ABSTRACT

Title of Document: ELECTRONIC PART TOTAL COST OF OWNERSHIP AND SOURCING DECISIONS FOR LONG LIFE CYCLE PRODUCTS

Varun Jonathan Prabhakar, Doctor of Philosophy, 2011

Directed By: Professor Peter Sandborn, Department of Mechanical Engineering

The manufacture and support of long life cycle products rely on the availability of suitable parts from competent suppliers which, over long periods of time, leaves parts susceptible to a number of possible long-term supply chain disruptions. Potential supply chain failures can be supplier-related (e.g., bankruptcy, changes in manufacturing process, non-compliance), parts-related (e.g., obsolescence, reliability, design changes), logistical (e.g., transportation mishaps, natural disasters, accidental occurrences) and political/legislative (e.g., trade regulations, embargo, national conflict). Solutions to mitigating the risk of supply chain failure include the strategic formulation of suitable part sourcing strategies. Sourcing strategies refer to the selection of a set of suppliers from which to purchase parts; sourcing strategies include sole, single, dual, second and multi-sourcing. Utilizing various sourcing strategies offer one way of offsetting or avoiding the risk of part unavailability (and its associated penalties) as well as possible benefits from competitive pricing.

Although supply chain risks and sourcing strategies have been extensively studied for high-volume, short life cycle products, the applicability of existing work to long life cycle products is unknown. Existing methods used to study part sourcing decisions in high-volume consumer oriented applications are procurement-centric where cost tradeoffs on the part level focus on part pricing, negotiation practices and purchase volumes. These studies are commonplace for strategic part management for short life cycle products; however, conventional procurement approaches offer only a limited view for parts used in long life cycle products. Procurement-driven decision making provides little to no insight into the accumulation of life cycle cost (attributed to the adoption, use and support of the part), which can be significantly larger than procurement costs in long life cycle products.

This dissertation defines the sourcing constraints imposed by the shortage of suppliers as a part becomes obsolete or is subject to other long-term supply chain disruptions. A life cycle approach is presented to compare the total cost of ownership of introducing and supporting a set of suppliers, for electronic parts in long life cycle products, against the benefit of reduced long-term supply chain disruption risk. The estimation of risk combines the likelihood or probability of long-term supply chain disruptions (throughout the part's procurement and support life within an OEM's product portfolio) with the consequence of the disruption (impact on the part's total cost of ownership) to determine the "expected cost" associated with a particular sourcing strategy. This dissertation focuses on comparing sourcing strategies used in long life cycle systems and provides application-specific insight into the cost benefits of sourcing strategies towards proactively mitigating DMSMS type part obsolescence.

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by

Varun Jonathan Prabhakar

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Advisory Committee:

Professor Peter Sandborn, Chair
Professor Shapour Azarm
Professor Wedad J. Elmaghraby
Professor Jeffrey W. Herrmann
Professor Santiago Solares

Dedication

I would like to dedicate this dissertation to my wonderful family for their love and unwavering support. I would also like to dedicate this work to all my friends, colleagues, professors and staff members who have been a perpetual source of motivation and inspiration over the past five years.

Acknowledgements

I would like to acknowledge my advisor and mentor, Professor Peter Sandborn, for his support and guidance. I would also like to thank the more than 100 companies and organizations that support research at the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland annually. Specifically, I would like to acknowledge CALCE members, Ericsson AB, Textron and SiliconExpert, for the valuable feedback and insight into the practical applications of the methodology presented in this dissertation.

Table of Contents

Nomenclature

B^x = supplier learning index for corresponding support activity x
B_{TH} = learning index threshold
C^x = support costs for support activity vector x, i.e., C^{ia}, C^{pa}, C^{as}, etc.
C_{proc} = annual part procurement cost (exclusive of inventory)
C_{repair} = cost of repair per product instance
$C_{replace}$ = cost of replacing the product per product instance
C^{VAR} = cost of product-related resolutions as a function of N^{PROD}
C^{FIXED} = fixed component of disruption resolution cost
C^{wr} = cost of processing the warranty returns
C_{TCO} = part total cost of ownership (TCO)
C_{PPS} = part TCO per part site
$C_{\exp}$ = average expected cumulative TCO per part site
D_s = effective disruption date (obsolescence date) of a part procured through sourcing strategy s
$f(t)$ = PDF value of procurement life at time t
$F(t)$ = CDF value of procurement life at time t
f_{fail} = number part failures from supplier p calculated from supplier-related
f_{rep} = fraction of failures requiring replacement (as opposed to repair) of the product FIT rates (assuming a constant failure rate)
$F_{overbuy}$ = overbuy (buffer) quantity as fraction of lifetime buy quantity
h = holding/storage/inventory cost per part per year
i = year index (starting at 1)
j = end of part's support life cycle (years after start)
K_{TH} = ratio (threshold) of support cost for repeated support activities in sourcing strategy b with respect to support cost in single sourcing strategy a
L_P = part procurement life (years)
n = length of support activity vector x
N^T = number of part procured for assembly in a particular
N^{VOL} = number of parts sites for assembly
N_p^{PROC} = number of parts procured from supplier p
N^{PROD} = number of product designs that the part is used in
N^{fail} = number of failures under warranty
N_s^{SUP} = number of suppliers involved in sourcing strategy s
p = supplier index
P_p^{SUP} = part price from supplier p
Q = part quantity in storage/inventory

r = discount rate on money

α_p = fraction of total part usage that is purchased from supplier p

Vol_p^G = number of good parts before assembly process from supplier p, i.e., parts free from defects

Vol_p = volume of parts procured from supplier p

List of Figures

List of Tables

Chapter 1: Introduction

In today's market, materials and goods flow through a complex network of organizations called "supply chains" on their way to becoming a finished product. Original Equipment Manufacturers (OEMs) are product manufacturers that purchase or fabricate lower-level parts and integrate them into products that bear the organization's name. Each OEM interacts with suppliers and customers through the transaction of goods where the assembly of products relies on the availability of suitable parts with sufficient attributes from competent suppliers.

An OEM organization's reliance on the external procurement of necessary parts leaves it susceptible to supply chain risk. Consider the following example: On March 17th, 2000, a lightning bolt caused by a thunderstorm struck electric power lines feeding to Philips' chip-manufacturing plant in Albuquerque, New Mexico (Latour 2001). A small fire erupted that was extinguished by the automatic sprinkler system within ten minutes. The building suffered only minor damage but the production of chips was shut-down for three weeks. Thousands of semiconductor chips being fabricated at the plant were destroyed by water damage while the debris and smoke particles from the fire compromised the sterile environment contaminating millions of chips in storage. Six months later, Philips was only able to return to producing half the capacity it was producing before the incident. The overall damage caused by the fire at Philips was, in fact, far more severe than expected. Ericsson, a leading cell-phone manufacturer at the time, purchased many of its chips from Philips exclusively. According to Ericsson's statement in 2001, the drastic reduction in production and sales attributed to the shortage of millions of chips, many of which were expected to be used in important new products, cost the company more than $400 million. That year, Ericsson's mobile phone division alone lost $1.7 billion for a variety of reasons related to the fire at Philips and eventually withdrew from manufacturing mobile phones. On the other hand, Nokia, a Finnish competitor to Ericsson in the communications industry who attributes 70% of its $20 billion annual revenue to mobile phones, purchased chips from Philips as well. In fact, semiconductor procurement from Nokia and Ericsson together accounted for 40% of Philips' production. Following the incident at Philips, Nokia mobilized alternative sources, diverted capacity from other U.S. and Japanese suppliers, and managed to continue production with nearly no consequences (Waters 2007).

The assessment and mitigation of supply chain risk are critical to maintaining a robust supply chain and have been extensively studied in literature, including systems devised by Ericsson following Philips' incident (Norman and Jansson 2004). Events that lead to potential supply chain failures can be supplier-related (bankruptcy, changes in manufacturing process, non-compliance), parts-related (obsolescence, reliability, design changes), logistical (transportation mishaps, natural disasters, accidental occurrences) and political/legislative (trade regulations, embargo, national conflict). Part of the solution to mitigating the risk of supply chain failure is the strategic formulation of suitable part sourcing strategies. Utilizing various sourcing strategies offer ways of offsetting or avoiding penalties associated with part unavailability as well as possible benefits from competitive pricing.

Large electronics OEMs, such as Ericsson, Motorola, and Honeywell, have dedicated electronic part management groups that are responsible for identifying, selecting, qualifying, and purchasing electronic parts for specific products as well as qualifying the manufacturers and distributors of those parts. Often, electronic systems OEMs maintain databases that consist of hundreds of thousands of electronic parts (Pecht 2004). Part management tasks performed on a regular basis include determining the procurement status of parts, managing purchase orders, and part database maintenance. These tasks require considerable resources throughout the part's existence within the database. Assessing and mitigating supply chain risk is one of the responsibilities of these part management groups. Unfortunately, part selection for products is often driven or significantly influenced by procurement management processes that have little or no view into the effective cost of ownership or through-life cost ramifications of the part.

Procurement organizations are often motivated by minimizing procurement cost or selecting suppliers that offer parts at lower prices, and may not take into account many of the part selection and management group's activities listed above (or more importantly, how the cost of these activities may vary from part-to-part). Price has long been considered a driving factor in purchases (Evans 1981, Lehmann and O'Shaughnessy 1974) but more recent studies have shown that price has declined in relative importance as a selection criterion (Jackson 1985, Wilson 1994). A survey study by Bharadwaj (2004) found that, out of four key supplier selection criteria – delivery, price, quality, and post-sale service – price was indeed the penultimate decision criteria used by electronic component procurement organizations followed by post-sales service. The study by Bharadwaj also suggests that differences do not exist within the buying criteria across an array of electronic components. However, the implications of such policies and the impact of these decision criteria are yet to be explored.

Electronic products can be categorized into long life cycle and short life cycle products. Popular consumer electronics, such as computers, mobile phones, GPS (global positioning systems), and so on, have relatively short procurement lives since they become obsolete within a few years of their market introduction (usually 5 years or less) . On the other hand, long life cycle products, such as those used in aerospace, military, communications infrastructure, power plants, and medical applications, remain in use and must be supported for significantly longer (often 20 years or more). Long life cycle products must utilize electronic parts procured from the same supply chain as short life cycle products resulting in a high frequency of part obsolescence[1]. As a result, the management of parts used in long life cycle electronic products differs from their short life cycle counterparts.

Although supply chain risk has been extensively studied, the applicability of existing work to long life cycle products is limited. Existing methods used to study part management decisions are procurement-centric where cost tradeoffs on the part level focus only on part pricing, negotiation practices and purchase volumes. These studies are commonplace in strategic part management for short life cycle products; however, conventional procurement approaches offer only a limited view in the assessment of parts used in long life cycle products. Procurement-driven decision making provides little to no insight into the accumulation of life cycle cost (attributed to the adoption and use of the part), which can be significantly larger than

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[1] Integrated circuit fabrication facilities cost $1 Billion or more today. Long field life product sectors generally do not consume enough electronic parts to justify owning their own fabrication facilities or to support a dedicated electronic part supply chain.

procurement costs in long life cycle products. Therefore, a life cycle cost approach is necessary to assess part management decisions in long life cycle products.

1.1 Background

This section discusses the characterization of various sources of supply chain risk. A background into supplier risk management is presented that justifies the need for new methods in part management suitable for managing parts used in both short and long life cycle products. This section also provides an overview of various sourcing strategies that are commonly employed to mitigate supply chain risk. Finally, the characteristics of electronic part management groups within electronic OEM organizations and the differences between long life cycle and short life cycle electronic products are described.

1.1.1 Supply chain failure

A supply chain for a specific part or component is often made up of a network of several OEMs. Each OEM relies on part suppliers leaving the organization vulnerable to events that affect the intended functioning of the supply chain.

Some forms of supply chain failures discussed in literature include (Gaonkar and Viswanadham 2004):

(1) *Deviation* – a deviation occurs when certain performance measures are affected by one or more parameters (e.g., cost, demand, lead-time) straying from expected or mean values without affecting the supply chain structure.

(2) *Disruption* – a disruption is an unexpected event that causes a radical transformation in the supply chain structure. Supply chain disruptions affect part

procurement through supplier or part unavailability, warehousing, distribution facilities or transport options. Supply chain disruptions are usually a result of events such as natural disasters, shipment delays, and non-compliant suppliers to name a few. Two types of supply chain disruptions can occur:

i. *Short-term disruptions* are temporary problems that usually only affect a limited number of products that share the part for a short period of time, e.g., you receive a bad batch or lot of parts, or this week's delivery of parts is going to be two days late.

ii. *Long-term disruptions* refer to problems that make it impossible for an organization to continue using the part, e.g., reliability issues, changes made to the part by the part manufacturer, or the part becomes un-procurable (obsolete). Long-term problems such as a fundamental supply chain or wear out problem affects all products that share the part and require that a permanent solution (often a replacement part) must be found. Examples of long-term part supply problems are discontinuance of the part (obsolescence), supplier unavailability, functional design errors, counterfeit part issues, and part reliability problems.

(3) *Disaster* – a disaster is a temporary but irrecoverable shut down of the supply chain system due to unforeseen catastrophic system-wide disruptions. Disasters may be a result of a number of supplier disruptions or a single common-mode[2] disruption of sizeable magnitude.

Disruptions and disasters differ from deviations in severity, consequences and level of management required to mitigate the supply chain failure. Deviations are

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[2] A common-mode disruption is a supply chain failure of more than one supplier caused by a specific event (or an identical set of events). For example, alterations in trade policies may affect all offshore suppliers for a particular part in the same way.

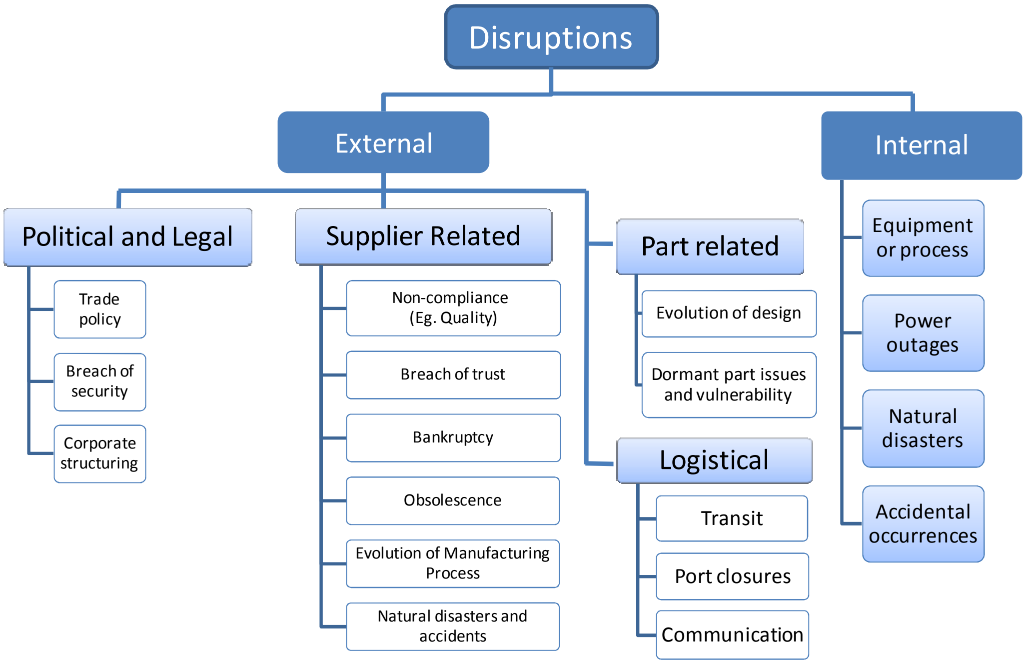

Figure 1.1 – Taxonomy of general supply chain disruptions (includes long-term and short-term disruptions).

mitigated on the tactical or operational level while disruptions and disasters are managed on a strategic level.

Disruptions may occur internally or externally (Figure 1.1). External disruptions are events outside the realm of the OEM control, which prevent the use of a part. External disruptions can be generally categorized by causes into: 1) political and legal, 2) supplier related, 3) part related, and 4) logistical disruptions. Internal disruptions are events that occur within the OEM organization, which affect the assembly of parts into products. Resolutions of internal disruptions are more likely to be under the control of the OEM while external disruptions require the supply chain to be restructured. The assembly of products by an OEM organization is subject to supplier related problems that affect how an OEM procures their parts. The result is an alteration in the intended supply chain structure or a supply chain disruption. Relevant supply chain issues and their categorization are depicted in the taxonomy shown in Figure 1.1.

1.1.2 Part sourcing strategies

Supply chain risk management can be divided into three categories (Gaonkar and Viswanadham 2004):

- *Tactical* – day to day management of activities
- *Operational* – task specific management
- *Strategic* – organizational level management of interacting groups

Management on each of the three levels is vital to the proper functioning of part management organizations. Strategic management allows part management groups within OEMs to manage resources proactively in order to limit damages and cost penalties attributed to supply chain disruptions. A large body of research (discussed in this section) addresses part sourcing strategies as a valid supply chain risk mitigation approach.

Part sourcing strategies are a common method of mitigating supply chain risks. A part sourcing strategy is a supply chain configuration that describes the number of suppliers from which to purchase parts and how they will be used during the period that the part exists in the OEMs database. Several sourcing strategies may be utilized to prevent the shortage of parts. Part sourcing strategies may be formulated to use more than one supplier or support backup suppliers from which to purchase parts should the primary supplier fail to meet demand (commonly referred to as "demand switching"). However, introducing suppliers and parts into the parts database involves additional resources and cost. Therefore, for efficient database management, the part manager is responsible for tradeoff decisions that determine the use of parts across multiple products and the use of suppliers over the part's life cycle. These decisions have a direct impact on the total cost of ownership (TCO) of parts incurred by the OEM.

Potential advantages of using multiple suppliers include (Pochard 2003):

- Creates the ability for OEMs to negotiate lower procurement prices during the supplier selection process
- Makes the OEM less susceptible to supply chain risk since OEMs may choose alternative suppliers in the event that the primary supplier is unable to deliver suitable parts
- Allows the OEM to be more selective with part characteristics, such as reliability, quality, and design specifications making the part/supplier selection process more efficient

Parts or components are more often purchased from outside sources either directly from component manufacturers (also called "suppliers") or through qualified third-party vendors. An important aspect of maintaining an appropriate set of parts begins with selecting an appropriate set of manufacturers or distributors from which to purchase the part. Like any customer in the component market, a product manufacturer must make smart and informed decisions when selecting a reliable component supplier. Manufacturers are assessed by criteria indicative of their reliability and performance in process control, corrective and preventative actions, part traceability, change notification procedures, handling, storage, and shipping

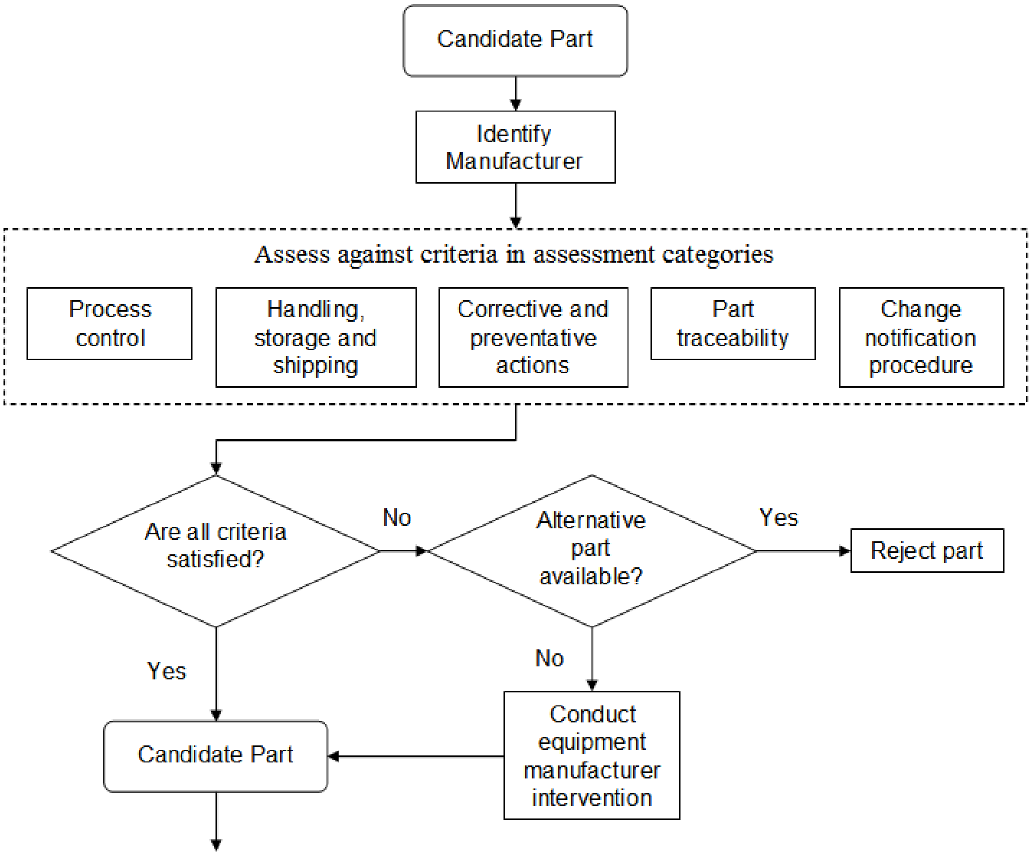

Figure 1.2 – Manufacturer (supplier) assessment process flow (Pecht 2004).

