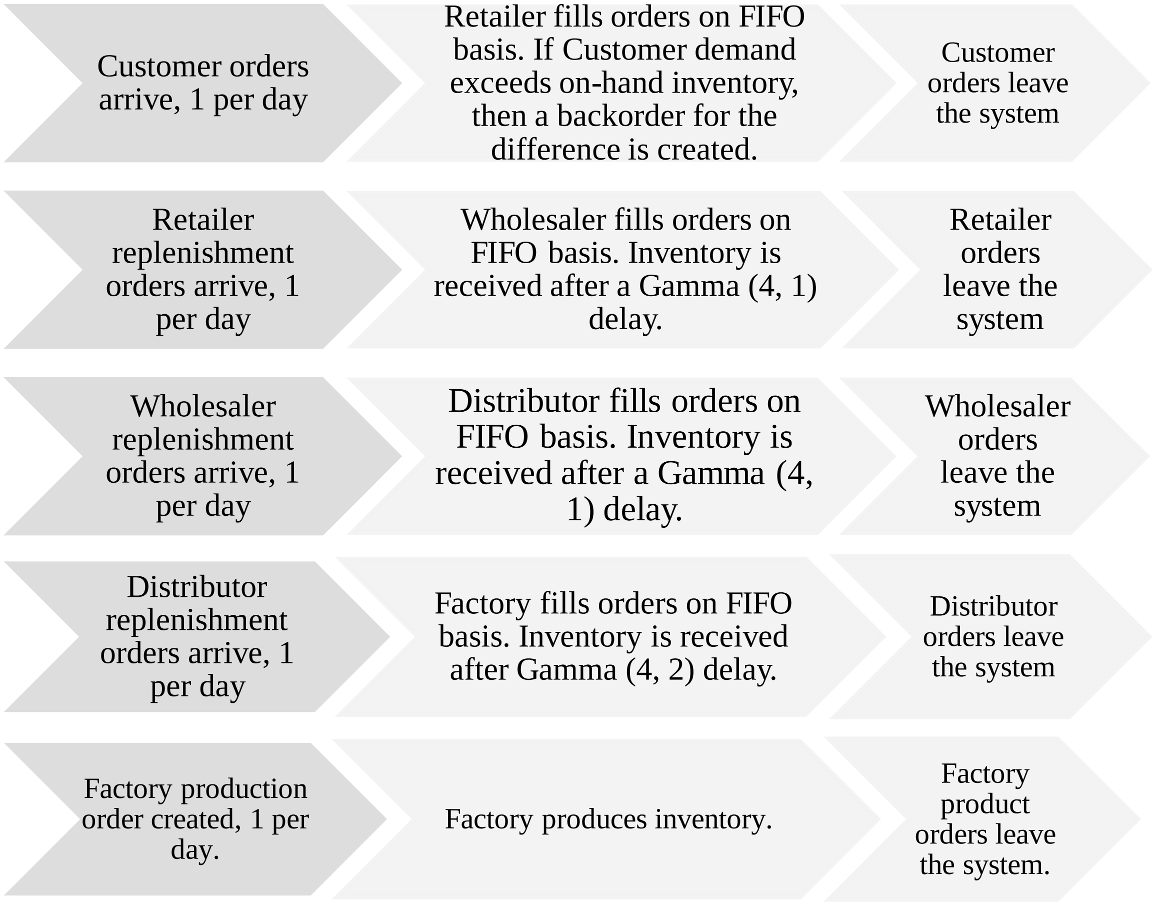


Figure 1: Model Flow Chart

Entities and Attributes:

- Customer orders

  Represent cumulative inventory sold to customers at a retail location in a day

  Attributes:

  - Arrival time – not used specifically used for calculations in this 1 per day that represents the sum of all individual customer orders from that day
  - Demand quantity – normally distributed

- Retailer replenishment orders

  Represent inventory purchased

  Attributes:

  - Arrival time – not specifically used for calculations in this model, 1 replenishment order per day
  - Demand quantity – assigned based on order-up-to-level, on-hand, and backorder

Resources:

There are no resources that need to be captured for orders to be satisfied.

Queues:

There are no queues in the system although there is a gamma (4, 1) delay in satisfying retailer replenishment orders to represent inventory lead time.

Key Variables and Related:

- Backorder Count – keeps a running count of how many stock-outs have occurred
- R – replenishment period, for this model is set to 1

- L – the lead time, Gamma (4, 1)
- S – the order-up-to-level, for an R, S system with R = 1 and L = 2
- Customer Demand – normally distributed
- Retailer, Wholesaler, Distributor Demand – quantity determined using S, L, R
- On-hand – the inventory quantity the retailer has in stock
- On-order – the inventory quantity the retailer has ordered from the supplier
- Backordered – the quantity that the retailer has sold, but did not have in stock
- Net-stock – on-hand - backordered
- Position – net-stock + on-order

Actions/Activities:

- Customer orders placed

  Entity acted on/involved: Customer demand order

  Customer demand order quantity attribute set using a normal distribution

  No resources or delay

- Retailer, Wholesaler, Distributor orders placed to replenish inventory

  Entity acted on/involved: Retailer replenishment order

  The quantity of the retailer replenishment order is based on the inventory position and the order-up-to-level, S. On-hand, backordered, netstock, on-order, position are updated. If position < S, then on-hand += S – position. If backordered, then backordered = 0

  No resources

A transportation delay of Gamma (4, 1) days happens before the variables are updated for every retailer replenishment order.

Logic/Flow Control:

- Movement through the supply chain is linear with 1 possible branch, if a backorder is needed or not.

Start & Stop Conditions:

- Start:

  The supply chain begins in an idle and empty state.

- Stop:

  The supply chain (and simulation) stops after 220 days. The first 20 days are used as warm-up and so the results are discarded.

Component	Details
Conceptual Model	R, S Inventory System This model represents an inventory system with an order-up-to-level of S and an order frequency of every period, R.
Entities	Customer orders Retailer orders Wholesaler orders Distributor orders Factory orders
Metrics	Number of replenishment orders Number of backorders (stock-outs) Variance of orders Number of information blackouts
Assumptions	There is one demand order placed for each stage per day. A replenishment order quantity is for the difference between S, the order-up-to-level, and the inventory position. All replenishment orders are filled to the full quantity of the order. Returns are allowed.

Table 2: Summary of model components.

3.3 MODEL ASSUMPTIONS

There are several assumptions involved in this model of a supply chain. First, this is a single product supply chain. While highly unusual in real supply chains, it is a common assumption in supply chain studies. The second assumption is that there is only one order at each of the stages of the supply chain per day. These single orders represent an aggregation of all orders placed during the day. This is also a common assumption in supply chain models. A third assumption is that the factory is always running at full capacity and never needs maintenance. Again, this is unrealistic, but common in supply chain literature.

Another large assumption is that the inventory counts are accurate. From personal experience working for a wholesaler/distributor, this is a very big assumption.

- This is a one product system.
- All customer orders are identical and have the same priority.
- There can be returns of inventory.
- The Factory never runs out of stock.
- Inventory counts are accurate.
- When more inventory is ordered than is on hand, the remainder becomes a back order.

3.4 OPERATIONALIZATION IN ARENA

Arena allows modelers to choose a distribution from a selection of standard distribution. For this model, customers arrive using a normal distribution and uses a time unit of a day. Two different distributions were used to verify this model. A normal 50, 20 distribution was theorized with a constant lead time of 4 days based on Chen et al. (2000). A normal 50, 10 distribution with a stochastic lead time was utilized for Chatfield (2013). For the stochastic lead times, a gamma distribution of 4, 1 was used.

The screenshot below is how the model appears in Arena. This model is single stage. After this single stage is verified against Chen et al. (2000) and Chatfield (2013), it is then used to build the multi-echelon model. Arrays hold the order quantities for each of the echelons. The backorders for the retailer are also captured in an array.

