ABSTRACT

Title of Document:	A SIMULATION APPROACH TO MODELING CONTINGENCY STRATEGIES FOR MANAGING ELECTRONIC PART SUPPLY CHAIN DISRUPTIONS
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Due to the nature of the manufacturing and support activities associated with long life cycle products, parts need to be dependably and consistently available. However, the parts that comprise long life cycle products are susceptible to a variety of supply chain disruptions. In order to minimize the impact of these unavoidable disruptions to product production and support, manufacturers can implement proactive mitigation strategies. Careful selection of the mitigation strategy (second sourcing and/or buffering) is key, as it can dramatically impact the part total cost of ownership. This thesis developed a simulation model that performs tradeoff analyses and identifies a near-optimal combination of second sourcing and buffering for specific part and product scenarios. In addition, this thesis explores the effectiveness

of traditional analytical models when compared to a simulation-based approach for the selection of an effective optimal disruption mitigation strategy. Several case studies were performed that: 1) tested the impact of popular analytical limiting assumptions, and 2) implemented realistic disruption data in the context of real part management. The first set of case studies demonstrated that the simulation model is capable of overcoming significant scenario restrictions prevalent within traditional analytical models: finite horizon (including non-zero WACC), fixed support costs, and unreliable backup suppliers are essential components for determining the effective optimal disruption mitigation strategy for a given disruption scenario. The second set of case studies demonstrates the importance of proper mitigation strategy selection in real electronic part supply chain scenarios. The results from the case studies not only justified the need for a simulation-based approach to disruption modeling, but also helped to cement the simulation model as an effective decision making tool for electronic part distributors.

A SIMULATION APPROACH TO MODELING CONTINGENCY STRATEGIES
FOR MANAGING ELECTRONIC PART SUPPLY CHAIN DISRUPTIONS

By

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Nomenclature

λ_{du} Probability of a disruption ending in a subsequent period

λ_U Probability of system *remaining* undisrupted in the subsequent period

ΔC_{TCO} Difference in cumulative Total Cost of Ownership of a part

C_{ASYi} Assembly Cost for a part in year i

C_{DISi} Disruption-Specific Cost for a part in year i

C_{FFi} Field Use Cost for a part in year i

C_{INVi} Holding (Inventory) Cost without Disruptions for a part in year i

C_{PROCi} Procurement Cost for a part in year i

C_{SUPi} Cost to Support a Source for a part in year i

C_{TCOj} Cumulative Total Cost of Ownership of a part after j years

D_i Downtime in year i (measured in years)

H_i Hoarding/Buffering Quantity held in year i

h Holding Cost (per part per year)

I_i* Backorder Quantity in year i

I_i Number of Parts in Inventory at the end of year i

i_{crit} Maximum number of consecutive ordering periods for which inventory management (buffering) is preferred to contingent rerouting (second sourcing from completely reliable supplier)

I_{Ei} Excess Inventory (positive values of I) in year i

K Ratio of $\Delta C_{TCO} / C_{SUP}$

m Forecasted Part Demand (per year)

M Number of state spaces representing the *minimum* disrupted periods

N Number of state spaces representing the *possible* remaining disrupted periods

P_B Base Penalty Cost (per part per year)

P_{BOi} Backorder Penalty Cost for a part in year i

r Weighted Average Cost of Capital (per year)

S/E_i Shortage/Excess on Backorder Quantity in year i

TCO Total Cost of Ownership

T_H Hoarding Duration (months)

Y_B Base Year for Money

Acronyms

A   Acceptance
CTCO   Cumulative Total Cost of Ownership
DMSMS   Diminishing Manufacturing Sources and Materials Shortage
CR   Contingent Rerouting
EOQ   Economic Order Quantity
IM   Inventory Management
ISDN   Integrated Services Digital Network
TCO   Total Cost of Ownership
OEM   Original Equipment Manufacturer
PSA   Product-Specific Approval
PSL   Preferred-Supplier List
SM   Sourcing Management
WACC   Weighted Average Cost of Capital

Chapter 1: Introduction

1.1: Objective Statement

The goal of this thesis is to create a method for determining the optimal sourcing mitigation strategy that minimizes the cumulative total cost of ownership of a part in the presence of supply chain disruptions. In particular, this thesis focuses on extending a generalized part-centric model developed by Prabhakar [1] to include a disruption-mitigation model that guides supplier management sourcing decisions. The application domain for this work is electronic parts.

1.2: Motivation

Modern electronic products can be categorized as: long life cycle products and short life cycle products. Short life cycle products such as cell phones, computers, and GPS devices, are classified as products that become obsolete (no longer produced or supported) within 5 years or less. The supply-chains associated with these products have been studied extensively and tend to employ procurement-driven management strategies [2]. Long life cycle products (such as products employed in aerospace, communications infrastructure, and military roles) have relatively low volume and differ in that they are often fielded and supported for more than 20 years, which significantly diminishes the benefits associated with traditional procurement-centric strategies (such as lean manufacturing).

Due to the nature of the manufacturing and support activities associated with long life cycle products, the parts that products require need to be dependably and consistently available. However, the parts that comprise long life cycle products are susceptible to a variety of supply chain disruptions. In order to minimize the impact of these unavoidable disruptions to production and support, manufacturers can implement various proactive mitigation strategies. Two mitigation strategies in particular are widely used to decrease the penalty costs associated with disruptions: second sourcing and buffering. Second sourcing involves selecting two distinct suppliers from which to purchase parts over the life of the part's use within a product or organization. Second sourcing reduces the probability of part unavailability (and its associated penalties), but at the expense of qualification and support costs for multiple suppliers. An alternative disruption mitigation strategy is buffering (also referred to as hoarding). Buffering involves stocking enough parts in inventory to satisfy the forecasted part demand (for both manufacturing and maintenance requirements) for a fixed future time period so as to offset the impact of disruptions. Careful selection of the mitigation strategy (second sourcing, buffering, or a combination of the two) is key, as it can dramatically impact the part total cost of ownership.

The selection of optimal sourcing strategies for electronic parts is a prevalent issue within the business management and operations research literature; however, the focus of existing analyses is typically on minimizing part procurement price. For example, lean manufacturing emphasizes the reduction of inventory size in order to cut costs. While this approach is largely effective for high-volume applications, it

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implicitly assumes that suppliers can provide parts for the manufacturing process without interruption [3], which is often not the case with electronic parts over long time periods (e.g., 10+ years or more). Disruptions events, defined as periods of time during which demand exceeds supply, not only stem from a variety of factors, they also have widely varying lengths (discussed further in Section 4). Disruptions in supply can be extremely problematic for systems that depend on electronic parts when popular lean manufacturing approaches are used.[1] According to Kaki et al. [4], "…in many companies, the goal of supply network management has shifted from short term cost savings to the pursuit of long term strategic benefits".

Several high-profile supply chain disruption events have caused shockwaves within the electronics industry in recent years. For example, in March of 2000 a fire at a major Phillips Electronics plant shut down production and damaged millions of existing microchips. Ericsson, one of their largest customers, was faced with a shortage of parts that lasted for months. As a result, Ericsson lost an estimated $400 million in sales [5]. Similarly, a Japanese earthquake disrupted the supply of parts to Kelly Micro Systems in 1994 [5]. Another Japanese earthquake (in 2011) led to a tsunami that forced the shutdown of several plants that "supply much of the world's silicon wafers, auto parts, flash memory, and other components" [6].

The model developed in this thesis allows the employment of proactive mitigation strategies in order to minimize the effect of disruptions events, especially supplier-specific disruptions.

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[1] Disruptions are also a problem when lean manufacturing approaches are used for high-volume products, but in the case of high-volume products, disruptions are usually relatively short in duration (e.g., hours or days), whereas in the case of low-volume, long field life products, disruptions due to allocation issues and obsolescence may have durations of months or even years.

1.3: Introduction to Electronic Part Supply Chains

1.3.1: Supply Chain Background & Terminology

A supply chain is a complex network of organizations (suppliers, manufacturers, distributors, and customers) through which materials and goods flow. While supply chains have many levels (or echelons), this thesis will focus on a single echelon of an electronic part supply chain in order to effectively isolate the effect of disruption mitigation strategies. In particular, this thesis will concentrate on the relationship between electronic part suppliers and original equipment manufacturers (OEMs). OEMs, in this context, are defined as manufacturers who integrate pre-fabricated parts and systems into larger products.

OEMs must perform several steps when selecting and implementing a part into a more complex product. First, manufacturers need to identify suitable parts from existing suppliers. If no such parts exist, manufacturers need to look into either in-house fabrication or specialized contracts with fabricators. After a specific part has been selected, the manufacturer needs to expend resources having both the part and the supplier(s) qualified to the standards of their organization or to the standards required by their customer.

Once a part and its supplier have been fully qualified, a steady supply of parts is needed in order to consistently manufacture new products and support existing products throughout their life cycle. While the primary purpose of manufacturing is to fill outstanding customer orders, product support comes into play through the

fulfillment of warranty claims and necessary part replacements. The additional parts needed to support fielded products are referred to as "spares".

If the supply of qualified parts is interrupted (unable to meet manufacturing and support demand), then customers' orders for new products or repaired products are left unfulfilled. These unfulfilled orders are known as "backorders", which can incur penalty costs over time. In order to safeguard against these lapses in supply, OEMs can order an excess of parts (called a "buffer") that allow for continued production during the disruption.

1.3.2: Low Volume, Long Life Cycle Electronic Products

Low volume, long life cycle electronic products appear in military, aerospace, oil, and communications infrastructure among other applications. None of these applications has any control over the supply chain for the electronic parts they use. During the initial design and manufacturing stage, these products can typically obtain their parts directly from high volume supply chains built to support consumer electronics. However, these long life cycle products differ from consumer electronics in that they need parts to be readily available for long periods of time (20 years or more). These long product life cycles can exceed part procurement lifetimes[2] (especially at the individual supplier level) and therefore the flow of parts needs to be carefully managed.

The relatively low volume (when compared to consumer electronics) of ordered parts for these long life cycle systems severely undermines the effectiveness

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[2] The part procurement life indicates the total length of time (in years) that the part was or will be procurable from its original source(s) [30].

of popular procurement-price based strategies. In particular, necessary support and qualification costs (which are typically overlooked in traditional cost modeling) become critical cost components as they are not balanced by a high level of production. A total cost of ownership approach was chosen for this thesis due to the incorporation of these underlying support and qualification costs.

1.4: Supply Chain Disruption Taxonomy

A supply chain disruption is a mismatch between supply and demand that would result in backordered parts if there were no mitigating factors such as buffered parts or second sources. While the primary effect of a disruption is the same, the source/cause of disruption events varies. Four disruption categories are discussed below: part-specific, supplier-specific, customer-specific, and external.

1) Part-specific: Situations related to individual parts (not suppliers) can impact the ability of a customer to obtain the part from any supplier. The most common part-specific disruptions are technology obsolescence and counterfeit part risk.

2) Supplier-specific: The three broad causes of supplier-specific disruptions are suppliers exiting the market, specific part obsolescence (particular part numbers that are discontinued by a supplier), and delivery delays.

3) Customer-specific: Poor estimation of part demand by the customer is the primary source of customer-specific disruption. Estimation issues are typically a result of unforeseen surges in demand and allocation issues.

4) External: Events that are beyond the control of the suppliers or customers may directly affect the efficient production of parts and subsequent delivery to customers. Common causes of external disruption include political/legislative events, transportation mishaps, and "Black Swan"[3] events.

Manufacturers periodically negotiate supplier contracts that set the price, lead times,[4] and volumes of selected part shipments. These contracts are deciding factors in the manufacturer's overall production schedule and as such variations from the contractual terms can be the basis for production or support disruption, whatever the cause.

1.5: Supply Chain Disruption Literature Review

In recent years, global supply chain disruptions have caused an increased interest in the development of proactive disruption mitigation models. Blackhurst et al. [7] presents a case study on global supply chain disruptions involving interviews and focus groups of industry executives. The article highlights the importance of supply chain visibility, and the development of real-time measures within the supply chain (i.e., the importance of data when producing an effective model).

Due to varying part demand throughout the life cycle of a product or group of products, part buffering (as presented in this thesis) is inherently a dynamic inventory

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[3] Disruption events that occur outside of reasonable or regular expectations, produce an extreme impact, and involve "retrospective predictability" [31]. Retrospective predictability indicates that the probability of occurrence can only be quantified after the event (or similar event) has taken place. Examples of black swan events impacting electronic parts include the 2011 Thailand flood and the 2011 Japanese earthquake.
[4] Lead time indicates the time in between the placement of an order for parts and its delivery.

policy. Various dynamic inventory policies and models have been presented in previous works. Karlin [8] introduced a variable inventory model based on a fluctuating demand distribution. Karlin's model incorporates backlogged demand and its associated penalty cost, but supply chain disruptions are not considered. Karlin's model is based on defined periods of equal duration, at the beginnings of which ordering decisions are made. Any time lags between order and delivery within the model are assumed to correspond to these pre-determined periods (i.e., a lag lasts a certain number of periods and the parts are delivered at the beginning of a period). Karlin only presents a model for a lag lasting one period. Supplier disruptions are inherently uncertain (when they occur and how long they last are uncertain), and as such a dynamic inventory policy that reflects this fact is necessary. Zipkin [9] developed a simplified version of Karlin's model. Zipkin's model assumes that each period is stationary and uncertainty only comes into play when the periods are combined. Iyer and Schrage [10] focused on the importance of collecting historical demand data to generate inventory control parameters; however they presented only a deterministic model. Disruption overlap and uncertainties in disruption date and duration are key factors in the Iyer and Schrage model.

A variety of models have been developed to study the effect of disruption events within a supply chain. Disruption models in the operations research realm focus on the study of dynamic inventory policies, in particular the selection of optimal buffer stock quantities. In fact, early disruption-specific models, such as Song and Zipkin [11], Parlar and Perry [12], and Ozekici and Parlar [13] focus exclusively on inventory control methods for accommodating disruption events. These models

developed robust disruption definitions and mathematical equations that serve as the basis for more complex disruption modeling approaches. However, with the exception of Ozekici and Parlar [13], these early disruption models did not incorporate the effect of discounting (i.e., time value of money).

Wang et al. [14] discuss the effect of both dual sourcing and process improvement as disruption mitigation strategies. While the proposed scenarios primarily explore random capacity and random yield supply uncertainty, they can easily be modified to represent disruption events (i.e., zero yield/capacity). The authors also utilize "quantity hedging"[5] in certain dual sourcing scenarios in order to counteract supply shortages in one of the suppliers.

Das [15] highlights the importance of supply chain flexibility as a way to deal with disruptions and demand uncertainty. Das recommends renting extra capacity when needed (as opposed to simply expanding overall capacity) and maintaining a pool of second tier suppliers that are able to fill in for primary suppliers, with an additional inspection cost, in the case of disruptions (a.k.a., emergency or backup sourcing). Das also mentions base level safety stock (a.k.a., buffering) as a management defined input. However, the focus of [15] is on the physical layout of the supply chain (distribution centers, plants, transportation) the importance of product flexibility, which is not within the part-centric scope of this thesis.

Tomlin [16], Schmitt and Snyder [17], and Chen, et al. [18] incorporate the concept of second sourcing as an additional disruption-management technique.

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[5] Wang et al. [14] defines quantity hedging as ordering more parts then demand calls for in order to "hedge" against shortages in supply. This is similar to buffering, except that quantity hedging is not tied to a finite duration of time (e.g., buffering is defined as ordering enough excess parts to cover the forecasted demand for a fixed future time period).

However, while these models clearly define the effect of various disruption mitigation strategies on cost, supplier qualification is not considered and the secondary supplier is assumed to be completely reliable (essentially an emergency/backup supplier that can always deliver). In addition, Tomlin, and Schmitt and Snyder present infinite horizon models, which assume that each ordering period takes place within an infinite part usage lifetime. The defining characteristic (in terms of this thesis) of infinite horizon models is that while the sequence and expected frequency of events and/or periods are taken into account, the effect of calendar time is ignored. The absence of calendar time has several notable ramifications for long life cycle products:

1) Individual periods and/or events are not differentiated based on when they occur in time, i.e., sequence of events is accounted for and only the state of the previous period in known for calculations, but the correlation to the clock and calendar are not accounted for. This assumption can detract from the accuracy of disruption models, as several historical disruption profiles, such as seasonal weather events, are dependent on calendar time.

2) Periodic adjustments (such as the weighted average cost of capital (WACC), inflation, and deflation) cannot be considered because the time duration between events is not accounted for. The case studies presented in Section 3.5 show that, over long periods of time, these adjustments can significantly impact the total cost of ownership of a system.

3) Time dependent costs, such as introduction (e.g., initial approval and qualification costs) or termination costs (e.g., obsolescence and end of

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life support costs), cannot be incorporated into calculations. These
support costs, as discussed Section 3, are key cost components for low-
volume, long life cycle systems.

While the implementation of an infinite horizon approach simplifies
disruption models and helps to insure the formulation of convex optimization
problems, the simplifying assumptions are not realistic for low-volume, long life
cycle products and lead to significant errors (as discussed in Section 3.5).

Although the restrictions surrounding the models developed by Tomlin [16],
Schmitt and Snyder [17], and Chen et al. [18] call into question their model's
usefulness as decision-making tools for most real applications, a fact which Tomlin
acknowledges in [16], they provide valuable insight into the effect of disruptions and
they provide some guidance on the number of necessary disruption-based inputs for
the simulation-based model developed in this thesis.

Schmitt and Singh [19] presented a simulation-based approach
implementation of Tomlin's model [16] that studies the propagation of disruptions
through infinite-horizon, multi-echelon supply chains and the resulting effect on
inventory flow. The simulation utilized in this thesis (as opposed to that of [19])
focuses on a single echelon of the electronics supply chain, more specifically the flow
of parts from supplier(s) to the original equipment manufacturer. Any disruptions that
occur before the parts reach the supplier(s) are assumed to be included in the
aggregate supplier disruption distribution. While Schmitt and Singh's model serves to

bridge the gap between analytical models[6] and simulation models, it is still

constrained to the limiting assumptions presented in [16] (infinite-horizon in

particular).

Tomlin supplemented his original paper [16] with an additional study in 2009

[20]. This paper presented a two-product newsvendor study that analyzes the impact

of a variety supplier/product/firm attributes on the optimal mitigation strategy. An

additional mitigation strategy (shifting demand to another product) is also considered.

While [20] implements a product-centric view, it is limited to a single period (as

opposed to finite long life-cycle systems).

Another realm of disruption management exists within the supply-chain, but is

not addressed in this thesis. Lin [21] studies disruption events stemming from

production uncertainty (i.e., imperfect production due to defective parts, machine

failure, and rework) at the manufacturer level. Lin utilizes a Markov chain based

probability matrix (similar to the one presented by Tomlin in [16]) to model process-

specific events. While imperfect production has a proven effect on the total cost of

ownership, it is not derived from the relationship between manufacturer and

supplier(s), and for that reason it is not considered in this thesis.

While the existing literature (outlined above) shows a growing interest in the

study of supply-chain disruption mitigation, no model has proven effective as a

general decision-making tool for supply chain managers. Instead, the existing

literature focuses on isolating key parameters and overarching trends for generalized

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[6] An analytical model is a mathematical model (based on a series of formal equations) that has a closed form solution (i.e., the solution can be expressed as an equation). Simulation models combine analytical and numerical modeling (i.e., time-stepping in the case of the model in this thesis) approaches to generate data and graphs that reflect the system's behavior over time.

supply scenarios. The model in this thesis utilizes a simulation approach in order to incorporate a greater number of parameters/inputs and allow for scenario flexibility. This thesis also emphasizes the importance of real-world disruption data as a catalyst for model development.

In addition, research in recent years has primarily focused on disruption mitigation for high-volume, short life cycle products. These products can typically be generalized using infinite horizon or economic order quantity (EOQ) approaches that place minimal emphasis on fixed support costs. An effective disruption model that considers parameters unique to low volume, long life-cycle parts (such as non-recurring support costs) has not been developed.

1.6: Thesis Overview

This thesis introduces a new method for isolating *effective*[7] (not formal) optimum disruption mitigation strategies for electronic part supply-chains. The approach developed strives to minimize the cumulative part total cost of ownership, depending on several parameters including: inventory level, backordered parts, disruption events, sourcing strategy, support costs. The work presented in this thesis will provide an effective decision making methodology for supply-chain managers. The total life-cycle cost through j years will be minimized according to the following equation:

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[7] The simulation model developed in this thesis utilizes an iterative approach to isolate near-minimum total cost of ownership values for given part and product scenarios. These near-minimum values are by no means formal optimums, but they act as effective decision-making tools for identifying the most successful disruption mitigation strategy.

$$C_{TCO_j} = \sum_{i=1}^{j} (C_{SUP_i} + C_{ASY_i} + C_{PROC_i} + C_{FF_i} + C_{DIS_i}) \qquad \text{Eq. 1}$$

The costs that compose the total life-cycle cost are as follows: support costs C_{SUP}, assembly costs C_{ASY}, procurement costs C_{PROC}, field costs C_{FF}, and disruption costs C_{DIS}. These costs will be further defined in Chapter 2.

Chapter 2 outlines the development of a part total cost of ownership model (and the accompanying simulation model) that incorporates disruption strategies and penalty costs due to backordered parts. Chapter 3 validates the simulation model by reproducing results from the analytical disruption model developed by Tomlin [16] and highlights limitations to common analytical disruption approaches. Chapter 4 presents a set of case studies that examine sourcing strategy selection in the context of realistic supply-chains. Chapter 5 summarizes the research, contributions, and identifies areas for future work.

1.7: Work Plan

In order to accomplish the objectives outlined above, the following work plan was developed and completed:

1) Expand the basic part total cost of ownership model (developed by Prabhakar in [1]) to include the effect of buffering, backordered parts, and penalty costs. Prabhakar addresses long-term (non-recurring) supply chain disruptions and specifically focuses on disruptions due to part obsolescence. The focus of this thesis is on frequent, smaller-scale disruption events and the appropriate selection of disruption mitigation strategies (not limited to single verses second sourcing).

2) Develop a simulation model that allows for the determination of the effective optimum disruption-mitigation strategies associated with a set of parameters. Trends observed from the outputs of sensitivity analyses performed in the part total cost of ownership model may allow for a reduction in necessary parameters.

3) Validate the simulation model against results produced and documented by existing analytical disruption models. In particular, reproduce the results of Tomlin [16]. In addition, isolate limiting assumptions that can be overcome with a simulation-based approach.

4) Determine key parameters for the proper selection of disruption mitigation strategies for low-volume, long-life cycle products. Specifically, run case studies with the modified part TCO simulation model to assess the importance of four limitations to common analytical models: 1) fixed costs are ignored, 2) disruptions last full ordering periods, 3) second/backup suppliers are perfectly reliable, and 4) assumptions associated with an infinite-horizon approach.

5) Explore the use of actual supplier and/or distributor historical data for establishing supplier disruption distributions (both duration and frequency). Original Equipment Manufacturers (OEMs) may have some "soft" knowledge from their own production lines that can be combined with limited public information on the performance of various suppliers, but a quantitative model is generally lacking in the electronics industry. In addition, utilize the compiled disruption data to run realistic case studies in the simulation model.

Chapter 2: Part Total Cost of Ownership Model (TCO) in the Presence of Supply Chain Disruptions

This chapter presents the development of a part total cost of ownership model that incorporates both mitigation strategies (second sourcing and buffering) and penalty costs due to supply-chain disruptions. The following sections discuss the importance and implementation of various model components as well as the presentation of an accompanying simulation model. The resulting model serves as the basis for calculations in the remainder of this thesis.

2.1: The Part TCO Model

The model developed by Prabhakar and Sandborn [22] determines the part total cost of ownership. The basic model developed in [22] for calculating the effective cumulative total cost of ownership through year j for a part is given in Eq. 2,

$$C_{TCO_j} = \sum_{i=1}^{j} (C_{SUP_i} + C_{ASY_i} + C_{PROC_i} + C_{FF_i} + C_{INV_i}) \qquad \text{Eq. 2}$$

This model has five major components: support costs (C_{SUP}), assembly costs (C_{ASY}), procurement costs (C_{PROC}), field failure costs (C_{FF}), and inventory costs (C_{INV}). All of these costs are adjusted to present value in the underlying calculations to account for the cost of money.

The target of the cost model in [22] was a study of the impact of support costs on the total cost of ownership for low volume, long life cycle parts. For this reason, several support costs (C_{SUP}) are included in the principal calculations: initial part approval and adoption costs, product-specific approval and adoption costs, annual

cost of supporting the part within the overall organization, production support and part management costs, obsolescence case resolution costs, and preferred-supplier list (PSL) qualification costs.