(Pecht 2004). The selection process involves qualifying suppliers, regular quality inspections, updating supplier information in databases, and part design verification and testing. A manufacturer selection process is shown in Figure 1.2.

For a particular part, the OEM may choose from a number of "sourcing strategies". Sourcing strategies commonly used by electronics OEMs are:

(1) *Sole sourcing* – parts purchased from a single available supplier due to lack of alternatives

(2) *Single sourcing* – selection of a single supplier from many alternatives by a "winner-take-all" auction

(3) *Dual sourcing* – selection of a primary and secondary supplier by a "split-award" auction

(4) *Second sourcing* – the option to utilize a licensed back-up supplier or second source should the primary supplier fail

(5) *Multi sourcing* – use of multiple suppliers simultaneously or as a combination of one or more sourcing strategies shown above

(6) *Parallel sourcing* – identical (or very similar) parts are procured from multiple suppliers where parts from each supplier are used in a specific product rather than being picked for use from a pool of common parts

The remainder of this section provides an overview of the various sourcing strategies employed by procurement management groups and the methods used to assess and select the ideal set of suppliers. It should be noted that a large body of literature exists on sourcing strategies and, although some terms are widely generalized, it is not uncommon for definitions to differ slightly based on the market structure.

Sole Sourcing

Sole sourcing is rarely employed as a definitive sourcing strategy but is imposed by the state of the market instead. Sole sourcing may be necessary early in the part's life cycle or as the part approaches obsolescence. For some "state-of-the-art" technologies, the required part may only be available from one specialized manufacturer. A change in the supply chain structure may occur in order to use additional suppliers when and if they emerge. Sole sourcing may also be observed following the use of other sourcing strategies as a customer may revert to sole sourcing to utilize the last remaining supplier in the market.

Single Sourcing

In “single sourcing” a buyer (OEM organization) selects a single exclusive supplier for a particular part. A single sourcing strategy is only possibly when more than one supplier exists in the market, a situation that is common as a part begins to mature and prior to a part phasing-out of the market place. The part and supplier selection is usually a result of a “winner-take-all” (WTA) auction.

A winner-take-all auction is a procurement process that involves selecting and awarding a contract to a winning supplier based on purchase price bids for a specific part. Single sourcing promotes strong customer-buyer relationships by providing opportunities for both parties (supplier and customer) to streamline procurement practices, reduce lead times, and reduce inventory (Larson and Kulchitsky 1998). The customer-supplier relationship also allows part and product decisions to be coordinated. An added benefit of single sourcing is reduced prices for large quantity purchases as a result of “economy of scale” (Yu *et al.* 2008). Although single sourcing puts the buyer at risk due to the probability of supply chain disruptions or failures, there may be sufficient confidence in the supplier’s ability to warrant its use. Single sourcing is often used when tooling costs are high and only one supplier is willing to commit to fabricating a particular part.

Second Sourcing

Second sourcing is a sourcing strategy that involves purchasing parts from a primary supplier while maintaining a qualified back-up supplier (or second source) in the event of a supply chain failure (Anton and Yao 1987). In second sourcing, replacing and incumbent primary supplier by transitioning to a second source (when required) is generally quicker than adopting a new alternative supplier should the primary supplier fail to meet demand.

Second sourcing promotes competition at bidding stages offering potentially lower part procurement prices (Anton and Yao 1990). Second sourcing does not compromise "economy of scale" since all of the required supply is procured from the primary supplier; however, the second source must be maintained on a regular basis to ensure that the supplier's status is up-to-date, which leads to added costs not incurred by single sourcing.

Dual Sourcing

Dual sourcing is a sourcing strategy that involves qualifying and purchasing parts from two suppliers simultaneously. The primary contract accounts for a majority of the required parts and is intended to maximize "economy of scale" while the secondary contract is expected to be more flexible to account for demand uncertainty. From a strategic perspective, a secondary supplier offers supply redundancy should the primary supplier fail to meet the OEMs demand for parts.

A dual sourcing strategy utilizes a "split-award" auction to determine the most cost effective suppliers to use from a procurement cost perspective (Perry and Sákovics 2003). The principles surrounding split-award auctions are that profit incentives are awarded to suppliers with lower price bids. In return, those suppliers are awarded larger volumes to compensate for lost profit. Bidding ensues with each supplier strategically quoting a price high enough to maximize profit but low enough to secure a contract. The total volume required is divided between the winning supplier and the runner-up supplier. The larger volume is awarded to the supplier with the lowest price bid and is the primary contract. The secondary contract is awarded to the runner-up or second-lowest price bid in the split award auction.

Like second sourcing, dual sourcing has been found to reduce procurement cost by promoting competition between suppliers in cases where tacit collusion is unlikely (Anton and Yao 1990). Crocker and Reynolds (1993) performed an empirical study on Air Force engine procurement contracts that suggests dual sourcing used in early stages of development reduces the chance of supplier opportunism since procurement contracts tend to be less complete. A customer may also find dual sourcing attractive when innovation is a key dimension in promoting R&D competition (Anton and Yao 1992). However, these benefits of dual sourcing have been debated by Laffont and Tirole (1993), Riordan and Sappington (1989), and Rogerson (1989) who argue that reducing suppliers' production rents affects incentives for R&D (Lyon 2006).

Multi-Sourcing

Multi-sourcing is a part sourcing strategy that utilizes more than two suppliers from which parts are simultaneously purchased. The volume of parts purchased from each supplier may be allocated evenly or hierarchically based on the supplier's standing with the OEM.

The use of multiple suppliers may involve a combination of attributes from all other sourcing strategies. Companies implement various multi-sourcing strategies to prepare for imminent and unpredictable events. To counteract the likelihood of supply chain disruptions, many organizations prefer "multi-sourcing" as a way to distribute part purchases among more than two suppliers should one or more suppliers fail to meet required purchase volumes (Burke *et al.* 2007). A large body of research, related to procurement organizations, addresses the benefits of multi-sourcing as promoting competitive prices as a result of pricing negotiations (Lyon 2006, Anton and Yao 1990). These studies are extensions of (or share attributes with) dual sourcing auction theory.

Parallel Sourcing

Parallel sourcing involves segregating the purchase of parts between multiple suppliers where parts from each supplier are used in unique products. Therefore, parallel sourcing offers the benefits of multi-sourcing (lower procurement cost from competitive pricing and contract auctions) while allowing commonality across product designs. Parallel sourcing resembles single sourcing in all aspects except that the part from a supplier is limited to a single product. This strategy limits the consequences associated with a specific supplier-related supply chain disruption but may still be susceptible to common mode supplier failures or disasters.

1.1.3 Electronic part management organizations

Few of the OEMs that make complex electronic end-products fabricate the individual electronic parts themselves leaving the majority of the electronic systems' hardware content, consisting of “chips” and other active and passive electronic components, to be procured from elsewhere.

A life cycle approach to managing parts within an OEM involves monitoring part characteristics from when a part is first introduced until phase-out. Large OEMs such as Ericsson and Honeywell, have dedicated part selection and management groups whose primary focus is identifying, selecting, qualifying, and purchasing parts for specific products, as well as qualifying the manufacturers and distributors of those parts. The tasks of these groups range from part adoption to obsolescence management and include numerous assembly and support activities that are performed on a regular basis such as determining the procurement status of parts, managing purchase orders, and part database maintenance. In addition, part-specific concerns such as reliability issues and long-term availability problems are the responsibility of these groups if and when they occur. Each part that exists as a unique part number in an organization’s database requires support activities and dedicated resources, which incur life cycle costs that can, in many cases, be significantly higher than the part’s procurement price. To complicate the role of the part selection and management group, actual product manufacturing may be performed by other organizations (e.g., contract manufacturers) that may be outside the control or influence of the part selection and management groups.

1.1.4 Long life cycle vs. short life cycle products

Products can be categorized as follows based on the length of the product’s manufacturing and support life cycle:

(1) Short life cycle products – products (often high-volume products) that are manufactured, fielded and supported for relatively short periods of time (1-3 years or less) and therefore only require that a part be available for a relatively short period of time. Examples include consumer electronics: cell phones, personal computers, iPods, televisions, DVD players, etc.

(2) Long life cycle products – products manufactured, fielded and supported for long periods of time (10 years or more – many are supported for 20-30 years or longer). These products often require relatively low volumes of parts and include: airplanes, medical systems, power plant control systems, infrastructure systems and military systems.

Distinguishing between these categories of products is important since they do not share common life cycle characteristics. Existing methods and studies related to managing short life cycle products (and their parts) may not be applicable to long life cycle systems.

The distinction between long life cycle and short life cycle products is, in part, due to the nature of the supply chain. Unlike many non-electronic parts, electronic parts are generally not custom produced for customers. Electronic OEMs utilize commercial "off-the-shelf" (COTS) parts which quickly become obsolete. Therefore it is not uncommon for electronic parts and their supply chains to change outside the control of all but the largest customers. Long life cycle products that generally deal with low volume production have virtually no control over a particular market segment further reducing their ability to interact with suppliers and guide market trends.

Long life cycle electronic system using COTS parts in low volumes are subject to the same supply chain constraints imposed by a market that is oriented towards short life cycle, high-volume products. The mismatch between short life cycle parts in long life cycle products increases the likelihood that parts will become unavailable with little or no forewarning. As a result, electronic parts are subject to high-frequency involuntary procurement obsolescence. Many electronic parts are only procurable from their original manufacturer for a few years, then they are discontinued in favor of newer, higher performing parts – approximately 3% of the global pool of electronic parts become obsolete every month (QTEC 2006). When parts become obsolete, considerable resources must be expended to resolve the problem.

1.1.5 DMSMS type part obsolescence

Obsolescence is defined as the loss or impending loss of original manufacturers (suppliers) of items or raw materials (Sandborn 2008b). The type of obsolescence addressed in this dissertation is referred to as DMSMS (Diminishing Manufacturing Sources and Material Shortages) and is caused by the unavailability of technologies (parts) that are needed to manufacture or sustain a product[3]. DMSMS means that due to the length of the system's manufacturing and support life, coupled with unforeseen life extensions to support the system, needed parts become unavailable (or at least unavailable from their original manufacturer). Obsolescence

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[3] Inventory or sudden obsolescence, which is more prevalent in the operations research literature, refers to the opposite problem to DMSMS obsolescence in which inventories of parts become obsolete because the product or system they were purchased for changes so that the inventories are no longer required, e.g., (Brown *et al.* 1964).

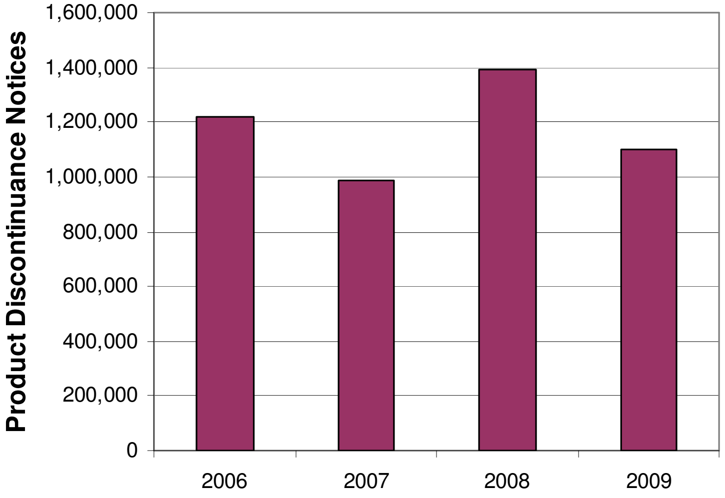

Figure 1.3 – The total number of discontinuance notices (notices from the original manufacturer that manufacturing of the part will be terminated) for electronic parts in years 2006-2009 from SiliconExpert Technologies, Inc. databases.

is one of many part supply chain problems that complicate the management of electronic systems (Murray *et al.* 2002).

The fundamental disparities in life cycle needs and business objectives impose inevitable obsolescence challenges. Many long field life products particularly suffer the consequences of electronic part obsolescence because they have no control over their electronic part supply chain due to their relatively low production volumes. DMSMS type obsolescence occurs when long field life systems must depend on a supply chain that is organized to support high-volume products. Obsolescence becomes a problem when it is forced upon an organization; in response, that organization may have to involuntarily make changes to products that it manufactures, supports or uses[4]. Figure 1.3 shows the magnitude of the

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[4] Researchers who study product-development characterize different industries using the term "clockspeed," which is a measure of the dynamic nature of an industry (Fine 1998). The type of

obsolescence problem today. The 1.1 million electronic part discontinuances in 2009 represents approximately 0.9% of the electronic parts available in the market.[5]

The majority of DMSMS obsolescence management today is reactive in nature – managing problems after they occur using a mixture of the mitigation approaches that include (Stogdill 1999): lifetime buy, last-time buy, aftermarket sources, identification of alternative or substitute parts, emulated parts, salvaged parts, and thermal uprating (Pecht and Humphrey 2006). Potentially larger cost avoidances are possible with pro-active and strategic management approaches (Sandborn 2008b). Pro-active management means identifying and prioritizing selected non-obsolete parts that are at risk of obsolescence and identifying resolutions for them before they are discontinued. Design refreshes ultimately occur as other mitigation options are exhausted and functionality upgrades (technology insertion) becomes necessary. Strategic management is done in addition to pro-active and reactive management, and involves the determination of the optimum mix of mitigation approaches and design refreshes (Singh and Sandborn 2006).

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industries that generally deal with DMSMS problems would be characterized as slow clockspeed industries. In addition, because of the expensive nature of the products (e.g., airplanes, ships, etc.) the customers cannot afford to replace these products with newer versions very often (i.e., slow clockspeed customers). DMSMS type obsolescence occurs when slow clockspeed industries must depend on a supply chain that is organized to support fast clockspeed industries.

[5] As of June 2010 SiliconExpert Technologies' parts database consisted of 157.2 million unique parts (approximately 120 million of which are not obsolete). Part count includes all derivations of part numbers based on part family name and generic codes as assigned by their manufacturers.

Chapter 2: Dissertation scope and problem statement

This chapter presents the objective, scope, and an overview of the solution strategy followed in this dissertation.

2.1 Problem Statement

The goal of this dissertation is to quantify supply chain risk and thereby enable supplier-selection under specific types of sourcing strategies (e.g., single, second, multi-sourcing) subject to long-term supply chain disruptions.

2.1.1 Dissertation Scope

This dissertation develops and demonstrates a methodology to quantify the risk of sourcing electronic parts that can be procured from multiple suppliers for use in long life cycle electronic products and systems. This dissertation focuses on part sourcing strategies and decisions (i.e., the number of suppliers and combination of suppliers from which to procure a part) subject to long-term supply chain disruptions, specifically part obsolescence. The comparison of various sourcing strategies for use in the support of long life cycle systems provides application-specific insight into the cost benefits of each strategy as a proactive approach to mitigate the effects of supply chain disruptions.

An effect of utilizing multiple suppliers or a specific combination of suppliers, which defines the characteristics of a particular sourcing strategy, is the potential to reduce the overall supply chain disruption risk; however, the benefit may be negated by the cost to qualify and support additional suppliers. The goal of this dissertation is to develop a new methodology that can identify the most “cost-effective” sourcing strategy to adopt in the procurement and support of particular parts. The quantification and comparison of various strategies involves the assessment of the supply chain risk that a sourcing strategy is exposed to over the part’s usage life cycle (the period of time that the part is used and supported within an organization). Risk is a combination of the following two features: 1) the consequence or severity of a risk related event, and 2) the likelihood that the event will occur.

The scope of this dissertation is:

- *Part-specific* – The type of supply chain constraints focused on in this dissertation are part-specific, not product-specific since the supply chain constraints considered (e.g., specifications, attributes, available suppliers, etc.) are part specific. In this dissertation product-specific data must be included (e.g., manufacturing volumes as a function of time, end of product support, etc.) and can be allocated on the part level. This approach is suited for the non-product-specific part selection and management groups that exist within large electronic systems OEMs.
- *Long life cycle electronic products and systems* – Existing supply chain risk and disruption studies rarely distinguish between long life cycle and short life cycle products and nearly all fall within the realm of short life cycle, high volume production with limited (or unknown) applicability to long life cycle, low volume production. This dissertation focuses on long life cycle (10+ years and often 20-30 year manufacturing and support life), low volume electronic products and systems.
- *Strategic parts management* – The focus of this dissertation is on strategic approaches to the mitigation of long-term supply chain disruptions. Tactical

solutions for solving short-term problems (e.g., brief lead time problems for delivery of parts to a high-volume manufacturing process) are not addressed within this dissertation. The problems addressed here are disruptions that cause permanent or long term shortages of parts and represent the complex decision making process within part selection and management groups that involve transactions and interactions with suppliers.

- *Life cycle approach* – The life cycle of a part selection decision and usage starts when the part is proposed for use in one or more products and ends when the last product that uses the part reaches its end of support. The planning horizon considered for most part procurement decisions ends when manufacturing is complete (and this is the end of the planning horizon considered in the majority of existing sourcing models). Many of the long field life systems that this dissertation is interested in are referred to as "sustainment dominated," i.e., their long term sustainment costs are considerably larger than their procurement costs (Sandborn and Myers 2008). As a result, for long life cycle, low volume product sectors, the life cycle cost of a part (the total cost of ownership of the part selection decision) may be significantly higher than the part's procurement price.
- *DMSMS type obsolescence risk* – Although the methodology developed has general applicability to various long term supply chain risks, this dissertation will focus on obsolescence risk in supply chains and present methods of estimating the probability or likelihood of DMSMS type obsolescence occurrence over time. The comparison and selection of sourcing strategies will be assessed based on the likelihood and consequence of part obsolescence.

2.1.2 Research overview

The goal of this dissertation is to develop and demonstrate a method to quantify supply chain risk (as expected TCO) over the part's entire support life cycle within an organization (*j* years) for a particular combination of available sources[6] or suppliers. The quantification of supply chain risk enables the selection of suppliers from which to procure parts when the number of suppliers that can be used, N_S^{SUP}, is predetermined. In addition, this solution provides a means to perform tradeoff analyses and identify the conditions under which a set of sourcing strategies with N_S^{SUP} suppliers will be cost-effective based on the organization's capability to stream-line qualification and support activities.

Let *S* be the entire set of possible combinations[7] of N_S^{SUP} sources or suppliers from a set of available/potential suppliers, *n*. Then, the number of combinations in set *S* can be calculated using the binomial coefficient in (2.1),

$$S = \begin{pmatrix} n \\ N_S^{SUP} \end{pmatrix} = \frac{n!}{N_S^{SUP}!(n - N_S^{SUP})!} \tag{2.1}$$

where, N_S^{SUP} is the number (integer) of suppliers that can be used in a particular type of sourcing strategy (i.e., single, second, multi sourcing). Each combination of suppliers constitutes a unique sourcing strategy, *s* where $s \subset S$.

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[6] Terms "sources" and "suppliers" are used synonymously in this dissertation.

[7] Sourcing combinations are assumed to be "non-repetitive," e.g., there can be only one combination of two suppliers. In other words, the combination of suppliers is assumed in this dissertation to be independent of order where a sourcing strategy with multiple suppliers shows no supplier preference. Permutations are used instead of combinations in situations where a sourcing strategy defines an order of supplier preference (e.g., "split-award" auctions - selection of primary and secondary suppliers has an effect on procurement cost through competitive pricing). This dissertation assumes (and later verifies) that advantages gained through reducing part price (as is the goal with competitive pricing) are negligible with respect to part Total Cost of Ownership (TCO) of low-volume long support life products and thus, no supplier preference is assumed.

No models currently exist that allow part management organizations to assess long life cycle part management decisions (such as part sourcing), let alone optimize them. The simulation part total cost of ownership (TCO) model developed in this dissertation (presented in Chapter 3) quantifies part TCO, i.e., the total cost of qualifying, procuring, holding, assembling, and supporting parts in multiple products in the presence of supply chain disruptions. Utilizing the new part TCO model, the consequence of supply chain disruptions can be quantified by accounting for the cost of implementing a sourcing strategy, *s* and effect of the disruption date occurring in year *D*. The simulation part TCO model was also used to determine when procurement price should (or should not) be considered in the part and supplier selection process.

This dissertation presents procurement life as a part-specific and supplier-specific attribute for dealing with the procurement of parts from multiple suppliers. Note that the distribution of *D* depends upon the sourcing strategy, *s*. Forecasting the distribution of *D* with respect to sourcing strategy *s* is the topic of discussion in Chapter 4. In Chapter 4, a data-driven method is presented to determine the likelihood of part obsolescence. The data-driven method for forecasting a part's procurement life is especially useful for parts with no identifiable parametric driver for obsolescence. The method utilizes historic part obsolescence data to forecast future obsolescence events via Maximum Likelihood Estimation (MLE). This new method offers a way to determine the likelihood of obsolescence as probability density functions (PDF) and cumulative density functions (CDF).

In Chapter 5, the part TCO of introducing and supporting a group of suppliers (from Chapter 3) is combined with the likelihood of disruption (from the data-driven method described in Chapter 4) to quantify the supply chain risk of a part sourcing strategy, *s*. Letting $E[C_{TCO}(s,D)]$ be the supply chain risk as expected TCO over the part's life cycle, the problem addressed in this dissertation can be stated as follows:

$$\begin{array}{l} minimize\ E[C_{TCO}(s,D)] \\ s \subset P \end{array}$$

Specifically, this dissertation solves the problem described above for obsolescence risk utilizing distributions for supplier-specific procurement life; however, other causes for supply chain disruptions (other risks) could be modeled similarly. The procurement life approach used to quantify supply chain risk offers a clear method in selecting the best single source and best combination of sources when second sourcing. The obsolescence risk results in this dissertation indicate that second sourcing is almost never viable if the cost to support the second source is the same as the first source within the scope of the systems considered in this dissertation.