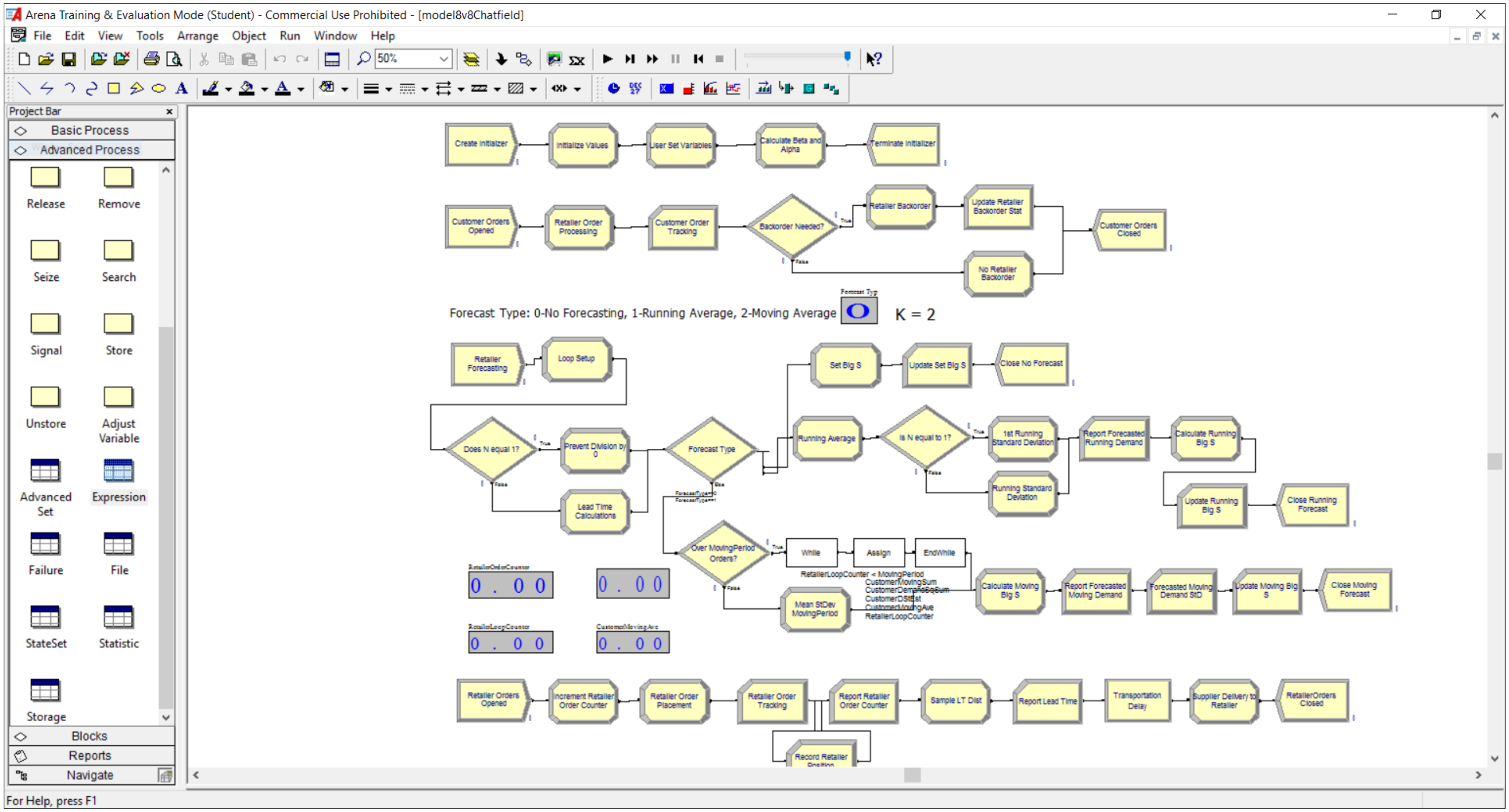


Figure 2: Initial Model in Arena

In this initial model that was used for preliminary verification against prior models, the top row of modules is a set of initiators for the model. It sets initial variable and attribute values. The second row represents the customers in the model. One customer per day enters the system and is assigned a demand value following a normal distribution of (50, 20). The retailer immediately fills the order and the customer leaves the system. The retailer updates its inventory levels. If the customer order was greater than quantity the retailer has on hand, the retailer fills the portion of the order it can and creates a backorder for the difference. The third row represents the retailers in the system. There three way split in the retailer path allows for the inventory counts to be managed using a steady Big S, a Big S calculated with a running average, or a Big S calculated using a moving average of a 15 day period. The bottom row of modules represents the factory operations.

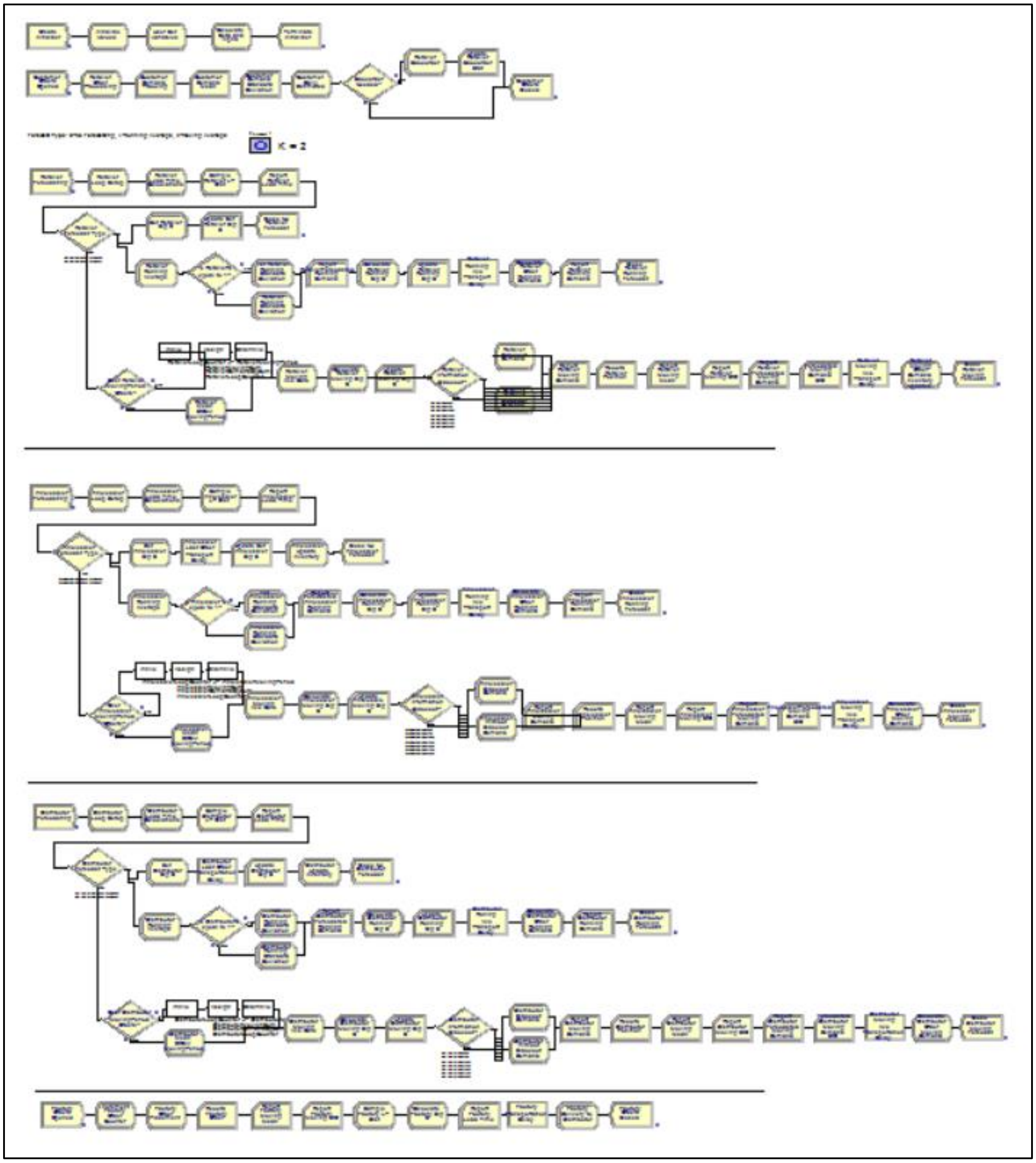


Figure 3: Multi-Echelon Model in Arena

This screen capture shows the full view of the multi-echelon model in Arena. The same layers as the previous model are present here, but in a more robust form. The wholesaler and distributor rows have been added to create the multi-echelon model.

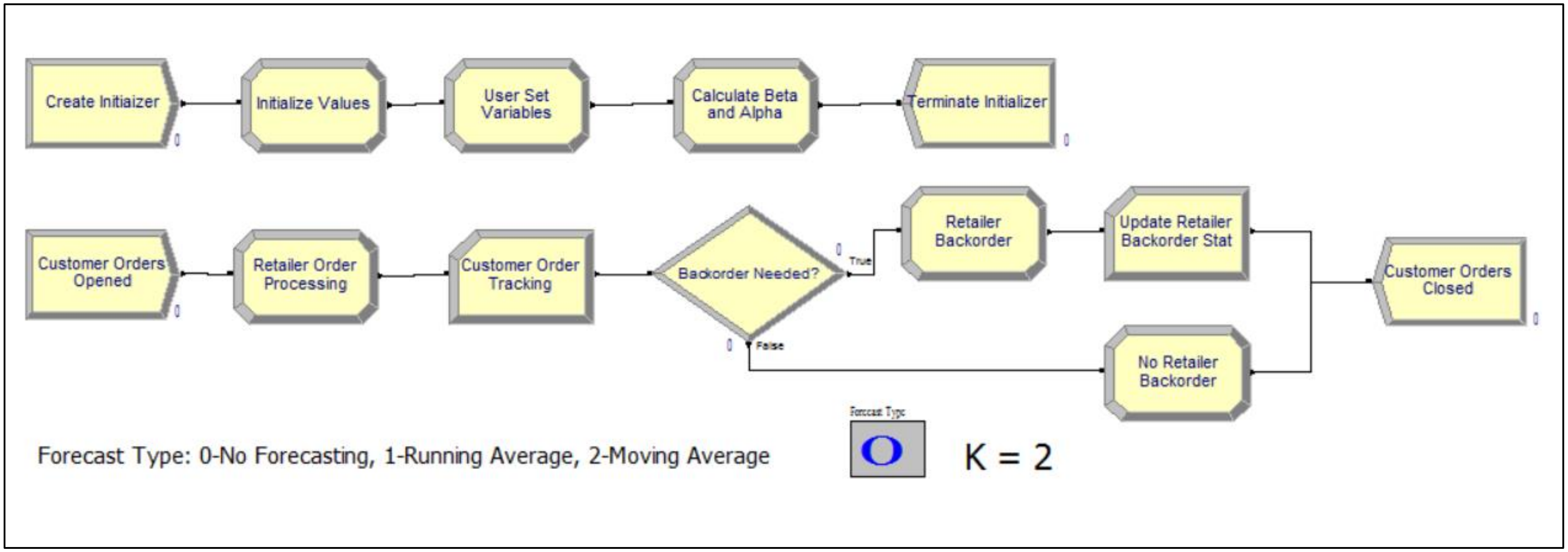


Figure 4: Zoom in on Initializer and Customer rows in Multi-Echelon Model in Arena

This screen capture shows the Initializer and Customer rows in the multi-echelon model. Neither of these rows changed in the expansion of the model from the two stage model. Several variables and two attributes were added to the Initialize Values assignment module. Everything else remained the same in these two rows.

There is a variable value view box for the value of the forecasting type variable. In the screen capture, it displays 0 because at the time of the screen capture the model was not running. When the model is running, the value is 0 when no forecasting is in use, 1 when the running average is used in the forecasting and the value is 2 when the 15 period moving average is used.