The remaining cost components capture recurring and non-recurring costs experienced throughout the lifetime of the part. The annual assembly costs (C_{ASY}) are defined as the recurring system assembly costs and the recurring functional test/diagnosis/rework costs. The annual procurement (C_{PROC}) and inventory (C_{INV}) costs are the recurring part purchase costs and inventory holding costs, respectively (in this model, the inventory cost is primarily utilized to store lifetime buys[8]). Finally, the field failure costs (C_{FF}) incorporate any costs incurred due to warranty fulfillment or part replacement. The approach outlined by Prabhakar and Sandborn in [23] addresses long-term (non-recurring) supply chain disruptions and specifically focuses on supply-chain disruptions due to part obsolescence. However, the authors note in [22] that this cost model could be extended to include the effect of shorter-term disruption events, which will be the focus of the remainder of this chapter.

The model employs an annual (end-of-year) review policy in terms of inventory replenishment decision-making. For a more detailed explanation of the terms in Eq. 2, see [1].

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[8] Lifetime buys refer to purchasing and storing a sufficient quantity of parts (when the part is discontinued) to satisfy all future demand (production and support).

2.2: Part Sourcing Strategies

2.2.1: Single Sourcing

Single sourcing, in the context of this thesis, is defined as an exclusive relationship between an original equipment manufacturer (OEM) and a single supplier with respect to a specific part. However, while single sourcing minimizes qualification costs and allows for greater supplier-manufacturer coordination, the manufacturer is more susceptible to supplier-specific disruptions.

2.2.2: Second Sourcing

In this thesis, second sourcing involves purchasing parts from a primary supplier while maintaining a backup/secondary supplier. This sourcing strategy decreases the impact of disruptions as production can be rerouted to the second supplier when the primary supplier is disrupted (not able to supply parts). However, while second sourcing is good for supplier negotiations (manufacturers can put pressure on the price), additional qualification and support costs can negate its benefits.

In Prabhakar and Sandborn [22] the additional cost to support a second source is modeled using a learning index, a factor that characterizes the support cost overlap between the primary and secondary supplier. The case study in [22] showed that the benefit of using a second sourcing strategy is dependent on the value of the ratio $K = \Delta C_{TCO}/C_{SUP}$ where ΔC_{TCO} is the difference in total cost of ownership (i.e., the cost avoided by extending the part's procurement life) and C_{SUP} is the cost to support a source. K can be used to calculate the effective learning index associated with

sourcing (see [22]). According to [22], the ratio K can be interpreted two different ways: 1) as a threshold value, K serves as an gauge for the organization's ability to avoid certain qualification and support activities for additional suppliers, and 2) as a target value, K can be used to estimate the maximum fraction of support cost that can be duplicated for the second source and still make second sourcing viable. This thesis utilizes the ratio, K, to assess the value of proactively qualifying a second source and/or buffering an inventory of parts to address the issue of recurring supplier-specific part disruption events.

Obsolescence mitigation (specifically DMSMS [diminishing manufacturing sources and materials shortage] obsolescence) was incorporated into Prabhakar and Sandborn's model [22] through strategic lifetime buys and the inclusion of second sourcing as a way to extend the part usage life without changing the procurement life from the original manufacturer. Prabhakar and Sandborn found that when the combined procurement and inventory costs are high, second sourcing offers increased cost avoidance by extending the part's effective procurement life (when compared to single sourcing). However, short-term supply chain disruptions are much more common than obsolescence-type events and have a direct impact on the TCO of each part (which will be explored in the remainder of this thesis).

2.3: Part Buffering

As mentioned in Chapter 1, buffering in this thesis is defined as the storage of a number of parts equal to the forecasted part demand (for both manufacturing and maintenance requirements) of a fixed future time period. Buffering is a common

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proactive mitigation strategy employed in the electronics industry so as to offset the impact of disruptions.

Due to the fact that the forecasted part demand changes throughout the life cycle of the part, the buffering quantity is not a pre-determined value. Instead, the buffering quantity changes from year to year. If the buffering duration (T_H, in months) is less than a year, the buffering quantity for each year (i) within the part's life cycle (with the exception of the final year of support, when no buffering is necessary) is given by:

$$H_i = m_i \left(\frac{T_H}{12}\right) \qquad \text{Eq. 3}$$

where m_i is the forecasted demand per year.

If the buffering duration (T_H) is greater than a year, then the buffering quantity for each year (i) is given by:

$$H_i = \left(\sum_{k=i}^{k=i+\left\lfloor\frac{T_H}{12}\right\rfloor-1} m_k\right) + m_{i+\left\lfloor\frac{T_H}{12}\right\rfloor}\left(\frac{T_H}{12} - \left\lfloor\frac{T_H}{12}\right\rfloor\right) \qquad \text{Eq. 4}$$

where : $\lfloor x \rfloor$ represents the floor function (round down to the nearest integer); therefore $\left\lfloor\frac{T_H}{12}\right\rfloor$ is the number of *full* years accounted for in the buffering strategy.

Equations 2 and 3 implicitly assume that the forecasted part demand (m, in parts/year), while varying from year to year, is consumed at a constant rate within any given year. The uncertainty associated with of the forecasted part demand impacts the total penalty cost, as discussed in the next section.

When a supplier disruption occurs, new parts are no longer being delivered and the production and support begins to rely on the buffered inventory. However, if the disruption extends past the buffering duration, parts are backordered with an

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additional penalty cost. The number of parts on backorder at the end of the disruption period is considered the backorder quantity.

While buffering can be shown to significantly decrease the penalty costs associated with disruption events (see Section 4.2), there are some negative impacts that need to be considered. For example, buffering (if left unchecked) can delay the discovery of counterfeit parts in the inventory. Similarly, long-term storage of parts can lead to part deterioration (such as the reduction of important solderability characteristics for electronic parts). For this reason, OEMs that utilize long-term buffering as a disruption mitigation strategy may need to regularly assess the status/condition of buffered parts.

2.4: Backorder Penalty Cost

One of the major consequences of supplier/production disruption is the accumulation of penalty cost. Whenever demand is not met, a penalty is charged. If disruptions are frequent and/or lengthy or there is a high base penalty cost, the cumulative TCO can be dramatically affected. The buffering strategy can be optimized so as to balance the holding cost associated with excess parts against the possible penalty cost.

In the model presented in this thesis, annual backorder penalty (P_{BO_i}) in year i was calculated using:

$$P_{BO_i} = \frac{P_B I_i^*}{(1+r)^{(i-Y_B)}}$$
<div align="right">Eq. 5</div>

where r is the weighted average cost of capital (WACC), discrete compounding is assumed, and Y_B is the associated base year for money. Equation 4 incorporates the uncertainty of part demand within the function I_i^*, which is defined as the maximum of the following three values: 0, the shortage/excess on backorder quantity (S/E_i), and the parts in inventory (I_i). This function essentially selects the population (due to lead time/disruption or demand uncertainty) affected by the base penalty cost per part per year (P_B). The parts in inventory (I_i) are defined within the model as the total number of parts available for production/support at the end of the year, typically as a result of demand uncertainty. A negative quantity indicates a shortage of parts while a positive quantity indicates excess inventory. If there is excess inventory (I_E) at the end of the year, a holding cost (h) is charged per part *instead* of a backorder penalty cost (as excess inventory inherently indicates that no parts are on backorder).

The shortage/excess on backorder quantity is defined as the number of parts that are unavailable for production/support during a disruption event- a negative quantity indicates a shortage of parts. This excess/shortage is essentially the error due to part demand and disruption uncertainty. For the first year of a supplier disruption, this value is calculated by:

$$S/E_i = H_i - m_i D_i \qquad \text{Eq. 6}$$

where D_i is the annual downtime. If the disruption extends past one year, the shortage/excess on backorder quantity is quantified for all subsequent years by:

$$S/E_i = I_i - m_i D_i \qquad \text{Eq. 7}$$

The sum of the annual backorder penalty cost and the holding cost on excess parts are added to the part cost of ownership (as calculated Section 2.1 using Eq. 2) to

produce the annual part TCO. The method presented in this thesis utilizes end-of-year

backorder counting. This method assumes that the part total cost of ownership for

year i is the cost accumulated between year i and year $i+1$.

2.5: Disruption-Specific Cost Terms

The disruption-specific cost terms outlined in the prior sections were used to

modify Prabhakar and Sandborn's [23] general total cost of ownership model. The

annual inventory cost term (C_{INV_i}) in Eq. 2 was replaced with a more generalized

disruption term (C_{DIS_i}) as shown in Eq. 8.

$$C_{TCO_j} = \Sigma_{i=1}^{j} (C_{SUP_i} + C_{ASY_i} + C_{PROC_i} + C_{FF_i} + C_{DIS_i}) \qquad \text{Eq. 8}$$

The annual disruption-specific cost (Eq. 9) is the sum of the annual buffering

cost incurred due to excess inventory (buffered parts, H_i) and the annual backorder

penalty cost (P_{BOi}) incurred due to insufficient inventory.

$$C_{DIS_i} = P_{BO_i} + \frac{hI_{E_i}}{(1+r)^{(i-Y_B)}} \qquad \text{Eq. 9}$$

The goal of the remainder of this thesis is to minimize the cumulative part TCO

in the presence of supply chain disruptions by identifying the most effective

mitigation strategy. To achieve this goal, a simulation-based disruption model was

created and driven with random disruption events over the lifetime of the part. The

effects of these disruption events and the applied mitigation strategies were then

calculated using the expanded part TCO equation (Eq. 8).

2.6: Model Assumptions

The model developed in this chapter adheres to the following assumptions:

1) Demand and order fulfillment are recorded at the end of each period/year. This method assumes that the part total cost of ownership for year i is the cost accumulated between year i and year $i+1$.

2) Supplier-specific disruptions that occur in period i impact the number of parts to be delivered in year $i+1$.

3) The model is limited to either single or second sourcing through the use of two distinct supplier disruption distributions. More suppliers can be considered if an aggregate disruption distribution is employed, however the effect of the individual suppliers cannot be considered if an aggregate distribution is used.

4) Unmet customer orders, due to discrepancies between supply and demand, are infinitely backordered (i.e., orders are not lost or rescinded over time).

5) Forecasted part demand (m, in parts/year), while varying from year to year, is consumed at a constant rate within the year it represents.

6) All unmet demand is delivered in full at the end of a disruption event (no ramp-up period). This assumption holds for discrepancies due demand uncertainty (i.e., excess demand in year i-1 is added to the order for year i and delivered in full at the beginning of the period).

7) The WACC and price change are constant throughout the life of the product (manufacturing and support).

8) All original assumptions outlined by Prabhakar in [1].

2.7: Simulation Process

      In order to efficiently and repeatably model real-world disruption events, a simulation model was developed from the underlying formulation discussed in this chapter. The simulation model employs several loops to determine the near optimum disruption mitigation strategy, which is the strategy (sourcing and/or buffering) associated with the lowest expected cumulative total cost of ownership (CTCO) per part site. Figure 1 details the simulation process that is implemented within a Monte Carlo analysis in order to calculate the expected CTCO per part site for each sourcing and buffering strategy considered. The effective disruption mitigation strategy can either be determined manually (the user can perform a select number of Monte Carlo analyses for predetermined sourcing and buffering strategy combinations), or automatically within a brute force "optimizer" (which runs through a range of buffering and sourcing strategy combinations).
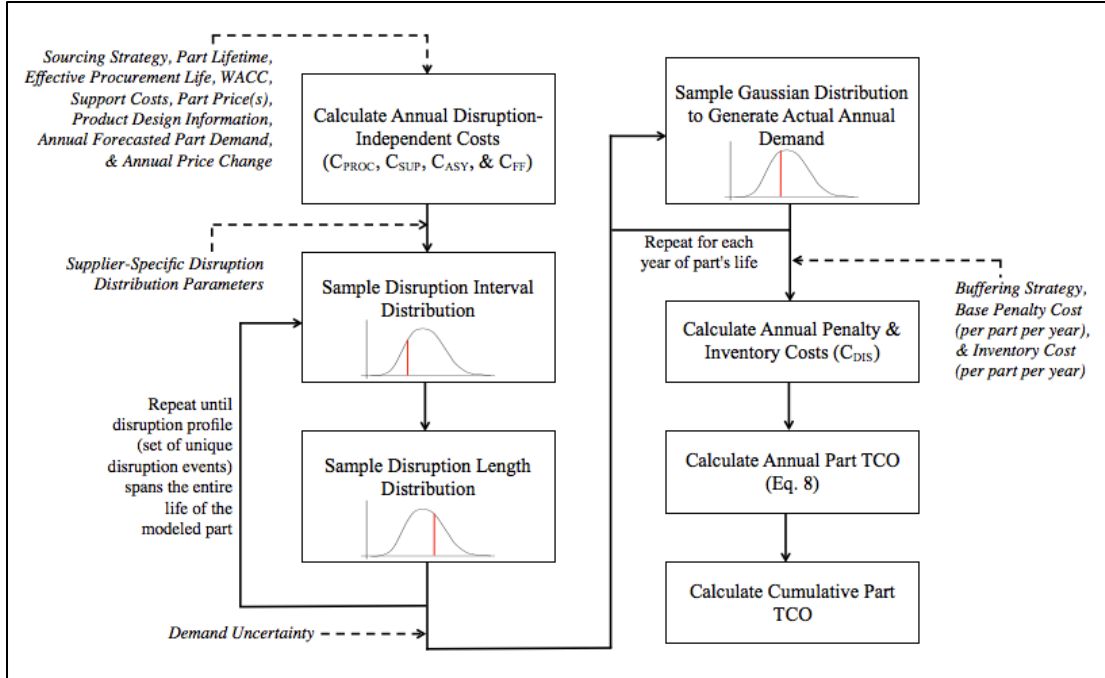
Figure 1: Simulation model process and inputs used to determine the cumulative TCO per part site for a unique set of disruption events

The simulation model employs four distinct steps to calculate the expected CTCO per part site:

1) Part-specific and product-specific inputs are compiled by the user (as shown in Figure 1) and used to calculate the annual support costs (C_{SUP}), assembly costs (C_{ASY}), procurement costs (C_{PROC}), and field failure costs (C_{FF}) according to the methodology development in [1]. These cost terms are not affected by demand or disruption uncertainty.

2) The simulation model utilizes a discrete event simulator to generate disruption events throughout the life cycle of a part. The disruptions are modeled using a three-parameter Weibull distribution (which was selected for generality, but any other distribution could be used). Figure 2 shows a comparison between a theoretical Weibull distribution (calculated using the three-parameter Weibull equation) and population of sampled points (a

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collection of 100 random samples drawn from the theoretical distribution).

The simulation model samples from two distinct distributions in order to

generate unique disruptions over the life cycle of the part: one governing

the length of disruption events, and the other governing the interval

between disruption events.
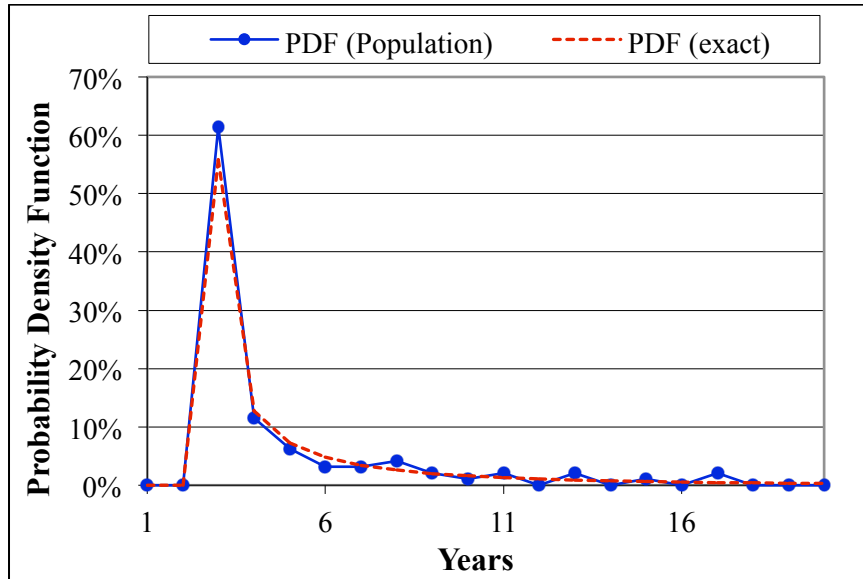
Figure 2: A comparison of the exact PDF produced from the three parameter Weibull equation and the corresponding PDF produced from a population of generated samples. (gamma=2 years, beta=0.5, eta=1.5 years)

In addition to the generation of disruption events, uncertainty comes into

play through the incorporation of demand uncertainty. For each year in the

part's life cycle, the simulation model samples a random value from a

Gaussian distribution (with the forecasted part demand acting as the mean

and a user-supplied value acting as the standard deviation) and sets that

value as the actual annual part demand. The annual penalty costs and

inventory costs associated with the generated disruption events and

demand discrepancies are then calculated using the method developed in

Section 4.

3)   The annual penalty costs and inventory costs (which, when summed, make up the disruption-specific cost term (C_{DIS}) as discussed in Section 4) are added to the annual disruption-independent cost terms calculated in step 1. The resulting annual cost represents the annual part total cost of ownership as described in Eq. 8. The annual TCO values are summed over the life of the part in order to calculate the cumulative TCO associated with the user-defined disruption mitigation strategy and the unique set of generated disruption events and actual annual demand values.

4)   In order to capture the effect of uncertainty, a Monte Carlo analysis is performed. The Monte Carlo analysis performs the three previous steps (which are broken down further in Figure 1) repeatedly for a set number of sample sets, recording the final cumulative TCO per part site associated with each individual sample set. The simulation model then compiles these final values in order to produce a distribution of the cumulative TCO per part site[9] over the support life of the product (or family of products) for the mitigation strategy in question. The mean value of this distribution is the expected CTCO per part site, which is used for comparison purposes in order to determine the near optimum disruption mitigation strategy.

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[9] A "part site" is defined as the location of a single instance of a part in a single instance of a product. For example, if the product uses two instances of a particular part (two part sites), and 1 million instances of the product are manufactured, then a total of 2 million part sites for the particular part exist. The reason part sites are counted (instead of just parts) is that each part site could be occupied by one or more parts during its lifetime (e.g., if the original part fails and is replaced, then two or more parts occupy the part site during the part site's life). For consistency, all TCO calculations are presented in terms of either annual or cumulative cost per part site.

As mentioned previously, one of the main outputs of the model is the expected part total cost of ownership for a given disruption profile (set of unique disruption events occurring throughout the life cycle of the part) and disruption mitigation strategy. Figure 3 shows the relevant annual part quantities (buffering strategy – H_i, parts on backorder – I_i^*, parts in inventory – I_i, part demand, and forecasted part demand (mean) – m_i) that are predicted and analyzed for a given disruption profile and a 20-year part lifetime.[10] The simulation model is able to concurrently analyzes the effect of both second sourcing and buffering on the part TCO so that companies are able to select the most effective management strategy for their specific needs.
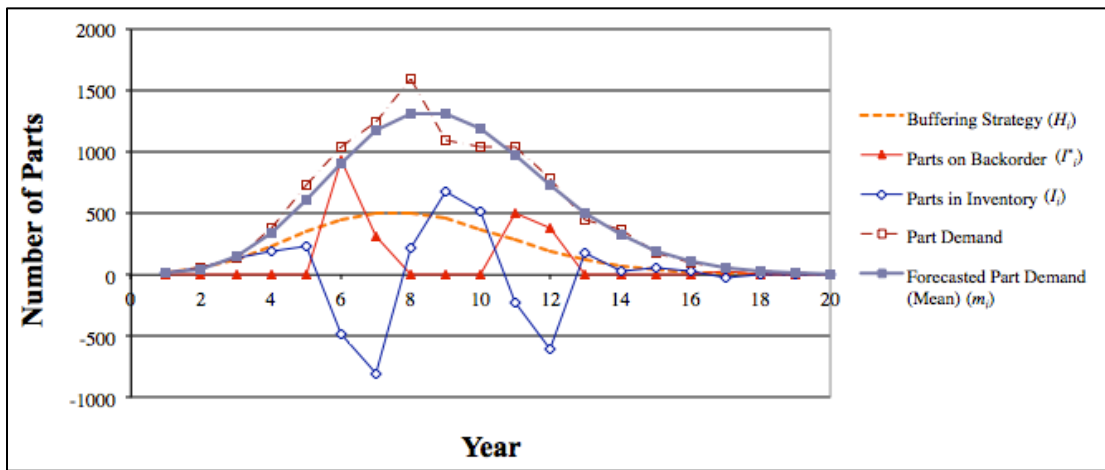
Figure 3: Relevant part quantities recorded by the simulation model for a single mitigation strategy (second sourcing and 20-weeks buffering) and disruption scenario

The parts in inventory (I_i), parts on backorder (I_i^*), and part demand are tied to both disruption and demand uncertainty. As such, their values should fluctuate for each run of the simulation model. The forecasted part demand (m_i) and buffered parts (H_i) are known values and should stay constant regardless of the disruption scenario. This compiled annual part quantity data is combined with cost information (i.e.,

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[10] The inputs used to produce Figures 2, 5, and 6 are detailed in the Appendix. The results do not reflect a fully analyzed case study as the inputs were chosen so as to produce clear figures. See Chapters 3 and 4 for complete case studies.

penalty costs, support costs, and procurement costs) to calculate the part TCO. The

most important thing to notice in Figure 3 is the difference between the number of

parts on backorder (which, when non-zero indicates a disruption period) and the

number of needed parts in the inventory (negative inventory). In the case shown in

Figure 3, the first instance of negative inventory within each disruption period is less

than the corresponding number of parts on backorder due to the buffering. Buffering

creates a gap between the start of the disruption and the point when production (or the

ability to support the product) stops (due to negative inventory) that allows for shorter

overall downtime or possibly no downtime at all.

Figure 4 shows the effect of generated disruption events on the cumulative

part TCO. It should be noted that the cumulative TCO per part site decreases over

time in this example case because additional part sites are added to the total

population each year. The resulting effect of penalty costs and initial support costs on

cumulative TCO is spread out amongst the additional part sites each year.
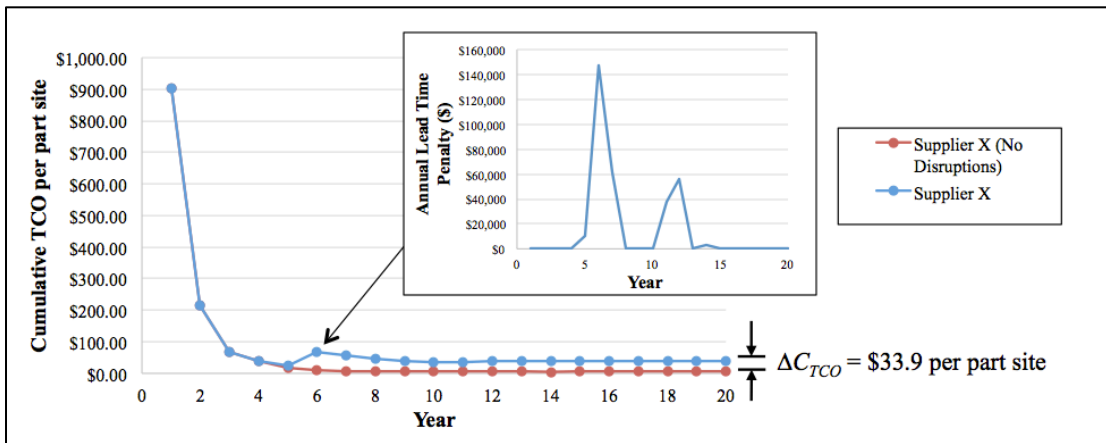
Figure 4: A comparison of the cumulative part TCO after 20 for a single sourcing case without
disruptions and a single sourcing case with the given disruption profile (three disruption events).