The maximum allowable cost and resources to support a second source in order for a second sourcing strategy to be viable can be calculated mathematically. Chapter 6 derives an analytical part TCO model to estimate the life cycle cost impact of long-term part sourcing based on simplifying assumptions specific to part sourcing in long life cycle electronic products and systems. Section 6.2 derives equations to determine the overlap in supplier-related support activities (via learning indices) that would be needed for the TCO of two sourcing strategies (single sourcing vs. second sourcing) to be equal or "break-even".

Let D_a and D_b be the part obsolescence dates (estimated from effective procurement lives) associated with the two sourcing strategies, *a* and *b*, being considered. Let B_s be the learning index of support activities for sourcing strategy *s*. Then, $[\Delta C_{TCO}]_{a,b}$ is the difference in C_{TCO} between sourcing strategies, *a* and *b*, as shown in (2.2),

$$[\Delta C_{TCO}]_{a,b} = \left[C_{TCO}\left(D_a, B_a, N_a^{SUP}\right)\right]_a - \left[C_{TCO}\left(D_b, B_b, N_b^{SUP}\right)\right]_b \tag{2.2}$$

In the context of this dissertation, learning indices for multi-sourcing support cost are said to be at "break-even" when the resulting TCO of the two sourcing strategies being compared, strategy *a* and strategy *b,* are equal; i.e., ΔC_{TCO} becomes zero. The objective of Chapter 6 is to solve $[\Delta C_{TCO}]_{a,b} = 0$ for "break-even" learning index B_b where strategies *a* and *b* are single sourcing (N_a^{SUP} = 1) and second sourcing (N_b^{SUP} = 2) strategies respectively. Determining the break-even learning index creates a target for reducing qualification and support activities; a part management organization capable of achieving a learning index below B_b can be expected to benefit from implementing multi-sourcing strategy, *b*.

The analysis includes Monte Carlo simulations based on uncertainties in sourcing-related disruption dates to determine the probability that the "break-even" learning index will exceed a threshold learning index (or minimum achievable learning index imposed on the part support process). This method is demonstrated in example case studies of linear regulators with a focus on the comparison of single and second sourcing.

2.2 Technical tasks

In order to meet the objectives described above, the following specific tasks have been completed:

Task 1. Construct a Part TCO Model that includes Multi Sourcing Extensions – Built a general TCO (life cycle cost) model for parts procured from multiple suppliers to enable part sourcing tradeoffs. The total cost of ownership approach captures costs incurred by parts at all stages of their procurement and support life cycle within an organization. The total cost of ownership approach is composed of part-related non-recurring design and selection/qualification activities, product manufacturing and assembly activities, product field support activities, and regular support activities critical to the management of electronic parts in long life cycle products. Include the effects of long-term supply chain disruptions into the TCO simulator. The cost (inclusive of disruption effects and penalties) is estimated as a function of disruption year.

Task 2. Obsolescence Risk Model Formulation – Formulate a methodology to estimate the probability (likelihood) of occurrence of a long-term supply chain disruption. The dissertation focuses on the particular risk of DMSMS type part obsolescence and uses historic part obsolescence data to formulate a model. Include the obsolescence risk likelihoods (probability distributions of disruption events) within the simplified TCO model to estimate the "expected TCO" of a sourcing strategy. This allows sourcing strategies to be compared based on obsolescence driven supply chain risk.

Task 3. Case Studies with Part TCO Simulator (determination of viable assumptions for the analytical model developed in Task 4) – Implement the part TCO model as a simulation to assess the life cycle cost of managing electronic parts. Surface mount capacitor case studies are used to establish the applicability of simplifying assumptions for long-term sourcing in long life cycle products.

Task 4. Analytical TCO Model – Derive an analytical part TCO model based on simplifying assumptions specific to the long-term sourcing of parts used in long life cycle products and systems (gathered from Task 3). Formulate a method to asses sourcing tradeoffs such as estimating the benefit (or cost) of extending the procurement life of a part by adding suppliers. Tradeoff analyses between part sourcing strategies help to make "evidence based" decisions by estimating the cost and risk tradeoffs between two sourcing strategies (for example, single versus second sourcing). The tradeoff analyses includes mathematically estimating learning indices for sourcing support costs that would be required for the TCO of two sourcing strategies (with different procurement lives) to be equal or "break-even".

Task 5. Determine the Viability of Second Sourcing Compared to Single Sourcing Parts – Viability of the second sourcing strategy is dependent on the probability that the "break-even" learning index will exceed a threshold learning index.

Chapter 3: Part sourcing total cost of ownership (TCO)

The model presented in this chapter focuses on optimal part management from a part selection and management organization's viewpoint as opposed to the optimum part management from a product group's perspective. These perspectives differ because the part selection and management group has a more holistic view of a part's cost of ownership than a product group, and a part (especially an electronic part) may be concurrently used in many different products within the same organization. This approach requires a cost model that comprehends long-term supply chain constraints that are associated with specific parts and their effects downstream at the product level, therefore the cost that we wish to predict and minimize is the effective total cost of ownership (TCO) of the part as used across multiple products. Assessing the total cost incurred over the life cycle of the part as an effective total cost of ownership will allow part management organization to quantify the cost spent (inclusive of procurement) per part for a specific sourcing configuration.

In Section 3.3, the part TCO model (described in Section 3.1) is applied in a general way to enable the estimation of part life cycle cost under various conditions of use representative of long life cycle product applications. Section 3.3.1 describes example case studies of an SMT capacitor to demonstrate the evaluation of part TCO. These example case studies will present the basis for key assumptions made in the formulation of an analytical part TCO model for parts used in long life cycle products in Chapter 6.

3.1 Part TCO model for single sourcing

The part TCO model discussed in this section estimates the total cost of introducing, procuring, storing, assembling, and supporting a part from a single supplier in multiple products. Let j be the part lifetime (the number of years in which the part will be used). Then, the part TCO, $C_{TCO}(s,D)$ after j years, if the product manufacturer chooses sourcing strategy s and a disruption occurs in year D, is the total cost spent at various stages of the part's life cycle: procurement (C_{PROC}), inventory (C_{INV}), support (C_{SUP}), assembly (C_{ASY}), and field failure repairs (C_{FF}). The part TCO can be calculated as shown in (3.1),

$$C_{TCO}(s,D) = C_{PROC}(s,D) + C_{INV}(D) + C_{SUP}(s,D) + C_{ASY} + C_{FF} \tag{3.1}$$

Modeling a part's total cost of ownership requires an understanding of the product's life cycle costs[8]. Life cycle cost represents the total cost of acquisition and ownership of a product over its full life, including the cost of planning, development, acquisition, operation, support, and disposal. General life cycle cost analyses of products have been treated by many authors, e.g., (Fabrycky and Blanchard 1991, Asiedu and Gu 1998). Existing models used to estimate part management cost tradeoffs tend to be either: a) primarily focused on manufacturing (containing little or no view into the post-manufacturing life cycle), b) product specific, and/or c) lack an understanding of the unique attributes of electronic part management. For example, the methodology presented by Boothroyd and Dewhurst (1994) presents an assembly (DFA) and manufacturing (DFM) approach to product cost modeling that does not

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[8] In this chapter the effective total cost of ownership refers to the life cycle cost of the part from the part customer's point of view, which should not be confused with Cost of Ownership (COO), which is a manufacturing cost modeling methodology that focuses on the fraction of the lifetime cost of a facility consumed by an instance of a product.

capture activities beyond the manufacturing of the system. In another example, Wang *et al.* (2007) establishes a decision-support model in order to enable part changes from a life cycle cost perspective, however, the cost model estimates static and dynamic costs from a product perspective as opposed to a part perspective.

Ellram and Siferd (1998) describe the common shortcomings of traditional cost analysis methods as being focused on price, de-emphasizing suppliers' performance, and disregarding internal costs. In addition, traditional cost analysis methods often tend to focus on aspects of an organization that lack efficiency rather than modeling all processes. Ellram and Siferd support the emergence of total cost of ownership (TCO) approaches to promote strategic decision making and that the true benefits of total cost of ownership is the marriage between strategic cost management concepts (focus on financial and accounting perspectives) and the fundamental approach of total cost of ownership as a holistic costing approach – concepts that are captured in the model presented in this section. The estimation of life cycle cost in electronic parts (besides procurement) include the assessment of part manufacturers and distributors (Jackson *et al.* 1999), qualifying and screening parts (e.g., Kim 1998), the impacts of part reliability (e.g., Alcoe *et al.* 2003), warranty, sparing and availability, obsolescence management (Sandborn 2008a), and support. The proposed part total cost of ownership (TCO) model is composed of the following three sub-models: part support model, assembly model, and field failure model. This TCO model contains both assembly costs (including procurement) and life cycle costs associated with using and supporting the part in multiple products.

From a traditional part management perspective, the term "part" is used to describe one or more items with a common part number. Several items with a common part number may be used in multiple products as an artifact of design reuse (Meyer and Lehnerd 1997). 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. In this dissertation, we focus on the "part sites" (instead of "parts") because when product repairs and replacements are considered there is effectively more than one part consumed per part site (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 cost calculations are presented in terms of either annual or total (cumulative) cost per part site.

Let N_i^{VOL} be the number of parts used (consumed by assembly operations) in year *i*. Then C_{PPS} is the total effective cost (TCO) per part site as shown in (3.2).

$$C_{PPS} = \frac{C_{TCO}}{\sum_{i=1}^{j} N_i^{VOL}} = \frac{C_{PROC} + C_{INV} + C_{SUP} + C_{ASY} + C_{FF}}{\sum_{i=1}^{j} N_i^{VOL}} \tag{3.2}$$

All computed costs in the model are indexed to year 1 (base year for money) for reference where year 1 refers to the period between time 0 and the end of 1 year.

3.1.1 Support cost model

The part support model captures all costs associated with selecting, qualifying, purchasing, and sustaining a part (these costs may recur annually, but do not recur for each part instance).

Table 3.1 – Example matrix of the characteristics of various support activities, *x*.

Support activities (x)	**Recurring**	**Fixed**
Initial Approval	No	Yes
Part NRE Cost	No	No
Product-Specific Approval	Yes	No
Supplier Qualification	No	Yes
Annual Part Data Management	Yes	No
Annual Production Support	Yes	Yes
Annual Purchasing	Yes	No
Obsolescence Case Resolution	No	No

Let x be a vector of support activities where C_i^x are cost components of the total support cost incurred during year i. For example, C_i^{ia}, C_i^{pa}, C_i^{as}, C_i^{ps}, and so on, are costs attributed to the management of electronic parts determined from an activity based cost model in which cost activity rates can be calculated by part type.[9] These support activities can be described as follows (and shown in Table 3.1):

- *Recurring Costs* – incurred on several occasions, often at fixed time intervals (e.g., annual costs). Conversely, *Non-recurring* costs are incurred once (e.g., product qualification).

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[9] Part type definitions are as follows: Type 1 – resistors, capacitors, inductors, and mechanical parts; Type 2 – integrated circuits, oscillators, filters, board connectors; Type 3 – ASICs, RF connectors, RF integrated circuits, DC/DC, synthesizers, optical transceivers (TRX); and Type 4 – RF transistors, circulators, isolators.

- *Fixed Costs* – not dependent on a specific independent variable and therefore, do not vary (e.g., initial approval). Conversely, *Variable* costs are driven by one or more independent variables (e.g., product specific approval costs are dependent on the number of products that the part is used in, N_{sup}).

Let C_i^{ia} be the initial part approval and adoption cost. The approval cost is assumed to occur only in year 1 (i = 1) for each new part. C_i^{ia} includes all costs associated with qualifying and approving a part for use (i.e., setting up the initial part approval). This could include reliability and quality analyses, supplier qualification, database registration, added NRE for part approval, etc.

Let C_i^{pa} be the product-specific approval and adoption cost. C_i^{pa} includes all costs associated with qualifying and approving a part for use in a particular product. This approval cost would occur exactly one time for each product that the part is used in and is a function of the type of part and the current approval level of the part within the organization when the part is selected. This cost depends on the number of products introduced in year i that use the part.

Let C_i^{as} be the annual cost of supporting the part within the organization. C_i^{as} includes all costs associated with part support activities that occur for every year that the part must be maintained in the organization's part database such as database management, PCN (product change notice) management, reclassification of parts, and services provided to the product sustainment organization. C_i^{as} depends on the part’s qualification level which can change over time.

Let C_i^{ps} be the total cost associated with production support and part management activities that occur every year that the part is in a product manufacturing (assembly) process. C_i^{as} includes all costs associated with volume purchase agreements, services provided to the manufacturing organization, reliability and quality monitoring, and availability (supplier addition or subtraction).

Let C_i^{ap} be the purchase order generation cost which depends on the number of purchase orders in year *i*.

Let C_i^{or} be the obsolescence case resolution cost. C_i^{or} is only charged in the year that a part becomes obsolete.

Let C_i^{nonPSL} be the cost to setup all non-PSL (Preferred Supplier List) part suppliers. C_i^{nonPSL} depends on the number of non-PSL sources that must be qualified in year *i*.

Let C_i^{design} be the non-recurring design-in costs associated with the part. C_i^{design} is only charged in years when new products are introduced and includes cost of new CAD footprint and symbol generation if needed.

Then, the total support cost, C_{SUP}, after *j* years, can be calculated as shown in (3.3) where *j* is the number of years that the part must be supported.

$$C_{SUP} = \sum_{i=1}^{j} \frac{\left(C_i^{ia} + C_i^{pa} + C_i^{as} + C_i^{ps} + C_i^{ap} + C_i^{or} + C_i^{nonPSL} + C_i^{design}\right)}{(1+r)^i} \qquad (3.3)$$

3.1.2 Assembly cost model

The assembly cost model captures all recurring (for each instance of the part) costs associated with the assembly of the part: system assembly cost (part assembly into the product or system), and recurring functional test/diagnosis/rework costs.

Let N_i^{VOL} be the total number of parts consumed by assembly operations in year *i*. Let Y_{pi}^{IN} be the yield of the assembly process in year *i* when parts are procured from supplier *p*. Let C_i^a be the assembly cost and P_i be the purchase price of one instance of the part in year *i*. Let C_i^{IN} be the annual incoming cost (per part) inclusive of part price (i.e., $C_i^{IN} = P_i + C_i^a$). Then C_{ASY} be the total assembly cost (for all products and inclusive of procurement cost) after *j* years, as shown in (3.4),

$$C_{ASY} = \sum_{i=1}^{j} \frac{N_i^{VOL} C_i^{OUT}\left(C_i^{IN}, Y_{pi}^{IN}, N_i^{VOL}\right)}{(1+r)^i} \tag{3.4}$$

where, C_i^{OUT} is the assembly cost (per part) during year *i*. C_i^{OUT} is calculated annually using the assembly cost model shown in Figure 3.1 where $C_{out} = C_i^{OUT}$, $C_{in} = C_i^{IN}$, $N_{in} = N_i^{VOL}$ and $Y_{in} = Y_{pi}^{IN}$. The model described in Figure 3.1 and Table 3.2 is based on a previously developed test/diagnosis/rework model for the assembly process of electronic systems (Trichy *et al.* 2001).[10] The approach includes a model of functional test operations characterized by fault coverage, false positives, and defects introduced during tests, in addition to rework and diagnosis (diagnostic

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[10] Note, several typographical errors should be corrected in (Trichy *et al.* 2001): In (2) and (3), the maximum of the summation should be *n*-1 instead of n, and (4a) can be used for either definition of f_p with $N_{d_{n+1}}$ changed to N_{d1_n}. In (13), the subscript of N_r should be *i*-1 instead of i when $i > 0$.

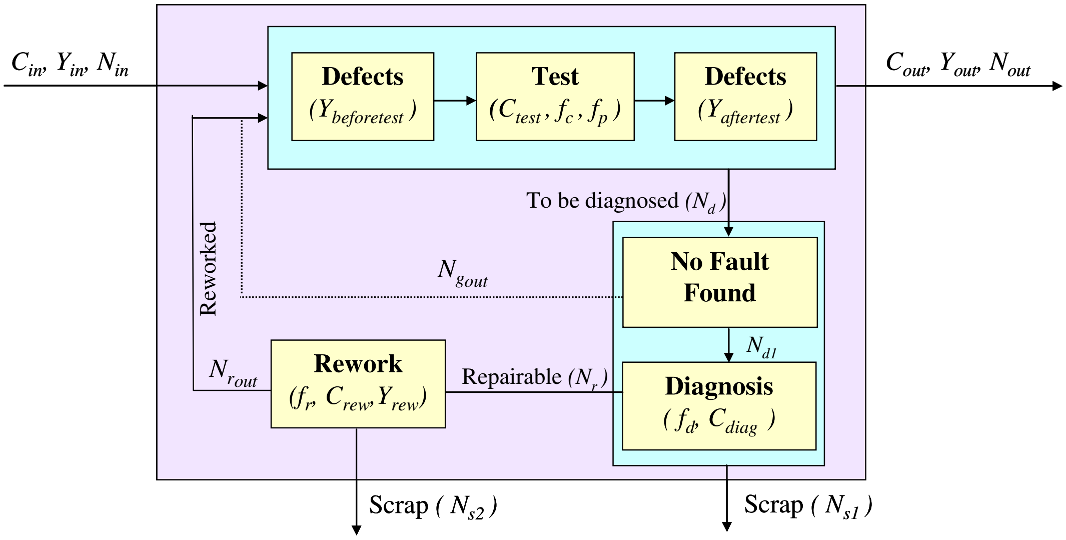

Figure 3.1 – Test/diagnosis/rework (TDR) model from Trichy *et al.* (2001). Table 3.1 describes the notation appearing in this figure.

test) operations that have variable success rates and their own defect introduction mechanisms. The model accommodates multiple rework attempts on any given product instance and enables optimization of the fault coverage and rework investment during assembly tradeoff analyses.

The model discussed in this chapter contains inputs to the test/diagnosis/rework model that are specific to the part type and how the part is assembled (automatic, semi-automatic, manual, pre-mount, lead finish[11], extra visual inspection, special electro static discharge (ESD) handling – see (Prasad 1997)). The output of the model is the effective procurement and assembly cost per part site. This model assumes that all part-level defects (either inherent in the part or introduced during the assembly process) are resolved in a single rework attempt (i.e., $Y_{rew} = 1$), that there are no defects introduced by the testing process (i.e., $Y_{beforetest} = Y_{aftertest} = 1$),

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[11] Lead finishes are very relevant for electronic parts since traditional tin-lead solder finishes were banned for many electronic product sectors in 2003 by the RoHS directive (Ganesan and Pecht, 2006).

and that there are no false positives in testing (i.e., $f_p = 0$). These assumptions for yields in the assembly process guarantee that Y_{out} will always be 1. As a result, $N_{in} = N_{out} = N_i^{VOL}$ and $N_{s1} = N_{s2} = 0$. Therefore, if part price is omitted from the calculation of C_i^{IN} (i.e., $C_i^{IN} = C_i^a$), then C_{ASY} is the total assembly cost exclusive of total procurement cost. Section 3.1.3 presents a model for calculating the part's procurement and inventory cost subject to disruption dates. The calculation of C_{ASY} is independent of disruption date if sufficient parts are procured through lifetime buys when a disruption occurs (also discussed in Section 3.1.3). The cost (and penalties) of other disruption mitigation strategies may be considered and is the topic of discussion in Section 3.2.5.

Table 3.2 – Nomenclature used in Figure 3.1.

C_{in}	= Cost of a product entering the test, diagnosis and rework process	N_{in}	= Number of products entering the test, diagnosis and rework process
C_{test}	= Cost of test per product	N_d	= Total number of products to be diagnosed
C_{diag}	= Cost of diagnosis per product	N_{gout}	= Number of no fault found products
C_{rew}	= Cost of rework per product	N_{d1}	$= N_d - N_{gout}$
C_{out}	= Effective cost of a product exiting the test, diagnosis and rework process	N_{out}	= Number of a products exiting the test, diagnosis and rework process, includes good products and test escapes
f_c	= Fault coverage	N_r	= Number of products to be reworked
f_p	= False positives fraction, the probability of testing a good product as bad	N_{rout}	= Number of products actually reworked
f_d	= Fraction of products determined to be reworkable	N_{s1}	= Number of products scrapped by diagnosis process
f_r	= Fraction of products actually reworked	N_{s2}	= Number of products scrapped during rework
$Y_{beforetest}$	= Yield of processes that occur entering the test	$Y_{aftertest}$	= Yield of processes that occur exiting the test
Y_{in}	= Yield of a product entering the test, diagnosis and rework process	Y_{out}	= Effective yield of a product exiting the test, diagnosis and rework process
Y_{rew}	= Yield of the rework process		

3.1.3 Procurement and inventory cost model

The part's total procurement and inventory costs depend on when part disruptions occur. For every year before the disruption occurs, the manufacturer purchases exactly the number of parts needed for that year. In the year of the disruption, the manufacturer makes a lifetime buy plus an overbuy quantity called a "buffer," a purchase of more parts than the demand forecasts. In subsequent years, the cost of procuring parts becomes zero, but the cost of inventory for the lifetime buy of parts is included.

Let N_i^{VOL} be the number of parts used by assembly operations in year *i.* Let $N_{pi}^{PROC}(D)$ be the number of parts purchased from supplier *p* in year *i* when the disruption occurs in year *D*. Note that *D* can range from 1 to *j*+1. Let *k* be the counter variable for each year after the disruption date until year *j*.