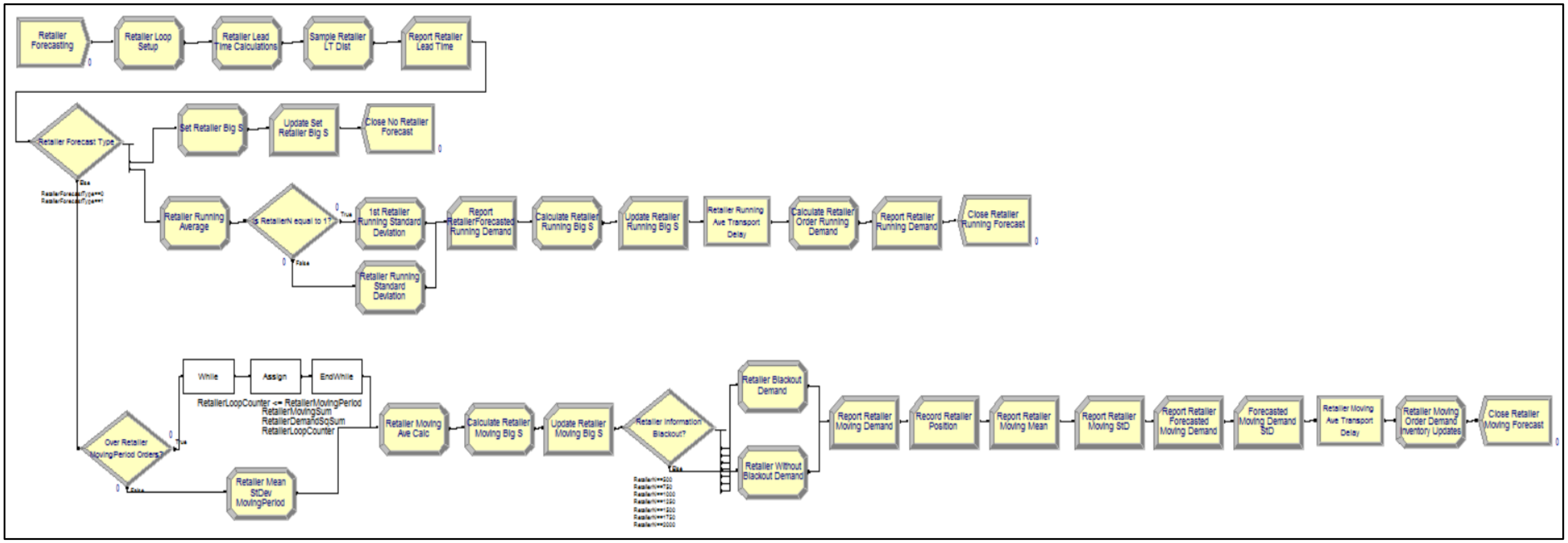


Figure 5: Zoom-in on Retailer row in Multi-Echelon Model in Arena

This zoomed-in screen capture shows the retailer row in the multi-echelon model. The first several modules set variable values. The first decision module (diamond shape) sends the model down the path the matches the decision criteria. In this case, it is the forecast type, the same variable viewable in the display box above. The path dropping straight down from the decision is the moving average forecast path which is the primary path used for this research. The decision block that starts this path splits the path based on the number of orders in the system, more than the moving period or less. This split is required for early order inventory calculations in the system.

The second decision block is where the information blackout takes place based on cascading failures research by Wu, Tang & Wu in 2016. All of the assign and record modules that come after that are updating inventory levels and recording the new values.

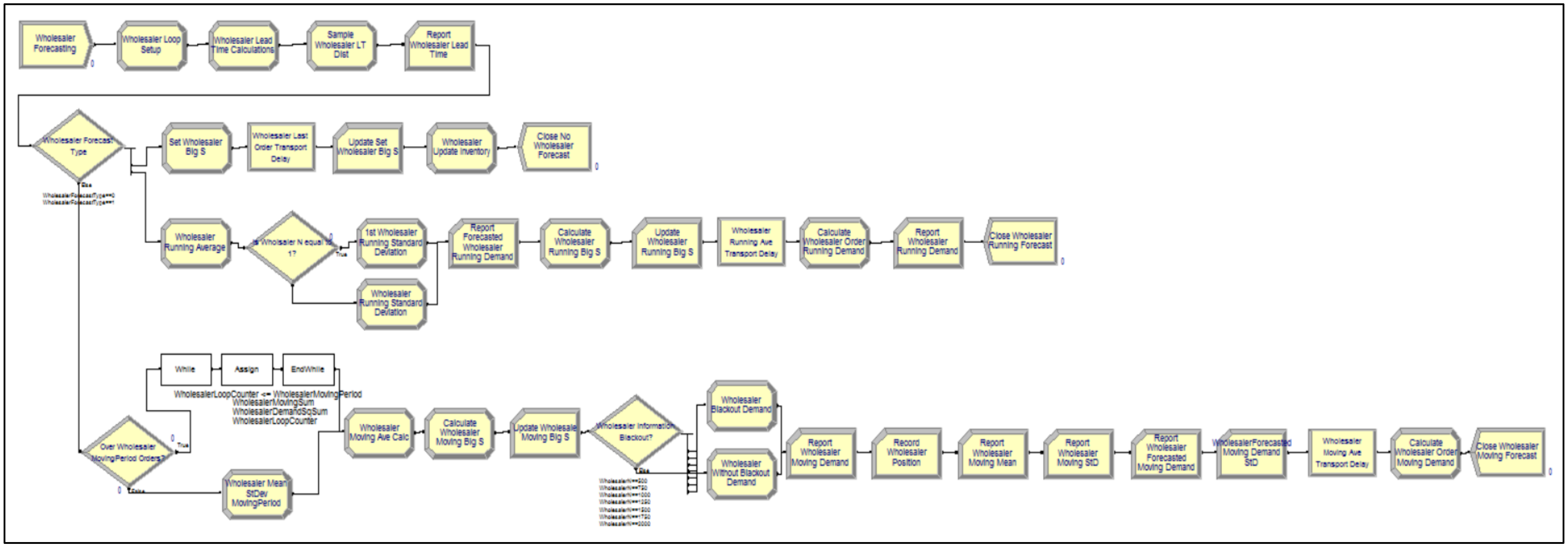


Figure 6: Zoom-in on Wholesaler row in Multi-Echelon Model in Arena

This zoomed-in screen capture shows the wholesaler row in the multi-echelon model. It operates in the same way that the retailer row does. The main difference in the two is that the input for the wholesaler row is from the retailer. It does not have knowledge of the order placed by the customer. The retailer has the possibility of having an information blackout. The wholesaler has its own possibility for having an information blackout. There is a remote possibility that both stages could experience an information blackout simultaneously.

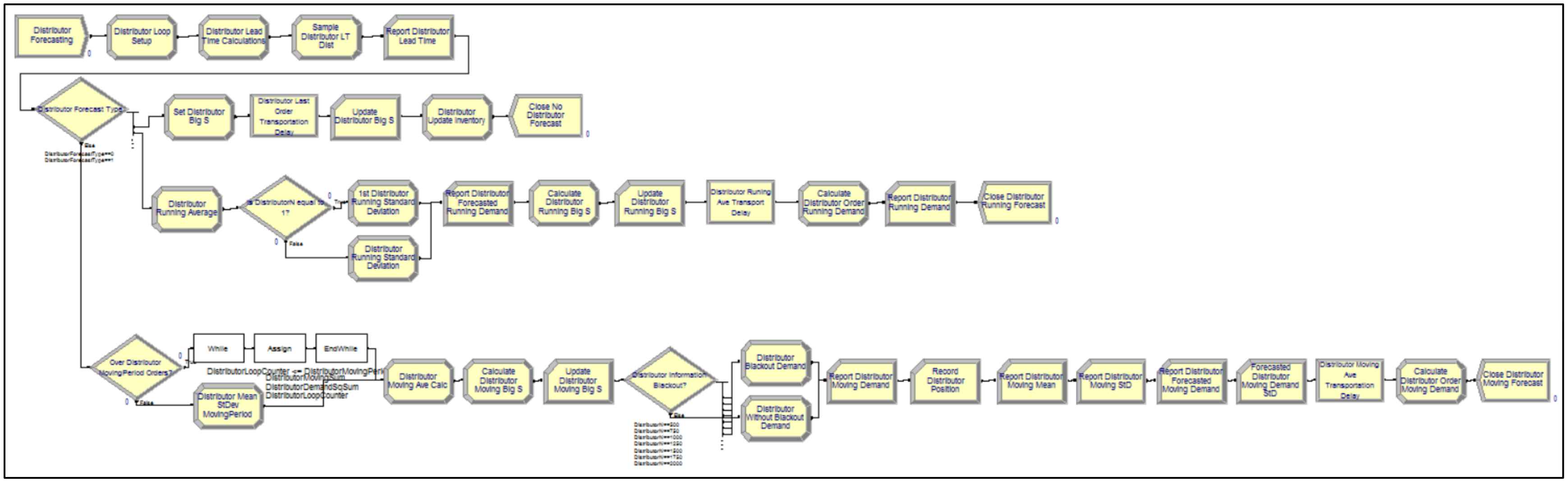


Figure 7: Zoom-in on Distributor row in Multi-Echelon Model in Arena

This zoomed-in screen capture shows the distributor row in the multi-echelon model. It also operates the same wat the retailer and wholesaler rows do. The modules are all the same. By the time the order information reaches the distributor, it has gone through two echelons. The distributor sends its order information on to the factory. The factory has the same lead time delay as the previous stages. It fills the distributor order completely and then updates its inventory levels.

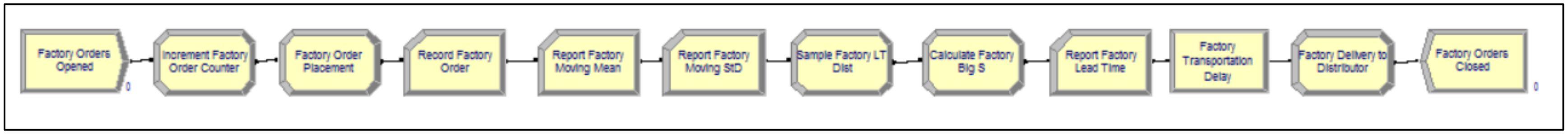


Figure 8: Zoom-in on Factory row in Multi-Echelon Model in Arena

This zoomed-in screen capture shows the factory row in the multi-echelon model. The factory receives the distributor order and fills it completely. The inventory is sent out after the lead time delay following the same gamma distribution as the previous stages. The factory then makes the needed quantity of inventory to have the order-up-to-level on-hand.

3.5 CONCLUSIONS AND DISCUSSIONS

Creating a discrete-event simulation of this size and complexity is tedious. Arena became unstable once the additional stages (wholesaler and distributor) were added. The software crashed frequently and often reported phantom errors. This made the process of running the experiments and making the necessary parameter changes required for the experiments difficult and time consuming.

The difficulties in running the experiments caused one to wonder if a traditional programming language would have been easier to use. For the initial set up of the supply chain and the verification experiments, the discrete-event simulation was much faster and easier to use than a traditional programming language would be. At the point where using a programming language would pay-off, the investment in the Arena model is too great to give up on the model.