The simulation model also allows the graphically analyses of the effect of

time on a selection of sourcing strategies (as compared to a baseline, non-disrupted

scenario). This graphical analysis allows one to further grasp the importance of the TCO approach, especially as opposed to short term cost analysis. Figure 5 depicts the cumulative TCO per part site for a given disruption scenario and buffering strategy (20-weeks). While the lower support costs associated with single sourcing causes it to be the most cost effective solution for the first seven years of the example part's life cycle, the disruptions accumulated over time gradually negate the benefits associated with single sourcing. As such, for the scenario shown in Figure 5, the most effective mitigation strategy in the long run is second sourcing.
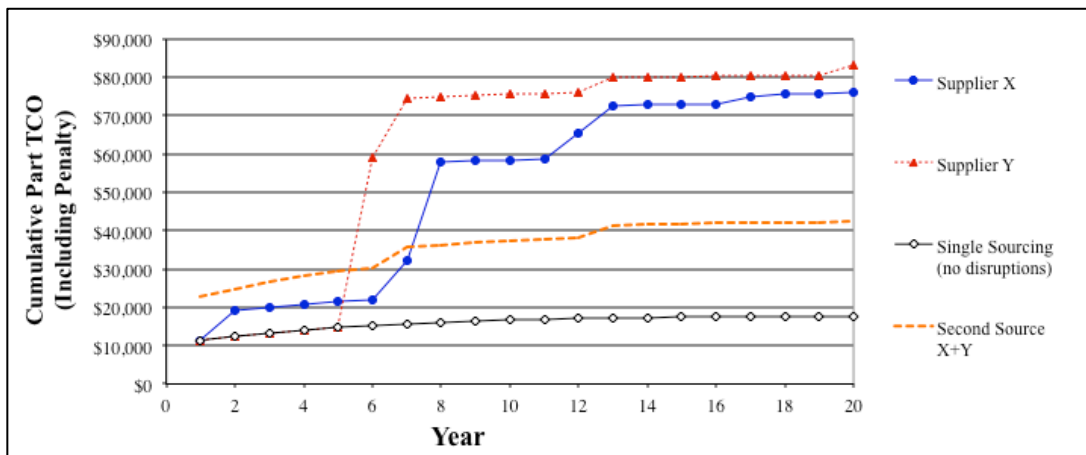
Figure 5: Cumulative part TCO (including penalty) over a 20 year period for a variety of sourcing strategies and a buffering strategy of 20 weeks (single disruption profile).

The distributions shown in Figure 6 are examples of the results produced by the Monte Carlo analysis. For the given example, second sourcing not only decreases the uncertainty (standard deviation) of the expected cumulative TCO per part site, it also decreases the mean value. For further reference, the simulation model interface and inputs are discussed in the Appendix.
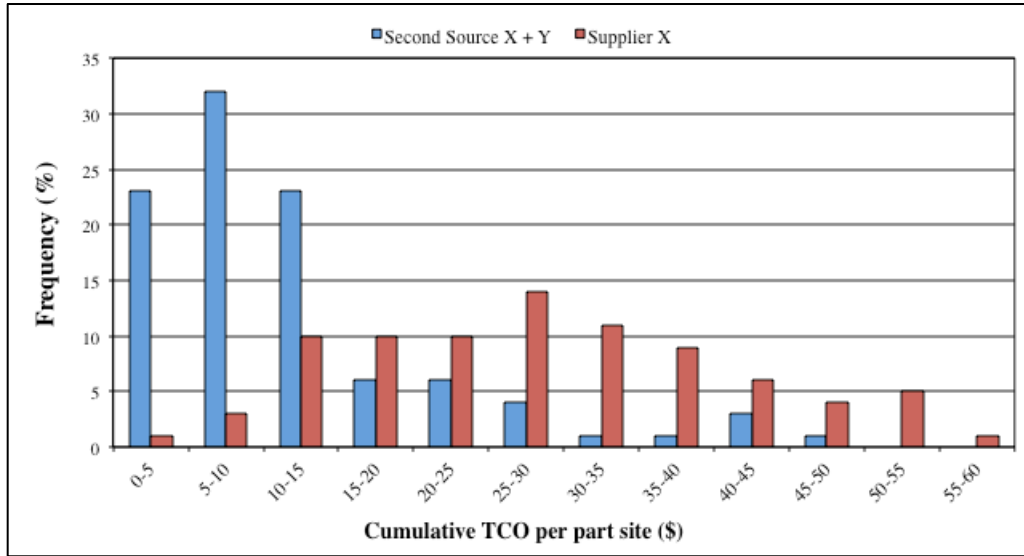
Figure 6: Expected cumulative TCO per part site (including penalty) for a selection of sourcing strategies and a buffering strategy of 20 weeks (Monte Carlo generated distributions).

Chapter 3: Validation of the Simulation Model

This chapter presents the contextualization and validation of the simulation model (developed in Chapter 2) against a well-known analytical disruption model from Operations Research literature. This chapter also highlights discrepancies between analytical and simulation-based disruption models, providing several case studies that show the impact of underlying analytical model assumptions.

3.1: Contextualization and Justification

As mentioned in Chapter 1, a set of generalized analytical disruption models exist outside of the simulation realm. These models were developed for use in supply chain management and they isolate trends and variable relationships within generalized scenarios. Tomlin, in his 2006 paper [16], presents a widely referenced cost model for finding the optimal sourcing policies to minimize cost during disruptions. His model utilizes a constrained infinite-horizon, periodic-review inventory system. Similar to the model developed in this thesis, all unmet demand in Tomlin's model is backlogged with instantaneous production and lead time. Tomlin's model allows for positive lead time, assuming that lead time is constant throughout the model.

Tomlin presents the idea of flexible capacity as a defining characteristic for underlying model selection. The simulation model developed in this thesis, on the other hand, does not include the effect of flexible capacity and production ramp-up time on the total cost of ownership. The sub-model most similar to the one developed

in this thesis has what Tomlin calls "Type II" flexibility. Type II flexibility implies that the emergency backup supplier can offer infinite and instantaneous capacity, essentially allowing for uninterrupted supply in the eyes of the consumer.

3.2: Limitations of Popular Analytical Disruption Models

While Tomlin's model helped to solidify a disruption approach and limit the number of required inputs, several limiting assumptions prevented Tomlin's model form being utilized directly in this thesis. Tomlin's model, in addition to the other analytical disruption models explored in Chapter 1, utilized a more formal optimization approach to isolate the effect of disruptions on the supply chain. Due to the inherent complexity of the supply chain, there are a large number of variables that can have a direct impact on cost. However, in order to numerically optimize the cost associated with a disrupted supply chain, several unrealistic simplifying assumptions needed to be made.

While the restrictions surrounding these models prevents them from being useful decision making tools, a fact which their authors acknowledge [16], they provide valuable insight into the effect of disruptions and they allowed the number of necessary disruption-based inputs for the simulation model to be limited in this thesis.

The calculation of the expected cost associated with disruption events can be iteration heavy, which lends itself to a simulation approach; the simulation-based model developed in this thesis is similar to a traditional optimization loop with added uncertainty from sampling probability distributions. According to Tomlin, it may be possible (but outside the scope of this thesis) to create an entirely analytical

disruption model, but the calculations would be extremely complicated and time-consuming [16].

Figure 10 (Chapter demonstrates that the simulation can be appropriately parameterized to generate the same solution as the analytical model of Tomlin [16]. While the model presented by Tomlin [16] effectively selects an optimal disruption mitigation strategy for a given set of inputs, it can only be applied to very restricted cases. The limitations that are inherent to the model are relatively common amongst analytical supply-chain models and are imposed by the models to insure that the formulation is convex (guaranteeing that an optimum solution can be found). For the simulation- based model, no such limitations are necessary. In particular, there are four key restrictions that are problematic when applying the existing analytical models to low volume, long life cycle systems (where support costs and procurement lives are critical):

1) Fixed costs of ordering are ignored. This assumption limits the use of the model to cases where the time scale for ordering is shorter than disruption time scale (i.e., order daily, disruptions last weeks). In addition, any fixed costs associated with supplier or part qualification (which were shown in [1] to have a direct effect on the total cost of ownership) cannot be considered. This assumption, while acceptable for traditional procurement-driven systems, severely limits the effectiveness of the model in low-volume, long life cycle environments. Tomlin notes in [16] that adding fixed/support costs and varying lead times might require simulation-based optimization.

2) Infinite-horizon model. This restriction, which works for an idealized high-volume, short life-cycle scenario, doesn't incorporate cost of money or price change over time, which are necessary components of long life-cycle products.

3) Disruptions last full ordering periods (i.e., disruptions are delivered in full or not at all). Tomlin, in particular, employs an idealized Markovian disruption model (discussed in Section 3.3).

4) Secondary (a.k.a., emergency/backup) supplier is completely reliable. This assumption indicates that second sourcing consistently allows for an uninterrupted supply of parts (as long as all the suppliers have enough notice and capacity). This restriction ignores overlapped supplier downtime (independent probability distributions), which is a more realistic scenario (especially when it comes to industry wide shortages).

Table 1: Summary of differences between Tomlin's model and the simulation model in this thesis

	Tomlin (analytical)	**This Thesis** (simulation)
Calendar Time	While the sequence and frequency of periods are important, the infinite horizon assumption does not consider calendar time.	Calendar time is incorporated through several time-dependent factors such as WACC and price change over time.
Disruption Model	Markovian	Sampled probability distributions[11]
Sourcing	Backup/secondary supplier is completely reliable (undisrupted)	The expected durations and frequency of disruption are supplier-specific.
Capacity	Studies the impact of flexible supplier capacity and ramp-up time on the long-run average cost.	Assumes instantaneous and infinite capacity from available (undisrupted) suppliers.
Fixed Costs	No fixed order costs are considered.	Periodic and aperiodic (such as initial and termination costs) fixed

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[11] A three-parameter Weibull distribution was chosen as the disruption model for the simulation because it can mimic a variety of popular distributions (such as exponential and normal). However, this underlying distribution can be changed without any effect on the accompanying equations.

		costs are considered.
	In addition, the infinite horizon assumption eliminates the effect of both initial support costs (such as qualification and approval costs) and termination costs (such as obsolescence resolution and end of life support).	

3.3: Development of Reimplementation Method

While Tomlin [16] thoroughly outlines the methodology he developed and utilized to calculate the long-run average costs associated with various disruption scenarios, the actual resultant cost values were not given (the results were presented in a graphical format to highlight overarching trends). Before the simulation model could be validated against Tomlin's results, specific test points needed to be reproduced using Tomlin's methodology. The remainder of this section will describe the modified reimplementation method used to verify and reproduce these test points.

Tomlin employs a basic Markovian disruption model that designates each period as either disrupted/"down" or non- disrupted/"up". This model specifies the probability of the disruption ending each period (λ_{du}), and the total expected number of disrupted periods. While Tomlin utilizes an infinite cumulative distribution function to calculate the resulting steady-state uptime, he did not provide detailed calculations. Consequently, the reimplementation method presented in this thesis employs a truncated transition state matrix (Figure 7). This matrix converges over time and specifies a steady-state probability of the system being "up". The steady state values were estimated by raising the transition state matrix to the 256th power (a

common numerical approach to steady state estimation). This "percent uptime" designates how many periods within the life of the part are not disrupted.

State	0	1	2	3	4	5	6	7
0	λ_U	$1-\lambda_U$	0	0	0	0	0	0
1	0	0	1	0	0	0	0	0
2	0	0	0	1	0	0	0	0
3	0	0	0	0	1	0	0	0
4	λ_{du}	0	0	0	0	$1-\lambda_{du}$	0	0
5	λ_{du}	0	0	0	0	0	$1-\lambda_{du}$	0
6	λ_{du}	0	0	0	0	0	0	$1-\lambda_{du}$
7*	1	0	0	0	0	0	0	0

Figure 7: Example Transition State Matrix: $M=4$, $N=3$

The transition state matrix shown in Figure 7 is defined by the following four characteristics:

1) Size of matrix: $1+M+N$

2) 1: State space 0 (no disruption occurring)

3) M: State spaces representing the minimum number of disruption periods

4) N: State spaces representing the possible remaining disrupted periods (in excess of minimum) with which there is a constant probability of the disruption ending. Ideally N is infinity, but steady-state probabilities converge when N is a finite large number

The number of state spaces is truncated (from infinity to $1+M+N$) in order to produce a practical model. As such, the final possible state has a transition rate of 1 (returning the system to state 0, no disruptions).

In order to isolate the minimum number of modeled states required to produce the expected steady-state value, several transition state matrices (of varying sizes)

were tested within Matlab. Figure 8 shows a transition state matrix with an expected steady state probability of 90.07% and a minimum number of disrupted periods (M) equal to 20. The number of additional state spaces modeled (N) was varied from 0 to 300.
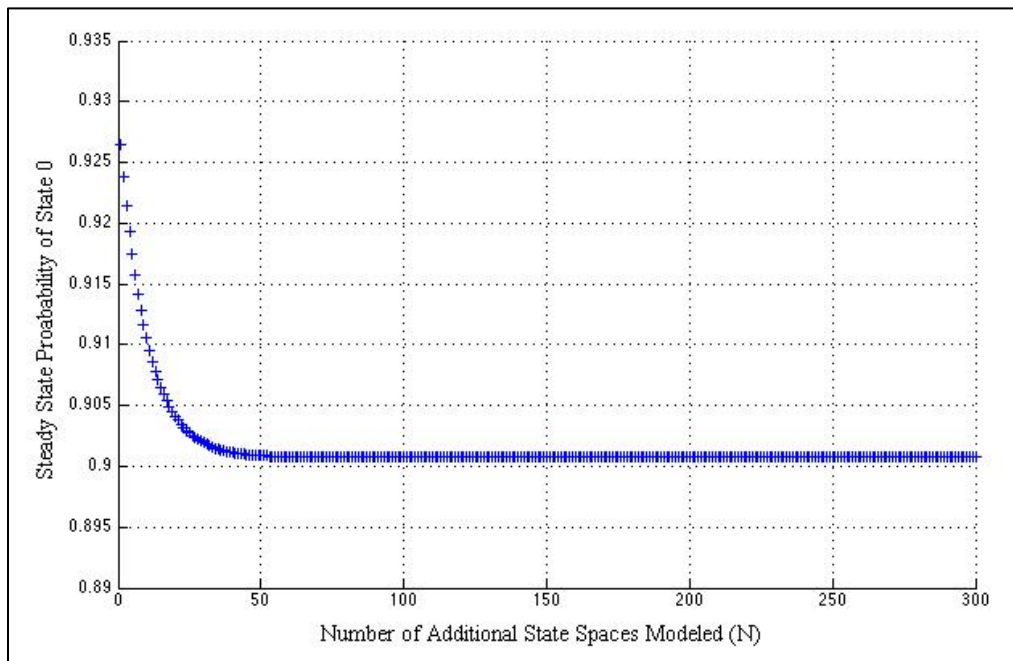
Figure 8: Steady-state probability of supply uptime (state 0) according to the number of modeled state spaces (N). The expected value for the shown scenario is 90.07% uptime.

As shown in Figure 8, the system converged to the expected steady-state value within 100 steps. Similarly, a transition state matrix with a steady-state probability of 80.01% and a minimum number of disrupted periods (M) equal to 40 was modeled and shown in Figure 9. The number of additional state-spaces modeled (N) was varied from 0 to 300.
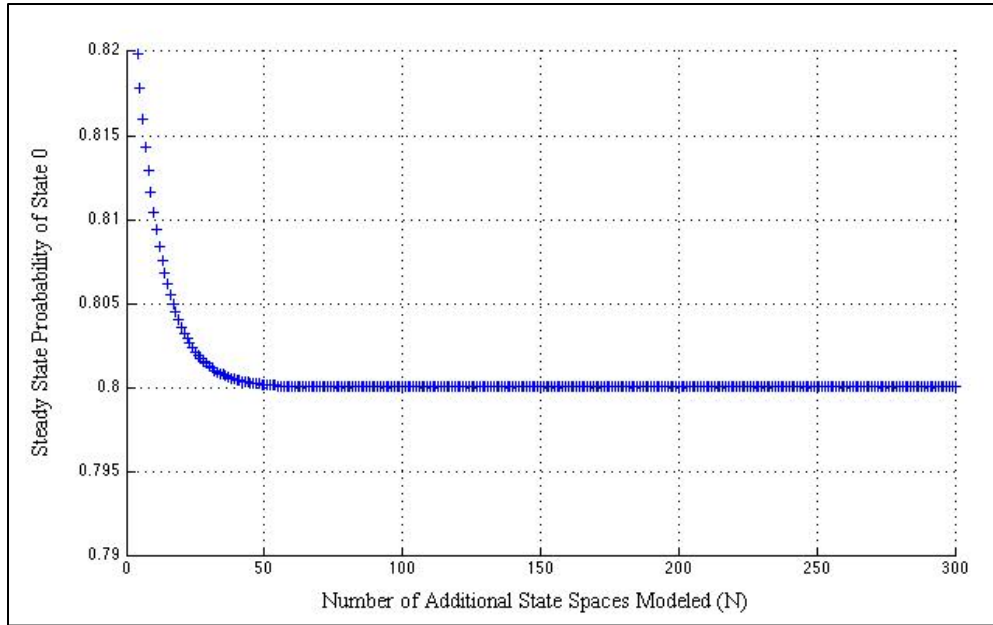
Figure 9: Steady-state probability of supply uptime (state 0) according to the number of modeled state spaces (N). The expected value for the shown scenario is 80.01% uptime.

Figure 9 shows that, once again, the system converged to the expected steady-state value within 100 steps. In addition to the Markovian disruption model discussed above, Tomlin developed equations utilizing this steady-state uptime and the resulting disruption probability distribution (along with a variety of other factors) to determine the optimal buffer quantity.

Tomlin specified a set of disruption scenarios (scenario: expected downtime, minimum downtime, % uptime) that were utilized in conjunction with specific case study inputs and equations to calculate the average expected cost associated with each of the three main sourcing strategies: contingent rerouting (or acceptance, a subset where the rerouted production = 0), inventory management, and sourcing management.[12] Before the outputs of the simulation model (Section 2.7) could be

[12] While Tomlin utilizes different terms to describe disruption mitigation strategies, each strategy can be directly linked to second sourcing and/or buffering. The three mitigation strategies he describes are: contingent rerouting [pure second sourcing (no buffering), rerouting production to the second/backup

verified against Tomlin's results, several test points had to be calculated. These points were calculated using only Tomlin's equations, inputs, and steady-state probability model. The output of these test points, shown in Figure 10, represents the mitigation strategy that produces the lowest average expected cost. As seen in Figure 10, with the exception of a few boundary points[13], Tomlin's results were reproduced using his methodology.
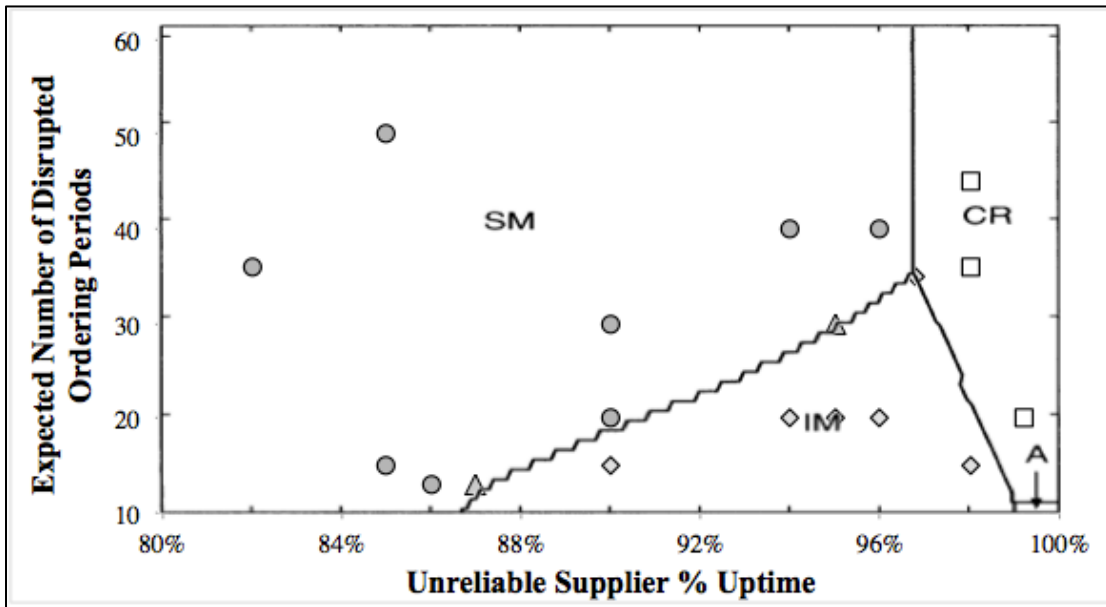
Figure 10: Optimal sourcing strategies organized according to total supplier uptime and expected disruption length. Scenario-specific inputs and equations that result in the solid lines shown are given in Tomlin [16]. The overlaid points show the mitigation strategy associated with *calculated* test points: Circles represent Sourcing Management, diamonds represent Inventory Management, squares represent Contingent Rerouting (CR), and the triangles represent equal cost for both Sourcing Management (SM) and Inventory Management (IM).

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supplier in the event of disruption], inventory management [pure buffering, single sourcing], and sourcing management [single sourcing from a reliable supplier, no buffering].

[13] In some cases near the region boundaries the calculated long-run average costs for boundary points were so similar that (in order to account for any possible rounding errors) two strategies were marked as equivalent. For example, for 95% unreliable supplier uptime and 30 expected disruption periods the long run average cost of buffering (IM) was found to be $1.050078, while the cost associated with single sourcing from the reliable supplier was found to be $1.050000. The discrepancy between the two values was too minute to allow for the prescription of one strategy as effectively dominant.

3.4: Simulation Model Modification

In order to make the simulation model match Tomlin's environment, several important model inputs were set to zero (support and termination costs - C_{sup}, cost of money - $WACC$, demand uncertainty,[14] price-change[15]). Removal of these effects, while necessary to reproduce Tomlin's result, severely impacts the realism of the modeled system (which will be shown in Section 3.5). The steady-state probability distribution for each scenario (scenario: expected downtime, minimum downtime, % uptime) was utilized in the simulation model in conjunction with Tomlin's case study inputs and equations to calculate the average expected cost (from a Monte Carlo analysis[16]) associated with each of his three main sourcing strategies. The calculated costs were then compared, and the optimal sourcing strategy (the strategy associated with the smallest cost) was selected. This method was employed repeatedly to generate points on a graph that correlated to the output presented by Tomlin shown in Figure 11. It is important to note that Tomlin's infinite-horizon assumption (infinite number of ordering periods) and Markovian disruption model (ordering periods are either fully disrupted or non-disrupted) are best applied to short ordering periods. In

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[14] Demand uncertainty, expressed as an annual standard deviation from the mean, is used within the simulation model to generate actual part demand from the forecasted part demand. Any unmet demand is backordered according to the equations given in Section 2.4.

[15] Due to ongoing relationships with part suppliers and the emergence of new technology, part prices generally decrease each year. Within the simulation model, this price change is modeled as a constant percentage of annual price reduction.

[16] The following Monte Carlo stopping criterion was employed to calculate an effective sample size (number of model runs): $(\frac{standard\ deviation}{0.015(mean)})^2 \leq sample\ size$. Due to time constraints, a standard error on the mean of less than 1.5% was employed (as opposed to 1%). A sample size of 100 model runs was found to meet the criterion for Tomlin's scenario.

order to recreate Tomlin's scenarios (Figure 11) the simulation model had to be run for 100-1300 simulated ordering periods. In the electronic part industry, ordering periods are typically a year in length and as such modeling 1300 ordering periods is unrealistic. Lifelike cases (which don't pertain to the limitations outlined in Section 3.2) will primarily have part lifetimes of less than 35 years or ordering periods.

The cases in Figure 11 are organized according to overall supplier uptime and expected disruption length (the combination of which characterizes the frequency of disruption). Scenario-specific inputs and equations that result in the solid lines shown in Figure 11 are given in Tomlin [16]. With the exception of a few boundary points, the simulation results aligned closely with Tomlin's results. This correlation serves not only to verify the results produced by the simulation model, but also to highlight the effectiveness of the simulation model as a decision-making tool.

Figure 11: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with *simulation* test points: Circles represent Sourcing Management, diamonds represent Inventory Management, squares represent Contingent Rerouting (CR), and the triangles represent equal cost for both Sourcing Management (SM) and Inventory Management (IM).

It should also be noted that allocation cannot be specified within the simulation model (i.e., it is not possible to specify ahead of time how much demand each supplier is responsible for) when implementing a second sourcing strategy. Instead, as mentioned in Section 3.1, this thesis focuses on the concept of instantaneous and infinite supplier capacity. It is therefore assumed that the primary unreliable supplier is contracted to supply all necessary parts, calling on the backup supplier for fulfillment of orders only in the case of a disruption event.

3.5: Validation Case Studies

The previous sections demonstrated that the simulation model described in this thesis is capable of reproducing the results obtained by Tomlin [16]. However, the simulation model does not have the same core restrictions. A simulation-based approach, while not capable of guaranteeing a formal optimum, is able to produce a practical, near-optimum value that incorporates both a greater amount of uncertainty and more complex parameters. This effective optimum can be calculated for realistic supply systems, and therefore can be more readily utilized as a decision-making parameter. In order to determine the impact of common analytical model assumptions, several case studies were performed. It should be noted however, that while the following case studies highlight important areas of weakness within common analytical models, they do not represent a comprehensive design of experiments analysis.