Let $F_{overbuy}$ be the lifetime buy quantity buffer expressed as a fraction of the lifetime buy quantity. Then $N_i^T(D)$ is the total number of parts purchased in year *i*. In the case of a single supplier, $N_i^T(D) = N_{pi}^{PROC}(D)$.

$$N_i^T(D) = \begin{cases} N_i^{VOL} & \rightarrow \text{if } \ i < D \\ \left(1 + F_{overbuy}\right)\sum_{k=D}^{j} N_k^{VOL} & \rightarrow \text{if } \ i = D \\ 0 & \rightarrow \text{if } \ i > D \end{cases}$$

Let $C_{PROC}(p,D)$ be the total procurement cost after *j* years when supplier *p* is selected and the disruption occurs in year *D*. The supplier-specific part price in year *i* is P_{pi} when the parts are procured from supplier *p* and may be subject to an annual cost change due to inflation or deflation.

$$C_{PROC}(p,D) = \sum_{i=1}^{j} \frac{P_{pi} N_i^T(D)}{(1+r)^i} \tag{3.5}$$

Let $Q_i(D)$ be the number of parts in inventory at the beginning of year *i* when the disruption occurs in year *D*. Then, $Q_i(D) = N_i^T(D)$ for $i \le D$ and $Q_i(D) = Q_{i-1}(D) - N_{i-1}^{VOL}(D)$ for $i > D$. Let h_i be the cost of holding one part in year *i*. Then $C_{INV}(D)$ is the total inventory cost after *j* years when the disruption occurs in year *D*.

$$C_{INV}(D) = \sum_{i=1}^{j} \frac{h_i Q_i(D)}{(1+r)^i} \tag{3.6}$$

3.1.4 Field failure cost model

The field failure model captures the costs of warranty repair and replacement due to product failures caused by the part.

Let N_i^{fail} be the number of failures under warranty in year *i*. This is calculated using 0-6, 6-18 and > 18 month FIT rates[12] for the part, the warranty period length (an ordinary free replacement warranty is assumed with the assumption that no single product instance fails more than one time during the warranty period), and the number of parts sites that exist during the year. Let C_{repair} be the cost of repair per product instance for failures under warranty. Let f_{rep} be the fraction of failures requiring replacement (as opposed to repair) of the product. Let $C_{replace}$ be the cost of replacing the product per product instance. Let C_i^{wr} be the cost of processing the warranty returns in year *i*. Then, C_{FF} is the total cost of field failures after *j* years as shown in (3.7).

---

[12] FIT (Failures in time) rate – Number of part failures in 10^9 device-hours of operation.

$$C_{FF} = \sum_{i=1}^{j} \frac{N_i^{fail}\left(1 - f_{rep}\right) C_{repair} + N_i^{fail} f\, C_{replace} + N_i^{fail} C_i^{wr}}{(1+r)^i} \tag{3.7}$$

Section 3.3 presents case studies using the TCO model for single sourcing (described in Section 3.1) to explore the true impact of variability in procurement cost on a part's TCO when used in long life cycle applications. These case studies provide the basis for simplifying assumptions in the formulation of an analytical part TCO model. Section 3.2 modifies the models presented in Section 3.1 to address the cost impact of using multiple part sources.

3.2 Modifications to address multi-sourcing

This section describes the formulation of a multi-sourcing part TCO model for electronic parts based on the part TCO model described in Section 3.1. The inclusion of sourcing-related effects enables the life cycle cost impact of sourcing decisions to be quantified. In Section 3.2, the total cost of ownership is determined as a function of the sourcing strategy used, *s* and the forecasted date of a long-term supply chain disruption, *D* – determining the probability and thereby forecasting the risk of supply chain disruptions will be addressed in Chapter 4 and Chapter 5 respectively.

The value of multi-sourcing involves modeling the cost benefits of price auctions as well as the added cost needed to support multiple suppliers. In order to accurately assess a sourcing strategy, one must capture all facets of the supplier selection decision and the effects of long-term supply chain problems over the life of the electronic part. Modeling sourcing strategies as a total cost of ownership helps quantify the consequences of long-term supply chain disruptions.

The electronic part total cost of ownership model discussed in Section 3.1 computes the effective lifetime cost of a part's selection based on the part's properties, the characteristics of the organization using the part, financial costs, the quantity of parts used, and the quantity and mix of products that use the part. An observation from the case studies that will be described in Section 3.3 is that for low-volume parts used in long life cycle products, a significant portion of the total cost of ownership is attributed to assembly and support activities, and specifically the supplier setup component of support cost contributed significantly to a part's total cost of ownership. The effects of adding a supplier to the procurement plan (transitioning from a single source to a multi-source strategy) would be expected to drive part procurement prices down as a result of competitive pricing, but it will also increase the total support cost since a majority of the support activities will need to be repeated for additional suppliers. Some supplier related costs include: a) initial approval – supplier qualification, reliability and quality analyses, database registration, etc., b) annual maintenance support – maintaining a part in an organization's database, and c) annual production support – volume purchase agreement work, reliability and quality monitoring, etc. In short, for long life cycle systems, TCO is driven by a number of recurring and non-recurring support costs that are duplicated with the addition of suppliers.

In the existing literature related to optimum sourcing, an emphasis is placed on aspects such as procurement cost benefits via auction theory (Anton and Yao 1992, Riordan and Sappington 1989, Laffont and Tirole 1993) under demand uncertainty (Li and Debo 2009) and supplier uncertainty (Gurnani and Ray 2003).

The risk of supply chain disruptions, for a particular supply chain structure, has also been addressed as delivery lead times (Gaonkar and Viswanadham 2004) and logistics of the part (Ruiz-Torres and Tyworth 2000), i.e., transportation, inventory, etc. These studies, although important on the operational and tactical level, neither capture long-term disruptions (and their effects) nor consider costs beyond procurement-related processes (negotiation practices, customer-supplier relationships, etc.).

The only known existing work addressing sourcing for long-field life systems is from (Lyon 2006). Lyon performs an assessment of three popular sourcing strategies used by the United States Department of Defense (DoD) in the procurement of missiles[13] – sole-sourcing, dual sourcing ("split-award" auction) and single sourcing ("winner-take-all" auction). The assessment involves studying the impact of sourcing strategies on a missiles' "flyaway cost" (a term used to describe the total cost spent by the U.S. Government on each missile). Lyon uses "flyaway cost" as a metric to test the applicability of the following hypotheses found in high-volume, short life cycle sourcing literature:

> *Hypothesis 1:* Dual sourcing is more likely to be used after the incumbent [supplier] charges a high price.
>
> *Hypothesis 2:* Dual sourcing is more likely to be used after the incumbent producer delivers products with quality defects.

---

[13] Procurement of missiles by the U.S. Department of Defense adheres to procurement regulations related to long-term, high-technology defense programs that require the use of competitive bidding by law (Kratz *et al.* 1984).

> *Hypothesis 3:* Dual sourcing is more likely for technologically complex [systems] without substantial economies of scale or steep learning curves, and in early periods of production.
>
> *Hypothesis 4:* Dual sourcing is likely to be followed by a winner-take-all auction.

Lyon concludes that the benefit to dual sourcing is two-fold: 1) dual sourcing reduces information asymmetries in suppliers reducing procurement prices through competitive bidding in subsequent auctions, and 2) dual sourcing gives the buyer more control over non-contractible dimensions of quality. The empirical study by Lyon finds a 20% procurement cost reduction in missile systems that employ a dual sourcing policy. Indeed, technological uncertainty at early stages of production limits the suppliers' ability to coordinate bids in a "split-award" auction thereby reducing their ability to achieve monopolistic prices. The studies support the prediction that program managers resort to dual sourcing significantly more often when the supplier experiences quality control problems. The empirical results, although not statistically significant at standard levels, indicate additional procurement cost savings to the government when a "winner-take-all" auction is conducted following periods of dual sourcing. A switch from dual sourcing to a winner-take-all auction (single sourcing) is frequently observed in the data set.

Sourcing decisions are made at the discretion of program managers responsible for the procurement of defense systems. Lyon's study captures the tendency of program managers towards specific sourcing decisions but offers only very limited insight into the true life cycle cost of each sourcing strategy. The primary shortcoming of the Lyon work is the focus on price rather than production cost in developing learning curves. General conclusions based on the data set of missiles cannot be translated to procurement of electronics without the verification of cost contributions from each stage of the life cycle. As established in Section 3.3, the procurement cost of electronic parts is a minute contributor to life cycle cost; so Lyon's study does little to justify the use of dual sourcing in electronics (from a life cycle perspective) based on the available empirical results. Furthermore, the use of learning curves from a top-down perspective offer some disadvantages. For example, Lyon's method does little to help in assessing part management decisions since recurring and non-recurring cost components are dealt with as a total cost instead. These recurring and non-recurring costs vary based on the selection of a part or supplier so, in order to utilize them for part management decision making purposes, an understanding of management processes is necessary. The remainder of this section discusses the total cost of ownership model from a part sourcing perspective.

3.2.1 Support cost model

Cost changes for additional suppliers can be represented empirically as "learning curves," which reflect improvements in management, methods, processes, tooling, and engineering time. Learning curve models have been applied to relate production cost to the number of units produced for various industries such as airframes (Wright 1936), machine tools (Hirsch 1952), automotive (De Jong 1964), construction (Everett and Farghal 1994), chemical processing (Lieberman 1984), software development (Raccoon 1996), and integrated circuits (Dick 1991). Lyon applies learning curves to represent learning effects responsible for inducing collusion in dual sourcing (Lyon 2006). Lieberman (1984) discusses the conditions to reliably use price data for estimating such learning curves. However, the application of learning curves to support activities cannot be found in existing sourcing literature. An implementation of the Crawford or Boeing model (Crawford 1944) for supplier-related support cost is shown in (3.8). In (3.8), learning curves are applied to support activities to maintain the "bottom-up"[14] costing approach. Incorporating learning curves into the total cost of ownership offer a means to capture the decrease in support activity cost when supporting multiple suppliers wherein information gathered on prior attempts reduces the time (or effort) needed for subsequent attempts of the same activity.

The following is an extension to the support cost model presented in Section 3.1.1 to address multi-sourcing. Let C_i^x be the annual contributions to support cost from a support activity *x*. Let *n* be the number of support activities in vector *x*. Then $C_{SUP}(D, B^x, N_s^{SUP})$ is the total support cost after *j* year*s* when a disruption occurs in year *D*, assuming that the cost of support activities, *x* (part and product qualification, annual data management, production support, annual purchasing, etc.), are subject to a learning index (B^x).

---

[14] A "bottom-up" approach to cost modeling assesses life cycle cost by the accumulation of cost components (Sandborn and Prabhakar 2008).

$$C_{SUP}(D,B^x,N_s^{SUP}) = \sum_{i=1}^{j} \frac{\sum_{x=1}^{n} \sum_{p=1}^{N_{sxi}^{SUP}} C_i^x(D) p^{B_i^x}}{(1+r)^i} \tag{3.8}$$

In (3.8), if B_i^x = 0, then no learning occurs and all support activities are completely repeated for each subsequent supplier (e.g., the cost of supporting two suppliers is exactly double the cost of supporting one supplier). If $B < 0$ then support activities (and thereby, support cost) decreases for subsequent suppliers (e.g., the cost of supporting two suppliers is less than double the cost of supporting one supplier). For example, when $B = -\infty$, then the addition of subsequent suppliers requires no support activities and therefore adds no support cost. Similarly, if $B > 0$ then support cost increases for subsequent suppliers (e.g., the cost of supporting 2 suppliers is more than double the cost of supporting one supplier).

The number of suppliers, N_s^{SUP}, is dependent on the sourcing strategy used, s. For example, N_s^{SUP}=1 for single sourcing and N_s^{SUP} = 2 for second sourcing. However, the number of suppliers that actually require a particular support activity may be unique to the type of sourcing strategy and varies annually. In practice, the activities performed for certain sourcing strategies may differ despite using the same number of suppliers. For instance, second sourcing and dual sourcing both use two suppliers. However, when second sourcing, parts are procured from the two suppliers interchangeably. On the other hand, when dual sourcing, parts are procured from both suppliers simultaneously (i.e., purchase orders are separated effectively doubling the resources needed for generating purchase orders). In order to distinguish between two sourcing strategies, an array of N_{sx}^{SUP} is used to define the characteristics of the

Table 3.3 – Example matrix for the number of suppliers (N_{sx}^{SUP}) for which support cost components (x) are applicable with respect to various sourcing strategies.

Support cost components (x)	**Number of suppliers (N_{sx}^{SUP})**		
	Single	**Second**	**Dual**
Initial Approval	1	2	2
Part NRE Cost	1	2	2
Product-Specific Approval	1	2	2
Supplier Qualification	1	2	2
Annual Part Data Management	1	2	2
Annual Production Support	1	1	2
Annual Purchasing	1	1	2
Obsolescence Case Resolution	1	1	2

sourcing strategy to model support cost (where $N_{sx}^{SUP} \le N_{s}^{SUP}$). An example matrix of the variable N_{sx}^{SUP} with respect to various support activities, x is shown in Table 3.3.

3.2.2 Assembly cost model

The assembly cost is dependent on the effective incoming yield of purchased parts as discussed in Section 3.1.2. The quality of parts for each batch received is dependent on their supplier's manufacturing and quality control process. Therefore, the incoming yield of parts changes based on supplier selection.

Let N_{si}^{SUP} be the number of suppliers from which parts are purchased in year i when sourcing strategy s is used. Let α_{pi} be the fraction of total part usage that is purchased from supplier p. Let Y_p be the yield of parts purchased from supplier p. Then Y_{si}^{IN} is the effective incoming yield of parts entering the assembly process (from multiple suppliers) during year i.

$$Y_{si}^{IN} = \sum_{p=1}^{N_{si}^{SUP}} \alpha_{pi} Y_p \tag{3.9}$$

$$\alpha_i = \sum_{p=1}^{N_{si}^{SUP}} \alpha_{pi} = 1 \tag{3.10}$$

For example, consider the case where a part is procured from two suppliers with indices, $p = 1$ and $p = 2$, and corresponding yields, Y_1 and Y_2. The fractions of the total part usage volume procured from each supplier are α_1 and α_2 respectively. Let Vol_p^G be the number of good parts from supplier p before the assembly process begins i.e., parts free from defects. Let $N_{pi}^{PROC}(D)$ be the volume of parts procured from supplier p in year i when the disruption occurs in year D. Let N_i^T be the total number of parts procured for assembly in year i. Then, the effective incoming yield for parts procured from the two suppliers for a particular year is,

$$Y^{IN} = \frac{Vol_1^G + Vol_2^G}{N^T} = \frac{Y_1 N_1^{PROC}(D) + Y_2 N_2^{PROC}(D)}{N^T}$$

$$Y^{IN} = \alpha_1 Y_1 + \alpha_2 Y_2$$

where, $\alpha_p = Vol_p / Vol_T$

The model in Section 3.1.2 assumes that the effective yield of incoming parts is known and remains constant over the entire simulation period. However, using (3.9), the effective incoming yield can be estimated from supplier-specific yield values. The multi-sourcing assembly model assumes that parts from each supplier can be treated as identical within the assembly process and incur the same assembly-related costs.

3.2.3 Procurement and inventory cost model

Part price may vary from one supplier to the next and so the procurement cost (exclusive of inventory) incurred after j years for a part varies based on the volume purchased from each supplier. This procurement and inventory cost model for multi-sourcing is based on the model presented in Section 3.1.3.

Let p be a supplier that is selected in sourcing strategy s where $p \in s$ and s consists of N_s^{SUP} suppliers. Let $N_{pi}^{PROC}(D)$ be the number of parts purchased from supplier p in year i when the disruption occurs in year D (the last year parts are available from any supplier). Note that D can range from 1 to $j+1$. Assuming that a lifetime buy is made in year D, let $F_{overbuy}$ be the lifetime buy buffer expressed as a fraction of the lifetime buy quantity. We assume that the buffer quantity is apportioned among the available suppliers by α_{pi}, the fraction of total part usage that is purchased from supplier p in year i, if multiple supplier-specific disruptions occur in year D.

Let P_{pi}^{SUP} be the supplier-specific part price in year i (subject to annual cost changes due to inflation or deflation) when supplier p is selected. Let k be the counter variable for each year after the disruption date until year j. Let α_{pi} be the fraction of total part usage, N_i^{VOL} that is purchased from supplier p in year i. $N_{pi}^{PROC}(D)$ can be calculated for sourcing strategy s as follows,

$$N_{pi}^{PROC}(D)=\begin{cases} \alpha_{pi}N_i^{VOL} & \rightarrow \text{if } \; i<D \\ (1+F_{overbuy})\sum_{k=D}^{j}\alpha_{pi}N_k^{VOL} & \rightarrow \text{if } \; i=D \\ 0 & \rightarrow \text{if } \; i>D \end{cases}$$

Then, $C_{PROC}(s,D)$ is the total procurement cost after j years when sourcing strategy s is selected and the disruption occurs in year D for a case with multiple suppliers.

$$C_{PROC}(s,D)=\sum_{i=1}^{j}\sum_{p=1}^{N_{si}^{SUP}}\frac{P_{pi}^{SUP}N_{pi}^{PROC}(D)}{(1+r)^i} \tag{3.11}$$

Inventory cost is unaffected by a supplier sourcing decision because parts in storage are assumed to be indistinguishable and incur the same inventory cost (per part). Any lifetime buy buffer (overbuy) quantity that is included in Q is assumed to be held until the demand for the part has terminated, i.e., until the end of support of the last product using the part. Then the total inventory/storage cost, $C_{INV}(D)$ when a disruption occurs in year D can be calculated by (3.6) as discussed in Section 3.1.3.

3.2.4 Field failure cost model

The number of field failures (under warranty) of a part depends on the failure characteristics of the purchased parts. Because part volumes may be distributed across more than one supplier, part failures may be correlated to the reliability of each supplier's parts. The field failure cost of a part for a given set of suppliers can be estimated using (3.12).

Let N_{si}^{SUP} be the number of suppliers from which parts are purchased in year *i* for sourcing strategy *s*. Let f_p^{fail} be the supplier-related FIT rate (assuming a constant failure rate) of supplier *p* in year *i*. Let α_{pi} be the fraction of total part usage that is purchased from supplier *p* in year *i*. Then, N_i^{fail} is the total number of failures under warranty in year *i* and can be calculated from known supplier-related FIT rates as shown in (3.12).

$$N_i^{fail} = \sum_{p=1}^{N_{si}^{SUP}} \alpha_{pi} f_p^{fail} \tag{3.12}$$

Part reliability differs from yield since reliability is used in the context of failures during operation (quantity over time) while yield refers to the fraction of defective parts that (if identified in the assembly process) are either repaired or scrapped before the product is fielded (yield impacts initial quality).

The model assumes that all defective parts are fully repaired after a specified number of test/diagnosis/rework cycles as discussed in Section 3.1.4. The field-failure cost model in (3.12) allows the suppliers to have different reliabilities; however, the model may assume that parts from all suppliers have identical reliability distributions during the warranty period.

3.2.5 Disruption resolution (re-qualification)

Long-term disruptions are distinguished from short-term disruptions based on whether the OEM can continue procuring the part from its approved set of suppliers. Because long-term disruptions prevent the further use of the initially qualified part, permanent solutions to long-term disruptions must be sought. For example, when a long-term disruption occurs, an alternate part must be found or a product-level resolution must be performed in order to continue production; these reactive solutions to long-term disruptions are often more costly and cumbersome than short-term disruption resolutions.

The consequence of each part disruption scenario depends primarily on the occurrence of a supplier disruption relative to the part's obsolescence date. These resolution costs can be divided into fixed and variable (product-related resolution) cost components that are incurred in the year of implementing the resolution. Each cost component can be calculated from resolution activities and/or tooling investment involved with assessing, formulating, and implementing the resolution. For example, using an alternate/substitute supplier may incur both fixed and variable costs (for part and product qualification) while a product redesign (to use a pre-qualified part from the database) may be almost entirely variable costs that are product usage dependent.

Let $C_{PR}(D)$ be the total cost of resolving a disruption that occurs in year *D* at the product-level. Let N_D^{PROD} be the number of product designs that the part is used in during year *D*. Let $C_D^{VAR}(N_D^{PROD})$ be the total product-related (redesign) cost across N_D^{PROD} products. Let C_k^{FIX} be the fixed component of disruption resolution cost during year *D*.

$$C_{PR}(D) = \frac{C_D^{VAR}(N_D^{PROD}) + C_D^{FIX}}{(1+r)^D} \tag{3.13}$$

For part management decisions related to electronic part used in low volume, long life cycle products, it has been concluded from the work presented in Sandborn *et al.* (2008) that product-level decisions, such as optimizing design reuse or platform design, are vital in the reduction of part costs. The example cases show that the effects or consequences of a disruption increases (effectively multiplies) with the number of products using the part (i.e., "breadth of use" determines the extent of damage incurred as a result of a supply chain disruption). Therefore, design reuse is critical in the assessment of sourcing tradeoffs as it offers apparent life cycle cost benefits through "economy of scale" but also contributes to supply chain disruption cost. Design reuse of parts subject to long-term supply chain disruptions is discussed in detail with example case studies of an SMT capacitor in Appendix A.