CHAPTER 4

4. RESULTS

This section discusses the results of the experimental models tested in the simulation. There are seven experimental scenarios. The supply chain the scenarios use is the same as the baseline model with only a few parameters changed between the difference experiments.

The supply chain all the experiments share has a customer, retailer, wholesaler, distributor, and factory. Each stage places and order with the adjacent stage up the chain and receives inventory from the same node. The factory simply generates whatever quantity is needed by the distributor.

Each of the experimental models has information blackouts occur in at least one stage of the supply chain. There are also models with information blackouts in multiple echelons. The unexpected finding was that an information blackout at all levels does not cause a greater change than if the information blackout only occurred at two of the stages.

4.1. MODEL DESCRIPTIVES

Models from previous literature shaped those used in this research. As discussed in the literature review, Sterman’s Beer Game serves to create the basic structure. There is a customer, retailer, wholesaler, distributor, and factory. There is a single order each day at each echelon that represents the cumulative of all orders. This is a more sophisticated model than many in two ways. First, it allows returns at all stages and second it is a single multi-stage model, instead of using sequential pairs as many studies do.

For the experimental scenarios run in this study, a moving average of 15 periods was employed for analyzing demand. Use of a 15 period moving average is well established in the literature. The model has been designed and built with three possible forecasting techniques. These are a constant order-up-to level (no forecasting), a forecast using a moving average (used in this study), and a forecast using a running average. Expansions of this research include exploring the constant and running average techniques.

The model in this study was checked against previous studies, one with constant lead time and one with stochastic lead time. For the experimental scenarios, a stochastic lead time of 4, 1 was used. This helps make this study more closely represent actual supply chains.

4.2. VERIFICATION

Before the model was expanded to include the Wholesaler and Distributor stages, it was verified against two previous studies. The Chen et al. (2000) study theorized a customer demand based on a normal distribution with a mean of 50 and a standard deviation of 20. They also used a constant lead time of 4 units. Chatfield (2013) used a stochastic lead time with a Gamma distribution of 4, 1. Table 4 provides the standard deviations from Chen et al. (2000) and Chatfield (2013) and compares them with the study model using the appropriate specifications.

The second study used for model verification was Chatfield (2013). This study used a normal distribution for customer demand, but with a mean of 50 and a standard deviation of 10. The lead time is stochastic with a gamma distribution of 4, 1. Using these parameters the model for this study produced a variance amplification of 1.87.

Model / Effected node	Chen et al. (2000)	Rasnick Model with Chen at al. (2000) specifications	Chatfield (2013)	Rasnick Model with Chatfield (2013) specifications
Customer	19.99	20.0102	20.06	20.0079
Retailer	27.55	27.4595	30.57	29.0017
Wholesaler	40.01	40.1662	51.77	51.2399
Distributor	60.27	61.666	92.27	96.183
Factory	93.13	91.3049	163.10	160.69

Table 4: Standard deviations of the baseline model compared to Chen et al. (2000) and Chatfield (2013).

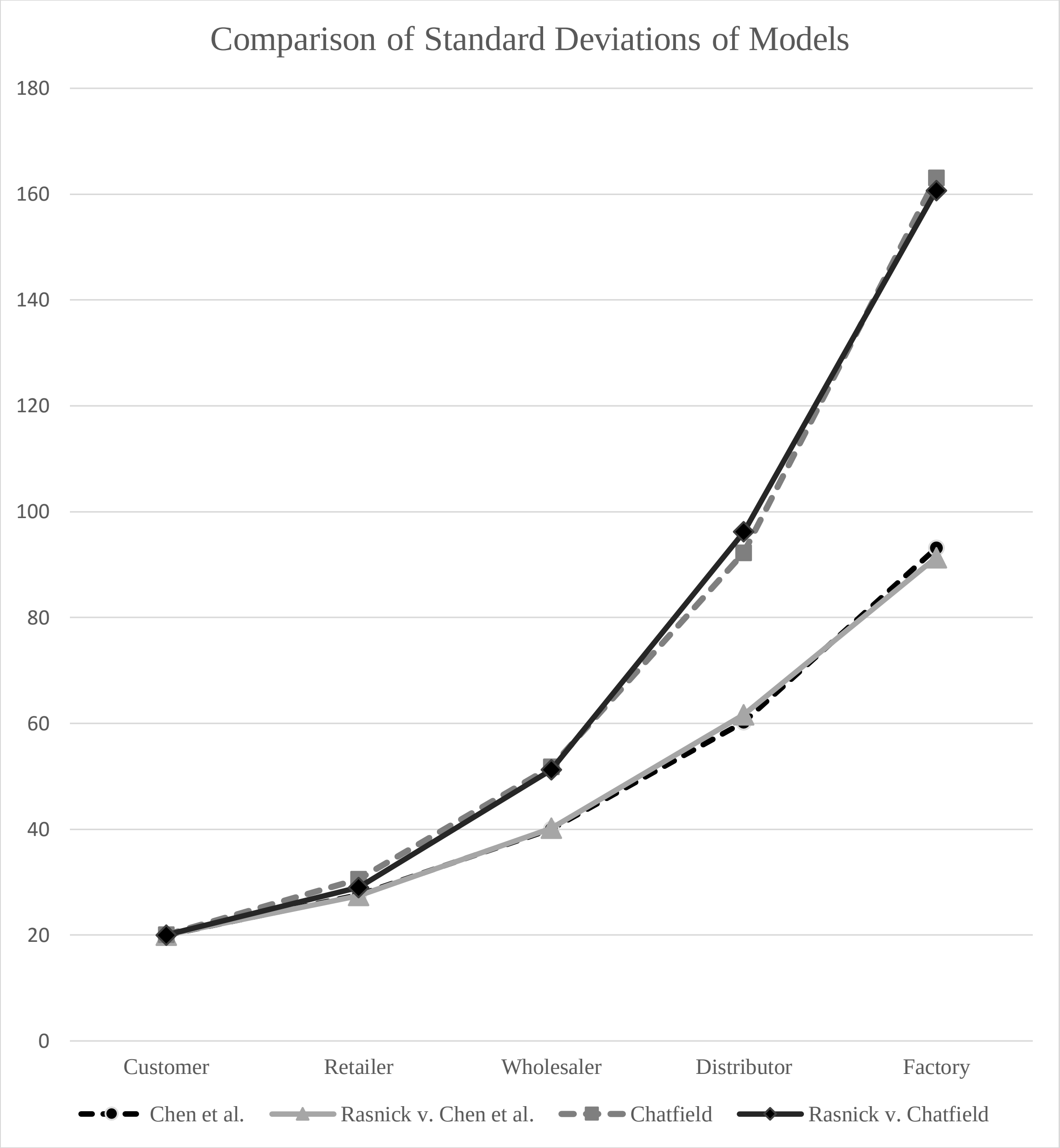


Figure 9: Standard deviations of the Rasnick models compared to Chen et al. (2000) and Chatfield (2013).

Due to differences in modeling software, rounding, and modeling techniques, it is unrealistic to expect exact matching of all standard deviations. With that said, it necessary for the standard deviations to be relatively close to ensure the models are functioning the same way.

Model / Effected node	Chen et al. (2000) Lead Time: Constant (4)	Rasnick Model with Chen at al. (2000) specifications	Chatfield (2013) Lead Time: Gamma (4, 1)	Rasnick Model with Chatfield & Pritchard (2013) specifications
Retailer TVA	1.89	1.8871	2.32	2.2725
Wholesaler TVA	4.01	4.046	6.66	6.4889
Distributor TVA	9.09	9.53	21.15	19.8502
Factory TVA	21.70	20.9355	66.10	64.7364

Table 5: TVAs of baseline model compared to Chen et al. (2000) and Chatfield (2013).

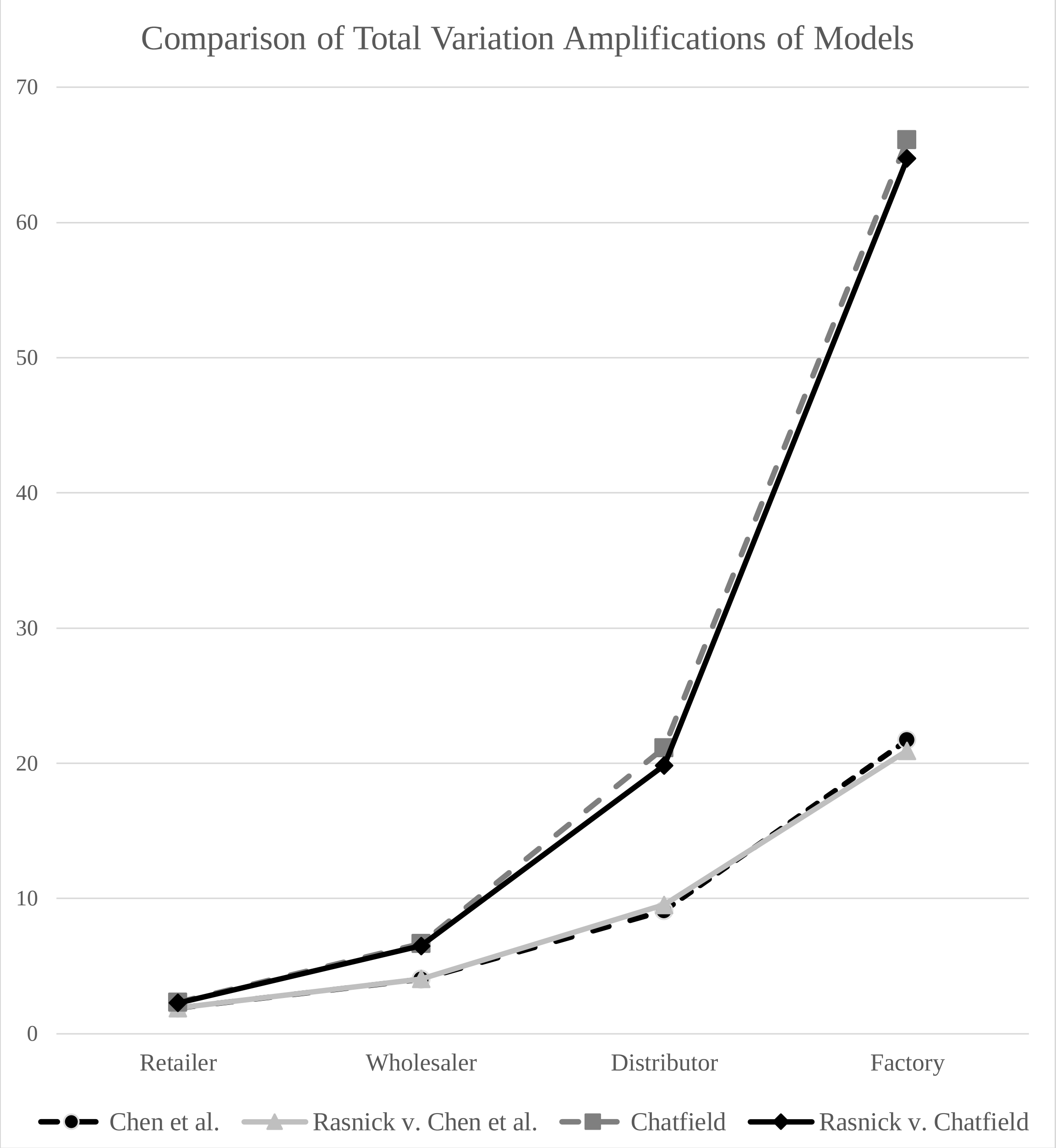


Figure 10: TVAs of baseline model compared to Chen et al. (2000) and Chatfield (2013).