3.5.1: Fractional Disruption Periods

One of the underlying assumptions within the validation case (Section 3.4) is

the Markovian format of the disruption model. In Tomlin's [16] work, ordering

periods (defined as a full rotation of orders and fulfillment) are either up (non-

disrupted) or down (disrupted) as seen by the OEM. However, this generalized

model, while appropriate for scenarios where disruptions always last at least several

ordering periods, does not accommodate small-scale disruption events (such as

delivery delays) or disruptions that start/stop within an ordering period (resulting in

the delivery of a fractional order).

The simulation model presented in this thesis employs disruption distributions

(non-Markovian), which allow fractional orders to be delivered due to downtime in

the previous order cycle. In order to test the validity of Tomlin's model in these types

of disruption events, a modified version of the validation case study was performed.

The following model assumptions are important to note:

1) Disruptions in period i affect the order size delivered in period $i+1$. For

   example, if the disruption lasts 25% of year i (three months), then 25% of year

   $i+1$'s order will not be delivered on time.

2) Infinite-horizon assumptions are still in place (no cost of money or fixed costs

   are considered).

3) All of the inputs used in Section 3.4 (Appendix A.2) were preserved for this

   case study, with the exception of the expected disruption lengths.

4) When implementing fractional disruption periods into Tomlin's formulas for

   identifying i_{crit} [16] and the optimal inventory level, the number of modeled

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periods was rounded up to the nearest integer. The calculated values of i_{crit} are therefore a conservative estimate.

Figure 12: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with fractional disruption test points: Circles represent Sourcing Management, diamonds represent Inventory Management, and squares represent Contingent Rerouting.

As seen in Figure 12, the inclusion of fractional disruption periods has minimal impact on the optimal mitigation strategy. The simulated points still follow the underlying pattern defined by Tomlin.

3.5.2: Finite Horizon (WACC)

In order to study the impact of the infinite-horizon assumption within the validation case, a non-zero WACC ($r = 2\%$/period) was incorporated into the case study outlined in Section 3.5.1. Tomlin utilizes very long life cycles (100-1300 periods) and minimal recurring costs, so a WACC of 2%/period was chosen (as opposed to a more common value of 10-12%/year) in order to maintain reasonable differences between the cumulative total cost of ownership (CTCO) per part site

values. For example, in one of the most extreme cases (1250 modeled years and 98% supplier uptime) the CTCO per part site for second sourcing was found to be $0.040799998 and the CTCO per part site for single sourcing from the unreliable supplier was found to be $0.04080001 (a discrepancy of 10^{-8}). If the WACC was increased to a more standard rate, the CTCO per part site values would decrease even further (diverging even more from Tomlin's results). For the realistic case studies outlined in Chapter 4, a WACC of 10%/year was used.

Tomlin's model formulation [16] assumes that the WACC is zero (this is implicit in the definition of infinite horizon). Alternatively, the simulation model identifies the optimal mitigation strategy and inventory level by running a Monte Carlo analysis for each case and selecting the strategy with lowest expected cumulative part TCO, and any value of WACC can be used.

The optimal buffering strategy no longer aligns with the results from Tomlin's equations. Instead, the inclusion of cost of money (even at the very small WACC used) shifts the optimal buffering strategies so that fewer buffered parts are needed in the optimal strategy. For future times the WACC decreases the present value associated with each part, and the added value of buffering an additional part also decreases. In addition, the optimal mitigation strategies no longer match up with Tomlin's overlaid infinite-horizon results (shown in Figure 13). Instead, second sourcing (or a combination of second sourcing and buffering) becomes a much more viable option.
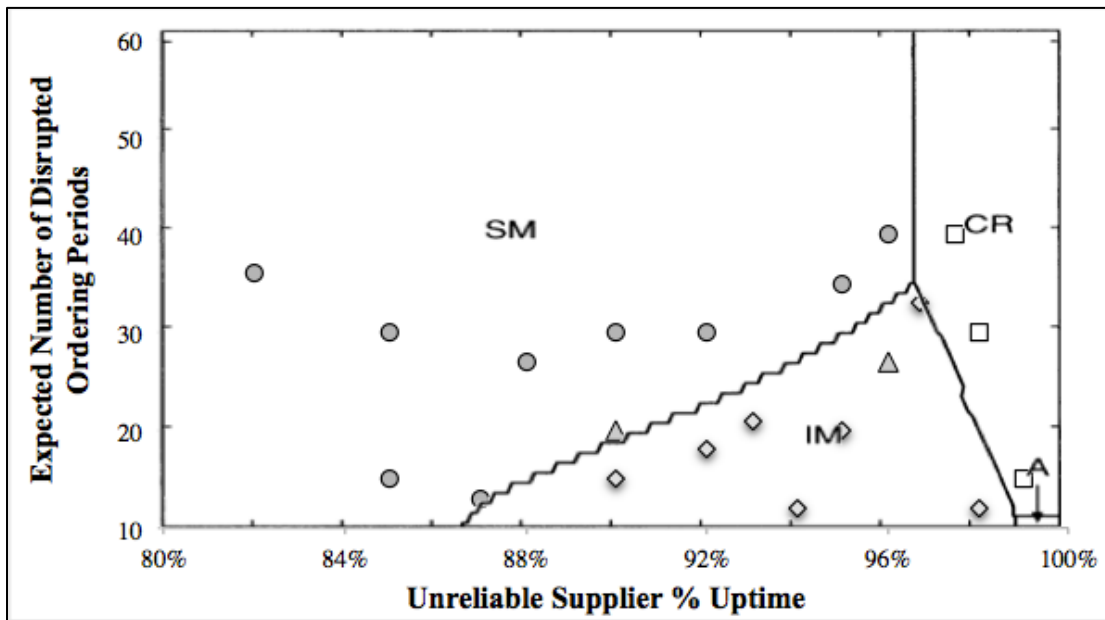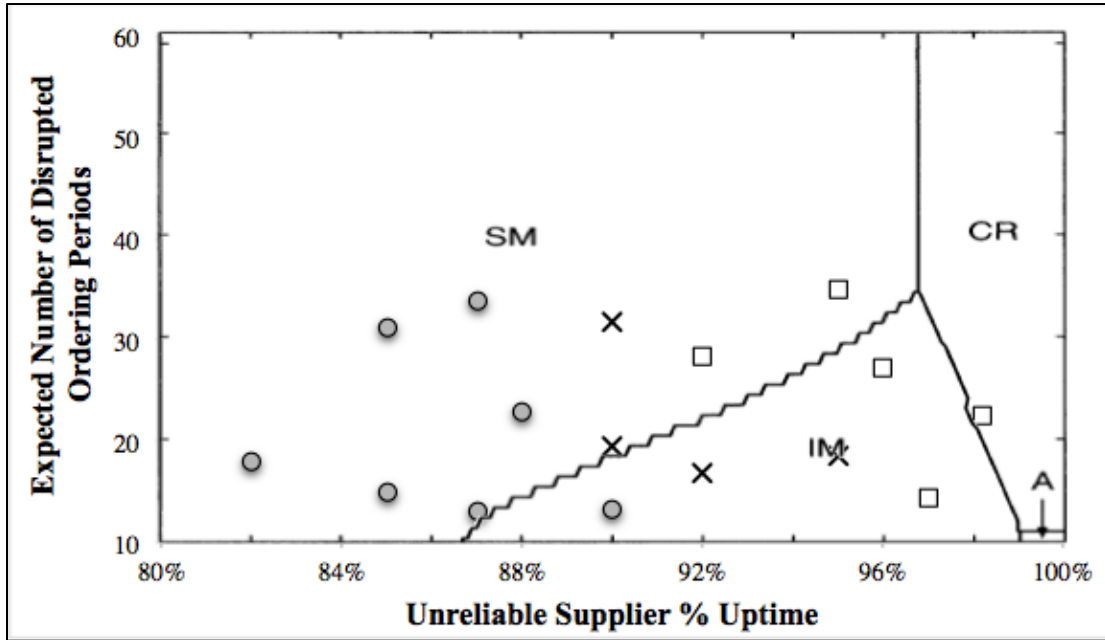
Figure 13: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with cost of money test points: Circles represent Sourcing Management, squares represent pure Contingent Rerouting, and X's represent a combination of both Contingent Rerouting and Inventory Management.

3.5.3: Unreliable Backup Supplier

The case study performed in this section assesses the effect of maintaining a completely reliable backup supplier. As mentioned in Section 3.2, this assumption gives manufacturers the option to pay a premium part price in order to ensure a consistently uninterrupted supply of parts. In realistic supply chains, however, supplier disruptions can never be completely prevented at any price and depending on the nature of the disruption, a backup supplier may be affected the same as the primary supplier.

An additional disruption profile was implemented into the simulation model in order to generate disruption events for the backup supplier. The parameters used to describe the disruption profile (Weibull distributions) are shown in Table 2. The parameters were selected to reflect significant disruption events (expected length: 1.6

ordering periods) that occur on average every 5.5 years. All of the other inputs used

for this case study are discussed in Section 3.5.1 and detailed in Appendix A.2. Once

again, the simulation model's internal optimization capabilities were utilized to

identify the optimal inventory level instead of Tomlin's [16] formulas.

Table 2: Weibull parameters used to generate disruption events for the backup supplier (Y).

	Backup Supplier (Y)		
	gamma (years)	beta	eta (years)
Interval	5	1	0.5
Length	1	1	0.6

The unreliability of the backup supplier, while less significant than the

unreliability of the primary supplier (i.e., less accumulated disruption) is further

exacerbated in this case study by the higher backup part price. As detailed in the

Appendix, the primary supplier has a set price of $1.00 per part and the backup

supplier has a set price of $1.05 per part (unless acting in emergency/secondary

backup capacity, in which case they charge $2.63 per part). In Tomlin's original case

study, the accumulated penalty costs associated with the unreliable primary supplier

outweighed the elevated price of the backup supplier because a continuous stream of

parts was guaranteed when single sourcing from the backup supplier. However, the

addition of disruption events at the backup supplier increases the total cost of

ownership and makes single sourcing from the less expensive unreliable supplier

generally more cost effective. In addition, in regions where single sourcing from the

backup supplier is more cost effective (relatively low values for unreliable supplier

percent uptime and high values for the expected number of disrupted ordering

periods) a small buffer is necessary in order to offset disruption events and achieve
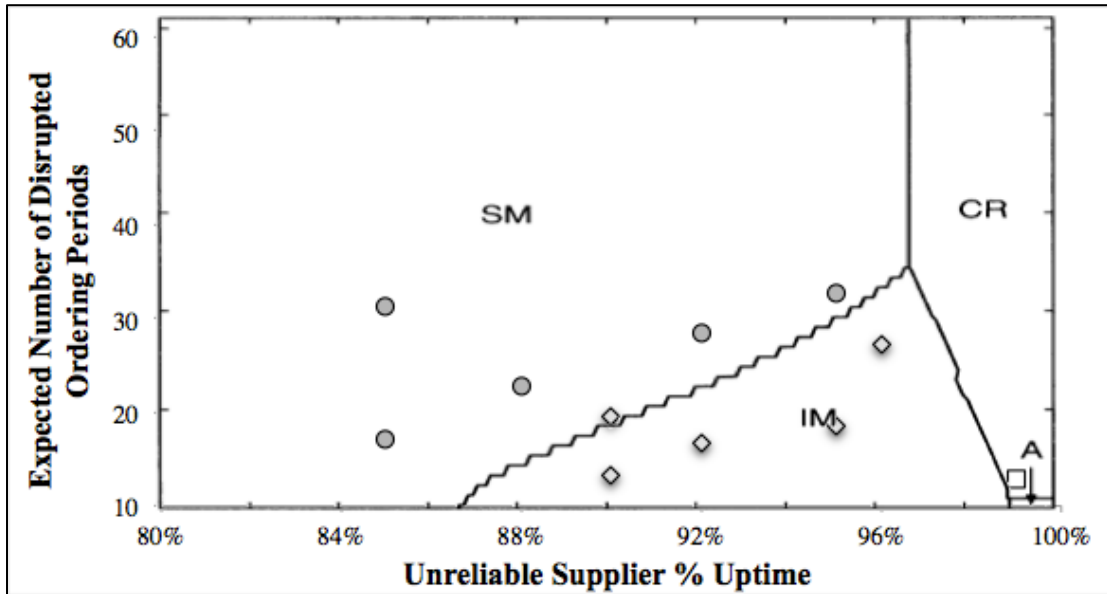
the lowest expected cumulative part TCO.
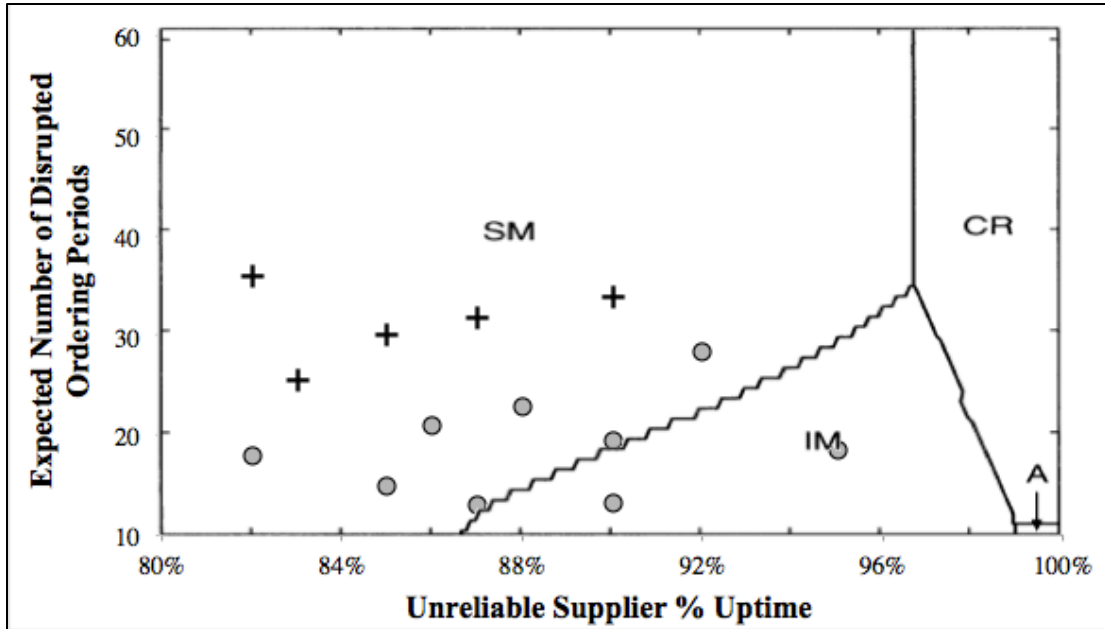
Figure 14: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with unreliable backup supplier test points: Circles represent Sourcing Management and +'s represent a combination of both Sourcing Management and Inventory Management.

3.5.4: Fixed Costs (Qualification and Support)

In his 2010 dissertation, Prabhakar [1] noted the impact of fixed costs (support costs in particular) on the part total cost of ownership of low volume electronic parts and systems. Low volume, long life cycle products cannot spread the effect of fixed costs over a large part population, so elevated support costs directly impact the TCO per part site. The majority of analytical disruption models, however, focus on long run average costs due to the minimal impact of initial support costs on high volume consumer electronics. In order to study the effect of the fixed costs omission within the validation case, a $1000 product specific approval cost was added to the case study outlined in Section 3.5.1. Similar to the reasoning behind the use of a small WACC in Section 3.5.2, a relatively small product specific approval cost was employed in this case study so as not to unduly offset the small CTCO per part site values accumulated in Tomlin's original case study. Product specific approval costs

are a common form of support costs that are incurred each year a product is introduced and charged for each contracted supplier.
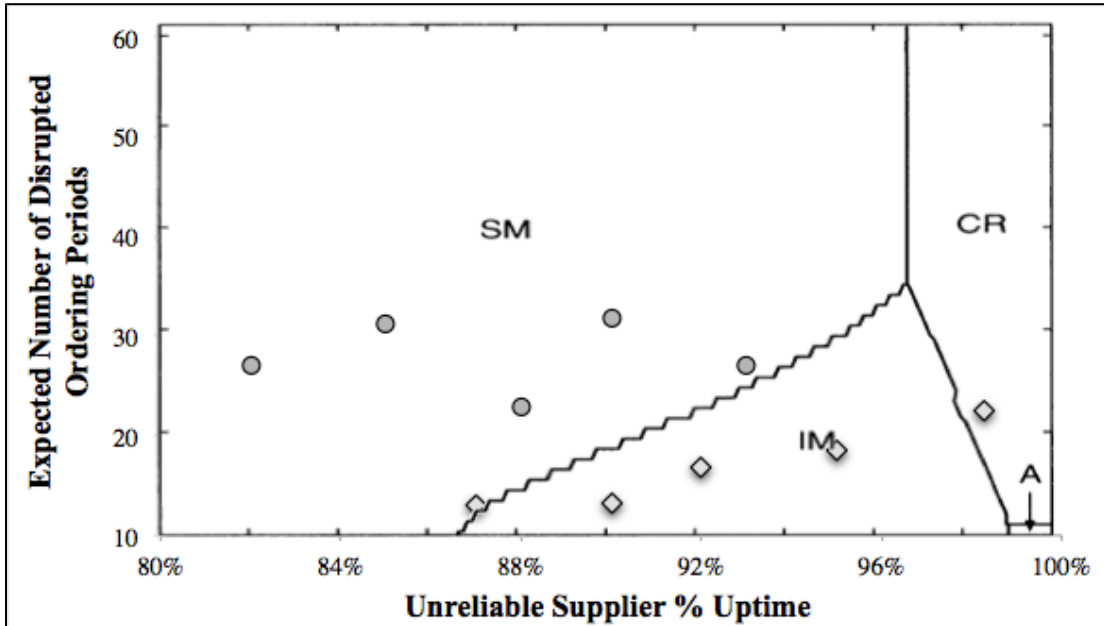
Figure 15: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with support cost test points: Circles represent Sourcing Management and diamonds represent Inventory Management.

As shown in Figure 15, the addition of fixed costs does not have a marked effect on Tomlin's original case study results for disruption scenarios with relatively small-moderate values of overall percent uptime. However, for scenarios with a higher percent uptime (less accumulated disruptions), the effective optimal disruption strategy switches from contingent rerouting to inventory management. This change in results is due to the fact that support costs are duplicated (K factor of 1) when the manufacturer contracts two suppliers. The combination of elevated support costs and a premium emergency part price ($2.63 per part from the backup supplier when acting in an secondary/emergency capacity) causes contingent rerouting to be less cost effective than inventory management.

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Chapter 4: Implementation of Real-World Disruption Data

This chapter presents historical supply-chain data gathered from a variety of sources. The part delivery data is then transformed into inputs for the simulation-based model and used in case studies that focus on realistic issues in modern electronic part supply chains.

4.1: Historical Supply-Chain Disruption Data

As of now, no standard record-keeping practices exist for disruption events within the low volume, long life cycle electronic part industry. Instead, individual companies are responsible for selecting and preserving data that they deem relevant to their own interests. For this reason, historical supply-chain disruption data varies greatly and stems from a variety of sources. In this section, the following sources of historical electronic part supply-chain disruption data are explored: public electronic part demand information, supplier and manufacturer lead time quotes, manufacturer supply-chain databases, and electronic part distributor delivery data.

4.1.1: Public Electronic Part Demand Information

Figure 16 shows the worldwide market billings for semiconductors recorded by the Semiconductor Industry Association between July 2011 and June 2012 [24]. This publicly available part demand information was compared against the lead-time fluctuation data from SiliconExpert [25] (Figure 17) for the same time period. Intuitively, one would expect that the periods associated with the greatest lead times (March, May, and August of 2012) would coincide with the periods of highest

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demand, as manufacturers rush to fill outstanding orders and keep up with growing

demand. However, as shown in Figures 16 and 17, there doesn't appear to be a

correlation between customer demand trends (inferred from market billings) and

supplier lead time. It should be noted, however, that suppliers typically bill

manufacturers for *delivered* parts (as opposed to ordered parts), so the market billings

shown in Figure 16 may need to be shifted by the parts' lead time in order to truly

represent demand.
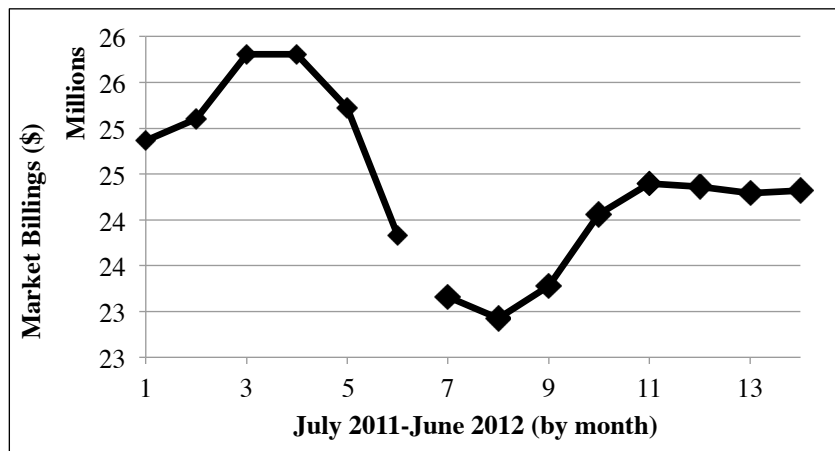
Figure 16: Worldwide market billings (three-month moving averages) recorded by the Semiconductor Industry Association (SIA) [24]
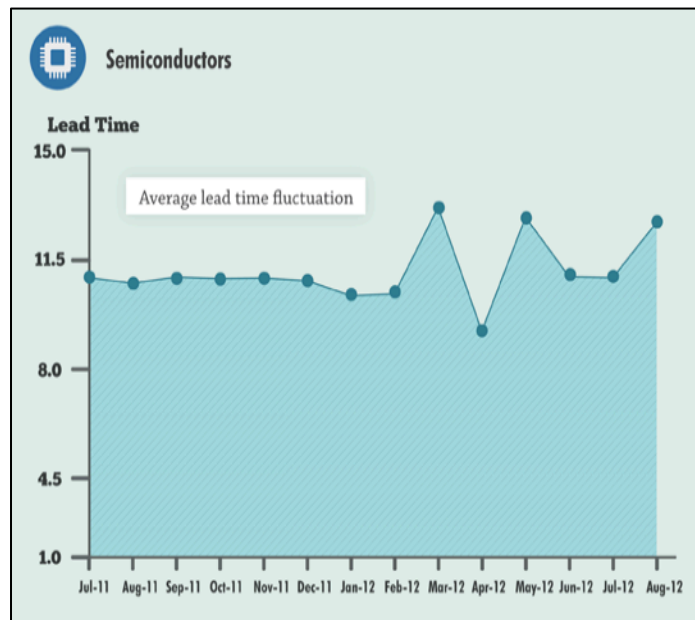
Figure 17: Semiconductor lead time fluctuations recorded by SiliconExpert [25]

Figure 18 shows the decrease in price experienced by a selection of transformers as recorded by Arrow (an electronic part distributor). While this data does not reveal any disruption-specific information, it does provide average values for annual part price-changes. Similar to the effect of the WACC, annual part price decreases can dramatically affect the cumulative part TCO (especially for long life-cycle products) and as such should be monitored and considered in cost calculations. Transformer T4 experiences a 7% annual price decrease on average, as determined from Figure 18. This value was used as the annual single-sourcing price-change in the case studies presented in the following sections.
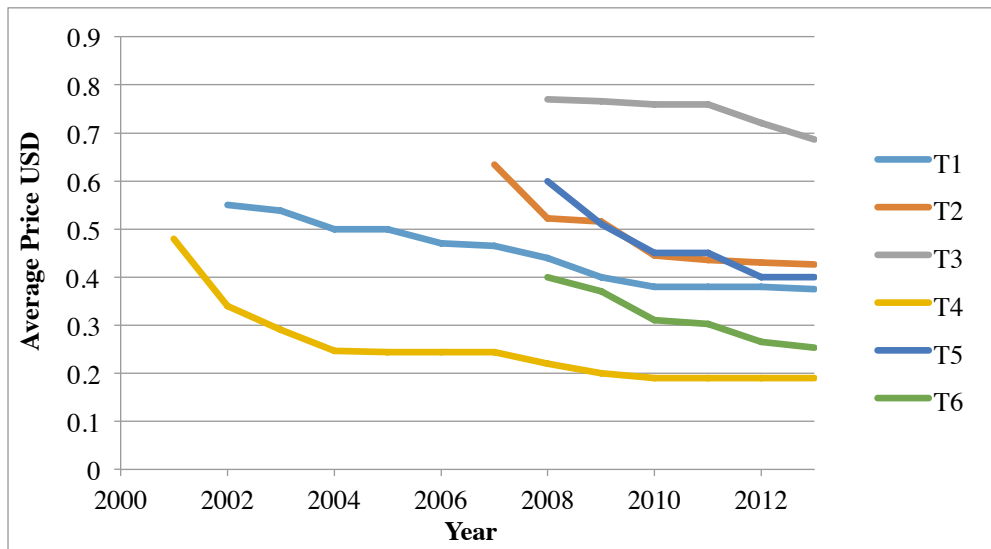
Figure 18: Average prices recorded by Arrow for a selection of electronic parts (specifically transformers) from 2001-2013. [26]

4.1.2: Supplier and Manufacturer Lead Time Quotes

Figure 19 shows a compilation of 2010-2011 supplier lead-time quotes for select electronic parts from the SiliconExpert database. This data does not take bulk negotiations or customer priority into account. While the given data is by no means exhaustive, there seems to be some correlation between part type and lead time.