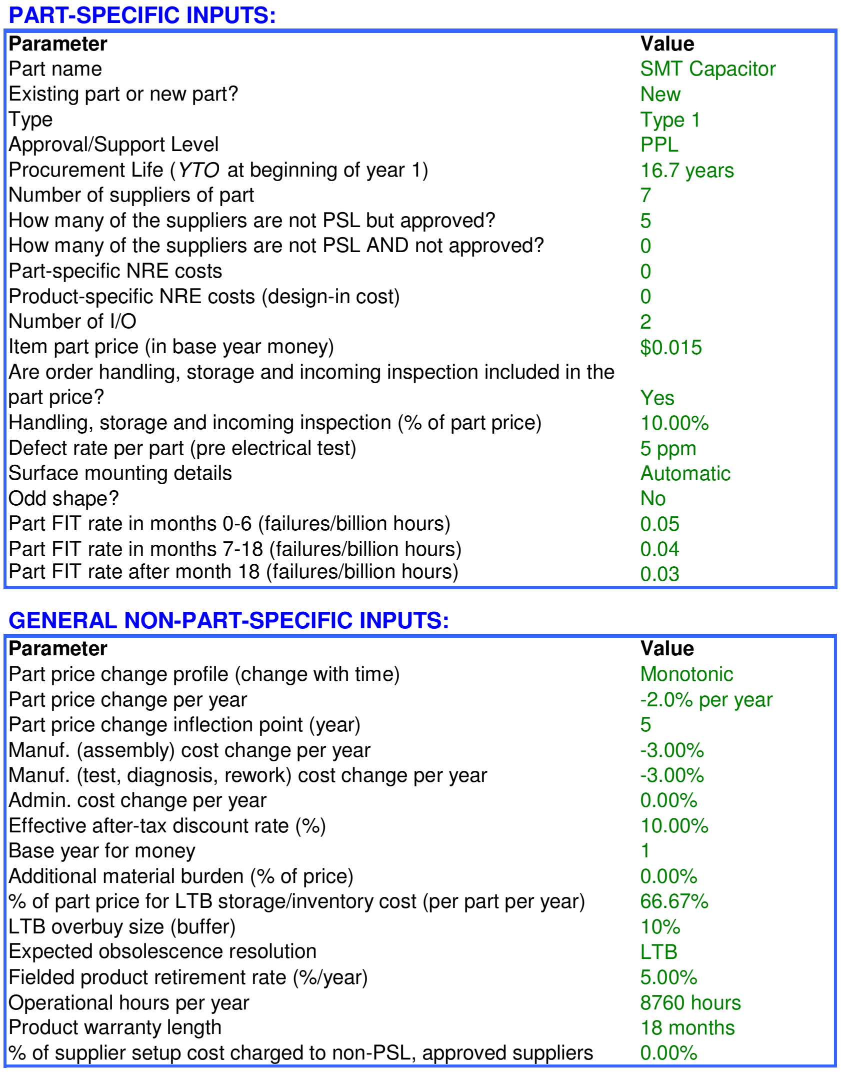
3.3 Evaluating part TCO

This section includes single sourcing example analyses performed using the model described in Section 3.1. The model was populated with data from Ericsson AB for a generic surface-mount capacitor (Type 1 component). Figure 3.2 shows a summary of inputs to the model that correspond to all of the example analyses presented in this chapter. A part site usage profile indicating the number of part sites used for each product annually is provided as an input to the model (Figure 3.3). The profile in Figure 3.3 also describes the number of unique products using the part in each year and the total quantity of part sites assembled each year (N_i^{VOL}). In all cases, inflation or deflation in cost input parameters can be defined (electronic part prices generally decrease as a function of time).

3.3.1 Part TCO example case study (SMT capacitor)

As an example of the part total cost of ownership model, consider the part data shown in Figure 3.2. For this part used in multiple products given in Figure 3.3

(for which a resultant total annual part site usage is also shown), the results in Figure 3.4 are obtained. The plots on the left side of Figure 3.4 show that initially, the part's TCO is almost entirely from support costs i.e., initial selection and approval of the part. Assembly and procurement costs approximately follow the production schedule shown in Figure 3.3. This example part becomes obsolete in year 17 (*YTO* is 16.7 years at year 0) and a lifetime buy of 4,000 parts is made at that time indicated by the small increase in procurement and inventory costs in year 17. Year 18 is the last year of manufacturing after which field use costs dominate.



PART-SPECIFIC INPUTS:

Parameter	Value
Part name	SMT Capacitor
Existing part or new part?	New
Type	Type 1
Approval/Support Level	PPL
Procurement Life (*YTO* at beginning of year 1)	16.7 years
Number of suppliers of part	7
How many of the suppliers are not PSL but approved?	5
How many of the suppliers are not PSL AND not approved?	0
Part-specific NRE costs	0
Product-specific NRE costs (design-in cost)	0
Number of I/O	2
Item part price (in base year money)	$0.015
Are order handling, storage and incoming inspection included in the part price?	Yes
Handling, storage and incoming inspection (% of part price)	10.00%
Defect rate per part (pre electrical test)	5 ppm
Surface mounting details	Automatic
Odd shape?	No
Part FIT rate in months 0-6 (failures/billion hours)	0.05
Part FIT rate in months 7-18 (failures/billion hours)	0.04
Part FIT rate after month 18 (failures/billion hours)	0.03

GENERAL NON-PART-SPECIFIC INPUTS:

Parameter	Value
Part price change profile (change with time)	Monotonic
Part price change per year	-2.0% per year
Part price change inflection point (year)	5
Manuf. (assembly) cost change per year	-3.00%
Manuf. (test, diagnosis, rework) cost change per year	-3.00%
Admin. cost change per year	0.00%
Effective after-tax discount rate (%)	10.00%
Base year for money	1
Additional material burden (% of price)	0.00%
% of part price for LTB storage/inventory cost (per part per year)	66.67%
LTB overbuy size (buffer)	10%
Expected obsolescence resolution	LTB
Fielded product retirement rate (%/year)	5.00%
Operational hours per year	8760 hours
Product warranty length	18 months
% of supplier setup cost charged to non-PSL, approved suppliers	0.00%

Figure 3.2 – Inputs used in the basic part total cost of ownership cost model for the examples provided in this chapter.

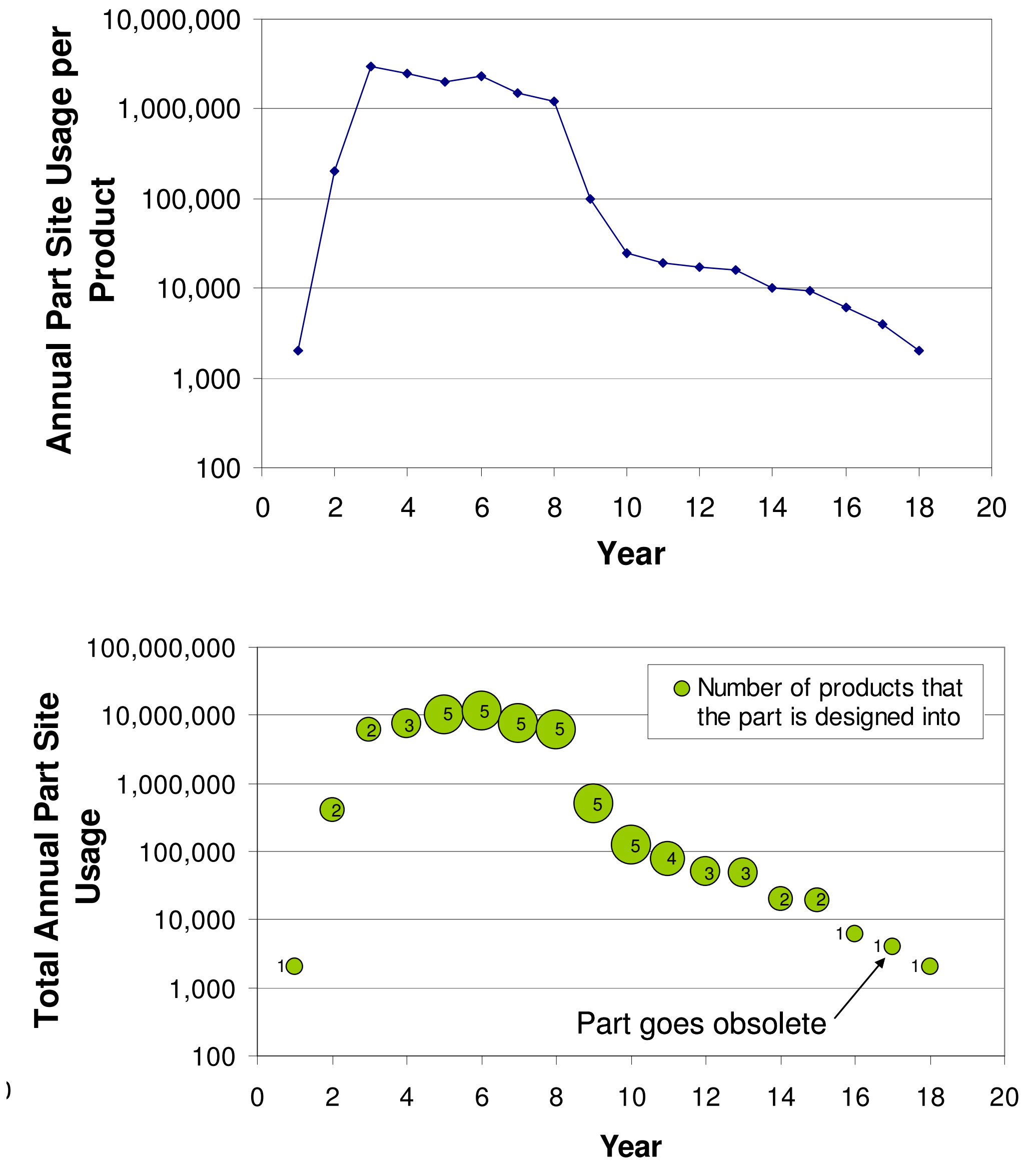
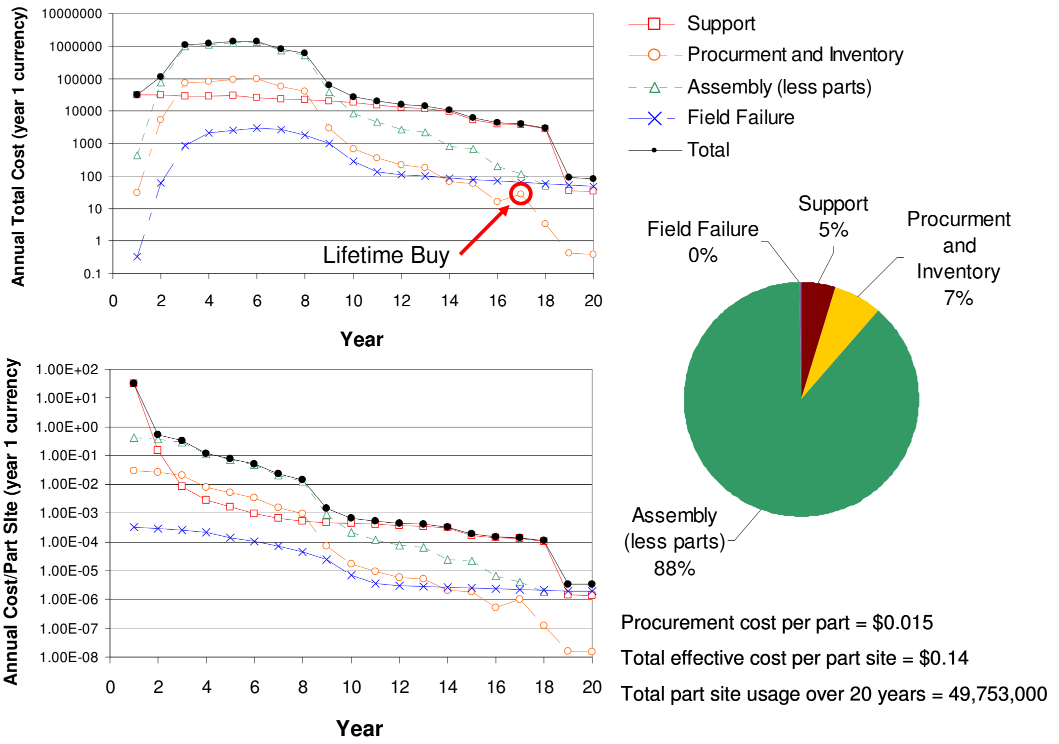


Figure 3.3 – Example (top) part usage profile per product and (bottom) total part and product usage over time for the high-volume cases provided in this chapter.



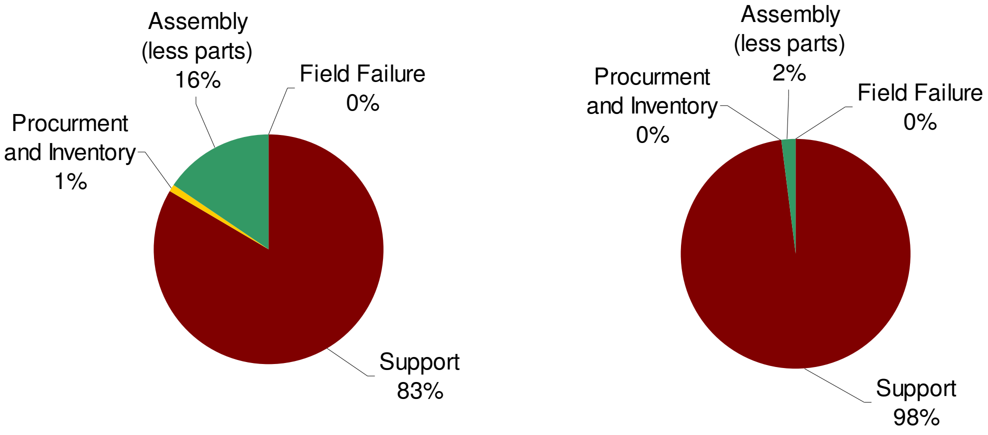
Procurement cost per part = $0.015

Total effective cost per part site = $0.14

Total part site usage over 20 years = 49,753,000

Figure 3.4 – Example part cost of ownership modeling results (high-volume case).

For the case shown in Figure 3.4, the initial procurement price per part ($0.015/part) is only 11% of the total effective cost per part site (C_{PPS} = $0.14/part site) during a 20 year usage life. The results in Figure 3.4 show that, at high volumes, the procurement and inventory cost after 20 years is 7% of the total effective cost per part site, C_{PPS}. Assembly contributes to 88% while support activities contribute to 5% of the part TCO (a combined share of 93%). The organization dedicates an annual average of $1.85 per operational hour of support cost over 20 years for all 49,753,000 part sites in this high-volume case.



Procurement cost per part = $0.015
Total effective cost per part site = $0.78
Total part site usage over 20 years = 497,530

Procurement cost per part = $0.015
Total effective cost per part site = $6.63
Total part site usage over 20 years = 49,752

Figure 3.5 – Part total cost of ownership results for different part volumes (low volume cases).

At lower volumes, support costs dominate with significant contributions from fixed and variable costs that may be a hundred times larger (for example, in the case of production support costs) than costs incurred by field failures, procurement and inventory. The effect of "economy of scale", a benefit of high-volume production, is demonstrated in Figure 3.5, which compares two lower-volume cases as variations of the SMT capacitor considered in Figure 3.4. Support costs make up 83% of the $0.78 spent per part site (shown on the left side of Figure 3.5) when a total of 497,530 parts are consumed over 20 years. When the volume consumed is further reduced to 49,752 parts over 20 years (shown on the right side of Figure 3.5), support costs contribute to 98% of the $6.63 spent per part site.

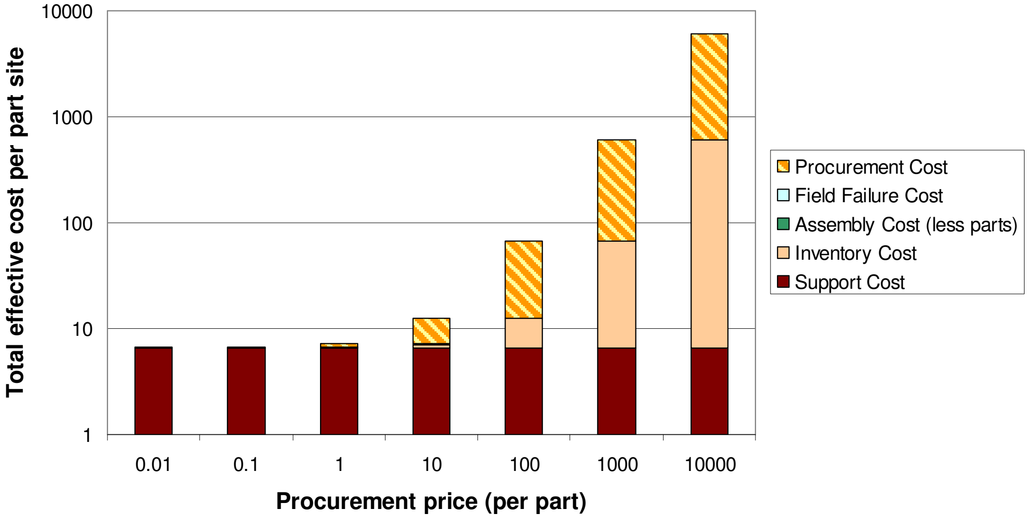


Figure 3.6 – Part TCO results vs. procurement price for low volume case (total part usage of 49,752 parts).

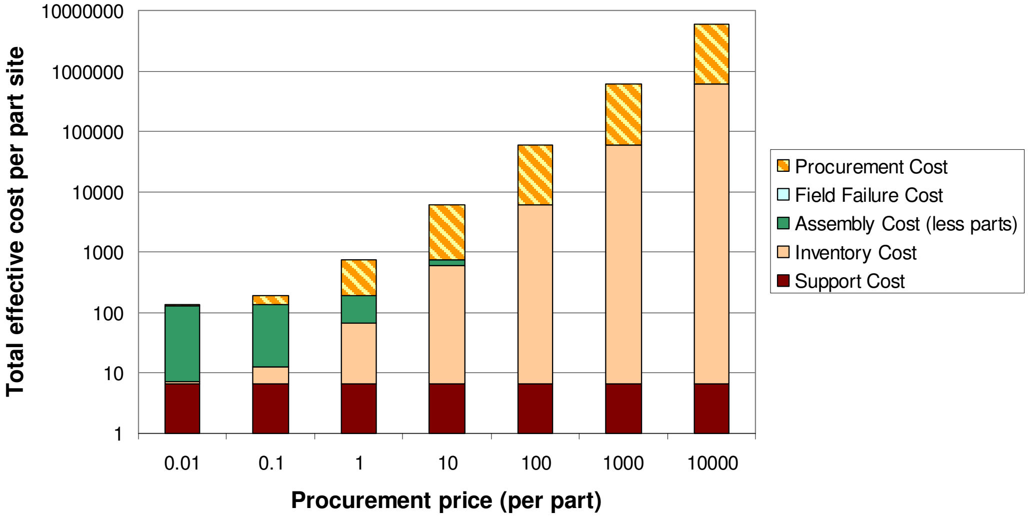
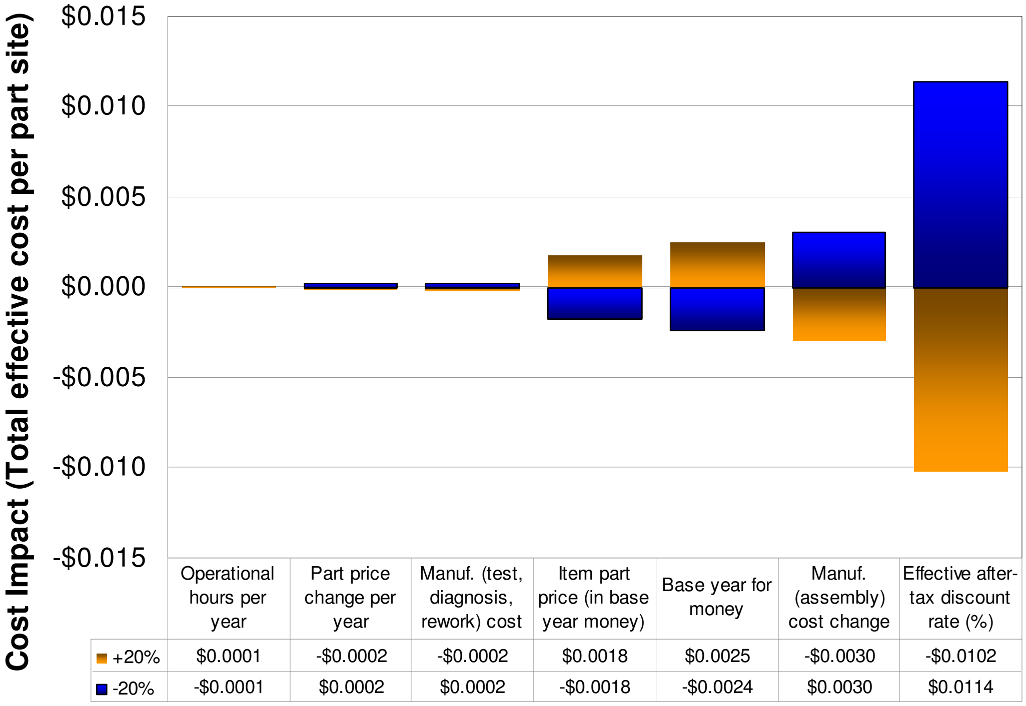


Figure 3.7 – Part TCO results vs. procurement price for high volume case (total part usage of 49,753,000 parts).

Figure 3.6 and Figure 3.7 shows results for a low volume case and high volume case respectively where procurement cost is varied from \$0.01 per part to \$10,000 per part showing the break-down of total effective cost per part site over 20 years. The part TCO is dominated by support cost when the part price and inventory cost (per part) is low. The total effective cost per part site increases because the non-NPV procurement and inventory costs are directly proportional to the part procurement price. In this example, inventory cost is 10% of the procurement price and assessed at the beginning of each year for the annual part usage until the part is obsolete. Following a lifetime buy, the annual inventory cost (per part) is assessed at 10% of the part price (assuming the price trend continues with a deflation of 2%) for the quantity remaining in inventory at the beginning of every year.