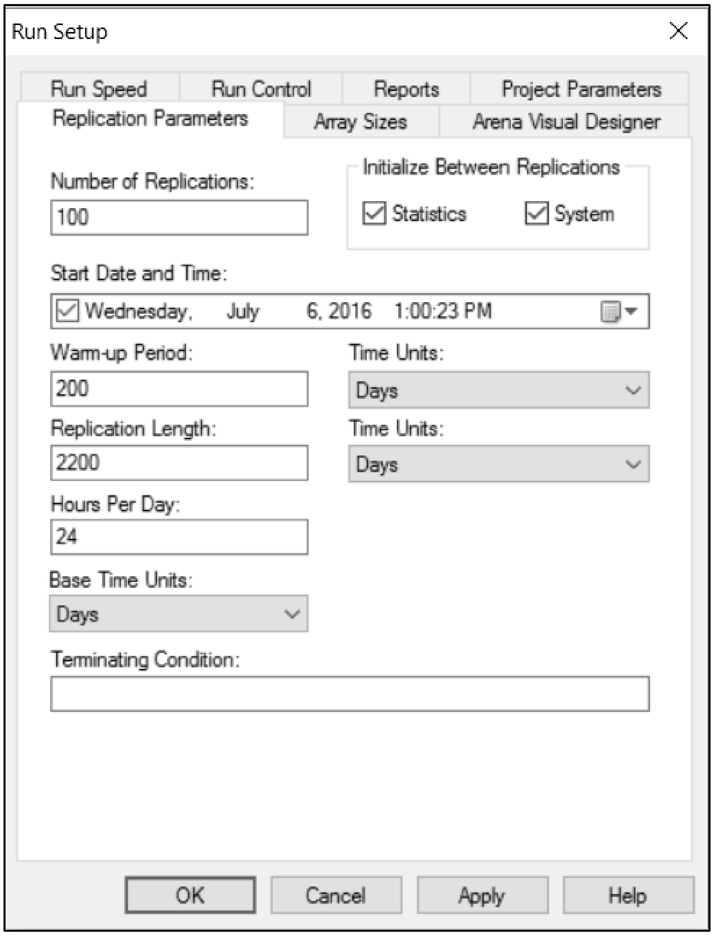
Another check of the experimental model's reliability is possible by comparing the total variance amplifications to those of previous studies. As with the standard deviations, due to differences in software rounding and model structure, an exact match is unrealistic.

4.3. EXPERIMENTAL DESIGN

This study has a baseline model from which are of the experimental models were derived. The baseline model has no information blackouts. All of the experimental models have at least one stocking point experiencing information blackouts. One model has the retailer, wholesaler, and distributor each experiencing information blackouts.

There is a separate model to test each of the information blackout scenarios. These scenarios have information blackouts occurring at the retailer, the retailer and wholesaler, the retailer and distributor, the wholesaler, the wholesaler and the distributor and the distributor. The reason to run each of these scenarios is that there are times when events occur that take out part or all of a supply chain. Looking at all of these scenarios provides a more robust investigation. The information blackouts were set to occur at creation the 500th, 750th, 1000th, 1250th, 1500th, 1750, and 2000th order. The first information blackout did not occur until the 500th order to make sure the system had enough time to warm-up and for inventory levels to stabilize after initialization. They end at the 2000th order because the replication length is 2200. The information blackouts only last one period. The frequency is just over one a year for six year length of the run.

The time units for the replications are days. Each model is set-up to have a warm-up period of 200 days. This allows the system to level out after initialization. This means there are really only 2000 days of data used in creating the results. One hundred replications of each model are run. **Figure 11** shows what the Run Setup screen looks like in Arena.



Number of Replications: 100

Initialize Between Replications: ☑ Statistics ☑ System

Start Date and Time: ☑ Wednesday, July 6, 2016 1:00:23 PM

Warm-up Period: 200

Time Units: Days

Replication Length: 2200

Time Units: Days

Hours Per Day: 24

Base Time Units: Days

Terminating Condition:

Figure 11: Arena Run Setup

The output of importance for this study is the total variance amplification for each stage, in each of the different models. This is calculated using the standard deviations of the orders.

$$TVAmp_k = s^2_{D,k}/s^2_{D,0}.$$

The total variance amplification for node K is the quotient of the order variance for that node and the order variance for the customer node (node 0). The bullwhip effect is present when the amplification increases with each node along the supply chain.

4.4. SCENARIO RESULTS COMPARISON

This section gives the results for experimental scenarios. The results are given for an information blackout at the Retailer, Wholesaler, and Distributor stages. Then combinations of these stages are given information blackouts. The impact of the information blackouts is expressed in the total variance amplifications (TVA) which serves as the measure for the bullwhip effect.

	T-Statistic	**Significance Result**
Retailer Blackout	0.0001976165	No significant difference
Wholesaler Blackout	0.0000055335	No significant difference
Distributor Blackout	0.0978808005	No significant difference
Retailer & Wholesaler Blackout		
Retailer	0.0001976165	No significant difference
Wholesaler	0.0000001429	No significant difference
Retailer & Distributor Blackout		
Retailer	0.0001976165	No significant difference
Distributor	0.0000000022	No significant difference
Wholesaler & Distributor Blackout		
Wholesaler	0.0000055335	No significant difference
Distributor	0.0377120535	No significant difference
Complete Blackout	0.0000000718534	No significant difference
Retailer	0.0001976165	No significant difference
Wholesaler	0.0000001429	No significant difference
Distributor	0.0000000002	No significant difference

Table 6: Test for significant difference between baseline and experimental models.

The results of the experimental models were examined using a T-test to determine if the differences in the results of the models is statically significant. The models with information blackouts at the Retailer, Wholesaler, and Distributor stages were tested against the baseline model with no blackouts. The model with blackouts occurring at all stages was also tested.

The lack of significant difference may be due to the length of the information blackouts. In these experimental models, the information blackouts only lasted one day. While many information blackout causing events do last only a day, many last for many days. It is possible that testing with information blackouts of longer periods would prove to have a significant difference from the baseline model. This is another area of future research.

This failure to provide empirical evidence may be unimportant. There are differences in the results of the baseline model and the models experiencing blackouts. From a supply chain manager’s perspective, the empirical evidence could be unnecessary. It is enough to recognize there is an amplified bullwhip effect as a result of an information blackout. Having that knowledge alone may suffice for managers to be able to plan how they want to address information blackouts in the future.

	Retailer TVA	Wholesaler TVA	Distributor TVA	Factory TVA
Baseline, No Blackouts	2.272	6.488	19.850	64.736
Retailer Blackout	2.432	6.487	19.860	64.973
Wholesaler Blackout	2.272	7.155	19.844	65.776
Distributor Blackout	2.272	6.487	20.050	65.736
Retailer & Wholesaler Blackout	2.432	7.153	19.871	65.770
Retailer & Distributor Blackout	2.432	6.487	20.053	65.697
Wholesaler & Distributor Blackout	2.272	7.155	20.040	65.776
Complete Blackout	2.432	7.153	20.063	65.770

Table 7: Comparison of total variance amplifications at the specified stages under information blackouts at the given stage.