(noticeably different distributions). However, the data was censored to protect

proprietary supplier information, so the lead time trends may simply be supplier-

specific.
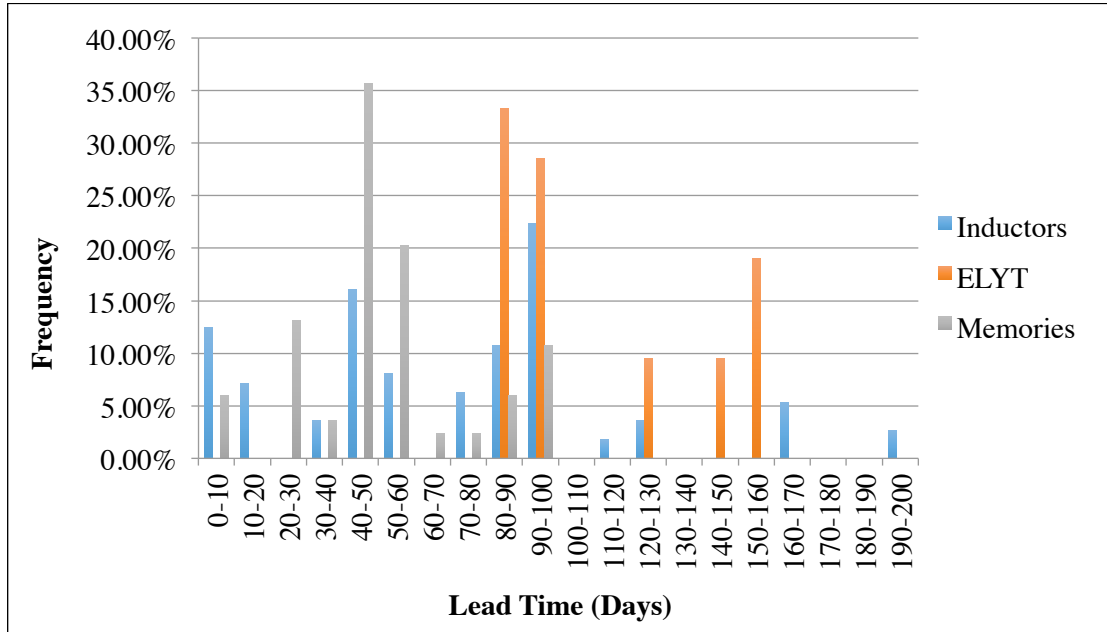
Figure 19: SiliconExpert supplier lead time quotes for a selection of inductors, ELYT, and memories in 2010-2011. [27]

Figure 20 shows the lead time data collected from Ericsson during the same

time period (2010-2011) for similar electronic parts and suppliers. The quoted lead

time values provided by SiliconExpert far outlast the quoted lead times shown in

Figure 19. The inconsistency of recorded lead time quotes prevents them from being

effective indicators of disruption events and backordered parts.
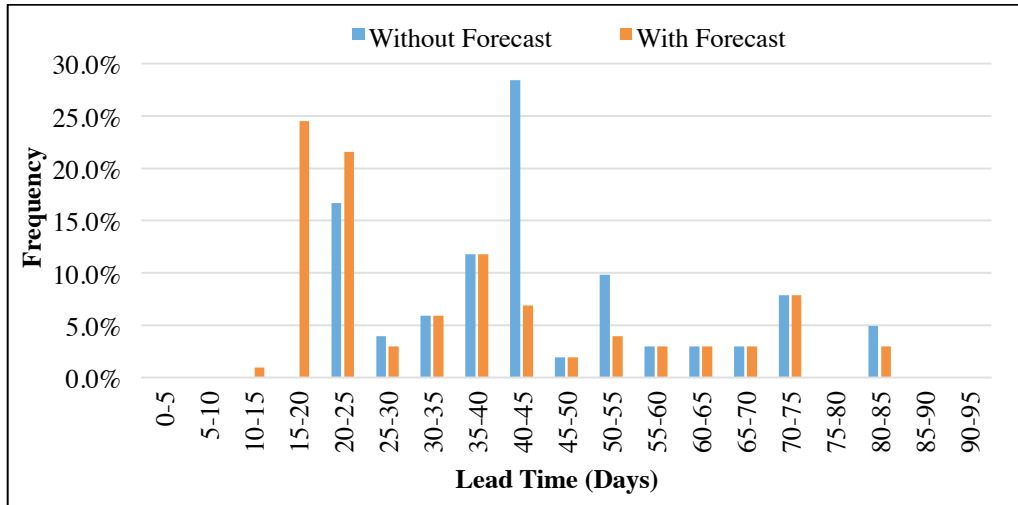
Figure 20: 2010-2011 Supplier lead time quotes supplied by Ericsson for a selection of electronic parts.
[28]

4.1.3: Manufacturer Supply-Chain Databases

Some manufacturers are beginning to centralize their disruption data within overarching supply-chain databases. Figure 21 shows an example of Ericsson's efforts to compile and study disruption information for a sampling of electronic parts. The communication infrastructure company notes how long (in weeks) it takes for a supplier to deliver ordered parts after the onset of a disruption event.
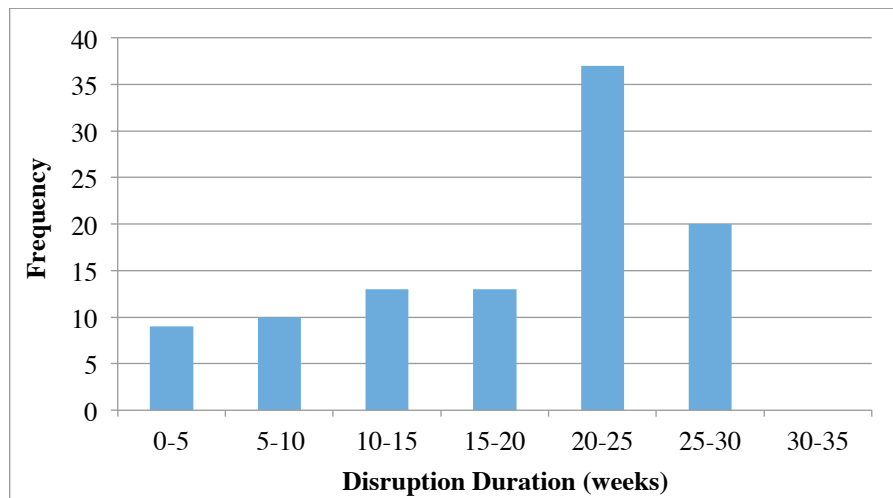
Figure 21: Time to first delivery from the onset of a disruption for a compilation of electronic parts (as recorded by Ericsson from 2010-2011). [28]

However, while this data definitely helps to quantify manufacturer-specific disruption risk, the centralization of disruption data is a relatively new concept. Manufacturers that are just beginning to track and store disruption data won't necessarily have part disruption histories of an adequate length or scale to perform statistical analysis.

4.1.4: Electronic Part Distributor Delivery Data

Figure 22 shows electronic part distributor delivery data from 2007 to 2013. This data not only serves to highlight the size and frequency of part orders as seen by the distributor, it also allows the isolation of discrepancies between scheduled and actually delivery dates. The graph in Figure 22 shows how long it took delayed parts to reach the distributor.
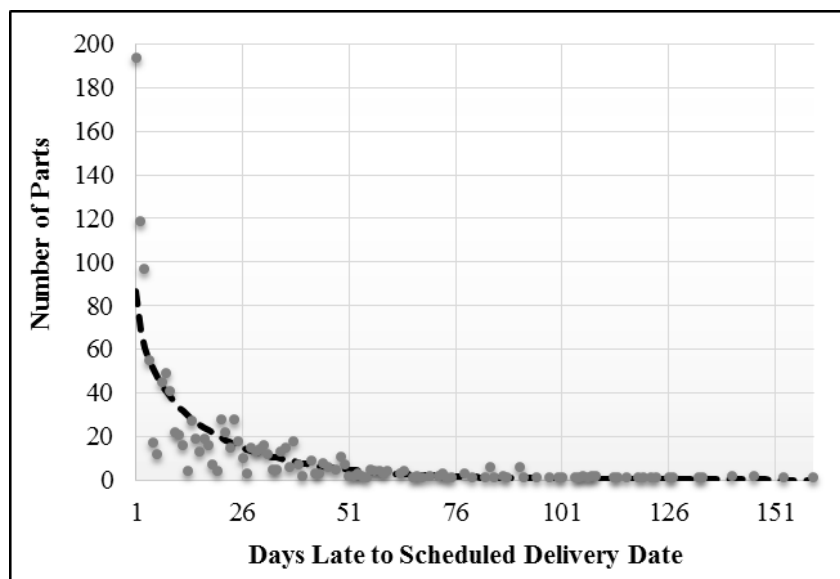
Figure 22: 2007-2013 Distributor delivery data for a sampling of integrated circuits and transformers. [29]

While the data in Figure 22 does not fit into a traditional Markovian format (a common input for existing analytical models), it can be transformed into a useful input for the disruption model where its effect on the total cost of ownership can then

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be quantified and studied. While the data received is directly connected to disruptions at the distributor level, an additional offset factor could be applied to the parameters in order to effectively modify the data for use by original equipment manufacturers (essentially left- censoring the data to accommodate distributor mitigation activities) Ideally, one could build and generalize the disruption models so that they can be applied on a part, product, or supplier specific basis.

The raw delivery data (such as the data shown in Figure 22) was organized into frequency bins according to disruption length, i.e., 20 parts experienced a one-week delay, ten parts experienced a two-week delay, etc. The binned data can then be used to generate a disruption probability distribution. In this thesis, Weibull++ software was used to fit the data to a three parameter Weibull distribution. The parameters used to describe this distribution (shape, scale, and location) are direct inputs for the model. Figure 23, shows the curve that was generated using the delivery data and Weibull++.
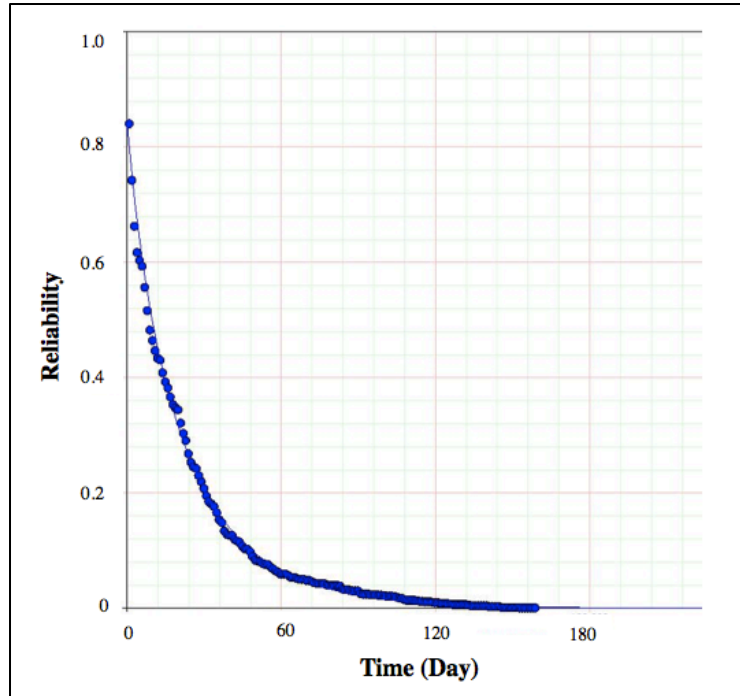
Figure 23: Weibull curve fit of the distributor data in Figure 22. The curve parameters are automatically calculated by the software and listed beside the output (beta: 0.834, eta: 18.726 days, gamma: -2.358 days)

In the model, each time a disruption begins (intervals between disruptions are governed by a second Weibull distribution) a random value is selected from this probability distribution and set as the length of the disruption event. The penalty costs associated with these events are then calculated for each year of the part's life and added to the base part TCO. These two steps are then repeated for a series of Monte Carlo runs in order to produce a distribution for the expected part total cost of ownership.

4.2: Case Studies

While the theoretical case studies performed in Section 3.5 helped to isolate the importance of individual parameters, the modeled scenarios were simply not

realistic. As shown in Section 4.1, part and disruption data can be very complex in the real world. The following case studies focus on the implementation of realistic data from low-volume electronic parts. In particular, the case studies were selected to reflect the following popular issues within the low volume, long life cycle electronics industry: proactive disruption mitigation strategy selection, identification of the effect of part volume on the optimal mitigation strategy, and the implementation of time-dependent disruption profiles.

4.2.1: Mitigation Strategy Case Study

The primary case study performed using the simulation model was developed in order to analyze the effect of both second sourcing and buffering on realistic electronic part supply chains. As discussed in Section 2.3, the purpose of buffering is to delay the negative effects associated with supplier disruption. In other words, part buffering allows production to continue during a supplier disruption. This extension of the available production period reduces the penalty cost associated with unfulfilled demand. All the data used for the example case in this section is provided in the Appendix. The inputs were chosen to mimic the real-world costs associated with an ISDN transformer.

Figure 24 shows a comparison of cumulative TCO for a given part and a unique set of disruption events assuming no buffering. The modeled disruption events and the correlating backordered parts associated with Figure 24 are shown in Figure 25. A K value of 1 (see Chapter 2) was assumed in order to demonstrate the worst case of second sourcing, i.e., complete duplication of support costs. Figure 24 shows

that for a unique set of generated delivery delays and the given inputs, second

sourcing is much more cost effective than single sourcing.
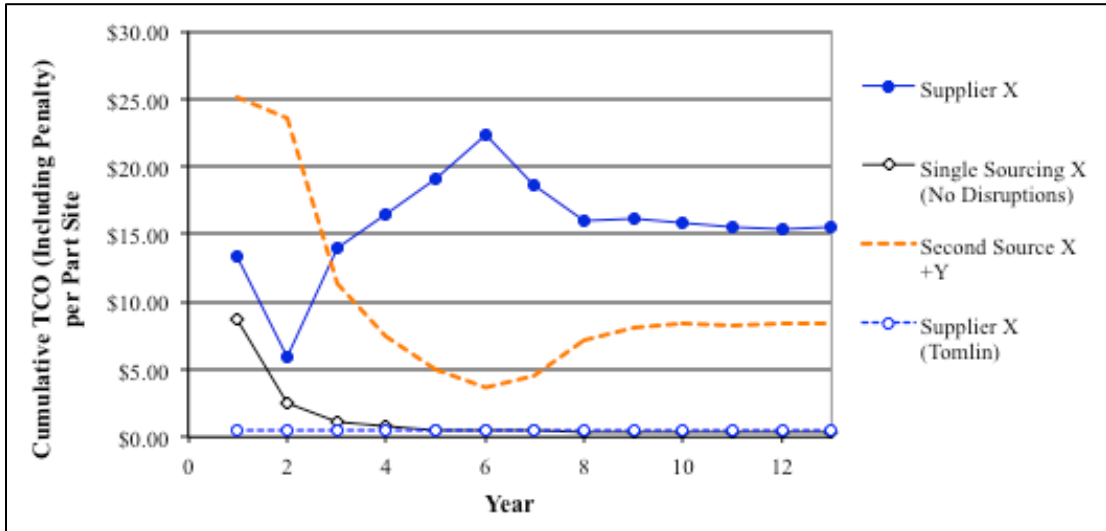
Figure 24: Cumulative part TCO (including penalty) over a 13 year period for a selection of sourcing strategies and no buffering.
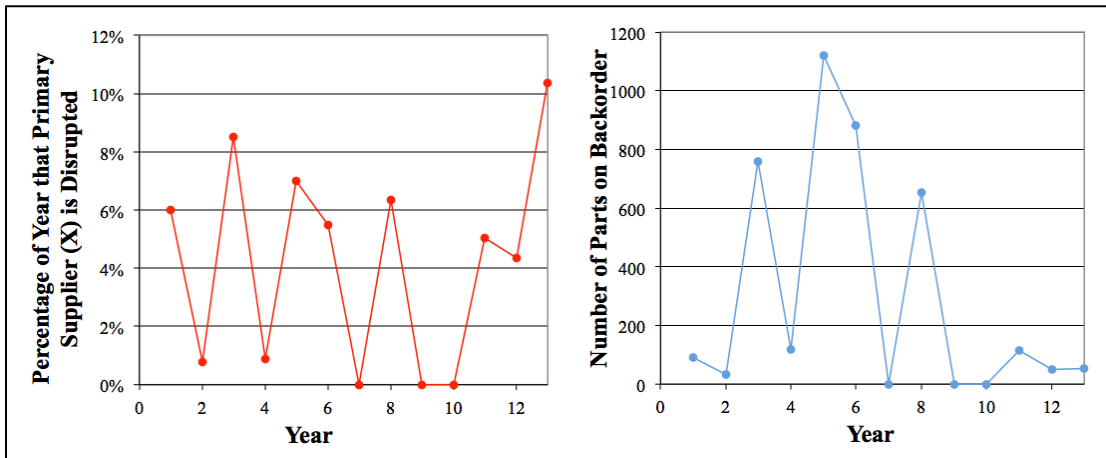
Figure 25: The percentage of each year in the parts 13-year life cycle that the primary supplier is disrupted (left), and the total number of backordered parts due to the disruptions (right). The parts on backorder correspond to a single sourcing strategy with no buffer.

A Monte Carlo analysis was performed in order to accommodate disruption

uncertainty and isolate the expected cumulative TCO. As shown in Figure 26, second

sourcing decreases the mean cost per part site from $20.93 to $11.99, which (for the

100,000 part population modeled) correlates to a total cost avoidance of $894,000.

However, a large variance in possible values exists. This variance, i.e., uncertainty, is major source of risk for a company.
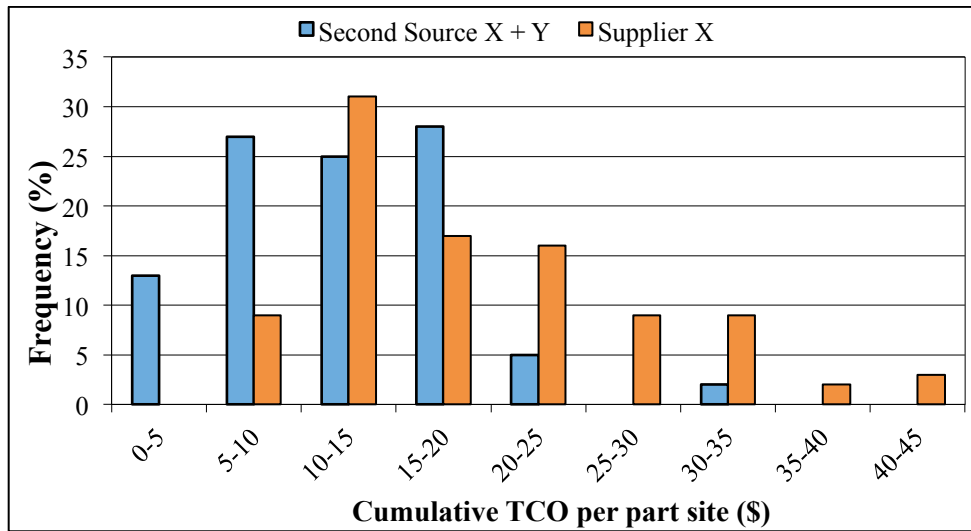
Figure 26: A comparison of the expected cumulative TCO for two sourcing strategies (without any buffering) for the given inputs.

The effect of buffering, on both single and second sourcing strategies, is shown in Figures 27 and 28. Figure 27 shows that while second sourcing was once again preferred over single sourcing for a generated set of disruption events, the addition of a 10-week buffering strategy caused the final cumulative TCO's associated with each strategy to be much less than their counterparts in Figure 24.
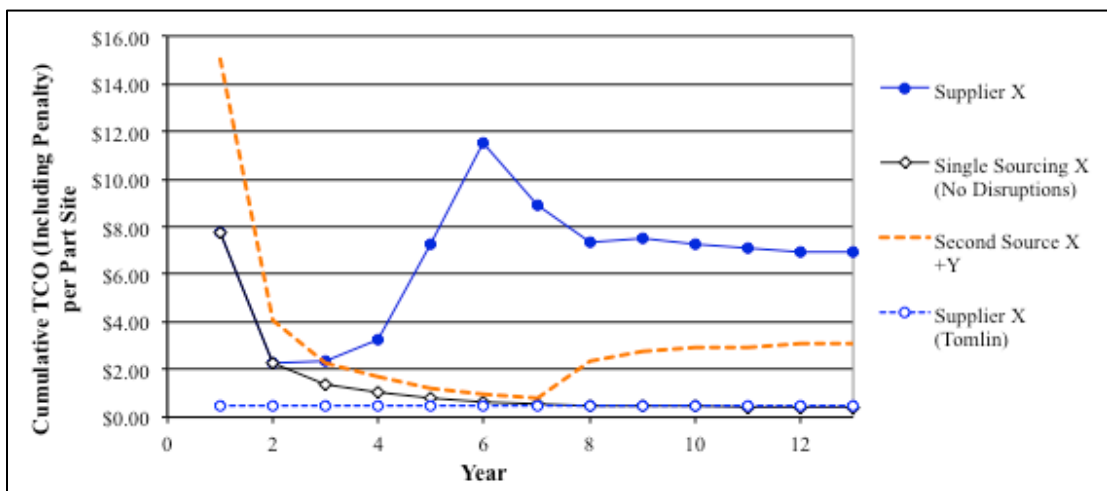
Figure 27: Cumulative part TCO (including penalty) over a 13 year period for a selection of sourcing strategies and 10-weeks buffering.

After the performance of a Monte Carlo analysis, the incorporation of a 10-week buffering strategy was found to further diminish the mean cumulative TCO when compared to the non-buffering cases in Figure 28. Also, by reducing the effect of supplier downtime, the spread of the possible TCO was significantly decreased for both sourcing strategies. For the second sourcing case with no buffering (shown in Figure 26), the standard deviation was $5.99. When a 10-week buffering policy was incorporated in Figure 28, the standard deviation was reduced to $3.94.
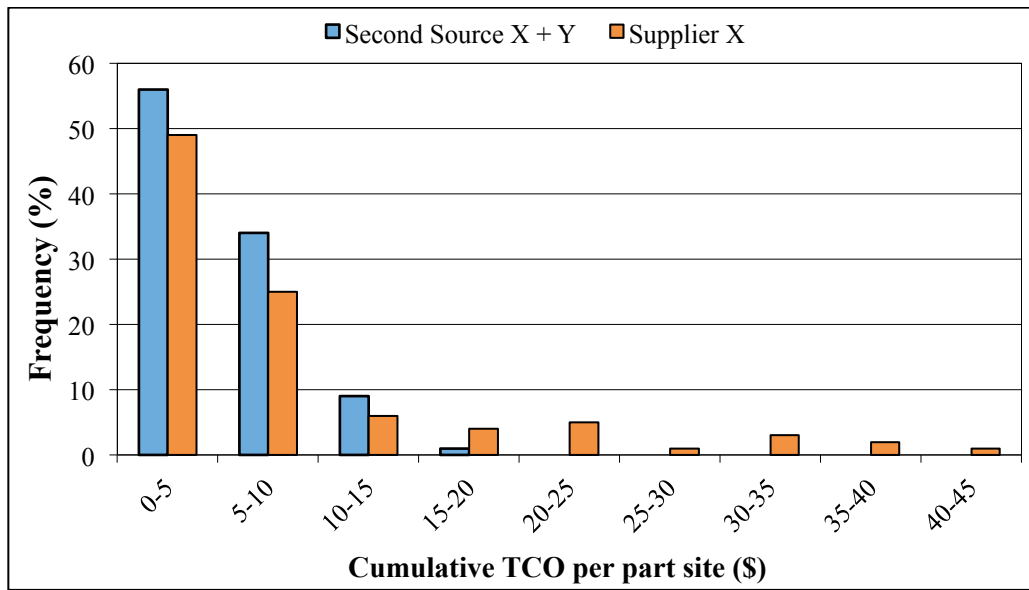
Figure 28: A comparison of the expected cumulative TCO for the two sourcing strategies considered in Figure 26 after the incorporation of a 10-week buffering strategy.