A sensitivity analysis was conducted to determine the effects of the input parameters on the total effective cost per part site for the example case considered in this section. In Figure 3.8, a variability of ±20% for each input parameter was introduced to study the response of the model results. Effective after-tax discount rate was found to contribute significantly to changes in total effective cost per part site. The relative value of currency in a particular year is affected by the after-tax discount rate, d. The variation observed is a common effect in long life cycle products and is a source of uncertainty in the TCO estimation. Considering the case study results, a 20% saving on the procurement price of the part saves a negligible amount in effective cost per part site. If the procurement price per part is doubled to \$0.03 per part then the procurement cost per part site increases by only \$0.01 or 6.6% of total effective cost per part site in the high volume base case (1.2% in the low volume case



	Operational hours per year	Part price change per year	Manuf. (test, diagnosis, rework) cost	Item part price (in base year money)	Base year for money	Manuf. (assembly) cost change	Effective after-tax discount rate (%)
🟧 +20%	$0.0001	-$0.0002	-$0.0002	$0.0018	$0.0025	-$0.0030	-$0.0102
🟦 -20%	-$0.0001	$0.0002	$0.0002	-$0.0018	-$0.0024	$0.0030	$0.0114

Figure 3.8 – Tornado Chart of cost impact as change in total effective cost per part site due to ±20% variability in input values.

of 497,530 parts). Savings at the procurement stages lead to minimal savings in total effective cost per part site due to the limited contribution from the procurement and inventory level when compared to costs incurred due to support (at low volumes) and assembly (at high volumes) activities.

The assembly cost is dependent on the quantity of parts consumed every year, which, in turn, is dependent on the number of products the part is "designed into". The capacitor considered in Figure 3.4 is designed into a maximum of 5 concurrently produced products (between year 5 and 10). When the part is used in no more than one product, the total effective cost per part site increases to $0.17. The assembly cost increase is approximately proportional to the number of parts consumed by assembly processes. Despite lower product design-in costs C^{design} (since fewer products need to be qualified) and annual purchasing costs C^{ap} (fewer purchase orders made), support costs begin to take over with a share of 12% of the total cost per part site since the largest contributor, production support costs C^{ps}, remains.

The negligible contribution observed from field failures (in Figures 3.4 and 3.5) is a result of the part's reliability and is characteristic of the short-term product warranty policy employed. The products using the part considered in this case – a SMT capacitor were assumed to follow an 18 month warranty repair policy. Field failure costs tend to be significantly larger if the part is used in sustainment-dominated systems[15] where the product is expected to function for 10 year or more (as long at 30+ years for many systems). Field failure costs for parts used in sustainment-dominated systems may be driven by repair processes (similar to the test, design, and rework model used in the assembly cost model). Many sustainment-dominated electronic systems, such as rack-mounted servers used by banks or insurance companies, employ maintenance strategies that must adhere to stringent availability[16] policies or contracts (Ng *et al.* 2009). Field failures of these systems require immediate attention, and repairs that cannot be resolved quickly decrease the system's availability for which significant availability cost penalties may be incurred. Such penalties may be attributed to the failure of a particular part and contribute to the part's field failure cost. The example case presented here accounts for the cost of

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[15] Products for which the cost sustainment (operating and supporting) is significantly larger than the cost of procurement, e.g., airplanes, military systems, infrastructure communications systems, and power plant controls (Sandborn and Myers 2008).

[16] Operational availability is the probability that a system will be able to function when called upon to do so. Availability depends on the system's reliability (how often it fails) and its maintainability (how quickly it can be repaired or restored to operation when it does fail).

site visits, down time, transportation, and handling in the event of system failures; however, specific financial penalties associated with reduced availability are assumed to be zero.

3.4 Discussion and conclusions

The part total cost of ownership model presented in this chapter enables fundamental part management decisions by assessing the life cycle cost incurred when introducing, assembling, and supporting a part. The approach involves the estimation of a part's life cycle cost that begins when a part is first adopted into a product design and may continue until (or even beyond) the part's obsolescence. The model takes a part-specific (rather than a product-specific) approach since supply chain constraints and disruptions are part-specific. The application of the model has been demonstrated in a total cost of ownership estimation of a surface-mount capacitor as well as design reuse case studies. The model could also potentially be used to quantify savings associated with part number reduction, retirement of parts from databases, and organizational adoption of new parts to name a few.

The model demonstrates that for electronic parts, savings at the procurement level may only translate into minimal savings over the life cycle since costs due to procurement and inventory may be much smaller than costs due to manufacturing and support. Significant effort is dedicated to negotiating lower procurement prices but it becomes apparent that, for low-volume part site usage over long-term production, the benefit is low compared to the potential for cost avoidance through better management of the part over a long life cycle.

The examples in Chapter 5 involve the cost of mitigating obsolescence to estimate the related risk consequences where the timing of the disruption events (affecting suppliers) is uncertain. The next chapter deals with determining the uncertainty associated with disruption events with a focus on electronic part obsolescence.

Chapter 4: Forecasting long-term supply chain disruptions due to DMSMS type obsolescence

This chapter involves forecasting the likelihood of long term supply chain disruption events over long product life cycles (Task 2). The likelihoods of supplier-related disruptions (e.g., part obsolescence, earthquakes, etc.) can be represented as a probability that the event will occur over a particular time period.

This chapter focuses on DMSMS (Diminishing Manufacturing Sources and Materials Shortages) obsolescence, which is defined as the loss of the ability to procure a technology or part from its original manufacturer. Forecasting when technologies and specific parts will become unavailable (non-procurable) is a key enabler for pro-active DMSMS management and strategic life cycle planning for long field life systems. The methodology can be used to predict the obsolescence dates for electronic parts that do not have clear evolutionary parametric drivers. The method is based on the calculation of procurement life using databases of previous obsolescence events. The methodology has been demonstrated on a range of different electronic parts and for the trending of specific part attributes.

The key enabler for pro-active and strategic management of DMSMS obsolescence is the ability to forecast the obsolescence events for key parts. The remainder of this chapter addresses forecasting DMSMS events or electronic part obsolescence. The obsolescence forecasts will be used in Section 4.2 and Chapter 5 to formulate supply chain disruption risk by incorporating risk likelihoods into the part TCO models.

4.1 DMSMS obsolescence forecasting

Most long-term electronic part obsolescence forecasting[17] is based on the development of models for the part's life cycle. Traditional methods of life cycle forecasting are ordinal scale based approaches, in which the life cycle stage of the part is determined from a combination of technological and supply chain attributes such as level of integration, minimum feature size, type of process, number of sources, etc., e.g., (Henke 1997, Lai 1997, Josias *et al.* 2004), and those available in several commercial databases. The ordinal scale based approaches work best as short-term forecasts, but their accuracy in the long-term has not been quantified. For ordinal scale approaches the historical basis for forecasts is subjective and confidence levels and uncertainties cannot be generally evaluated. To improve forecasting, more general models based on technology trends have also appeared including a methodology based on forecasting part sales curves, (Solomon *et al.* 2000, Pecht *et al.* 2002), and leading-indicator approaches (Meixell and Wu 2001, Wu *et al.* 2006). A method based on data mining the historical record that extends the part sales curve forecasting method and which is capable of quantifying uncertainties in the forecasts has also been developed (Sandborn *et al.* 2007). Gravier and Swartz (2009), present a general statistical study of a set of 235 parts drawn from a cross section of IC functions, technologies and voltage levels to determine the probability of no suppliers (effectively the probability of obsolescence) as a function of the years since the introduction of the part.

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[17] DMSMS obsolescence forecasting is a form of product deletion modeling, e.g., (Avlonitis *et al.* 2000), that is performed without inputs from or the cooperation of the part manufacturer.

Existing commercial forecasting tools are good at articulating the current state of a part's availability and identifying alternatives, but are limited in their capability to forecast future obsolescence dates and do not generally provide quantitative confidence limits when predicting future obsolescence dates or risks. Pro-active and strategic obsolescence management approaches require more accurate forecasts or at least forecasts with a quantifiable accuracy. Better forecasts with uncertainty estimates would open the door to the use of life cycle planning tools that could lead to more significant sustainment cost avoidance (Singh and Sandborn 2006).

4.1.1 Procurement life forecasting

Previously proposed data mining methods for forecasting obsolescence (Sandborn *et al.* 2007) have been shown to work well when there are identifiable evolutionary parametric drivers. An evolutionary parametric driver is a parameter (or a combination of parameters) describing the part that evolve over time. For example, for flash memory chips an evolutionary parametric driver is memory size, traditionally for microprocessors it has been clock frequency (although recently this has begun to give way to power consumption). Unfortunately, for the majority of electronic parts, there is no simple evolutionary parametric driver that can be identified and previously proposed data mining approaches cannot be used.

In this chapter, a methodology for formulating obsolescence forecasting algorithms based on predicting the part's procurement life from a database of historic part obsolescence data (shown in Figure 4.1) is presented. The method does not depend on the identification of an evolutionary parametric driver for the part. The procurement life for a part is defined as,

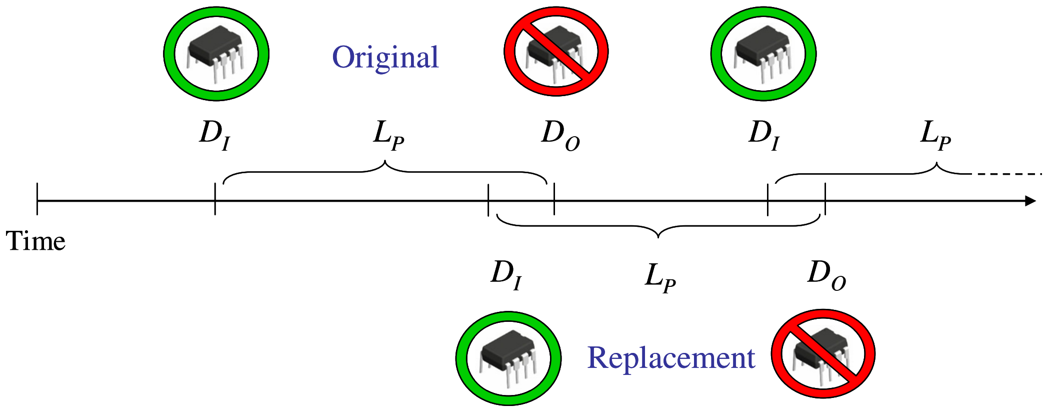

Figure 4.1 – Procurement life (L_P) as a measure for length of a part's procurement life cycle.

$$L_P = D_O - D_I \tag{4.1}$$

where

L_P = procurement life, amount of time the part was (or will be) available for procurement from its original manufacturer

D_O = obsolescence date, the date that the original manufacturer discontinued or will discontinue the part

D_I = introduction date, the date that the original manufacturer introduced the part

The concept of procurement life has also been referred to as "product lifetime" by (Bayus 1998) and "duration time" in the marketing literature, e.g., (Helsen and Schmittlein 1993). This dissertation explores the correlation between procurement lifetime and introduction date for electronic parts. Two specific results are of interest for forecasting uses: first, the mean procurement lifetime as a function of introduction date (the topic of discussion in Section 4.1.3) and second, the effective worst case procurement lifetime as a function of introduction date. Before discussing the forecasting methods, the data used in this analysis is briefly described in Section 4.1.2.

4.1.2 Electronic part obsolescence data

A part database from SiliconExpert was used for the analysis in this chapter. The part database was created and is maintained using parts data that is sourced via web crawling of manufacturers' websites for revision control and through direct relationships with manufacturers where feeds of component data are supplied on a weekly, monthly or quarterly basis. The frequency of updates is dependent upon how often datasheets and product information are revised by document controllers internally at each manufacturer. In addition, data feeds provided via direct relationships enlist datasheets and parametric information for new products introduced to the market. Organization of the database is done through a strict taxonomy. Revisions to the taxonomy occur only for expansion and contraction of existing product lines to ensure valid differentiation between various subcategories. As of December 5, 2008, the database contained over 150 Million electronic parts spanning 337 product lines from 9,520 manufacturers.

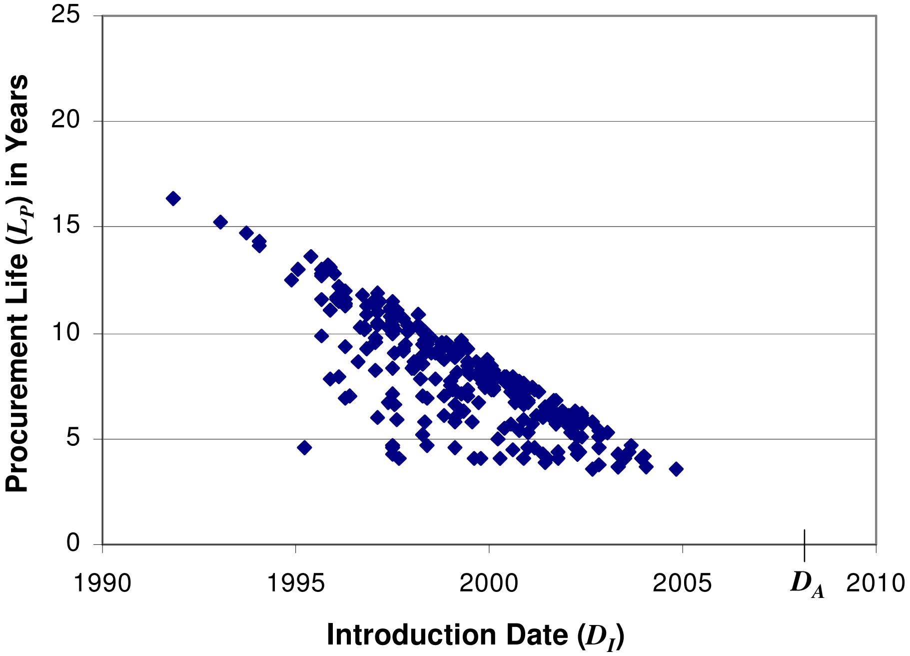

Figure 4.2 – 347 obsolete linear regulators from 33 manufacturers. D_A = 2008, the analysis date (the date on which the analysis was performed).

Figure 4.2 shows an example plot of procurement life versus introduction date for obsolete linear regulators (a common electronic part that is a voltage regulator placed between a supply and the load and provides a constant voltage by varying its effective resistance) mined from the SiliconExpert database described above.

4.1.3 Determining mean procurement lifetimes

The mean procurement lifetimes for parts can be analyzed using the statistical framework for failure time analysis (Helsen and Schmittlein 1993). This approach has been previously used to determine the mean product life cycle lengths for personal computers, (Bayus 1998). The approach in (Bayus 1998) and (Helsen and

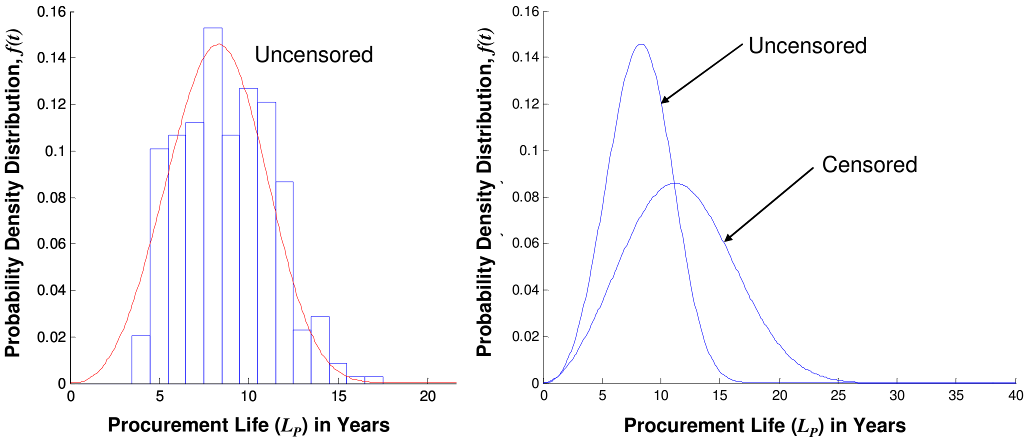

Figure 4.3 – The distribution of procurement lifetimes for linear regulators. The histogram on the left side corresponds to the data in Figure 4.2. The mean procurement lifetime (censored) = 11.63 years, $\beta = 2.84$, $\eta = 13.06$. The parameters are based on a maximum likelihood estimate (MLE) using a two-parameter Weibull fit.

Schmittlein 1993), however, have never been applied to the forecasting of obsolescence or to the procurement of electronic parts.

The event of interest in this dissertation is the discontinuance (obsolescence) of an instance of a part. The data used includes the introduction dates of all the parts of a particular type and the obsolescence dates for the parts that have occurred up to 2008. An obsolescence event is not observed for every part in the data set since some of the introduced parts had not gone obsolete as of the analysis date, i.e., the observations are right censored.

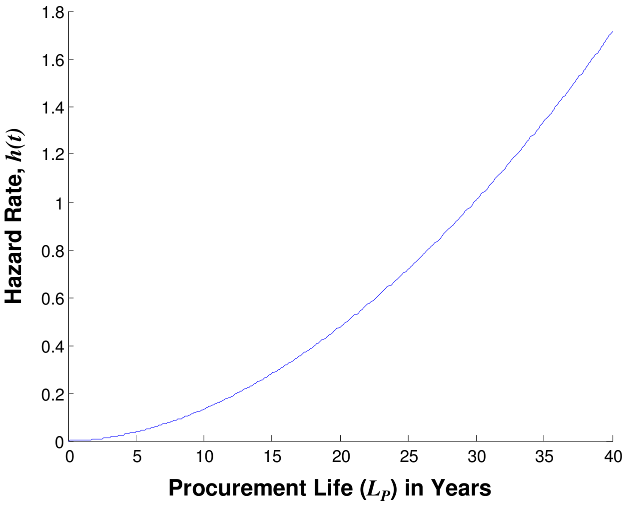

Figure 4.4 – Hazard rate corresponding to the censored distribution of procurement lifetimes for linear regulators in Figure 4.3.

Following the analysis method in (Helsen and Schmittlein 1993) and representing the data for the linear regulator example shown in Figure 4.3 as a distribution of procurement lifetimes (event density), $f(t)$, with a corresponding cumulative distribution function, $F(t)$, the hazard rate, $h(t)$ is given by,

$$h(t) = \frac{f(t)}{1 - F(t)} \tag{4.3}$$

The hazard rate is the probability that a part will become non-procurable at time t assuming it was procurable in the interval (0, t). Figure 4.3 shows $f(t)$ and the corresponding hazard rate, $h(t)$ for linear regulators is shown in Figure 4.4. To determine $f(t)$ the data was fit with a 2-parameter Weibull,

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{4.4}$$

where the parameters were estimated using MLE (Maximum Likelihood Estimation) assuming right censoring and that the censoring mechanism is non-informative (the knowledge that the observation is censored does not convey any information except that the obsolescence dates of some parts within the data set lie beyond the censoring date, which is the analysis date (D_A) in our case).[18] In Figure 4.3, the uncensored distribution ignores the introduced parts that had not gone obsolete as of D_A. Obviously, the mode is shifted to the left (smaller procurement lifetimes) when the non-obsolete parts are ignored. In the case of linear regulators, the hazard rate shown in Figure 4.4 increases with time ($dh(t)/dt > 0$), indicating that the longer the procurement lifetime, the more likely the part is to go obsolete. The analysis described in this section has been applied to a variety of electronic parts; Table 4.1 provides results for selected part types. In the case of the linear regulators, there are 347 obsolescence events out of a total of 847 introduced parts.

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[18] The MLE parameter estimation was performed using the MatLAB Statistics package.

Table 4.1 – Procurement lifetimes for various electronic part types through 2008. β and η refer to 2 parameter Weibull fits of the censored and uncensored PDFs. *LKV* is the negative log-likelihood function (larger negative values indicate a better fit).

Part Type	**Censored**				**Uncensored**			**% of parts not obsolete**	**Total number of parts not obsolete**
	Mean (years)	β	η	***LKV***	**Mean (years)**	β	η		
Linear Regulators	11.63	2.84	13.06	-1205	8.25	3.47	9.17	59.46%	509
Buffer & Line Drivers	38.39	2.02	43.33	-3042	9.82	4.01	10.83	91.08%	1279
Bus Transceivers	15.39	2.29	17.37	-1746	9.28	4.99	10.11	57.26%	1057
Decoder & Demux	20.74	1.71	23.25	-914.9	9.30	4.51	10.19	62.30%	565
Flip Flop	16.23	2.25	18.33	-1727	9.64	5.15	10.48	58.27%	1052
Inverter Schmitt Trigger	18.13	1.83	20.40	-1125	8.58	4.06	9.453	64.13%	750
Latch	14.99	2.29	16.92	-1391	9.19	4.95	10.01	55.46%	818
Multiplexer	18.83	1.82	21.19	-844.0	8.84	4.10	9.734	63.70%	552

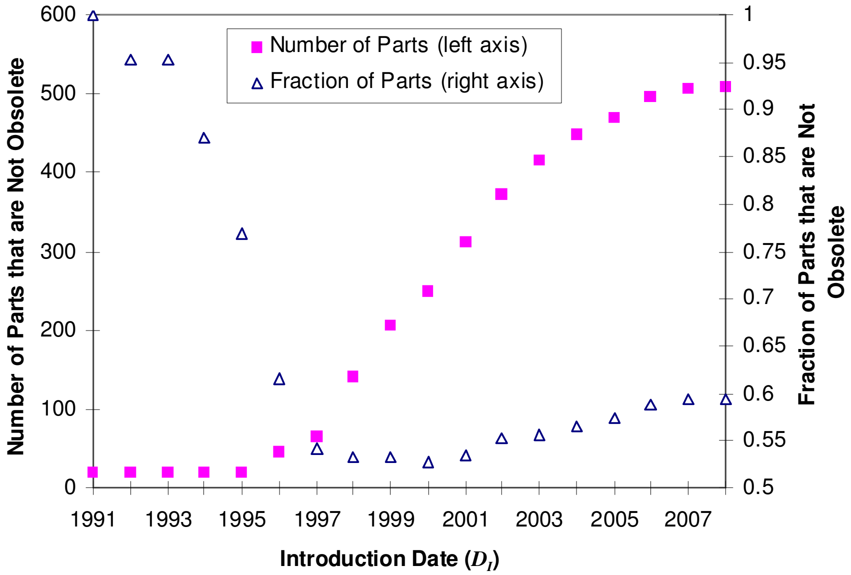


Figure 4.5 – Quantity and percentage of linear regulators that are not obsolete as of 2008 as a function of time.