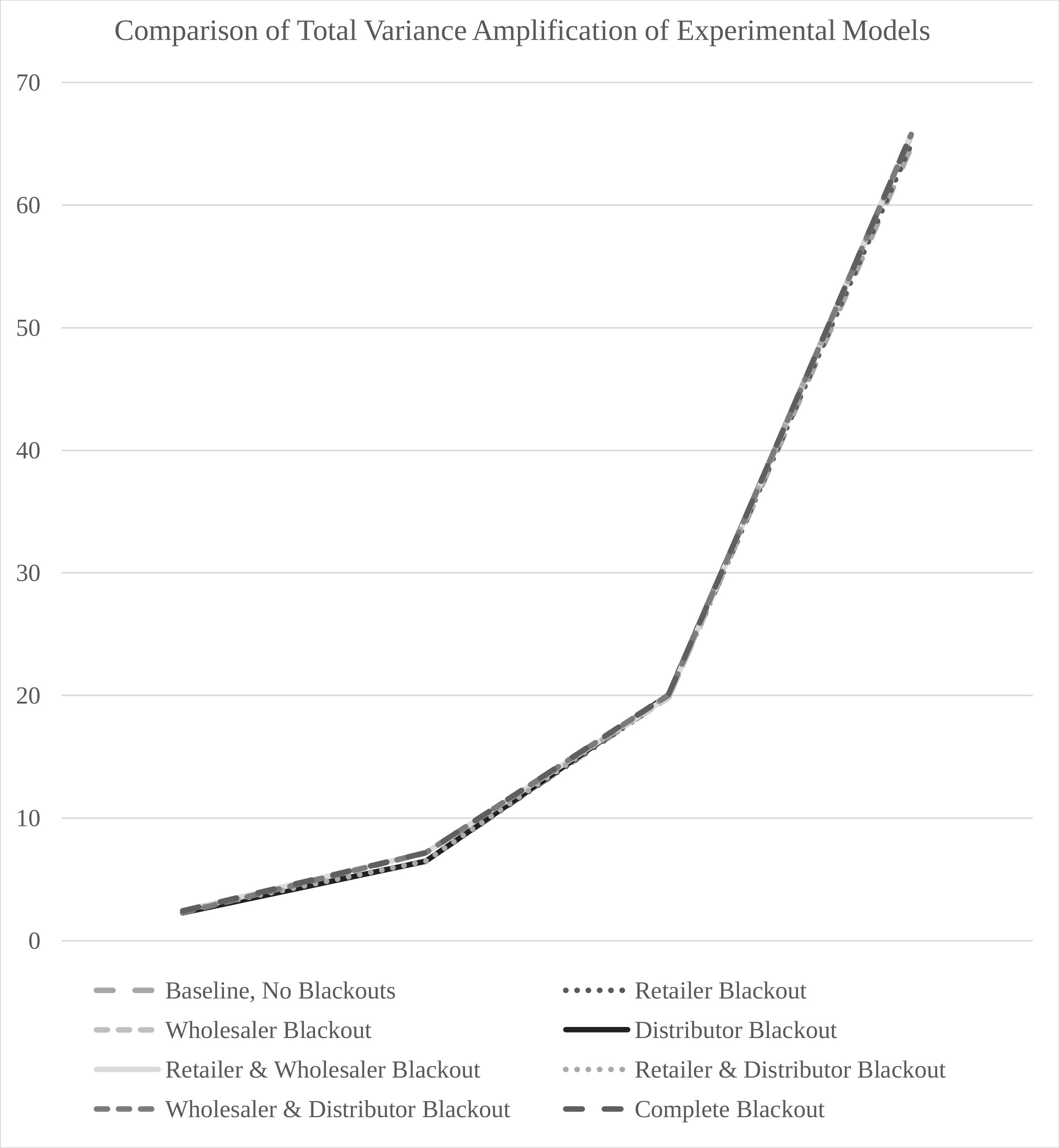


Figure 12: Comparison of total variance amplifications at the specified stages under information blackouts at the given stage.

Any time there is an information blackout at the Retailer, there is a change in the Retailer's performance. The rest of the supply chain responds slightly. As expected, there is no change noted in the Retailer when information blackouts happen further along in the supply chain.

When the Wholesaler experiences an information blackout, there is an impact on the Distributor and Factory. The overall decrease in performance is greater when another node is also experiencing an information blackout.

With information blackouts at the Distributor, the Factory also suffers a decrease in performance. Surprisingly, the bullwhip effect was not greater when all three stages experienced information blackouts.

4.5. CONCLUSION AND DISCUSSION

This discrete-event model built in Arena provides a closer look into the reaction of a supply chain to an information blackout. While it is theoretically better to have a multi-echelon model to simulate the operations of a supply chain, it may be better to reduce the level of detail or use another modeling tool. Arena became slightly unstable after all the stages and their functionality were added. Frequent saving and making complex changes to the models in stages alleviated this problem.

This was a first attempt to simulate an information blackout in a supply chain. More studies of this event are required to better understand the real impact of information blackouts on supply chains. The model in this study used a moving period of 15 to calculate the order average to use during an information blackout. Future studies will want to try moving periods of different lengths.

This study also used information blackouts of the same length. It may will be the case that information blackout of a day are not long enough to cause a significant difference between the baseline and experimental models. Further research may determine a minimum length of an information blackout to truly impact a supply chain. Such knowledge would be valuable to managers in information blackout situations. Those blackouts of a length too short to markedly effect the supply chain performance could be ignored.

CHAPTER 5

5. FINDINGS AND CONTRIBUTIONS

This research has produce two major findings for supply chain research and three significant contributions to supply chain management. This dissertation has introduced and defined the concept of information blackouts. Preliminary research was conducted to empirically prove that information blackouts do effect the performance of supply chains. The evidence of this effect is weak at this point. Future research will likely prove this effect more strongly.

5.1. SUMMARY OF MAJOR FINDINGS

There are two major findings of this dissertation. The first is the concept of information blackout. Information blackouts cause exaggerated variations in the ordering patterns of supply chains during and immediately following the catastrophes that cause them. This disruption of the flow of information between nodes in a supply chain as the result of an abruptly and temporary disaster. This concept is new to the supply chain disruption literature. There is a strong emphasis in supply chain research on disruptions. Identifying a new disruption supports these research efforts.

The second major finding is that there is empirical evidence, weak though it is, that information blackouts reduce the performance of supply chains. Extending this research to information blackouts of greater length will likely provide strong empirical evidence of the impact of information blackouts on supply chain performance. Supply chain managers are likely to find the strength of the evidence unimportant in the face of any evidence that supply chains do react to information blackouts.

5.2. IMPLICATIONS FOR STUDIES ON SUPPLY CHAINS

The primary implication of this research to the supply chain management literature is the introduction of the concept of information blackout. An information blackout is a sudden and unexpected, short-duration interruption in the information flow between nodes of a supply chain, usually due to a disaster. The information flow may be disrupted to or from one or more node of the supply chain. Adding this event to the supply chain disruption literature will assist in a more comprehensive understanding of the supply chain operations.

This study also adds a multi-echelon discrete-event supply chain model to the literature. Many discrete-event studies of supply chains have been conducted, however, most are limited to customer, retailer, and factory levels. The model created for this dissertation has a stocking-point that is adjunct to two other stocking-points. This provides more realistic results, as they more closely represent common retail supply chains. This Arena model can now be used in future studies that can expand on the foundation that was created here.

In adding this multi-echelon model to the literature, a non-trivial volume of simulation model development took place. The development process was iterative and began by mimicking previous models. These previous models were simplistic compared to the final experimental models in this research. As each iteration was completed, it was verified against the model on which it was based. A cycle of every increasing complexity continued until the point was reached that there were no more models on which to base the need complexity. From that point on the model development was exploratory. At one point the modeling limits of the Student version of Arena were reached. Arena was contacted and after some begging, a Research version of the software was secured to complete this dissertation.

A final contribution of this research is a first attempt at empirically proving the impact of information blackouts on supply chains. The limitation of information blackouts to only one day have produced weak evidence indicating a greater bullwhip effect as a result of information blackouts. While the increase in the variance amplifications was not statistically significant, it is present. From a practical perspective for a supply chain manager, this is sufficient to be meaningful.

CHAPTER 6

6. CONCLUSIONS AND RECOMMENDATIONS

This research began with the intention of defining the term information blackout, modeling the occurrence of an information blackout in a discrete-event simulation, and providing empirical evidence of an information blackout. Information blackouts cause exaggerated variations in the ordering patterns of supply chains during and immediately following the catastrophes that cause them. This dissertation has introduced and defined the concept of information blackouts. Preliminary research was conducted to empirically prove that information blackouts do effect the performance of supply chains. The evidence of this effect is weak at this point. Future research will likely prove this effect more strongly.

6.1. FUTURE STUDIES AND RECOMMENDATIONS

This study serves as a first endeavor at investigating information blackouts in supply chains. A considerable first step has been made in understanding how catastrophes impact supply chain operations. As this is a fledgling study, the possible extensions for it are numerous. The first is to examine variable length information blackout periods. It may will be the case that the support for the impact of information blackouts will be stronger for longer information blackout periods. To build on that, a study of variable length information blackout periods would also add to the robustness of these results.

To further tease out these initial study results, a study using different lengths of information blackouts may be useful for some supply chain managers. Some supply chains managers may decide to simply wait out short information blackouts if the expected effect will not be costly. Finding the length of an information blackout that produces an impact worth mitigating would be helpful. This would allow supply chain managers to plan in advance which events to spend resources preparing to address and which events can be waited out. In in supply chains, an ounce of prevention is worth a pound of cure.

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APPENDICES

Appendix 1: Customer Demand, generated by Arena
First 320 of 220099 Data Points

42.79432	11.91511	48.84976	46.0516	22.14427	55.28033	65.03057	41.62062
18.6325	59.95452	83.41496	69.53123	48.18898	31.0422	38.55682	37.10811
26.23914	55.48154	102.8142	19.11328	66.82385	40.92736	71.73254	51.6249
71.01596	40.29809	61.48936	49.01704	35.98409	69.38288	62.85979	33.74113
68.33392	44.24555	58.47219	50.29104	95.07027	47.11857	107.3816	40.14414
51.84002	5.573851	56.69225	45.80195	0.136514	24.52894	73.96109	39.11801
88.89052	52.34629	47.27419	64.71549	58.34001	59.1847	62.28043	85.43495
63.1259	35.43081	54.67036	46.90032	33.62616	38.41853	60.80057	18.69146
35.12503	67.65151	88.02699	71.74992	57.74454	20.82673	36.32028	55.82137
30.32396	43.45203	41.32838	41.0518	52.14359	58.8056	28.11677	85.57338
66.54999	4.30444	30.58973	13.86771	37.62411	2.482546	22.55384	37.3702
40.66606	47.67561	79.42833	18.26298	54.34627	25.54096	65.62568	44.86711
75.74616	65.09486	79.77454	26.25601	45.19477	81.84524	37.23567	35.09944
54.91451	26.81056	54.9416	40.93652	28.82429	58.93964	32.272	49.27926
56.97688	43.76113	45.83403	62.36709	58.14527	37.05203	36.06631	17.35364
6.215327	23.75121	54.3803	29.38537	90.27964	43.7396	30.93983	52.70971
54.96828	63.75059	80.94782	69.16089	41.22108	37.33162	39.30856	65.74954
-3.9638	75.06234	19.72144	17.26763	43.52045	67.04322	56.36985	74.3607
53.12279	61.08761	15.46593	44.34883	0.38386	62.45662	47.7929	63.1481
35.41996	33.46658	60.93905	71.75935	29.16033	55.16598	45.54509	39.20732
34.27277	16.62117	36.99019	20.24372	38.87013	55.2456	50.50808	99.59694
61.94943	37.19549	52.71338	54.93759	60.51734	81.25486	28.01427	54.02283
58.36944	65.39478	45.67308	90.29852	62.25086	54.27589	40.2942	25.55825
31.19706	27.65247	92.38593	74.28339	28.58473	76.34842	65.30197	51.69601
63.51721	54.35886	62.84863	56.12854	70.22042	48.52729	50.29229	68.21137
47.26594	51.09166	46.71684	82.5628	77.00857	60.03243	20.03774	65.44291
46.02915	35.0468	24.75708	79.79125	54.33346	74.0493	67.74195	58.55447
57.10453	86.89008	35.57093	45.54283	75.98306	35.2145	28.05183	54.55858
69.31926	32.01214	64.34063	43.59573	-0.5589	81.17001	42.64582	65.13179
34.18376	65.30522	85.46664	70.11369	25.31486	60.13072	46.15692	37.97725
78.63856	41.34818	62.04492	58.36153	47.64696	67.58067	26.79452	29.45707
61.78842	67.1469	51.87981	32.22318	34.64662	52.52187	64.2847	45.22906
56.28368	52.61729	58.23926	47.11377	39.1581	54.51493	52.30427	59.98341
63.60475	73.51015	72.13645	54.10862	41.9107	52.52676	61.28321	75.84812
42.84109	69.87889	13.86342	31.346	62.79869	55.47777	45.71688	78.79248
31.82342	90.97385	71.81748	21.94766	29.34753	41.12235	80.08457	3.453784
50.09375	2.501541	86.93444	73.08865	26.68401	49.96109	1.467687	44.20092
68.12023	23.31566	65.43215	50.37532	50.71853	26.9032	56.23473	19.67238
49.09616	72.08287	54.88774	33.44703	52.78476	54.68532	41.20946	44.91921
23.72022	45.28038	35.19598	34.48542	56.16501	35.98081	28.73333	34.37577