While the implementation of buffering as a mitigation strategy was effective under the given set of conditions, buffering may not always reduce the part TCO. For example, as shown in Figure 29, if the holding cost (per part per year) associated with excess inventory is very large then buffering would only serve to increase part TCO.
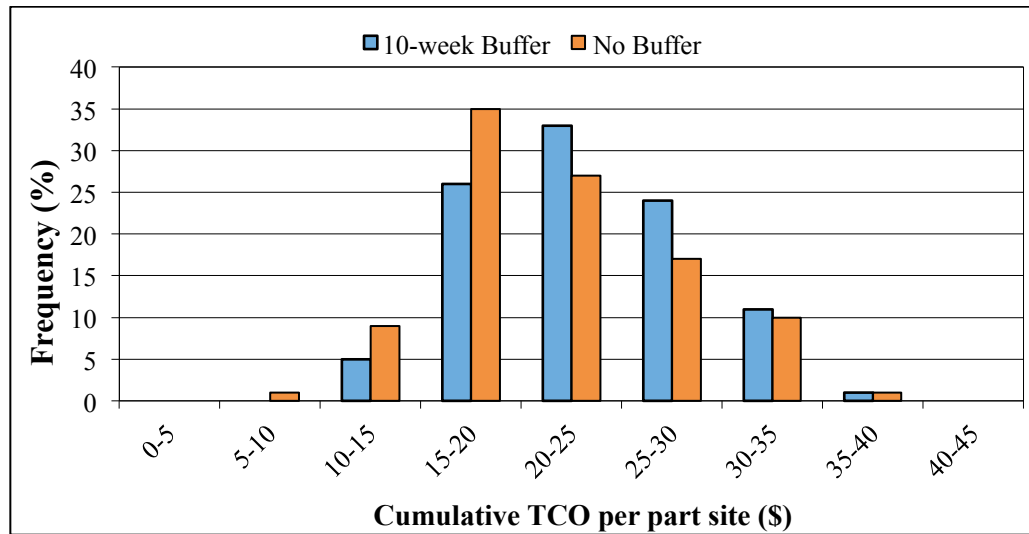
Figure 29: A comparison of the expected cumulative TCO for second sourcing with and without buffering given a holding/inventory cost of $125 per part per year.

The graph in Figure 29 was generated with the same inputs used in the case study with one notable exception: the holding cost per part per year was increased from $0.05 to $125. While this increase in holding cost is unrealistically large, for the given set of conditions in this case study, a 10-week buffering strategy effectively reduced the mean part TCO up to this level of holding cost.

In order to isolate the most effective buffering strategy for the given inputs (with the holding cost adjusted back to $0.05), the simulation model's internal "optimizer" was employed. The "optimizer" performs a Monte Carlo analysis for a specified range of buffering strategies. The expected CTCO per part site values are then calculated from the results of these Monte Carlo runs for both single and second sourcing. Figure 30 shows a plot of the expected CTCO per part site values for both single and second sourcing and range of buffer sizes. For the given inputs and disruption profile, single sourcing from the primary supplier with an 80-week buffering strategy is the near-optimum disruption mitigation strategy.
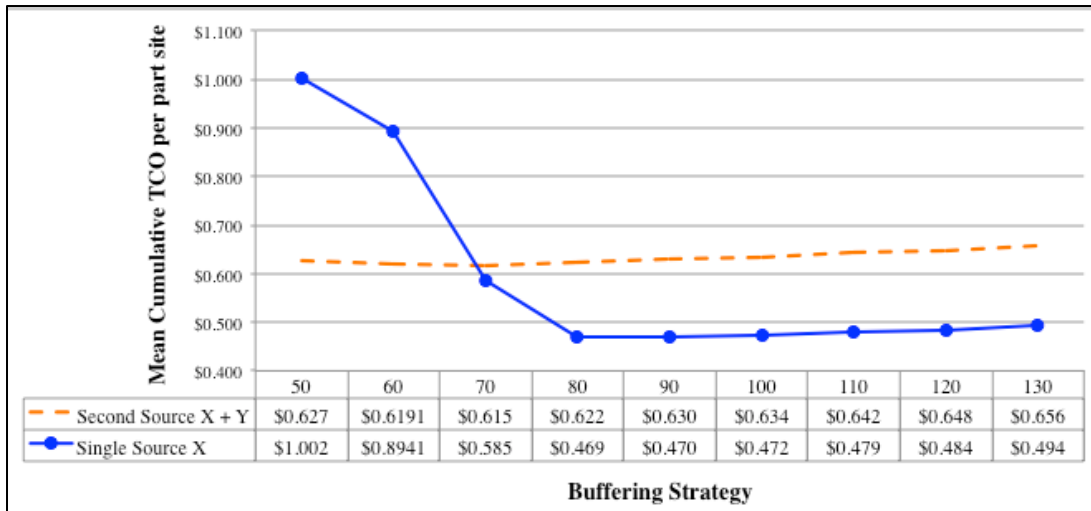
Figure 30: Mean cumulative total cost of ownership per part site for a range of buffer sizes and sourcing strategies.

The data presented in Figure 30 also reveals that when the buffer size is small (less than 70 weeks) second sourcing is more cost effective than single sourcing. However, the limited effect of accumulated holding costs combined with reduced support costs (when compared to the duplicated support costs associated with second sourcing) makes single sourcing the more economical option overall.

Tomlin's analytical disruption model (Section 3.3) was also utilized to analyze this case study, and all of the calculated CTCO per part site values were found to be equal to the initial part price ($0.48), as shown in Figure 31. Note, the majority of the inputs for this case study are not supported by Tomlin's model (WACC, support costs, part price change, and disruption uncertainty in particular). One of the most restricting factors (in this case study) stems from the fact that the Tomlin's model is only able to model disruptions that last full ordering periods. While Section 3.5.1 showed that the *incorporation* of fractional disruption periods has a minimal effect on the optimal disruption mitigation strategy, Tomlin's analytical model (as is) cannot accommodate non-Markovian disruption models and

therefore cannot be applied to scenarios where disruption events are shorter than ordering periods. As the probability of a disruption lasting a year for the given disruption profile (from distributor delivery data) is 6.27×10^{-5}, no disruption events were generated/modeled within Tomlin's approach.
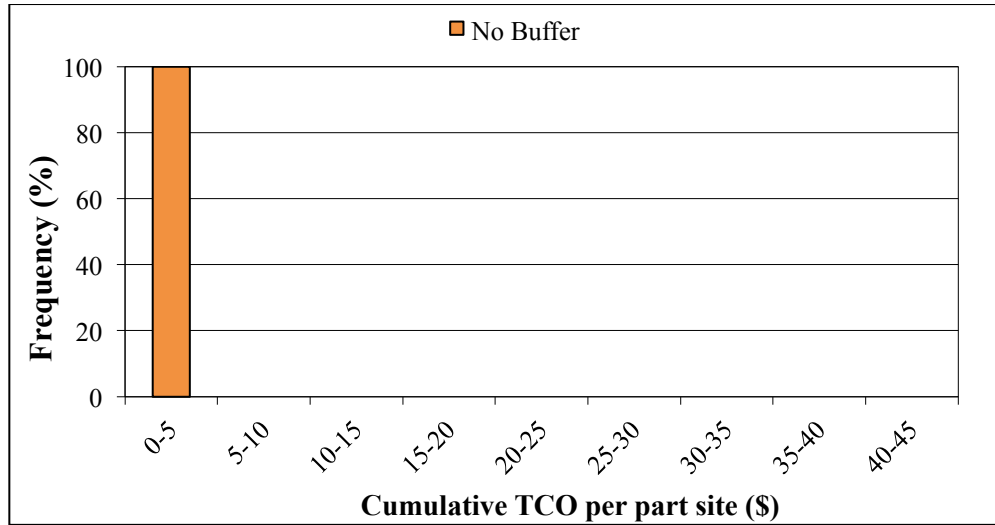
Figure 31: The expected cumulative TCO for second sourcing (without buffering) calculated used Tomlin's methodology.

This case study demonstrates the importance of utilizing proactive mitigation strategies in the presence of supply chain disruptions. The results, presented in Figures 24-30, quantitatively reveal how the implementation of second sourcing and buffering can directly affect the part TCO. In addition, Figure 30 exhibits just how much incremental changes to the mitigation strategy can affect the overall part TCO, highlighting the importance of careful strategy selection.

It should be noted that while the data for this case was carefully selected to produce realistic populations and results, some of the inputs do not represent true historical data. The disruption profile was taken from the delivery delay data presented in Section 4.1 (correlating to an expected annual disruption length of 0.05

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years). Each Figure .shows the results of a Monte Carlo analysis that was employed to include the impact of uncertainty on the part TCO.

4.2.2: Part Volume Case Study

One of the most prevalent and essential questions posed by low volume, long life cycle OEMs is how does the optimal disruption mitigation strategy relate to product volume? Manufacturers have noted that the additional verification costs incurred by maintaining additional suppliers can decrease favorability of second sourcing for low volume products. This case study assesses the relationship between the optimal mitigation strategy (lowest expected part TCO) and part volume in order to provide OEMs with an effective decision making tool. The following two variables will form the basis for the case study:

1) Part Volume (1,000 – 1,000,000): cumulative demand of all products

2) Product-Specific Approval (PSA) Costs (0 - $100,000): incurred each year a product is introduced and charged for each contracted supplier. So while second sourcing can offset the impact of disruption events, it also carries increased support costs when compared to single sourcing.

The case study implements realistic data from low-volume electronic parts, primarily ISDN transformers. The full set of inputs utilized in this case study is detailed in Appendix A.6.

The disruption profile selected for the initial version of the case study generates rare but significant disruption events (e.g., the primary supply experiences about 40 weeks of disruption about every five years). A *K* factor of 1.0 was employed

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in order to model a complete duplication of support costs for each additional supplier.

A single product design (PSA cost only charged in year 1) was modeled in order to

isolate the effect of part volume. As the holding cost utilized in this case study is

minimal ($0.05 per part), buffering is a generally effective method for decreasing the

part TCO. The addition of second sourcing, as shown in Section 4.2, can offset the

effect of disruption even further by ensuring a redundant supply of parts. However,

the duplicated support costs associated with a secondary supplier can negate the cost

benefits of a redundant part supply.

  The results from the initial version of the case study, shown in Figure 32,

indicate that a combination of second sourcing and buffering is always preferable for

the given disruption profile and inputs (regardless of part volume or PSA costs). The

accumulation of penalty costs associated with the major disruption events was so

significant that the benefits of second sourcing outweighed the accompanying effect

of increased PSA costs regardless of the part volume.
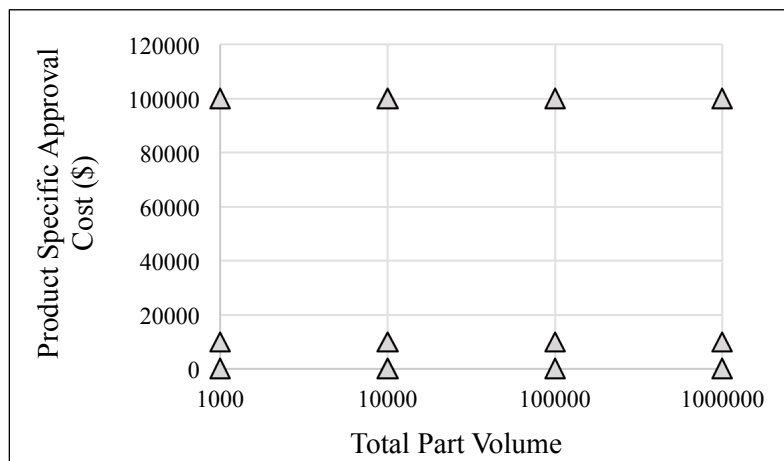
Figure 32: Optimal sourcing strategies for select combinations of product specific approval cost and
total part volume. As indicated by the triangles, the optimal sourcing strategy was always a
combination of second sourcing and buffering for the given inputs.

In addition, the optimal buffer levels for each modeled case were tracked, in increments of 30 weeks, and compiled in Figure 33. The buffering strategy remained relatively constant (at 210 weeks) regardless of part volume or support costs. However, for a total part volume of 1,000 parts, the optimal buffering strategy was one increment lower (180 weeks). This discrepancy is due to the fact that the simulation model only models full parts (as opposed to fractional parts). As mentioned previously, the buffering strategy accounts for a *fraction* of the forecasted annual part demand. When the total part volume decreases, the effect of rounding down to the nearest part increases, which in turn results in a lower buffering strategy.
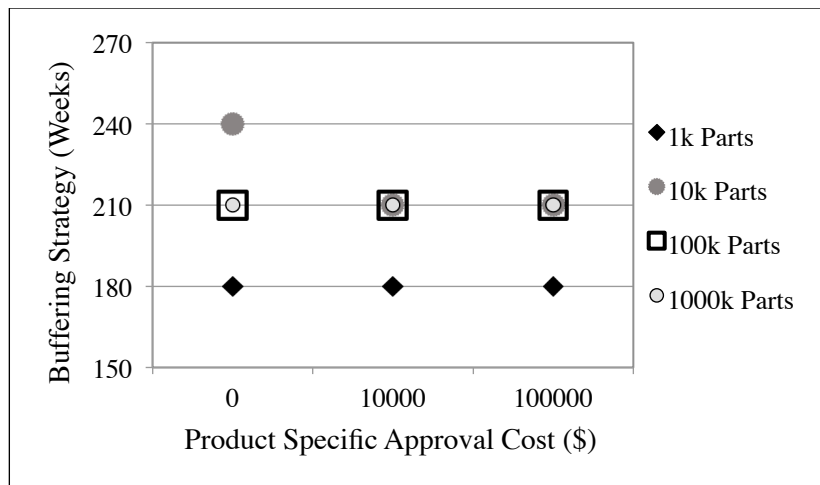
Figure 33: Optimal buffering strategies for various part volume and support cost scenarios.

A second version of the case study was developed to test this hypothesis and further study the effect of part volume on the optimal sourcing strategy. This modified case study retained all of the same inputs, with the exception of the disruption profile. The modified disruption profile was developed to reflect rare, small-scale disruption events (detailed in Appendix A.6). Figure 34 shows the optimal sourcing strategies resulting from this case study.
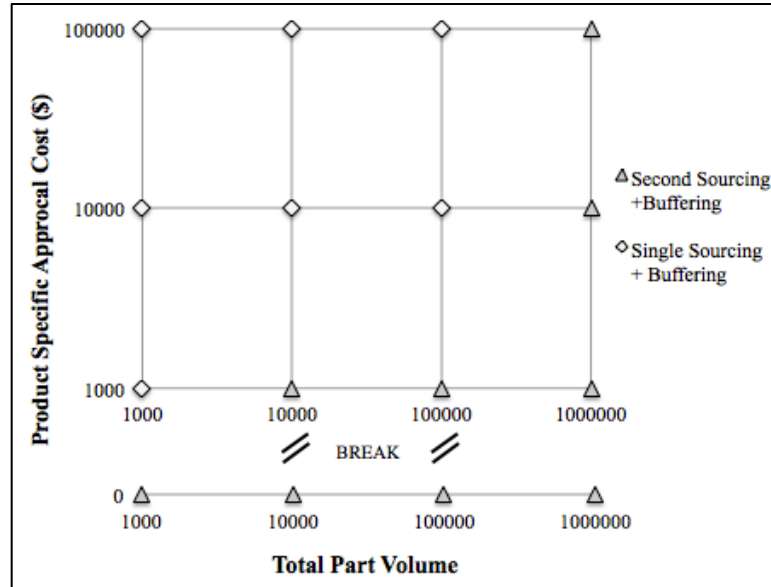
Figure 34: Optimal sourcing strategies for select combinations of product specific approval cost and total part volume. Triangles indicate cases where the optimal sourcing strategy was a combination of second sourcing and buffering. Diamonds indicate cases where the optimal sourcing strategy was single sourcing and buffering.

As shown in Figure 34, for low volume parts with significant PSA costs, the optimal mitigation strategy switched (when compared to the previous case study iteration) from second sourcing to buffering. The results of this case study show that the cost of maintaining a second supplier decreased the favorability of second sourcing for low volume products.

This case study isolates a definitive connection between total part volume and support costs, product specific approval costs in particular. As the total amount of accumulated penalty costs increases (due to an increase in either base penalty cost or total disruption time), the favorability of second sourcing also increases regardless of the part volume. However, if penalty costs are outweighed by necessary support costs, then single sourcing becomes increasingly more cost effective (when compared to second sourcing) especially as the total part volume decreases.

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4.2.3: Time-Dependent Disruption Case Study

Up to this point, the case studies in this thesis have focused on assessing the affect of disruption profiles based on constant distributions. However, real-world disruption profiles are rarely constant for the entire life cycle of a part (especially for long life-cycle products and systems). Most likely, manufacturers will have to assume and model several disruption profiles over time to account for fluctuating disruption probabilities. This case study assesses how the optimal mitigation strategy (lowest expected part TCO) is affected by non-stationary disruption profiles. All of the inputs utilized within the case study were taken from the mitigation strategy case study (Section 4.2.1) and are detailed in Appendix A.5. The secondary disruption profile parameters are given in Table A.16.

Figure 35 shows the expected CTCO per part site after 13 years for a set of generated disruption events if only a small-scale disruption profile is employed. The applied disruption profile is identical to that utilized in Section 4.2.1 (based on delivery delay data). For the unique set of delivery delays generated in Figure 35, second sourcing is the most cost effective mitigation strategy. Figure 36 incorporates the uncertainty associated with the disruption profile and shows that second sourcing is generally more effective for the given inputs.
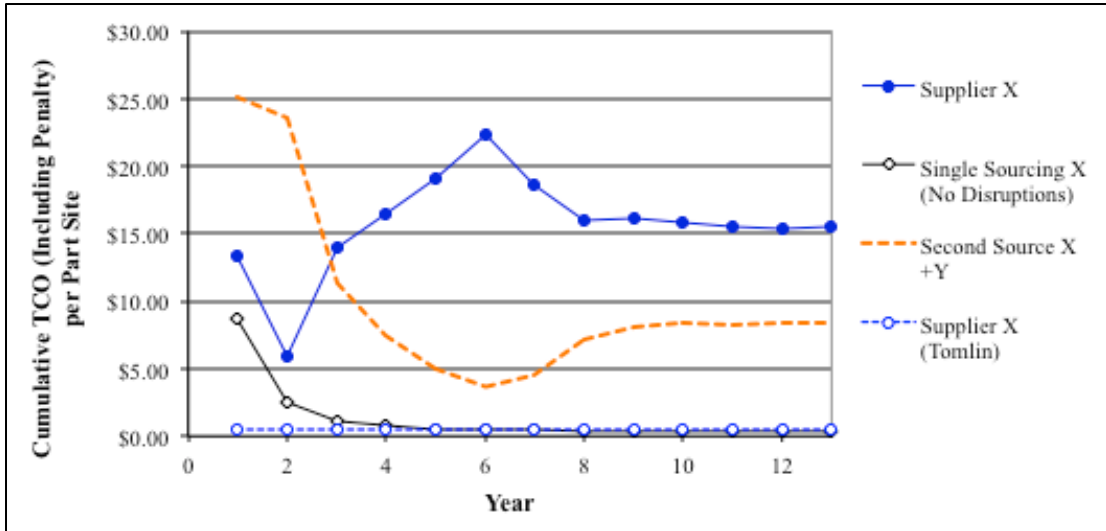
Figure 35: Cumulative part TCO (including penalty) over a 13 year period for a variety of sourcing strategies (unique disruption events generated from single disruption profile based on delivery delay data).
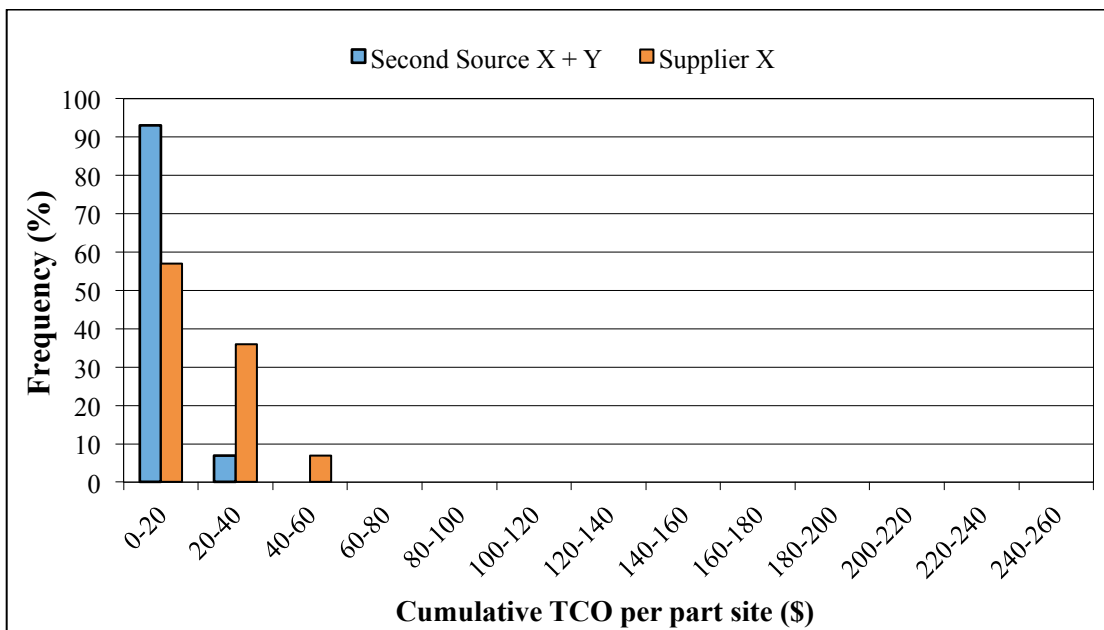
Figure 36: A comparison of the expected cumulative TCO after 13 years for two sourcing strategies and no buffering (single disruption profile based on delivery delay data).