Figure 4.5 shows the quantity and fraction of non-obsolete parts as a function of time. This plot shows that a large fraction of the parts introduced in 1990-1996 have not gone obsolete yet (but the total number introduced during this period is also relatively small). An alternative way to look at this is to perform the analysis described above for determining the mean procurement lifetime on the data set as a function of time (Figure 4.7). In this case, to generate the mean procurement lifetime at a particular date (or before), the parts that had been introduced on or before that date in the analysis are only considered (although all observations are made in 2008). The mean procurement life is analogous to the mean time-to-failure (*MTTF*). The mean procurement life for a given Weibull distribution can be calculated using,

$$\overline{L_p} = \eta \Gamma \left(1 + \frac{t}{\beta} \right) \tag{4.5}$$

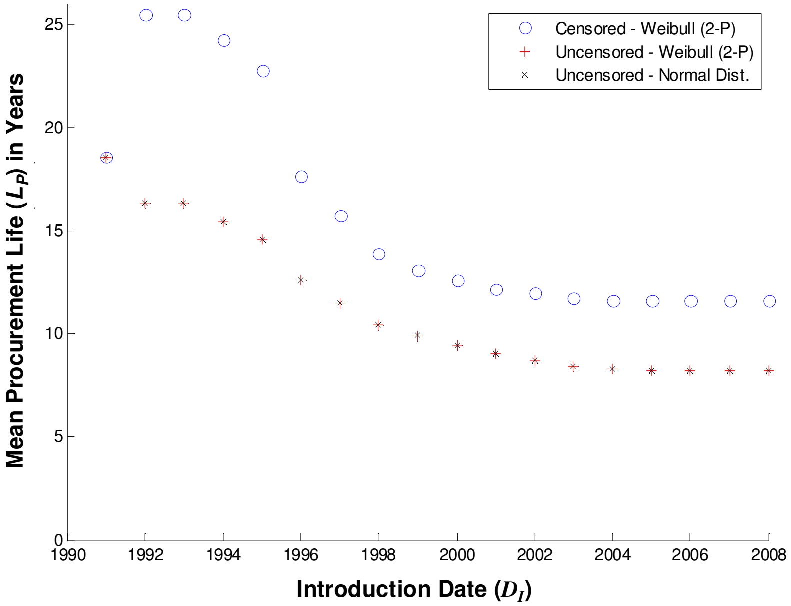


Figure 4.6 – Mean procurement lifetime for linear regulators as a function of time (parts introduced on or before the date).

where β and η are the Weibull parameters corresponding to the data fits limited by D_I. Figure 4.6 indicates the appropriate mean procurement lifetime to assume for parts with introduction dates at or before the indicated year. So a part introduced in 1998 or before has a mean procurement lifetime of 14 years (Censored – Weibull (2-P) in Figure 4.6). In order to determine the mean procurement lifetime for part introduced in a particular year (rather than in or before a particular year), “slices” of the data must be used. In this case, to generate the mean procurement lifetime at a particular date, the parts that have been introduced within one year periods in the analysis are only considered and once again, all observations are made in 2008. Figure 4.7 shows the mean procurement lifetimes for one year slices with and without right censoring assuming that the observation is made in 2008. For a part introduced in 1998, Figure

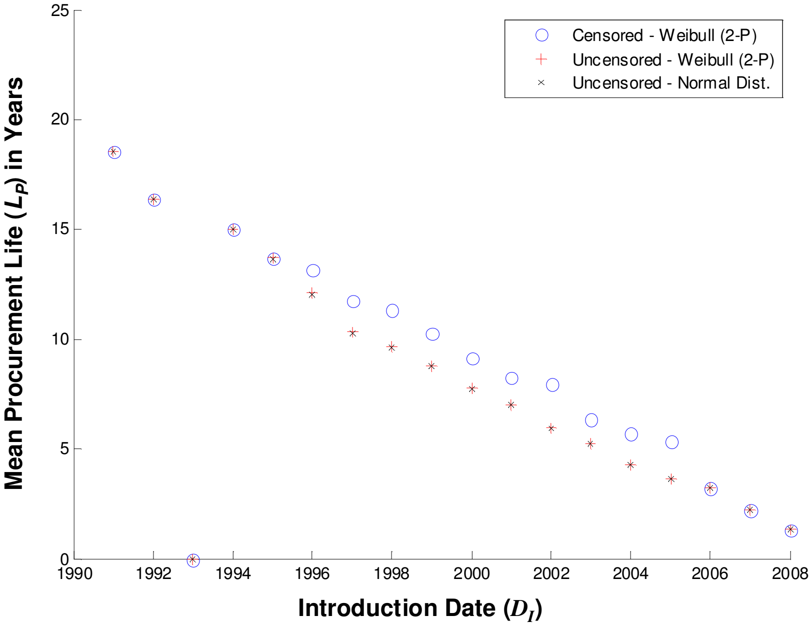


Figure 4.7 – Mean procurement lifetime for linear regulators as a function of time (parts introduced on the date). Note, there were no parts introduced in 1993.

4.7 predicts that the mean procurement lifetime will be 11.5 years (smaller than the 14 years predicted by Figure 4.6). Figure 4.7 and the comparison of Figures 4.6 and 4.7 indicate that older linear regulators (smaller D_I) have longer procurement lifetimes (L_P) than newer linear regulators.

Using the data from Figure 4.7 for 1990-2005 (excluding 1993 since no parts were introduced in 1993), the mean procurement life trend is given by,

$$\overline{L_p} = 0.0211 D_I^2 - 85.222 D_I + 86096 \tag{4.6}$$

The analysis in this section provides a useful estimation of the mean procurement lifetime for parts, however, the worst case procurement lifetimes are also of interest to organizations performing pro-active and strategic DMSMS obsolescence management. Sandborn *et al.* (2007) provides a more detailed interpretation of (procurement life versus introduction date profiles) and discusses the generation of worst case forecasts.

4.2 Supplier-specific obsolescence likelihood (MLE)

The methodology described in Section 4.1 can also be applied to specific manufacturer data as shown in Section 4.2. The procurement lives (L_P) observed for a subset of the historic part data can be fit with a Weibull (2-parameter) using Maximum Likelihood Estimation (MLE) to provide estimates for parameters β (shape) and η (scale). The resulting distribution is representative of the uncertainty in procurement life for a subset of parts within a particular part type; in this case, the data and results are supplier-specific. This method can also be applied to address the obsolescence likelihoods of supplier-specific part obsolescence events.

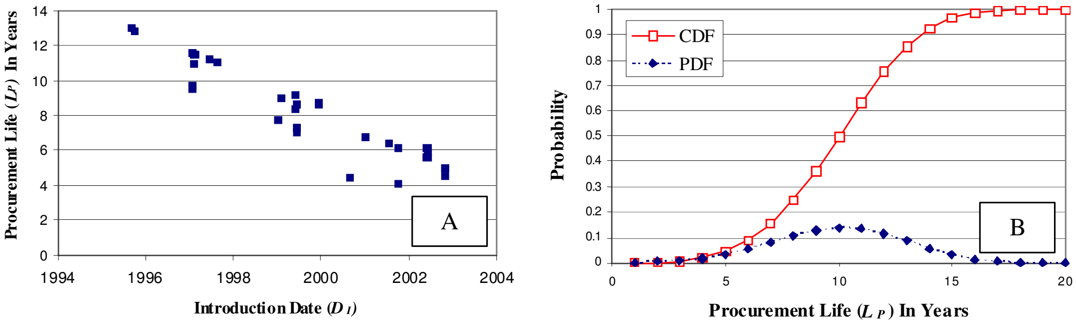


Figure 4.8 – Supplier-specific procurement life data for linear regulators (ON Semiconductor): (A) raw obsolescence data from SiliconExpert; (B) censored PDF and CDF of obsolescence risk likelihood over time.

Censored PDF and CDF distributions for procurement life (L_P) shown in Figure 4.8.(B) can be generated from raw supplier-specific data (data for ON Semiconductor is shown in Figure 4.8.(A) using MLE as described in Section 4.1.

Note, the Weibull distribution, like most parametric fits, evolves over time as more data is accumulated. The method in described in Section 4.1 generates censored Weibull distributions to account for the fact that the data is right-censored, i.e., the dataset used in this study contains introduction dates for all parts, 347 of which have obsolescence dates and 509 of which were not obsolete as of 2008. The supplier-specific dataset for linear regulators from ON Semiconductor consists of 39 obsolete parts and 34 non-obsolete parts as of 2008.

The censored CDF of L_P (Figure 4.8.(B)) can be interpreted as the probability (likelihood) that a part will be obsolete L_p number of years after it is introduced. The supplier-specific CDFs will be used in Chapter 5 to estimate effective CDFs for second sourcing strategies. Similarly, the PDF of L_P is the probability (likelihood) that a part will become obsolete during specific intervals of time after it is introduced. PDFs are used in Section 5.1, (5.1) to quantify obsolescence risk annually.

Let $F(i, p)$ be the supplier-specific CDF value in year *i* for supplier *p*. Then, the effective probability of obsolescence or CDF of a sourcing strategy, *s* where the part can be procured from N_s^{SUP} sources during year *i* can be calculated as shown in (4.8).

$$F(i, N_s^{SUP}) = \prod_{p=1}^{N_s^{SUP}} F(i, p) \tag{4.8}$$

Chapter 5 applies the CDF distributions of single sourcing and second sourcing combinations to assess and compare the obsolescence risk of various sourcing strategies.

4.3 Summary and discussion

In this chapter, a methodology has been presented for constructing distributions that can be used to forecast the procurement lifetime, and thereby the obsolescence date, of technologies based on data mining the historical record. Unlike previous methods for forecasting DMSMS type obsolescence, this method is applicable to technologies that have no clear evolutionary parametric driver. Results from the methodology applied to several different electronic part types and sourcing strategies have been included.

Long-term forecasting techniques generally involve methods of trend extrapolation. Although, trending the worst case procurement lives should be done using just the uncensored data (only the obsolete parts), trends in the mean procurement life must be done using the censored data set (both obsolete and non-obsolete parts) from Figure 4.7 corresponding to (4.6).

It has been suggested that the "age" of electronic parts is not necessarily a factor in determining what goes obsolete (Carbone 2003). The age of a part can be interpreted two ways; either it represents how long ago the part was introduced (D_A - D_I) where D_A is the analysis date (D_A - D_I is referred to as "design life" in Gravier and Swartz 2009), or how long the part was procurable for (L_P). The results in this chapter suggest that age is a factor in predicting the obsolescence of the part for parts that do not have strong evolutionarily parametric drivers. Gravier and Swartz (2009) also conclude that age is correlated to obsolescence by showing that the probability of no suppliers varies with design life. However, Gravier and Swartz (2009) do not distinguish between part types (except for military and non-military parts) or parts with or without strong evolutionary parametric drivers.

For the procurement lifetime forecasting algorithms developed using the methodology suggested in this chapter to be useful, one must assume that past trends are a valid predictor of the future. In some cases, particular technologies or parts may be displaced by some unforeseen new disruptive technology, thus accelerating the obsolescence of the existing parts faster than what the historical record would forecast. Alternatively, new applications may appear that extend or create demand for specific technologies or parts also causing a change in the historical obsolescence patterns for the parts. Application of the proposed method depends on having access to sufficient historical data to support a statistical analysis; this is especially true when one wishes to refine the forecasts (to particular vendors or particular part attributes).

The obsolescence date of a part or technology from the original manufacturer may or may not be a critical date in the management of a product or system depending on how the part or technology is used. Original manufacturer obsolescence dates when combined with the forecasted future need for the part and the available inventory of the part determine whether the obsolescence of the part is a problem or not, or when the obsolescence of the part will become a problem. For example, minimum buy sizes for many inexpensive electronic parts (e.g., resistors and capacitors) may far exceed the number of parts needed to manufacture and support a low-volume product, so the obsolescence of the inexpensive part may be a non-issue because the available supply of parts will never be exhausted. For a high-volume product, the quantity of parts needed may quickly exceed what can be supplied by the existing inventory of parts and aftermarket suppliers, so forecasting the original manufacturers' obsolescence date is critical in order to enable strategic management of the product.

Chapter 5: Long-term sourcing risk model (DMSMS obsolescence)

This chapter addresses DMSMS (Diminishing Manufacturing Sources and Materials Shortages) type obsolescence, which is defined as the loss of the ability to procure a technology or part from its original manufacturer (Sandborn 2008a). Forecasting when technologies and specific parts will become unavailable (non-procurable) is a key enabler for pro-active DMSMS management and strategic life cycle planning for long field life systems. However, knowing when a disruption will occur is only part of the problem. The impact or consequence of a disruption is often related to the timing of the event and must be considered in the assessment of sourcing strategies.

Section 5.1 describes the method used to assess the risk that a sourcing strategy is exposed to. The example case study presented in this chapter utilizes the part TCO simulator to determine the consequence of an obsolescence event as part TCO (per part site). The part TCO simulator has been discussed in detail in Chapter 3. The obsolescence likelihood and consequence are then combined to quantify risk as an "annual expected TCO per part site," which is suitable for comparing various sourcing strategies over the part's life cycle (period of time that the part is used within an organization). Section 5.2 utilizes effective CDF and PDF distributions to assess the tradeoffs between single and second sourcing strategies in terms of obsolescence risk.

5.1 Part sourcing risk

The OEM's total cost of ownership of introducing and supporting a group of suppliers, for parts in long life cycle products, can be combined with the estimated likelihood of disruption to quantify the risk of a part sourcing strategy as a function of time.

Let $C_{TCO}(s,D)$ be the total cost of ownership (TCO) when sourcing strategy s is selected and subject to a disruption date of *D*. Chapter 3 discusses the modeling approach for TCO with respect to the part sourcing strategy used. Let $F_s(d)$ be the CDF during year *d* of the part's lifecycle with $F_s(0)=0$. Chapter 4 discussed the method for estimating the CDF with respect to the sourcing strategy and combination of suppliers/sources. *D* is treated as discrete, $P\{D=d\}=F(d)-F(d-1)$, and $P\{D>j\}=1-F(j)$. Note that *D* could be greater than *j*, in which case there is no disruption. In this case, the costs do not depend upon how much *D* exceeds *j*. Thus, we calculate the cost for $D=j+1$ to cover the case of no disruption. Then, $E[C_{TCO}(s,D)]$ is the obsolescence risk as the expected TCO for sourcing strategy *s* after *j* years.

$$E[C_{TCO}(s,D)]=\sum_{d=1}^{j} C_{TCO}(s,d)(F(d)-F(d-1))+C_{TCO}(s,j+1)(1-F(j))$$

Let C_{PPS} be the part TCO per part site as calculated in (3.2) where N_i^{VOL} is the number of parts used by production/assembly activities in year *i*. Then the expected TCO per part site for sourcing strategy *s* after *j* years, $E[C_{PPS}(s,D)]$, is calculated as follows,

$$C_{\exp} = \sum_{d=1}^{j} C_{PPS}(s,d)\big(F(d) - F(d-1)\big) + C_{PPS}(s,j+1)\big(1 - F(j)\big)$$

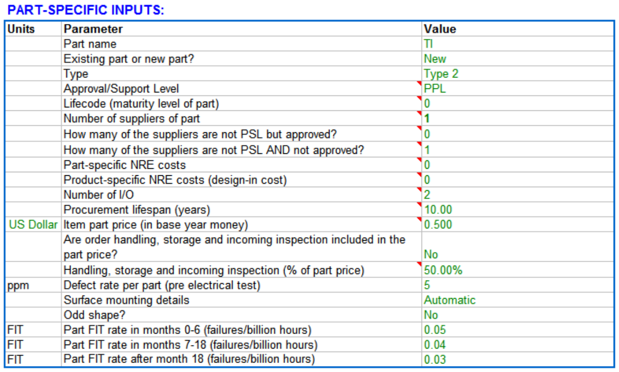
$$C_{\exp} = \frac{E[C_{TCO}(s,D)]}{\sum_{i=1}^{j} N_i^{VOL}} \tag{5.1}$$

5.1.1 Linear regulator case study

The examples in this section apply the methodology to quantify obsolescence risk to study the sourcing of linear regulators. The case study focuses on three specific linear regulator manufacturers: Analog Devices, ON Semiconductor, and Texas Instruments (TI). For the example case in this section, the part TCO simulation model was populated with data (shown in Figure 5.1) from Ericsson AB for a generic linear regulator. The study quantifies the risk of single sourcing (from each supplier) and second sourcing (3 combinations of 2 suppliers) as well as compares the tradeoffs between each strategy. Using (5.1), the expected TCO per part site can be calculated. Part-specific inputs, non-part-specific inputs, and the characteristic part usage for the part within the OEM are shown in Figure 5.1 and are used in all the sourcing cases that follow. The example cases assume that when obsolescence occurs, the OEM performs a lifetime buy of the future projected demand plus a 10% buffer quantity. The lifetime buy is procured at the current price based on inflation and incurs inventory costs annually for the quantity kept in storage at the beginning of each year. The examples also assume that parts from all suppliers are introduced at year 0 and that parts must be supported until year 20 (*j* = 20 years).

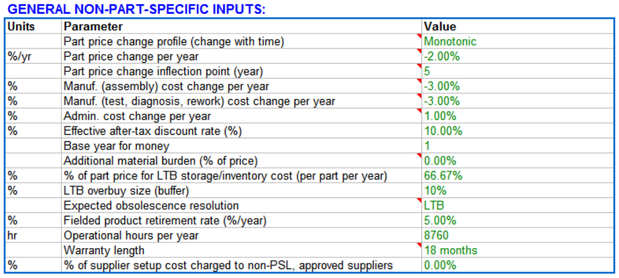
Single Sourcing Example

The right-censored PDF and CDF of single sourced linear regulators from the three suppliers are shown in Figure 5.2. The Weibull parameters for the three suppliers and their corresponding log-likelihood values are shown in Table 5.1. The expected part TCO per part site, (C_{exp}) is plotted over time (independent variable, *d* varied from 1 to *j*) in Figure 5.3 and 5.4 for price independent and price dependent cases respectively.



PART-SPECIFIC INPUTS:

Units	Parameter	Value
	Part name	TI
	Existing part or new part?	New
	Type	Type 2
	Approval/Support Level	PPL
	Lifecode (maturity level of part)	0
	Number of suppliers of part	**1**
	How many of the suppliers are not PSL but approved?	0
	How many of the suppliers are not PSL AND not approved?	1
	Part-specific NRE costs	0
	Product-specific NRE costs (design-in cost)	0
	Number of I/O	2
	Procurement lifespan (years)	10.00
US Dollar	Item part price (in base year money)	0.500
	Are order handling, storage and incoming inspection included in the part price?	No
	Handling, storage and incoming inspection (% of part price)	50.00%
ppm	Defect rate per part (pre electrical test)	5
	Surface mounting details	Automatic
	Odd shape?	No
FIT	Part FIT rate in months 0-6 (failures/billion hours)	0.05
FIT	Part FIT rate in months 7-18 (failures/billion hours)	0.04
FIT	Part FIT rate after month 18 (failures/billion hours)	0.03



GENERAL NON-PART-SPECIFIC INPUTS:

Units	Parameter	Value
	Part price change profile (change with time)	Monotonic
%/yr	Part price change per year	-2.00%
	Part price change inflection point (year)	5
%	Manuf. (assembly) cost change per year	-3.00%
%	Manuf. (test, diagnosis, rework) cost change per year	-3.00%
%	Admin. cost change per year	1.00%
%	Effective after-tax discount rate (%)	10.00%
	Base year for money	1
	Additional material burden (% of price)	0.00%
%	% of part price for LTB storage/inventory cost (per part per year)	66.67%
%	LTB overbuy size (buffer)	10%
	Expected obsolescence resolution	LTB
%	Fielded product retirement rate (%/year)	5.00%
hr	Operational hours per year	8760
	Warranty length	18 months
%	% of supplier setup cost charged to non-PSL, approved suppliers	0.00%

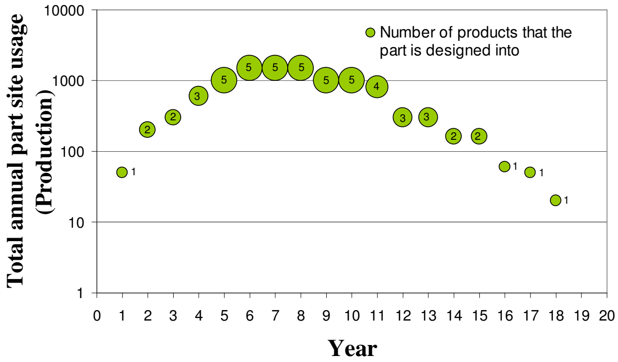


Figure 5.1 – Part TCO model inputs used in the example linear regulator case study (total production volume = 10,500 part sites).