Appendix 2: Retailer Demand, calculated using variables
First 320 of 220098 Data Points

-198.5330	-173.0968	-174.1223	-172.2253	-169.9880	-171.0598	-171.2369	-169.9844
-170.3452	-169.7439	-169.2941	-169.0716	-168.5329	-168.8193	149.2531	149.5498
155.7255	151.5759	142.0564	129.2830	136.2974	122.6992	118.2299	127.5171
138.4738	132.2883	133.8018	120.7244	130.6594	124.3277	150.0016	151.2227
158.2381	160.6776	160.4272	157.8996	151.5884	154.9324	160.2682	150.4413
152.5015	150.1394	143.0167	141.8454	149.0659	127.1230	127.9418	119.7423
104.2830	111.8178	108.6262	99.3624	108.2433	112.4522	117.2782	112.4362
114.3830	125.8288	120.8967	123.8973	133.6005	146.2284	152.6390	172.5415
167.9066	178.1150	192.4749	173.5483	184.3657	189.8670	197.2592	200.0786
194.6521	191.4105	190.8032	187.5794	172.6956	165.8949	154.9883	151.5069
150.7074	135.2483	150.0147	127.7437	132.7994	133.0104	127.7802	127.3005
118.9242	114.3857	108.1602	111.9081	110.9014	113.2286	108.1271	98.3814
97.1703	83.1891	105.4786	92.7335	71.8720	81.2772	82.1306	86.4538
85.9510	85.0810	83.8664	87.3657	92.2195	99.1581	95.5648	102.1063
108.9437	90.1578	90.0300	91.5138	93.6026	104.5693	113.2838	109.4324
110.4394	106.6282	118.7811	102.4363	106.7220	116.4962	112.4123	126.0832
126.9919	136.5483	139.9359	141.1775	130.2206	136.4178	149.7330	176.2652
173.4660	161.1735	175.9495	173.2201	178.6891	179.8579	171.0385	179.9879
204.9437	215.7636	213.5552	216.1278	203.7088	191.0493	166.1044	179.2778
181.4583	167.9977	165.7039	155.6617	155.4937	148.2323	142.7675	103.9871
91.3511	77.3266	68.1959	82.0727	89.1632	88.5873	89.6872	87.4222
90.8436	94.0596	93.7296	105.0044	103.2685	109.3670	110.1526	126.3729
124.1588	129.8699	120.7852	113.6603	116.3477	105.5841	118.0494	116.6224
136.6215	134.9981	134.7775	124.1664	121.6656	124.5625	109.5618	112.7269
111.5896	111.3649	126.9802	132.1517	135.6761	132.9670	128.0695	101.7731
-115.6318	74.5394	98.9906	142.3287	177.3093	179.5181	173.9754	164.8429
188.7799	179.9341	172.6917	179.8616	184.8456	193.7192	200.6374	198.2343
197.7885	163.6533	150.5251	148.8577	141.3517	143.4729	142.0891	142.5972
148.0452	152.8669	133.6742	119.5669	124.0793	140.8345	145.4906	130.6839
138.7078	151.4351	143.2924	153.6083	170.2354	176.4008	159.1710	152.7377
152.2674	153.3604	158.5405	150.0337	130.1096	121.0210	137.8253	127.2937
119.7077	145.4396	133.7380	112.8799	101.4547	99.5659	98.7809	103.6473
113.8428	124.2208	134.9241	133.8673	161.2696	147.2870	147.5134	145.3546
135.5416	146.1707	150.8993	156.1580	163.2474	166.4499	161.1577	153.2825
147.6538	153.5424	167.9176	136.9655	135.9443	134.7774	132.2088	119.1352
108.0539	97.4072	87.8153	75.4677	76.2716	94.6647	91.1527	84.0818
61.1013	59.1831	64.9342	57.2635	70.6995	64.8897	66.6919	63.8946
64.2978	87.2194	86.8941	83.4229	69.5110	86.1237	78.9901	87.7827
75.0308	78.5028	93.7166	89.2237	107.3040	107.8052	105.9118	104.1031
82.2279	85.8188	98.5244	93.4558	92.8821	93.0799	91.1409	101.7712

Appendix 3: Wholesaler Demand, calculated using variables

First 320 of 219898 Data Points

-222.533	-222.533	-222.533	-222.533	-222.533	-222.533	-222.533	-222.533
-222.533	-222.533	-222.533	-222.533	175.308	180.862	196.683	176.303
146.998	156.207	209.181	221.222	311.750	332.892	370.438	377.622
394.980	428.624	430.108	410.386	422.374	419.620	383.777	351.242
359.379	353.797	348.877	344.846	357.294	342.301	350.473	353.841
339.425	336.868	346.634	330.926	329.365	330.841	322.480	308.021
300.566	305.905	295.530	298.863	297.706	288.600	280.663	279.768
290.091	283.107	283.435	275.173	282.659	305.262	304.053	298.459
321.821	300.415	311.547	326.214	331.045	355.495	363.703	376.429
388.256	396.179	410.658	397.107	389.885	392.377	391.509	376.962
378.204	367.967	368.152	367.244	360.403	352.577	348.702	330.675
314.984	293.700	292.695	279.190	276.109	265.167	252.857	227.550
220.444	242.121	205.855	191.874	204.171	196.781	198.720	189.018
179.867	178.682	178.945	176.134	180.049	182.274	183.345	185.356
172.762	173.016	181.972	182.556	204.258	199.941	199.671	195.741
196.978	197.451	202.017	215.168	219.692	215.103	232.430	239.753
239.888	244.684	250.985	246.620	273.290	276.536	304.855	294.317
313.789	317.544	323.893	330.495	334.656	337.740	343.454	373.994
390.428	398.049	406.891	396.117	371.113	370.527	399.488	400.726
397.137	395.406	387.314	388.976	374.712	338.915	330.961	336.888
321.708	304.876	321.461	308.384	303.441	284.100	282.596	266.202
260.487	256.125	239.384	227.648	215.789	215.475	230.352	219.757
225.582	214.482	210.271	213.933	222.129	220.546	240.002	242.397
246.836	234.056	237.662	242.724	230.548	239.857	242.964	244.601
259.143	257.153	267.855	264.068	264.768	230.747	-43.432	158.972
285.907	270.191	260.634	268.348	255.416	256.785	248.849	263.192
266.080	270.615	273.741	279.219	292.240	304.602	300.493	294.674
297.714	319.153	297.670	311.761	312.490	316.554	318.879	319.297
306.698	305.214	287.227	278.922	290.774	291.710	278.348	278.334
283.265	293.627	283.564	297.184	292.597	288.870	289.589	292.341
298.768	296.380	293.656	277.557	283.911	290.128	276.339	295.541
291.108	278.098	254.834	250.518	241.607	245.244	251.601	252.566
253.769	254.834	246.965	264.457	261.385	258.393	248.183	257.506
260.794	266.943	280.706	279.468	277.618	283.831	274.218	282.289
303.018	302.887	272.833	270.709	271.656	270.727	266.628	254.762
244.655	221.873	221.979	225.443	234.925	221.292	218.994	185.935
192.007	184.471	191.189	181.320	175.059	160.267	152.985	166.264
156.485	160.138	134.596	130.083	148.044	150.236	147.288	136.122
152.367	143.195	161.809	164.729	168.667	166.703	170.201	146.206
155.412	168.115	172.905	171.359	167.389	171.321	175.064	172.721

Appendix 4: Distributor Demand, calculated using variables
First 320 of 219698 Data Points

-204.533	-182.913	-183.272	-162.795	-167.793	-170.611	-171.828	-173.366
-174.549	-175.164	-175.937	-176.440	-694.254	-746.149	-892.677	-883.077
-797.974	-761.065	-729.643	-670.475	-567.924	-516.573	-479.964	-408.909
-305.496	-266.905	-172.065	-58.269	12.294	63.279	123.470	116.121
109.541	52.467	102.914	58.491	105.778	109.892	69.180	27.207
74.046	83.802	94.951	149.870	154.711	100.062	111.274	101.524
148.283	104.172	130.905	119.704	112.048	148.203	147.112	93.089
83.625	71.566	27.152	62.028	67.020	67.736	73.257	34.597
78.467	45.726	9.847	41.906	57.032	115.970	179.414	200.325
227.411	222.763	249.181	244.168	251.866	206.748	254.059	254.489
254.198	293.219	281.909	235.136	216.257	149.552	127.311	103.900
109.810	88.309	126.078	76.735	88.318	37.499	26.990	41.219
22.820	-22.910	2.741	-9.602	33.737	-19.045	-29.657	-33.704
-42.490	-78.827	-49.409	-43.893	-37.505	-43.477	-4.738	-4.619
33.993	34.027	40.329	39.526	40.805	44.298	44.356	54.341
56.272	66.324	101.263	100.709	108.871	76.222	76.553	79.421
87.325	97.925	114.963	152.526	122.683	165.855	172.026	217.102
234.303	194.244	249.637	204.958	257.368	275.071	294.103	301.308
327.925	278.569	307.366	300.757	319.264	268.758	280.575	278.311
338.145	339.450	407.493	395.951	337.067	276.290	281.682	212.856
243.715	235.021	269.243	222.189	234.279	208.781	183.669	122.290
79.541	50.081	1.820	5.705	41.390	30.358	26.994	44.373
42.312	44.128	59.567	39.351	13.233	26.607	69.062	45.728
53.538	100.145	101.432	115.156	127.482	168.736	165.748	161.091
165.975	162.593	201.761	239.184	-208.522	192.943	168.618	311.414
300.549	254.526	213.201	191.901	166.833	118.575	150.069	100.718
77.902	93.944	121.513	126.700	82.173	36.295	55.354	83.826
115.316	158.237	206.042	210.798	257.406	201.942	258.916	294.065
284.693	228.937	215.593	219.590	217.527	197.456	183.073	227.098
207.000	152.180	158.223	160.256	155.217	163.084	178.018	138.586
192.027	191.850	192.786	243.333	237.297	200.167	155.910	148.331
195.109	148.700	134.566	188.669	168.117	110.384	141.935	125.285
103.005	140.803	136.453	142.148	143.487	143.711	161.980	163.900
213.219	167.282	165.421	177.544	234.807	194.621	214.094	189.417
143.604	148.640	157.781	158.183	213.703	204.843	203.061	198.353
195.860	182.690	167.153	148.920	178.076	150.142	151.587	188.012
161.439	128.906	132.696	99.091	57.828	35.856	18.736	22.434
8.894	0.781	3.579	3.840	-19.132	8.759	4.225	-19.872
-35.549	-11.979	-0.296	4.583	10.656	-10.661	22.686	36.638
48.869	19.268	-8.066	25.277	26.601	3.395	33.001	58.653