A part that is subjected to significant disruption events throughout its life cycle accumulates, intuitively, more penalty costs than a part subjected only to small-scale delays. Figure 37, below, shows the CTCO per part site for a set of generated disruption events after 13 years if only the significant disruption profile is employed. Once again second sourcing is the most cost effective solution, but both strategies

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reflect significantly larger part-specific costs. The Monte Carlo analysis of this

scenario, shown in Figure 38, solidifies this comparative result.
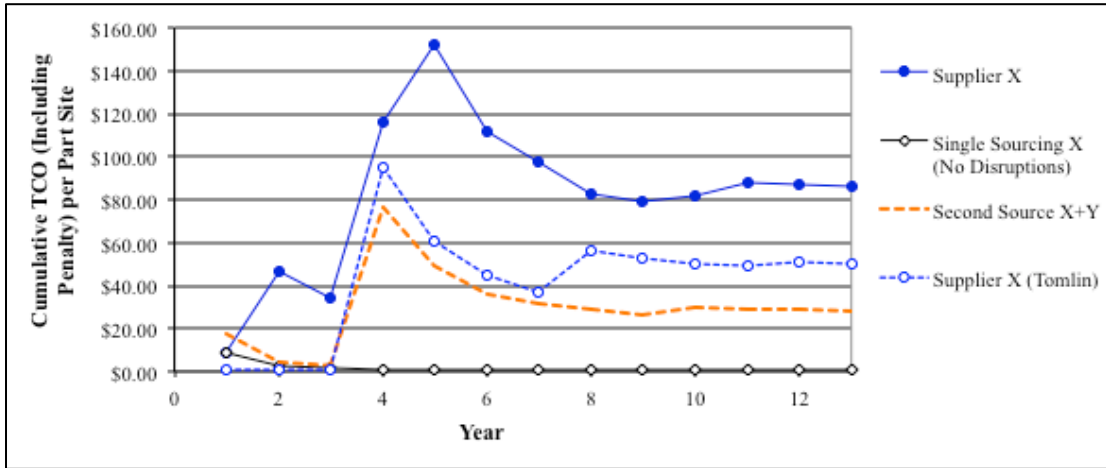
Figure 37: Cumulative part TCO (including penalty) over a 13 year period for a variety of sourcing strategies (unique disruption events generated from single disruption profile based on significant disruption events).
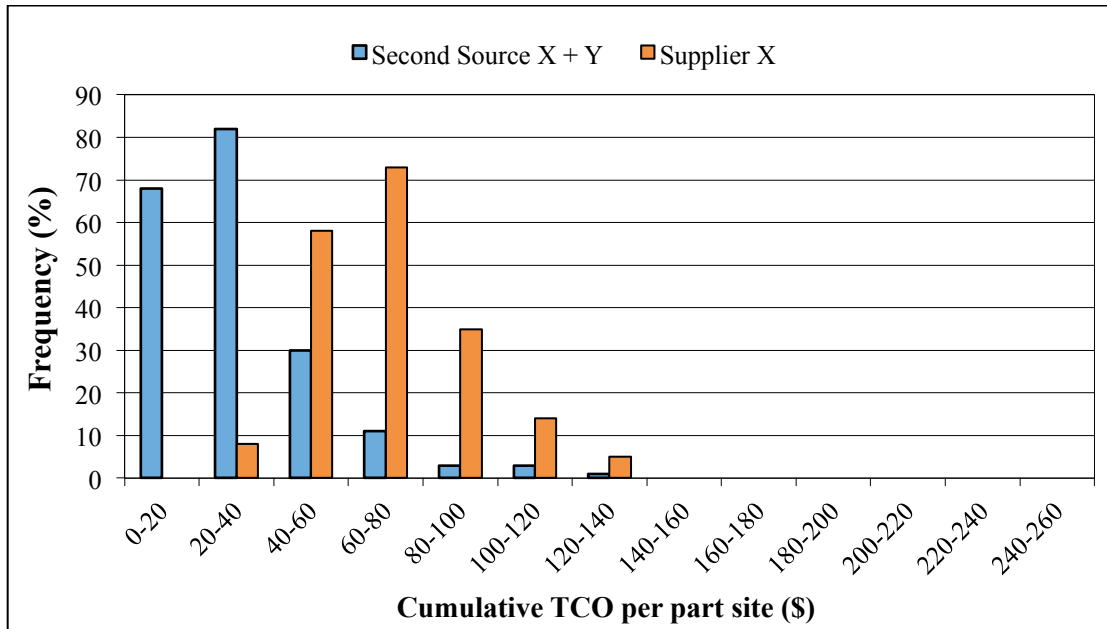
Figure 38: A comparison of the expected cumulative TCO after 13 years for two sourcing strategies and no buffering (single disruption profile based on significant disruption events).

Figure 39 shows the cumulative TCO per part site for a single set of disruption

events generated (from two distinct disruption profiles) throughout the 13-year life

cycle of a part. For the first six modeled years, the part is subjected to a disruption

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profile dependent on small-scale disruptions. For the remaining seven years in the part's life cycle, the disruption profile changes to reflect significant disruption events (months of disrupted production due to a black swan event). Figure 40 shows the cumulative distribution functions associated with each of the disruption profiles.
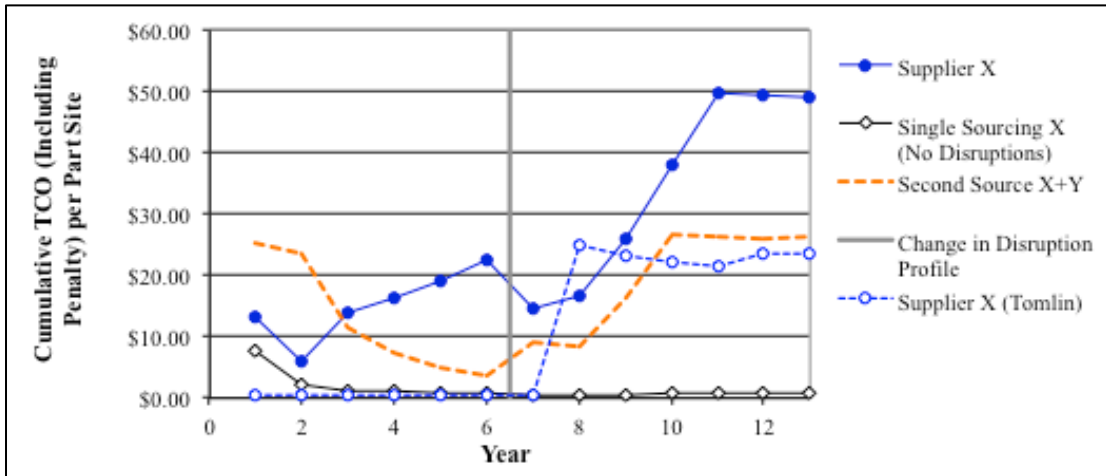
Figure 39: Cumulative part TCO (including penalty) over a 13 year period for a variety of sourcing strategies and no buffering. The disruption profile changes 6 years into the part's life cycle (marked by the vertical grey line) from a delivery delay based profile to a significant disruption based profile.
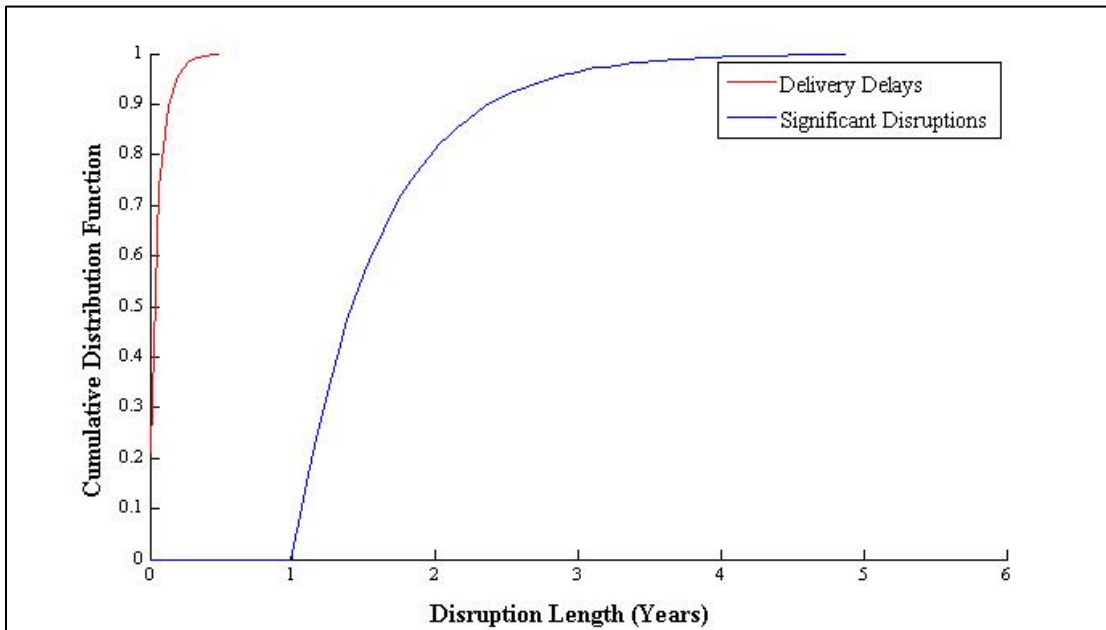
Figure 40: Cumulative distribution functions for both disruption profiles utilized in this case study. The delivery delay distribution is applied to the first 6 years of the part's life cycle, and the significant disruptions distribution is applied to the second 7 years of the part's life cycle.

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For the first six years in the part's life cycle, the incurred penalty costs are small (reflecting small-scale delays to production). As soon as the secondary disruption profile takes over in year seven, however, single sourcing becomes noticeably and increasingly unfavorable as penalty costs associated with large-scale disruption events are accumulated.

When both disruption profiles are used (as in Figure 41), a dominant sourcing strategy is still evident from the resulting data (second sourcing). However, the expected CTCO per part site becomes more uncertain. Figure 41 shows the expected CTCO per part site for both single and second sourcing (no buffering) under the time-dependent disruption profile. The standard deviation for the part TCO per part site associated with single sourcing has increased from $12.20 (Figure 36) and $32.07 (Figure 38) to $71.62.
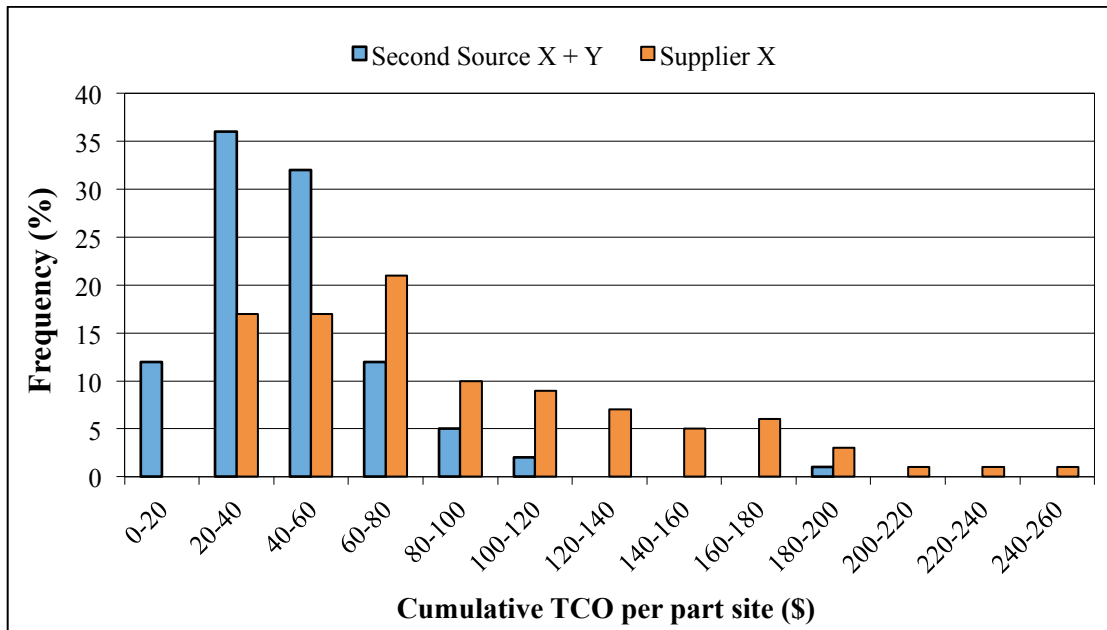
Figure 41: A comparison of the expected cumulative TCO after 13 years for two sourcing strategies and no buffering. The disruption profile changes 6 years into the part's life cycle from a delivery delay based profile to a significant disruption based profile.

The implementation of a time-dependent disruption distribution has been proven in this case study to directly affect both the expected CTCO per part site and the uncertainty associated with the final result. While this case study does not show a change in the effective optimal mitigation strategy for the modeled inputs, it also does not contradict or disprove the concept. Further work in this area may unveil a greater significance of non-stationary disruption distributions when modeling disruption events in the supply chain.

Chapter 5: Summary & Conclusions

This chapter presents a summary of the topics covered within this thesis and details the contributions it makes. In addition, areas of possible future work are outlined.

5.1: Summary

Long life cycle products, and the parts they are composed of, are susceptible to a variety of supply chain disruptions. Proactive mitigation strategies exist that can reduce the impact of supply chain disruptions. Two mitigation strategies in particular have been proven to greatly decrease the penalty costs associated with disruptions: second sourcing and buffering. Second sourcing involves selecting two distinct suppliers from which to purchase parts over the life of the part's use within a product or organization. Second sourcing reduces the probability of part unavailability (and its associated penalties), but at the expense of qualification and support costs for multiple suppliers. An alternative disruption mitigation strategy is buffering (also referred to as hoarding). Buffering involves stocking enough parts in inventory to satisfy the forecasted part demand (for both manufacturing and maintenance requirements) for a fixed future time period so as to offset the impact of disruptions. Careful selection of the mitigation strategy (second sourcing, buffering, or a combination of the two) is key, as it can dramatically impact the part total cost of ownership.

This thesis presented a total cost of ownership-based simulation model developed to help perform tradeoff analyses and identify an effective optimal combination of second sourcing and hoarding for a specific part and product scenario. The results produced by this simulation model were validated against a popular analytical disruption model developed by Tomlin [16]. In addition, this thesis studied the effectiveness of traditional analytical models compared to a simulation-based approach for the selection of an optimal disruption mitigation strategy. Four assumptions, in particular, were found to limit the realism of most analytical models but can be ignored in the simulation-based model. These limiting assumptions are: 1) no fixed costs associated with part orders, 2) infinite-horizon, 3) perfectly reliable backup supplier, and 4) disruptions lasting full ordering periods (as opposed to fractional periods). The final limiting assumption (disruptions lasting full ordering periods) was modeled in Section 3.5.1 and found to have minimal effect on the optimal disruption mitigation strategy. The remaining assumptions, however, were found to have a direct and significant impact on the optimal disruption mitigation strategy and therefore cannot be ignored in realistic case studies.

A variety of case studies were performed within the simulation model. The first set of case studies (described in Chapter 3) show that the model is capable of replicating results from operations research models, and overcomes significant scenario restrictions that limit the usefulness of analytical models as decision-making tools. The second set of case studies (shown in Chapter 4) was developed to show the impact of proper mitigation strategy selection within realistic electronic part supply chain scenarios.

5.2: Contributions

To the best of this author's knowledge, this thesis represents the first simulation-based total cost of ownership approach to modeling and quantifying supply-chain disruption events in the context of low-volume, long life cycle electronic supply chains. This thesis makes the following contributions:

- Quantitatively assessed the underlying assumptions of popular analytical disruption models and determined that finite horizon (including non-zero WACC), fixed support costs, and unreliable backup suppliers are essential components for determining the effective optimal disruption mitigation strategy for a given disruption scenario.

- Expanded an existing analytical part total cost of ownership model (developed by Prabhakar in [1]) to include the effect of buffering, backordered parts, and penalty costs. The inclusion of non-idealized scenarios through the implementation of disruption uncertainty allows a more realistic expected part TCO to be calculated.

- Created and validated a supply chain disruption simulation model that not only removes the identified limitations of infinite-horizon analytical models, but can also serve as an effective decision making tool. The part TCO based simulation model allows for the determination of the effective optimum disruption-mitigation strategies associated with a set of parameters. The model also provides a platform for sensitivity analyses within the supply chain realm,

especially for low volume, long life cycle parts that have not been studied as exhaustively as high volume parts.

- Developed method for translating supply chain (distributor) compiled disruption information into the supply chain disruption modeling process. In addition, successfully implemented actual distributor historical data (both duration and frequency) into realistic case studies for low volume, long life cycle parts.

- Demonstrated the importance of effectively selecting proactive disruption mitigation strategies, particularly in terms of low volume, long life cycle products through the performance of realistic case studies. Specifically, established the effect of buffering and second sourcing on the part TCO.

5.3: Future Work

The work performed within this thesis can be enhanced in the following ways:

- One of the primary contributions to any type of disruption event is human error. Whether it is under-preparedness, miscommunication, poor training, or strained relationships, human behavior has a direct effect on the disruption events that impact part total cost of ownership. As the number of workers goes down (due to an increase in technological capability), the effect of their individual responsibilities increases. For this reason, future work in the realm of disruption management should focus on the incorporation of human-related risk.

- The most relevant source disruption data uncovered within this thesis was a database of delivery delay information retrieved from an electronic part distributor. Due to the fact that Original Equipment Manufacturers (OEMs) are buffered from many of the disruptions experienced by distributors, the case studies in this thesis are really most useful to the distributor. The buffering techniques that distributors use soften the effect of disruptions as seen by their clients (the OEMs). Further work (beyond the scope of this thesis) is needed to map a connection between distributor disruption data and OEM-specific disruption events.

- Another proactive mitigation strategy that is commonly employed within the electronic part industry is product redesign. This strategy involves approving an alternative product design that does not include an obsolete or disrupted part. As of now, this strategy cannot be modeled (for comparison purposes) in the part-specific simulation model. Future work efforts may expand the simulation model to include a comparison of the part TCO associated with the effective optimal mitigation strategy against specified product redesign cost estimates.

Appendices

Appendix A: Case Study Inputs

Appendix A.1: Inputs for simulation example figures used in Section 2.7

Table A.1: General inputs used to produce the sample figures in Section 2.7

General Inputs	
Population Type	Poisson Generated
Ratio, K	1.00
Part Lifetime (years)	20.00
Eff. Procurement Life (years)	20.00
Cost of Money	10.00%/year
Base Year for Money	1
LTB overbuy	10.00%
Inventory Cost (per part)	$0.07
Price per part (all suppliers)	$1.00
Price decrease (per year)	8.50%
Demand Uncertainty[17]	0.2
Backorder Penalty (per part per year)	$300
Scrap Cost (per part)	$0

Table A.2: Support costs modeled within the example figures in Section 2.7

Support Costs ($)	
Product-Specific Approval	200
Initial Approval	0
Annual Part Data Management	200
Annual Production Support	600
Annual Purchasing	400
Obsolescence Case Resolution	7500
PSL Qualification	10000

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[17] Demand uncertainty is expressed in terms of standard deviation from the annual quantity.

Table A.3: Supplier specific Weibull parameters used to generate disruption events in the example figures in Section 2.7

	Supplier X			Supplier Y		
	gamma (years)	beta	eta (years)	gamma (years)	beta	eta (years)
Interval	3	1	0.5	4	1	0.5
Length	0.5	1	0.6	1	1	0.6
Procurement Life	20	0	0	20	0	0
Analysis Run-In Time	25	0	0			

Table A.4: Annual forecasted part demand and product design data used to produce the example figures in Section 2.7

Year	Product Designs	Forecasted Part Demand
1	1	11
2	1	50
3	2	150
4	2	337
5	2	607
6	2	911
7	2	1171
8	2	1318
9	2	1318
10	2	1186
11	2	970
12	2	728
13	2	504
14	2	324
15	2	194
16	1	109
17	1	58
18	1	29
19	0	14
20	0	6

** Forecasted part demand generated using a total volume of 10,000 parts and a peak usage year of 9

Table A.5: General inputs used to re-implement Tomlin's methodology within the developed simulation model

General Inputs	
Population Type	Known
Ratio, K	1.00
Cost of Money	0.00%/year
Base Year for Money	1
LTB overbuy	0.00%
Inventory Cost (per part)	$0.0015
Price change (per year)	0.00%
Supplier X Price (per part)	$1.00
Supplier Y Backup Price (per part)	$2.625
Supplier Y Base Price (per part)	$1.05
Product Designs	1
Annual Forecasted Part Demand	10
Demand Uncertainty	0
Backorder Penalty (per part per year)	$0.15
Scrap Cost (per part)	$0

Table A.6: Support costs modeled within the reimplementation Tomlin's methodology

Support Costs ($)	
Product-Specific Approval	0
Initial Approval	0
Annual Part Data Management	0
Annual Production Support	0
Annual Purchasing	0
Obsolescence Case Resolution	0
PSL Qualification	0

Table A.7: Supplier specific Weibull parameters used to generate disruption events that emulate Tomlin's methodology within the developed simulation model

	Supplier X			Supplier Y		
	gamma (years)	*beta*	*eta (years)*	*gamma (years)*	*beta*	*eta (years)*
Interval	100	5	1	3000	0	0
Length	0	1	10	0	0	0
Analysis Run-In Time	0	0	0			

Appendix A.3: Modified Inputs for Finite Horizon case study

Table A.8: General inputs used in the Finite Horizon case study (Section 3.5)

General Inputs	
Population Type	Known
Ratio, K	1.00
Cost of Money	**10.00%/year**
Base Year for Money	1
LTB overbuy	0.00%
Inventory Cost (per part)	$0.0015
Price change (per year)	0.00%
Supplier X Price (per part)	$1.00
Supplier Y Backup Price (per part)	$2.625
Supplier Y Base Price (per part)	$1.05
Product Designs	1
Annual Forecasted Part Demand	10
Demand Uncertainty	0
Backorder Penalty (per part per year)	$0.15
Scrap Cost (per part)	$0

All other inputs used in this case study are found in Appendix A.2

Appendix A.4: Modified Inputs for Fixed Costs case study

Table A.9: Support cost inputs used in the Fixed Costs case study (Section 3.5)

Support Costs ($)	
Product-Specific Approval	**1000**
Initial Approval	0
Annual Part Data Management	0
Annual Production Support	0
Annual Purchasing	0
Obsolescence Case Resolution	0
PSL Qualification	0

All other inputs used in this case study are found in Appendix A.2

Appendix A.5: Inputs for Mitigation Strategy case study

Table A.10: General inputs used for Mitigation Strategy case study (Section 4.2.1)

General Inputs	
Population Type	Poisson Generated
Ratio, K	1.00
Part Lifetime (years)	13.00
Eff. Procurement Life (years)	13.00
Cost of Money	10.00%/year
Base Year for Money	1
LTB overbuy	10.00%
Inventory Cost (per part)	$0.05
Supplier X Price (per part)	$0.48
Supplier Y Backup Price (per part)	$0.48
Supplier Y Base Price (per part)	$0.48
Price decrease (per year, single sourcing)	7.00%
Price decrease (per year, second sourcing)	11.00%
Demand Uncertainty	0.25
Backorder Penalty (per part per year)	$200
Scrap Cost (per part)	$0

Table A.11: Support cost inputs used for Mitigation Strategy case study (Section 4.2.1)

Support Costs ($)	
Product-Specific Approval	200
Initial Approval	0
Annual Part Data Management	200
Annual Production Support	600
Annual Purchasing	400
Obsolescence Case Resolution	7500
PSL Qualification	10000

Table A.12: Supplier specific Weibull parameters used to generate disruption events within Mitigation Strategy case study (Section 4.2.1)

	Supplier X			Supplier Y		
	gamma (years)	*beta*	*eta (years)*	*gamma (years)*	*beta*	*eta (years)*
Interval	0	1	0.5	1	1	0.5
Length	-0.00646	0.834	0.0513	-0.00646	0.834	0.0513
Procurement Life	13	0	0	13	0	0
Analysis Run-In Time	25	0	0			

Table A.13: Annual forecasted part demand and product design data used Mitigation Strategy case study (Section 4.2.1)

Year	Product Designs	Forecasted Part Demand
1	1	1487
2	1	4462
3	2	8924
4	2	13385
5	2	16062
6	2	16062
7	2	13768
8	2	10326
9	2	6884
10	2	4130
11	1	2253
12	1	1126
13	1	520

** Forecasted part demand generated using a total volume of 100,000 parts and a peak usage year of 6

Appendix A.6: Inputs for Part Volume case study

Table A.14: General inputs used for Part Volume case study (Section 4.2.2)

General Inputs	
Population Type	Poisson Generated
Ratio, K	1.00
Part Lifetime	13
Eff. Procurement Life	13
Cost of Money	10.00%
Base Year for Money	1
LTB overbuy	10.00%
Inventory Cost (per part)	$0.05
Price change (per year, single sourcing)	7.00%
Price change (per year, second sourcing)	11.00%
Supplier X Price (per part)	$0.48
Supplier Y Backup Price (per part)	$0.48
Supplier Y Base Price (per part)	$0.48
Product Designs	1
Peak Year of Part Usage	6
Demand Uncertainty	0.25
Backorder Penalty (per part per year)	$200
Scrap Cost (per part)	$0

Table A.15: Support cost inputs used for Part Volume case study (Section 4.2.2)

Support Costs ($)	
Initial Approval	0
Annual Part Data Management	200
Annual Production Support	600
Annual Purchasing	400
Obsolescence Case Resolution	7500
PSL Qualification	10000

Table A.16: Supplier specific Weibull parameters used to generate disruption events for the significant disruption scenario within the Part Volume case study (Section 4.2.2) and the Time-Dependent Disruption case study (Section 4.2.3)

	Supplier X			Supplier Y		
	gamma (years)	*beta*	*eta (years)*	*gamma (years)*	*beta*	*eta (years)*
Interval	5	1	0.5	5	1	0.5
Length	1	1	0.6	1	1	0.6
Analysis Run-In Time	0	0	0			

Table A.17: Supplier specific Weibull parameters used to generate disruption events for the small-scale disruption scenario within the Part Volume case study (Section 4.2.2)

	Supplier X			Supplier Y		
	gamma (years)	*beta*	*eta (years)*	*gamma (years)*	*beta*	*eta (years)*
Interval	5	10	0.5	3	1	0.5
Length	0	10	0.3	0	10	0.5
Analysis Run-In Time	0	0	0			

This Appendix presents the Microsoft Excel spreadsheets that make up the

simulation model. The sheets, in order, are: 1) Common Inputs, 2) Product Interface,

3) Compiled Products, 4) Part TCO, 5) Disruptions, 6) Penalty, 7) Monte Carlo, and

8) Optimize.