Appendix 5: Factory Demand, calculated using variables
First 320 of 219498 Data Points

0.000	-246.000	-240.210	-238.356	-239.440	-238.559	-238.867	-239.260
-239.095	-239.319	-239.261	-239.427	-239.505	-823.243	-889.058	-847.077
-787.461	-669.420	-663.565	-596.193	-488.576	-380.738	-276.182	-213.949
-121.338	3.180	59.997	120.131	299.072	462.148	411.153	476.182
423.867	547.913	642.249	617.037	580.926	569.703	659.410	664.394
703.534	794.240	892.677	865.663	745.670	828.913	714.591	809.666
795.720	693.230	782.509	863.360	849.354	837.168	746.918	740.205
718.085	699.538	599.221	675.197	663.036	742.321	729.695	642.444
648.724	644.760	637.974	555.155	558.233	647.806	661.045	672.972
600.186	697.562	719.380	644.068	566.722	595.313	700.747	702.868
725.181	744.960	840.814	754.057	662.578	665.044	670.987	769.141
761.169	748.712	828.876	903.577	873.381	841.549	910.138	813.637
782.413	682.785	747.951	805.587	714.778	671.010	577.089	544.111
446.651	361.319	331.177	300.199	224.657	203.347	251.748	182.300
231.490	216.166	159.708	207.262	156.107	202.527	198.620	249.342
303.466	254.979	205.462	259.387	264.602	269.197	332.065	338.661
289.568	355.506	308.040	377.435	397.694	416.267	439.765	383.710
468.865	553.580	497.976	523.689	557.597	584.792	525.824	616.319
642.308	643.304	577.519	615.659	657.559	582.056	680.578	705.438
725.894	825.263	854.399	872.266	884.993	991.394	1003.196	1007.913
1097.121	1096.763	1082.068	974.250	1060.998	1043.116	1019.622	911.385
890.224	860.764	821.831	781.371	743.606	638.846	595.501	562.179
562.036	473.048	528.505	439.815	414.142	392.220	447.174	372.607
298.432	293.907	230.488	225.268	286.110	229.787	175.261	239.063
238.648	250.223	314.305	-246.000	223.699	148.773	256.691	253.830
286.633	310.319	365.151	395.086	366.594	448.043	384.220	447.694
466.977	456.722	464.935	481.538	481.951	487.483	494.349	519.234
606.254	572.456	492.912	570.679	580.478	672.359	595.000	520.222
539.633	555.549	573.852	583.325	582.223	585.866	582.834	573.489
566.817	635.379	629.161	547.945	543.253	540.429	608.802	602.781
587.444	580.917	582.659	508.524	574.553	575.868	504.844	581.202
576.809	500.422	569.720	565.275	566.751	561.154	551.760	484.865
476.903	465.287	528.120	524.527	519.407	584.809	510.332	501.576
506.199	498.071	503.011	576.002	506.800	519.361	593.271	526.402
533.148	538.985	549.254	548.252	563.110	566.254	565.956	567.122
500.445	426.274	420.435	486.306	469.863	459.443	515.269	443.781
372.005	353.310	330.440	249.461	297.667	277.001	321.869	366.044
406.923	385.958	319.499	301.318	239.539	220.769	254.913	287.551
229.837	221.400	256.969	209.279	202.220	155.785	157.796	161.227
117.482	162.139	157.857	197.257	201.512	211.567	177.629	222.304

VITAE

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Education

Degrees

Ph.D., Information Technology, Old Dominion University, Norfolk, Virginia, 2016
M.B.A., Information Technology, Old Dominion University, Norfolk, Virginia, 2011
M.S., Computer Science, Old Dominion University, Norfolk, Virginia, 2009
B.S., Computer Science, Longwood University, Farmville, Virginia, 1997

Certificates

Graduate Certificate, Modeling and Simulation, Old Dominion University, Norfolk, VA, 2013
Thermography, Level I Certificate, Infrared Training Center, Massachusetts, 2007, renewed 2015
Teaching Certificate, Computer Science and General Mathematics, Virginia, 1997, renewed 2004

Teaching Experience

Teaching Experience

Adjunct Instructor, Old Dominion University, Norfolk, Virginia, 2010 – 2016
Instructor, Tidewater Tech, Norfolk, Virginia, 2006
Teacher, Menchville High School, Newport News, Virginia, 2003 - 2005
Teacher, Woodside High School, Newport News, Virginia, 1997-1998

Teaching Interests

Integrating the technology we discuss in class is a key focus for me. My students learn how to use the technologies covered in class. They also discover how information technology can impact their lives beyond the classroom.

I design assignments to improve the information literacy of my students. Most students believe they have mastery of internet search skills and information, but when tested on it their understanding is much less than they expected. The right assignments improve students' mastery greatly.

Research

Research Experience

Social Classification System – Facet Approach to Collaborative Categorization and Classification, National Science Foundation Funded, 2008 – 2012

Graduate Research Assistant – Business Applications using Modeling and Simulation, Virginia Modeling, Analysis, and Simulation Center Funded, 2012 – 2015

Research Interests

Modeling and Simulation of Business Systems
Knowledge Networks and Management
Bibliometrics

Professional History

Academic Advisor, College of Business Undergraduate Advising Office, Old Dominion University, Norfolk, Virginia, Summer 2010, Summer 2011, Summer 2013

Office Manager, Pete Sessa & Associates, Inc, Virginia Beach, Virginia, 2004 – present

Office Assistant, DLM Architects, Virginia Beach, Virginia, 2009

Programmer Analyst, Quick Response Team, Ferguson Enterprises, Incorporated, Newport News, Virginia, 1998 - 2002

Conferences

Attendance

Student Capstone Conference, Virginia Modeling, Analysis, and Simulation Center, Suffolk, VA, 2016.

International Conference on Information Systems, 2015, Fort Worth, TX, 2015.

Decision Sciences Institute, 2015, Seattle, WA. Doctoral Student Consortium.

Student Capstone Conference, Virginia Modeling, Analysis, and Simulation Center, Suffolk, VA, 2015.

Americas Conference on Information Systems, 2014, Savannah, GA.

Decision Sciences Institute, 2013, Baltimore, MD.

Student Capstone Conference, Virginia Modeling, Analysis, and Simulation Center, Suffolk, VA, 2013.

Decision Sciences Institute, 2012, San Francisco, CA.

International Conference on Digital Libraries & Knowledge Organization, 2011. Management Development Institute, Gurgaon, India.

Presentations

Rasnick, E. 2016. A Study of the Impact of Information Blackouts on the Bullwhip Effect of a Supply Chain Using Discrete-Event Simulation. 2016 Modeling Simulation and Visualization Student Capstone Conference, Suffolk, VA.

Rasnick, E. and D.C. Chatfield. 2015. Simulating the Bullwhip Effect in a Multi-echelon Supply Chain. 2015 Modeling Simulation and Visualization Student Capstone Conference, Suffolk, VA.

Rasnick, E, J. Hilton, and F.G. Wilson. 2013. A Study of Contagion Spread among a Finite Human Population on a Naval Vessel. 2013 Modeling Simulation and Visualization Student Capstone Conference, Suffolk, VA.

Rasnick, E. 2012. Technology Adoption in the Home Inspection Industry. Decision Sciences Institute, 2012 Conference, San Francisco, CA.

Fu, L., Maly, K., Rasnick, E., Wu, H., and Zubair, M. 2011. In A. Jose, D. Madalli, & A. Prasad (Ed.) User Experiments of a Social, Faceted Multimedia Classification System. Proceedings of the International Conference on Digital Libraries & Knowledge Organization (156 - 167). Gurgaon: Management Development Institute.

Rasnick, E. 2008. Looking Outside the Box. Inframation 2008, Reno, NV.

Publications

Papers

He, W., Chee, T., Chong, D., and Rasnick, E. 2012. Using Bibliometrics and Text Mining to Explore the Trends of E-Marketing Literature from 2001 to 2010. International Journal of Online Marketing, 2(1), 16-24, January-March 2012.

Conference Proceedings

Rasnick, E. 2008. Looking Outside the Box. Inframation 2008, Reno, NV.

Coppage, S., Wu, H., and Rasnick, E. 2010. Collaborative Computing Behaviors in a Digital Archive. IABPAD Conference Proceedings.

Awards

Beta Gamma Sigma International Honor Society, Induction 2016

Outstanding Graduate Teaching Award – Classroom, 2015 – 2016 Academic Year

Alpha Iota Delta International Honor Society, Induction 2015

Virginia Modeling and Simulation Center Research Assistantship, 2012 – 2013 Academic Year, renewed 2013 – 2014 Academic Year and 2014 – 2015 Academic Year

Max B. Jones Endowed Scholarship, 2010 – 2011 Academic Year

Shining Star Teaching Award, Student Nominated Honor, 2010 – 2011 Academic Year and 2015 – 2016 Academic Year