Appendix B.1: Common Inputs Sheet

Key Parameters

The following values are intergral components of the underlying part TCO calculations, but they remain fairly constant for electronic components.

Ratio, *K*	1
Part Lifetime (years)	20
Eff. Procurement Life (years)	20
Cost of Money	10%
Base Year for Money	1
LTB Overbuy	10%
Inventory Cost (per part)	5%
Supplier X Price (per part)	$1.00
Demand Uncertainty	0.2

Support Cost Factors

Product Specfic Approval	2
Initial Approval	0
Annual Part Data Management	2
Annual Production Support	6
Annual Purchasing	4
Obsolescence Case Resolution	75
PSL Qualification	100

Populate Values

Check Values Against Expected Range

Appendix B.2: Product Interface Sheet

Total Lifetime of Part	20
Number of Products	5

Generate Poisson	Rank

Product	1	2	3	4	5	
Rank by Penalty Cost	2	4	1	5	3	
Include in Analysis?	Yes	Yes	Yes	Yes	Yes	
Total Product Volume	1200	1100	6250	2200	1900	
Peak Usage (Year)	14	24	38	7	32	
Penalty Cost ($)	112	250	100	330	200	
Product Specific Approval ($)	120	280	400	200	220	
Probablity of Part Usage	1	1	1	0.6	0.1	

Forecasted Product Demand (by year)

	1	2	3	4	5	
1	0	0	0	14	0	
2	0	0	0	49	0	
3	0	0	0	115	0	
4	2	0	0	201	0	
5	4	0	0	281	0	
6	10	0	0	328	0	
7	21	0	0	328	0	
8	37	0	0	287	0	
9	57	0	0	223	0	
10	80	1	0	156	0	
11	101	2	0	99	0	
12	118	3	0	58	0	
13	127	6	0	31	0	
14	127	10	0	16	0	
15	119	16	0	7	1	
16	104	24	0	3	1	
17	86	34	0	1	3	
18	67	45	1	1	5	
19	49	57	2	0	8	
20	34	69	3	0	13	

Appendix B.3: Compiled Products Sheet

| Total Lifetime of Part | 20 |
| Number of Products | 5 |

Calculate Part Demand

Forecasted Part Demand (by year)

Product	TOTAL	PSC	1	2	3	4	5
1	8	$200.00	0	0	0	8	0
2	29	$0.00	0	0	0	29	0
3	69	$0.00	0	0	0	69	0
4	123	$120.00	2	0	0	121	0
5	173	$0.00	4	0	0	169	0
6	207	$0.00	10	0	0	197	0
7	218	$0.00	21	0	0	197	0
8	209	$0.00	37	0	0	172	0
9	191	$0.00	57	0	0	134	0
10	175	$280.00	80	1	0	94	0
11	162	$0.00	101	2	0	59	0
12	156	$0.00	118	3	0	35	0
13	152	$0.00	127	6	0	19	0
14	147	$0.00	127	10	0	10	0
15	139	$220.00	119	16	0	4	0
16	130	$0.00	104	24	0	2	0
17	121	$0.00	86	34	0	1	0
18	114	$400.00	67	45	1	1	0
19	109	$0.00	49	57	2	0	1
20	107	$0.00	34	69	3	0	1

Appendix B.4: Part TCO Sheet

INPUTS:

Population Type	Poisson Generated
Sourcing	Second
Ratio, K	1.00
Part Lifetime	20.00
Eff. Procurement Life	20.00
Cost of Money	10.00%
Base Year for Money	1
LTB overbuy	10.00%
Inventory Cost (per part)	$0.07
Price (all suppliers)	$1.00
Price change (per year)	8.50%

Part Volume Parameters (Poisson)

Total Volume	10,000
Peak Usage (Year)	9
Demand Uncertainty	0.2

Second Sourcing

Price change (per year)	8.50%

Calculate Costs

Year (per part site)	Product Designs	Forecasted Part Demand (Mean)	Support Cost	Part Price	Pure Procurement Cost (NPV)	Lifetime Buy Inventory Qty.	Procurement and Lifetime Buy Inventory Cost	Annual TCO w/o Penalty (NPV)	Cumulative TCO w/o penalty (per part site)
Total		9,995	$43,206.39		$2,772.39		$2,772.39	$36,968.62	
			$4.32		$0.28		$0.28	$3.70	$3.70
1	1	11	$22,800.00	$1.00	$11.00	0	$11.00	$22,811.00	$2,073.73
2	1	50	$2,161.82	$0.92	$41.89	0	$41.89	$2,025.36	$407.15
3	2	150	$2,314.05	$0.85	$105.30	0	$105.30	$2,017.74	$127.27
4	2	337	$1,803.16	$0.78	$198.23	0	$198.23	$1,552.96	$51.84
5	2	607	$1,639.23	$0.72	$299.16	0	$299.16	$1,418.77	$25.82
6	2	911	$1,490.21	$0.67	$376.19	0	$376.19	$1,301.49	$15.07
7	2	1171	$1,354.74	$0.61	$405.16	0	$405.16	$1,169.87	$9.98
8	2	1318	$1,231.58	$0.56	$382.08	0	$382.08	$1,014.08	$7.31
9	2	1318	$1,119.62	$0.52	$320.14	0	$320.14	$842.45	$5.82
10	2	1186	$1,017.83	$0.48	$241.37	0	$241.37	$673.03	$4.93
11	2	970	$925.30	$0.44	$165.40	0	$165.40	$522.15	$4.40
12	2	728	$841.19	$0.41	$104.01	0	$104.01	$398.84	$4.08
13	2	504	$764.71	$0.38	$60.33	0	$60.33	$304.00	$3.89
14	2	324	$695.19	$0.35	$32.50	0	$32.50	$233.87	$3.79
15	2	194	$632.00	$0.32	$16.30	0	$16.30	$182.73	$3.73
16	1	109	$574.54	$0.29	$7.68	0	$7.68	$145.22	$3.73
17	1	58	$522.31	$0.27	$3.42	0	$3.42	$117.09	$3.70
18	1	29	$474.83	$0.25	$1.43	0	$1.43	$95.38	$3.69
19	0	14	$431.66	$0.23	$0.58	0	$0.58	$76.22	$3.69
20	0	6	$392.42	$0.21	$0.21	0	$0.21	$64.37	$3.70

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SUPPORT COST INPUTS:

Reference Cost	100.00	
Support Costs	**Cost Factor**	**Activity Cost**
Product-Specific Approval	2	200
Initial Approval	0	0
Annual Part Data Management	2	200
Annual Production Support	6	600
Annual Purchasing	4	400
Obsolescence Case Resolution	75	7500
PSL Qualification	100	10000

Appendix B.5: Disruptions Sheet

Sourcing Strategy	Second Sourcing
Supplier	Supplier Y
Population Type	Single Population
If Single Population, What Type?	Poisson Generated
Supplier X Price ($ per part)	$1.00
Supplier Y Backup Price ($ per part)	$1.00
Supplier Y Base Price ($ per part)	$1.00

Supplier X

	gamma	beta	eta
Interval (years)	3	1	0.5
Length (years)	0.5	1	0.6
Procurement Life (years)	20	0	0
Analysis Run-In Time (years)	25	0	0

Supplier Y

	gamma	beta	eta
Interval (years)	4	1	0.5
Length (years)	1	1	0.6
Procurement Life (years)	20	0	0
Analysis Run-In Time (years)	0	0	0

Disruption Testing

Minimum Length	0
Disruption Length	1
Icrit	1

Significant Disruptions

Populate Disruption Profile

Year	Forecasted Part Demand	Supplier X Disruption	Backup Sourcing	Backup Sourcing Cost (NPV)	Overlapped Disruption	TCO (with sourcing)
0	0	0.000	0.000	$0.00	0.000	$0.00
1	11	0.000	0.000	$0.00	0.000	$22,811.00
2	50	0.000	0.000	$0.00	0.000	$2,025.36
3	150	0.000	0.000	$0.00	0.000	$2,017.74
4	337	0.935	0.935	$0.00	0.000	$1,552.96
5	607	1.000	0.106	$0.00	0.894	$1,418.77
6	911	0.256	0.000	$0.00	0.256	$1,301.49
7	1171	0.000	0.000	$0.00	0.000	$1,169.87
8	1318	0.000	0.000	$0.00	0.000	$1,014.08
9	1318	0.301	0.301	$0.00	0.000	$842.45
10	1186	1.000	0.515	$0.00	0.485	$673.03
11	970	0.480	0.000	$0.00	0.480	$522.15
12	728	0.000	0.000	$0.00	0.000	$398.84
13	504	0.000	0.000	$0.00	0.000	$304.00
14	324	0.000	0.000	$0.00	0.000	$233.87
15	194	0.558	0.558	$0.00	0.000	$182.73
16	109	0.636	0.084	$0.00	0.552	$145.22
17	58	0.000	0.000	$0.00	0.000	$117.09
18	29	0.000	0.000	$0.00	0.000	$95.38
19	14	0.359	0.359	$0.00	0.000	$78.22
20	6	0.443	0.443	$0.00	0.000	$64.37

Appendix B.6: Penalty Sheet

Sourcing Strategy	Second Sourcing
Supplier	Supplier Y
Population Type	Single Population
If Single Population, What Type?	Poisson Generated
Backorder Penalty (per part per year)	$300.00
Hoarding Strategy (weeks)	20
MONTE CARLO SIMULATION:	
Population Size (N)	100

UPDATE (CURRENT RUN)

SOURCING STRATEGIES

Scrap Cost (per part, all suppliers)	$0.00
Scrap Cost for Second Sourcing (per part, all suppliers)	$0.00

Year	Part Demand	Hoarding Strategy	TCO (no disruptions)
Total	10,373		$36,968.62
1	11	20	$22,811.00
2	51	58	$2,025.36
3	139	130	$2,017.74
4	385	234	$1,552.96
5	727	351	$1,418.77
6	1043	451	$1,301.49
7	1246	507	$1,169.87
8	1601	507	$1,014.08
9	1094	457	$842.45
10	1047	374	$673.03
11	1037	281	$522.15
12	784	194	$398.84
13	448	125	$304.00
14	363	75	$233.87
15	183	42	$182.73
16	104	23	$145.22
17	56	12	$117.09
18	32	6	$95.38
19	17	3	$78.22
20	5	0	$64.37

Part Quantities (CURRENT RUN)

Penalties (CURRENT RUN)

Number of Parts

Year

Year

Cumulative Penalty Cost (NPV)

- - - Hoarding Strategy
— Parts on Backorder
— Parts in Inventory
- - Part Demand
— Forecasted Part Demand (Mean)
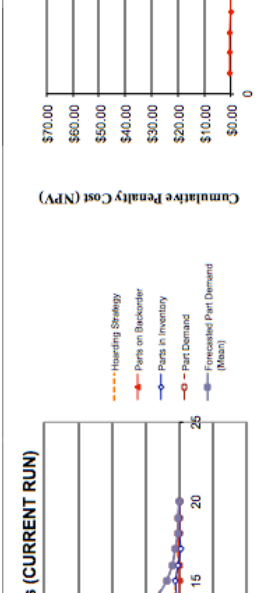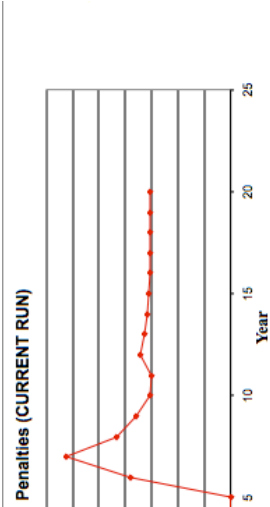
	Black Swan Event	
Model Event?		Yes
Length (weeks)		26
Probability		0.50
Expected Cost		$5,619.00

	Randomness	
Disruption Interval		On
Disruption Length		On
Procurement Life		On
Analysis Run-In Time		On
Demand		On
Infinite Lifetime		Off

	Total penalty cost per part site	$30.42
	TCO per part site (without lead times)	3.70
Current Run	Penalty as percentage of part TCO	822.26%
	TCO per part site (with penalties)	$34.1237

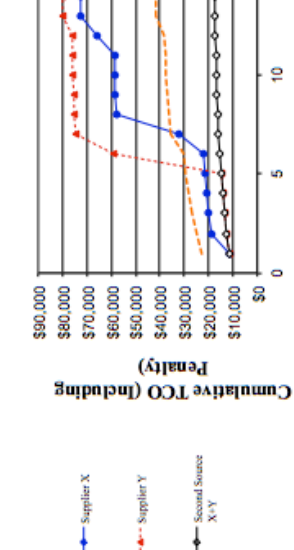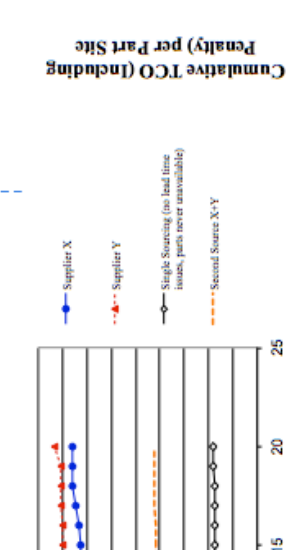| CALCULATION FOR BREAK-EVEN LEARNING INDEX:	
Average ΔCproc/inv	$13.64
Total support cost (per part)	$4.32
Ratio, K	3.15661467
Learning Index (β) from avg.	1.6579205

Backup Sourcing Penalty (NPV)	Parts on Backorder	Shortage/Excess (-/+) on Backorder Quantity	Parts in Inventory	Backorder Penalty (NPV)	Inventory Cost on Excess Parts (NPV)	Cumulative penalty cost (per part site)	Annual Penalty Cost (NPV)
$0.00	2164	-2124		$315,499.07	$85.79		$315,584.87
$0.00	0	0	29	$0.00	$1.40	$0.13	$1.40
$0.00	0	0	57	$0.00	$3.63	$0.08	$3.63
$0.00	0	0	141	$0.00	$8.16	$0.07	$8.16
$0.00	0	0	186	$0.00	$9.78	$0.04	$9.78
$0.00	0	0	231	$0.00	$11.04	$0.03	$11.04
$0.00	933	-482	-482	$89,765.22	$0.00	$38.12	$89,765.22
$0.00	320	-802	-802	$135,812.43	$0.00	$62.64	$135,812.43
$0.00	0	0	224	$0.00	$8.05	$43.37	$8.05
$0.00	0	0	681	$0.00	$22.24	$35.84	$22.24
$0.00	0	0	513	$0.00	$15.23	$30.73	$15.23
$0.00	503	-222	-222	$26,677.18	$0.00	$29.99	$25,677.18
$0.00	377	-599	-599	$62,963.75	$0.00	$34.30	$62,963.75
$0.00	0	0	181	$0.00	$4.04	$32.70	$4.04
$0.00	0	0	36	$0.00	$0.73	$31.51	$0.73
$0.00	0	0	53	$0.00	$0.98	$30.94	$0.98
$0.00	0	0	28	$0.00	$0.47	$30.63	$0.47
$0.00	31	-19	-19	$1,240.49	$0.00	$30.58	$1,240.49
$0.00	0	0	3	$0.00	$0.04	$30.49	$0.04
$0.00	0	0	0	$0.00	$0.00	$30.44	$0.00
$0.00	0	0	1	$0.00	$0.01	$30.42	$0.01

Cumulative TCO (Including Penalty) per Part Site

Cumulative TCO (Including Penalty)

Cumulative TCO (Including Penalty)			
Supplier X	Supplier Y	Second Source X+Y	Single Sourcing (no lead time issues, parts never unavailable)
$11,408.50	$11,408.45	$22,808.60	$11,408.00
$19,024.53	$12,425.62	$24,817.37	$12,424.03
$19,894.37	$13,294.96	$26,507.15	$13,292.09
$20,713.48	$14,115.01	$28,072.04	$14,109.55
$21,362.24	$14,763.39	$29,280.81	$14,754.62
$21,913.29	$59,160.98	$30,297.25	$15,302.75
$32,243.72	$74,678.83	$35,608.02	$15,760.53
$57,881.17	$75,058.29	$36,303.73	$16,137.12
$58,190.67	$75,366.30	$36,874.16	$16,444.86
$59,494.11	$75,671.47	$37,443.20	$16,746.47
$59,701.50	$75,879.01	$37,829.46	$16,952.47
$65,683.79	$76,048.92	$38,147.11	$17,122.17
$72,666.62	$79,970.13	$41,376.71	$17,262.20
$72,782.72	$90,086.43	$41,593.41	$17,377.63
$72,893.71	$80,197.51	$41,803.10	$17,487.78
$72,972.12	$80,275.54	$41,950.35	$17,565.70
$74,752.10	$80,339.79	$42,071.99	$17,629.68
$75,653.54	$80,408.35	$42,203.24	$17,697.94
$75,697.14	$80,452.17	$42,285.71	$17,741.27
$76,182.59	$83,250.67	$42,353.69	$17,777.07

Cumulative TCO (Including Penalty)

Legend: Supplier X; Supplier Y; Single Sourcing (no lead time issues, parts never unavailable); Second Source X+Y

Annual TCO (NOT Including Penalty)		
Supplier X	Supplier Y	Second Source X+Y
$11,408.00	$11,408.00	$22,808.00
$1,016.03	$1,016.03	$2,007.77
$868.06	$868.06	$1,687.67
$817.46	$817.46	$1,562.56
$845.07	$845.07	$1,204.80
$548.13	$548.13	$1,010.78
$457.78	$457.78	$840.14
$376.59	$376.59	$692.58
$307.55	$307.55	$568.70
$301.81	$301.81	$568.00
$206.00	$206.00	$384.37
$169.70	$169.70	$317.12
$140.03	$140.03	$261.96
$115.43	$115.43	$216.12
$110.15	$110.15	$208.62
$77.92	$77.92	$146.69
$63.97	$63.97	$120.81
$68.26	$68.26	$130.89
$43.33	$43.33	$82.15
$35.80	$35.80	$67.98

Penalty

Annual Lead Time Cost

Legend: Supplier X; Supplier Y; Second Source X+Y

MULTI-RUN RESULTS W.R.T. SOURCING STRATEGY:

Annual Penalty Cost (NPV)		
Supplier X	Supplier Y	Second Source X+Y
$0.50	$0.45	$0.80
$6,600.00	$1.14	$1.00
$1.78	$1.28	$2.11
$1.85	$2.59	$2.33
$3.09	$3.31	$3.89
$2.92	$43,849.46	$5.65
$9,872.65	$15,060.07	$4,470.63
$25,260.86	$2.87	$3.13
$1.96	$2.47	$1.73
$1.63	$1.36	$1.04
$1.39	$1.54	$1.89
$8,712.59	$0.21	$0.53
$6,942.80	$3,781.18	$2,867.75
$0.67	$0.87	$0.58
$0.84	$0.93	$1.07
$0.49	$0.11	$0.56
$1,716.00	$0.27	$0.03
$933.18	$0.30	$0.36
$0.27	$0.49	$0.31
$449.65	$2,762.70	$0.11

Cumulative TCO (Including Penalty) per Part Site

	Single Sourcing (no lead time issues, parts never unavailable)
	$11,408.00
	$12,424.03
	$13,292.09
	$14,109.55
	$14,754.62
	$15,302.75
	$15,760.53
	$16,137.12
	$16,444.66
	$16,746.47
	$16,952.47
	$17,122.17
	$17,262.20
	$17,377.03
	$17,467.78
	$17,565.70
	$17,629.68
	$17,697.94
	$17,741.27
	$17,777.07

Cumulative TCO (Including Penalty) per Part Site

Supplier X	Supplier Y	Second Source X+Y	Single Sourcing (no lead time issues, parts never unavailable)
$1,037.14	$1,037.13	$2,073.51	$1,037.09
$306.85	$200.41	$400.28	$200.39
$98.98	$66.14	$131.88	$66.13
$35.35	$24.09	$47.90	$24.08
$16.27	$11.24	$22.30	$11.24
$9.30	$25.11	$12.86	$6.50
$8.95	$20.73	$9.09	$4.38
$11.12	$14.43	$8.98	$3.10
$9.24	$11.97	$5.86	$2.61
$7.96	$10.30	$5.10	$2.28
$7.00	$9.05	$4.51	$2.02
$7.16	$8.30	$4.16	$1.87
$7.56	$8.32	$4.30	$1.80
$7.30	$8.03	$4.17	$1.74
$7.18	$7.89	$4.11	$1.72
$7.11	$7.82	$4.09	$1.71
$7.24	$7.79	$4.08	$1.71
$7.31	$7.77	$4.08	$1.71
$7.30	$7.76	$4.08	$1.71
$7.34	$8.03	$4.08	$1.71

	Supplier X	Supplier Y	Second Source X+Y	Single Sourcing (no lead time issues, parts never unavailable)
Total penalty cost per part site	$5.63	$6.31	$0.72	
TCO per part site (without lead times)	$6.49	$6.49	$12.74	$3.56
Penalty as percentage of part TCO	152.16%	170.59%	19.45%	
TCO per part site (with penalties)	$27.81	$30.39	$15.46	$1.71
ΔCproc/inv	$12.35	$14.93	$13.64	

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Appendix B.7: Monte Carlo Sheet

MONTE CARLO SIMULATION (RESULTS):
Cumulative TCO (per part site) w/ Penalty After 20 Years — Monte Carlo

Run	Supplier X	Supplier Y	Second Source X + Y
Average	39.67103926	41.08897499	40.94476377
1	43.89102189	38.00485581	44.67505991
2	47.79355716	42.63029653	48.01849363
3	30.18945711	30.23478977	33.20671974
4	41.09112694	37.44648462	38.92469773
5	44.14725501	34.9936383	37.8416332
6	25.44827552	28.36421849	36.12670773
7	26.97488062	42.63909993	34.64386331
8	35.6394341	37.8962345	24.29682379
9	60.08799838	33.35117897	52.72799838
10	31.03112994	29.1584466	39.9328358
11	32.78866681	59.70752114	39.91419648
12	48.49874775	47.37677577	52.08535806
13	23.91945511	44.66028452	34.3184366
14	38.64198637	33.08045161	41.55165621
15	27.94142109	23.59479078	30.06118597
16	39.72985231	28.65540008	24.86036656
17	42.953244	42.19201739	44.41098887
18	32.5784466	33.57650563	33.2100384
19	32.45502289	42.1454441	43.87817047
20	45.39675376	43.5570429	58.43327302
21	28.31776426	37.65777027	27.41807342
22	37.66421849	30.82147512	46.27757517
23	52.10942909	39.97018047	28.78288582
24	31.47654765	40.89746511	56.00450463
25	31.9948358	46.57459668	31.9482395
26	38.34574125	51.74392434	43.819242
27	26.7564866	40.01261869	29.36645261
28	35.7300084	32.51395236	23.18767632
29	30.80039356	35.17658967	27.02434055
30	41.10070873	44.64925701	42.08554815
31	48.31030253	43.18146411	26.95448762
32	56.22899088	61.82519798	43.97622549
33	47.50973425	26.11822349	41.47653865
34	41.07054765	47.76376126	29.29226151

HISTOGRAM:

Start 5 | Bin Size 5.0 | End 40

Bin		Frequency	
	Supplier X	Supplier Y	Second Source X + Y
5	0	0	0
10	0	0	0
15	3	3	2
20	17	8	13
25	18	18	13
30	12	13	15
35	12	10	14
40		17	16

Histogram chart — Frequency (%) vs. Cumulative TCO per part site (bins 5–40). Series: Second Source X + Y, Supplier Y, Supplier X.

Appendix B.8: Optimize Sheet

Buffering Strategy	Mean CTCO per part site			Standard Deviation		
Weeks	Supplier X	Supplier Y	Second Source X+Y	Supplier X	Supplier Y	Second Source X+Y
0	$21.6377	$14.4036	$13.5954			
10	$9.3404	$4.2131	$4.7371			
20	$3.7477	$1.4130	$1.8127			
30	$2.9586	$0.7714	$0.9151			
40	$1.9934	$0.5810	$0.6685			
50	$1.0017	$0.4815	$0.6274			
60	$1.0430	$0.4659	$0.6111			
70	$0.5657	$0.4641	$0.6206			
80	$0.4694	$0.4677	$0.6217			
90	$0.4700	$0.4765	$0.6299			
100	$0.4725	$0.4832	$0.6337			
110	$0.4790	$0.4904	$0.6421			
120	$0.4839	$0.4968	$0.6475			

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