Table 5.1. Supplier-specific censored Weibull distribution parameters, β and η. *LKV* is the negative log-likelihood function (larger negative values indicate a better fit).

Weibull Parameters	Texas Instruments	ON Semiconductor	Analog Devices
β (shape)	3.3299	3.9668	2.1858
η (scale)	12.5831	11.0008	14.2503
LKV	-69.917	-113.246	-39.424

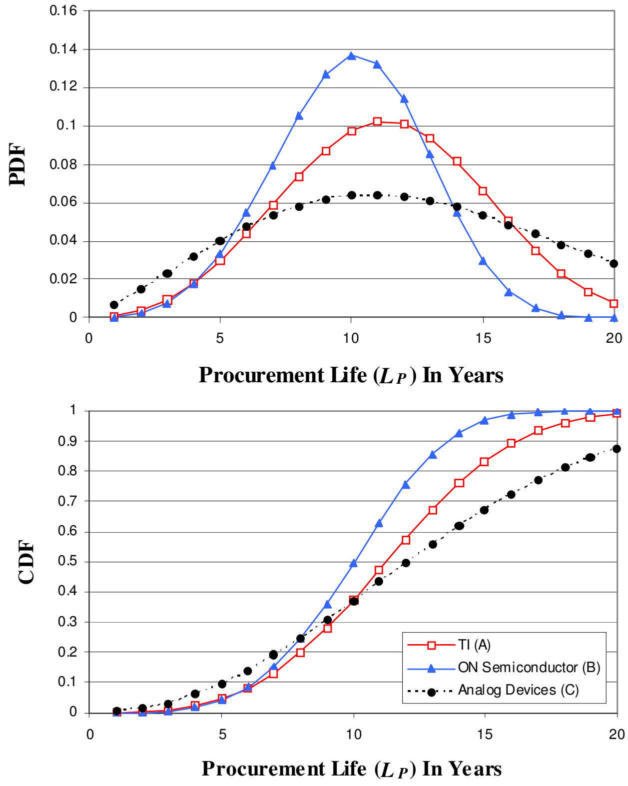
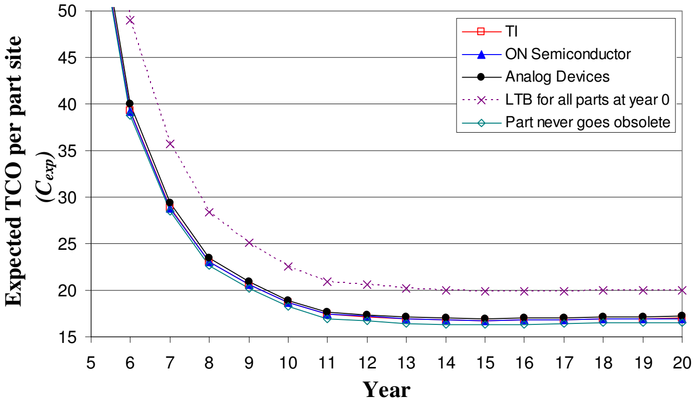
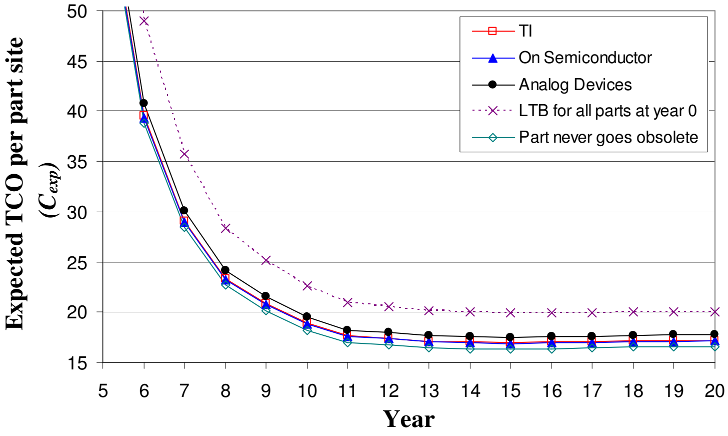


Figure 5.2 – Supplier-specific obsolescence likelihoods for linear regulators as (top) PDF and (bottom) CDF determined from historical data provided by SiliconExpert. The resulting Weibull fits are given in Table 5.1.



Suppliers	C_{exp} (at j = 20 years)
Texas Instruments	\$16.99
ON Semiconductor	\$16.99
Analog Devices	\$17.20
LTB for all parts at year 0	\$20.05
Part never goes obsolete	\$16.52

Figure 5.3 – C_{exp} over time for single sourcing (price-independent case for linear regulator example).



Suppliers	Part Number	Price (per part)	C_{exp} (at j = 20 years)
Texas Instruments	TPS720105DRVR	\$0.702	\$17.19
ON Semiconductor	NCP699SN30T1G	\$0.620	\$17.11
Analog Devices	ADP130AUJZ-0.8-R7	\$0.990	\$17.75

Figure 5.4 – C_{exp} over time for single sourcing (price differences included for linear regulator example).

Figure 5.3 and 5.4 each show C_{exp} plotted over time for two special cases: 1) lifetime buy (LTB) for all parts at year 0 – all the parts necessary to support all production forever are procured once at the beginning of the part's life cycle as a lifetime buy for all future production demand, and 2) the part never goes obsolete – the part never requires a lifetime buy and can be procured annually for the entire product life cycle. These two special cases describe bounding scenarios where life cycle cost is at extremes. When a lifetime buy is made at year 0, the total future production volume is stored in inventory from which parts for each year are drawn annually. Alternatively, when the part never goes obsolete, inventory cost is incurred only for the annual production quantity (assuming one purchase order is made every year for that year's production volume). Additional parts may be purchased to replace failed parts or defective parts that have been diagnosed during assembly. The difference in C_{exp} between these two bounding cases is $3.53/part site after 20 years.

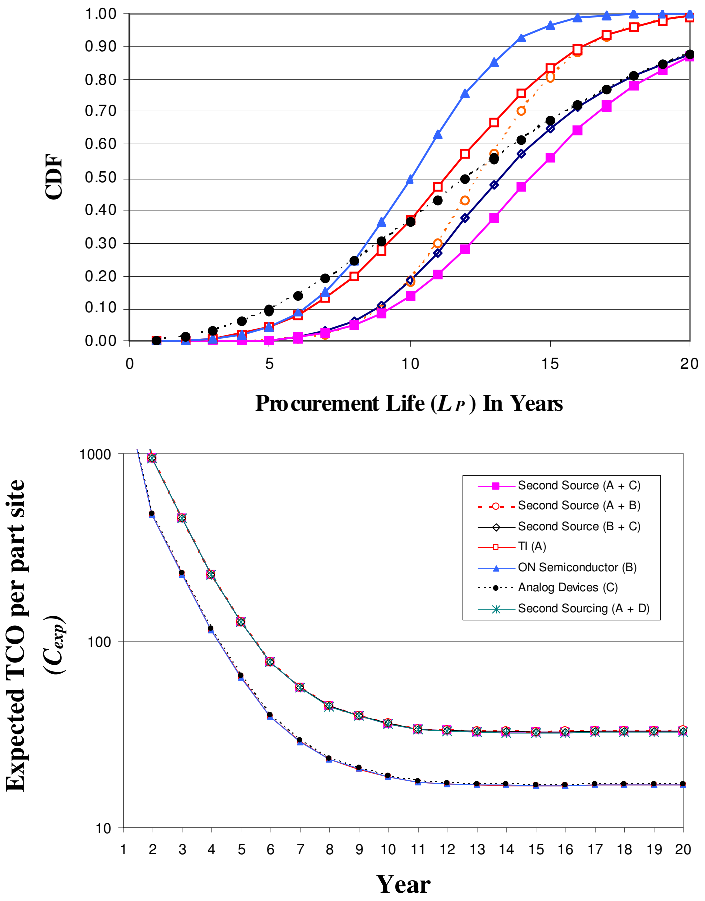
Figure 5.3 shows C_{exp} plotted over time for a price-independent single sourcing case where parts are procured at $0.50/part from all suppliers in year 0 (includes deflation in part price of 2% annually). In this case, TI offers the lowest value of C_{exp} based on the right-censored CDF of obsolescence risk as expressed in Figure 5. The maximum difference in C_{exp} between these suppliers is $0.21/part site in 2010 dollars or 1.2% of C_{exp} of ON Semiconductor after 20 years.

Figure 5.4 shows a price-dependent single sourcing case for specific linear regulator parts from each supplier. It is the same as Figure 5.3 except actual part prices are included. The maximum cost difference is $0.64/part site in 2010 dollars or 3.7% of C_{exp} of ON Semiconductor after 20 years. TI's part, being a more expensive part than ON Semiconductor's by \$0.082/part, exceeds ON Semiconductor in C_{exp} by \$0.080/part site. The CDF value of ON Semiconductor's part is the smallest of the three suppliers until year 6; as a result, the benefit to the overall TCO, for a slightly lower CDF early in the part's life cycle, is almost equal to the cost of having a much higher CDF late in the part's life cycle (year 8 to year 20). Statistically, this indicates that procuring parts from ON Semiconductor offers life cycle cost benefits over the other suppliers as a result of the part site usage and its effect on lifetime buy inventory cost. The part site usage shown in Figure 5.1 assumes an increase in part sites until year 6, a plateau between year 6 and 8, and a decline that follows thereafter. ON Semiconductor's parts are least likely to go obsolete during periods of high part usage thereby reducing lifetime buy inventory cost.

The single sourcing examples (Figures 5.3 and 5.4) show that, if you are going to single source linear regulators, there is no significant difference even with relatively large procurement cost differences. When parts are consumed in low volumes, procurement and assembly costs play a small part in the overall part TCO which are dominated by support costs instead. These examples show that low volume cases are insensitive to procurement price changes. However, for high volume part usage, price differences have a greater impact. An additional effect of high volume part usage is that large lifetime buys also lead to higher inventory cost, which enhances the benefit of selecting parts with longer procurement life. Therefore, for higher part production volumes, the procurement price of a part is expected to have an increasing role in sourcing tradeoffs.

Second Sourcing Example

The potential advantage of second sourcing is that the parts can be purchased from two suppliers interchangeably. However, when second sourcing is used, both suppliers (and the parts they supply) are subject to approval and qualification processes within the OEM. The purpose of second sourcing is to ensure a continuous



Annual expected cumulative TCO (C_{exp}) after 20 years @ $0.5/part:
TI + ON Semiconductor = 33.01 per part site
TI + Analog Devices = 32.92 per part site
ON Semiconductor + Analog Devices = 32.98 per part site

Figure 5.5 – (left) CDF of obsolescence likelihood by sourcing strategy and (right) annual expected cumulative TCO per part site over time by sourcing strategy (price independent case for linear regulator example).

flow of parts and avoid “down-time” (and related penalties) in the event of supply chain disruptions by offering a redundancy in the supply of parts. Essentially, the effective procurement life of a part that is purchased from more than one qualified supplier is the longest procurement life of all the suppliers used.

Consider the following low-volume linear regulator case (shown in Figure 5.5) to demonstrate the tradeoff between single and second sourcing, as well as possible benefits in supplier selection based on obsolescence likelihood. The second sourcing example in Figure 5.5 assumes the following: 1) both suppliers are capable of supplying the total annual demand if necessary, 2) no competitive pricing or “split-award” auctions are conducted (procurement price = \$0.50/part), 3) no cost to switch between suppliers (once they are qualified), 4) every supplier must be qualified before being used (qualification cost = \$100,000/supplier), 5) parts from both suppliers have the same introduction date (D_I), and 6) learning indices, B_x, for support activities x, are assumed to be 0 (no learning from supplier-to-supplier, i.e., worst case).

Figure 5.5 shows the calculated CDF distributions (left) and the corresponding obsolescence risk (right) over time to compare results between single sourcing (from Section 3.1) and their second sourcing combinations. C_{exp} after 20 years, for the second sourcing combination of TI and Analog Devices, is \$32.92/part site. This combination is marginally lower than the combination of ON Semiconductor and Analog Devices, which yields a C_{exp} of \$32.98/part site, due to the similarities between their second sourcing CDFs. However, the margin between C_{exp} is larger when second sourcing TI and ON Semiconductor due to consistently higher CDF

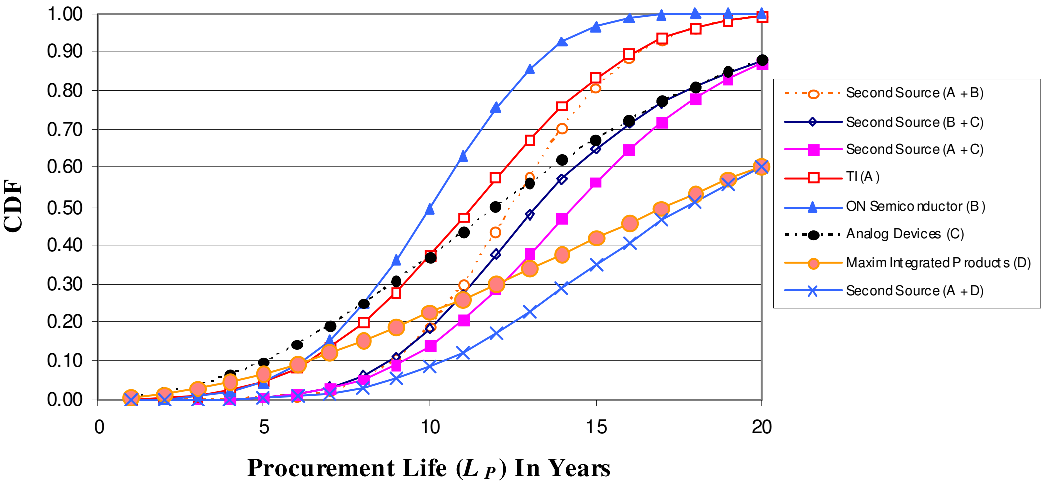


Figure 5.6 – CDF of obsolescence likelihood by sourcing strategy (linear regulators).

values. In this case study, the savings (over single sourcing) associated with extending the effective procurement life of the part through second sourcing is negated by the high qualification and support cost related with utilizing a second supplier.

The three suppliers, TI, ON Semiconductor, and Analog Devices, were selected to be used in the example case studies based on the completeness of the data set. Key factors in the selection of suppliers were the number of non-obsolete parts and the fraction of non-obsolete parts among the total number of supplier-specific data points. The outliers that exist within the linear regulator data set for which supplier-specific CDFs may be significantly different are a result of a high fraction of non-obsolete parts or a small number of valid data points within the supplier-specific data set (e.g., the CDF for Maxim Integrated Products is shown in Figure 5.6 is generated from a data set with 5 obsolete parts and 20 non-obsolete parts i.e., 80%

non-obsolete parts). I have included the Maxim supplier in the analysis that follows for demonstration purposes because it is significantly different than the other suppliers, however, the Maxim dataset has significantly fewer obsolescence events upon which to base a predictive forecast than the other suppliers.

5.3 Summary and discussions

This section presents a method to quantify obsolescence risk in order to compare sourcing strategies of electronic parts used in long life cycle products and systems. Existing methods used to address sourcing for high volume, short field life products are procurement-centric focusing on procurement pricing, negotiation practices and purchase volumes. The method described in this chapter adopts a life cycle approach utilizing a part total cost of ownership model and historic obsolescence data to quantify obsolescence risk, which is suitable for comparing sourcing strategies over long life cycles. This chapter presents a calculation for "expected part TCO (per part site)," which can be used as a metric to assess part risk. The methodology is applied in a comparison of single and second sourcing linear regulators from three suppliers: Texas Instruments, ON Semiconductor, and Analog Devices.

The single sourcing cases for linear regulators show that the particular supplier parts are procured from (if the only difference is procurement life and procurement cost) does not make a significant difference even for relatively large procurement cost differences. It was also found to be difficult to make a business case for second sourcing linear regulators based only on maximizing procurement life (if the second source requires qualification). However, the method can be implemented to identify the ideal combination of suppliers, from a life cycle perspective, if second sourcing is predetermined.

Chapter 6: Analytical part TCO model

This chapter presents an analytical part TCO model based on simplifying assumptions that are valid for long-term sourcing of electronic parts used in long life cycle products. The analytical part TCO model estimates the part TCO subject to known supply chain disruption events. Section 6.2 discusses the implementation of the analytical part TCO model to assess cost tradeoffs between two sourcing strategies[19] subject to part obsolescence (when the effective procurement lives are known). The method of comparing two sourcing strategies utilizes part TCO as a means to identify a "break-even" learning index, *B*, necessary to make a particular multi-sourcing strategy (with N_{sup} available suppliers) viable.

6.1 Problem statement

The part total cost of ownership (TCO) is the total cost spent at various stages of the part's life cycle: procurement (C_{PROC}), inventory (C_{INV}), support (C_{SUP}), assembly (C_{ASY}), and field failure repairs (C_{FF}). Let C_{TCO} be the part TCO calculated as shown in (3.1). This general form is the basis for the simulation part TCO model.

$$C_{TCO} = C_{PROC} + C_{INV} + C_{SUP} + C_{ASY} + C_{FF} \tag{6.1}$$

Section 6.1 presents assumptions and the formulation of an analytical part TCO model applicable to sourcing parts for long life cycle product applications. The part TCO can be represented as $C_{TCO}\left(D_s, B_s, N_s^{SUP}\right)$. Let D_s be the effective disruption

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[19] This chapter considers only supply chain disruptions associated with the obsolescence of COTS parts. The formulation of a sourcing strategy refers to the selection and qualification of a finite number of suppliers from which the COTS parts may be procured. The word "sources" refers to the part's "suppliers".

date and let B_s be the learning index of all support activities when sourcing strategy *s* is adopted. The sourcing strategy s is defined by the number of suppliers/sources used, N_s^{SUP}.

The difference in C_{TCO} between different solutions that use different sourcing strategies (strategies *a* and *b*) is given by,

$$\left[\Delta C_{TCO}\right]_{a,b} = \left[C_{TCO}\left(D_a, B_a, N_a^{SUP}\right)\right]_a - \left[C_{TCO}\left(D_b, B_b, N_b^{SUP}\right)\right]_b$$

Let D_a and D_b be the part obsolescence dates (estimated from effective procurement lives) associated with the two sourcing strategies, *a* and *b*, being considered. The uncertainty associated with the effective disruption dates are addressed in Chapter 4 through the forecasting of procurement life distributions.

The objective of this solution is to identify the “break-even” learning index between two potential part sourcing strategies. From the context of this dissertation, learning indices for multi-sourcing support cost, *B*, are said to be at “break-even” when the resulting TCO of the two sourcing strategies being compared, strategy *a* and strategy *b*, (subject to independent disruption dates) is equal; i.e., $\left[\Delta C_{TCO}\right]_{a,b}$ becomes zero. Determining a break-even learning index creates a target (for reducing qualification and support activities); a part management organization capable of achieving a learning index below the break-even learning index can be expected to benefit from the alternative multi-sourcing strategy.

6.2 Model assumptions and formulation

In order to evaluate the analytical C_{TCO}, several simplifying assumptions are made:

1. The cumulative part assembly cost, C_{ASY} is constant for a given part usage profile and is not affected by the sourcing strategy used. The total assembly cost, C_{ASY}, has been defined as being dependent on the part usage profile and the characteristics of the assembly process (yield as a result of defect testing, diagnosis, and rework). However, it is assumed that supplier-specific part quality (defect rates) are the same for all suppliers, therefore there is no change in the effective yield across the entire population of parts (i.e., $Y_1^{IN} = Y_2^{IN} = \ldots = Y_{N_s^{SUP}}^{IN}$). The assembly cost is then independent of the number and selection of suppliers from which the part is procured. Subsequent equations include assembly cost in order to maintain proportionality in part TCO and can be simply calculated as described in (6.2) as a function of annual part usage, N_i^{VOL}. Note: part procurement price will be considered independent of the assembly cost henceforth.
2. The product warranty period is shorter than the part's earliest possible wear-out failure under the expected operating conditions (most electronic parts, even in long field life applications, rarely reach wear-out). Failures due to infant mortality and random failures during the useful life are assumed to be negligible. Therefore, $C_{FF} = 0$. Note, based on this assumption, the number of parts (procured) and number of part sites are equal (i.e., no replacement parts are needed).

3. Non-recurring support activities (such as qualification and validation) are all performed in year 1.

4. Learning indices, B_i^x are assumed to be constant for all organization-specific support activities, x, and do not change over time. For example, $B_i^{as} = B_i^{ap} = \ldots = B_i^n = B$ and $B_1^x = B_2^x = \ldots = B_j^x = B$

5. TCO over the product usage life cycle of the part is an accumulation of spending up to year j; cost saved or recovered (e.g., part salvaging) is not considered in the TCO model, i.e., $C_{PROC} \geq 0$, $C_{INV} \geq 0$, $C_{SUP} \geq 0$, $C_{ASY} \geq 0$, $C_{FF} \geq 0$.

6. The number of suppliers, N_{sxi}^{SUP}, for a sourcing strategy s in year i does not change throughout the part's procurement life cycle unless the part is no longer procurable from a particular supplier involved in the sourcing strategy (i.e., supplier-specific part obsolescence). For example, $N_{sx1}^{SUP} = N_{sx2}^{SUP} = \ldots = N_{sxj}^{SUP} = N_{sx}^{SUP}$. Also, for a sourcing strategy, s, all suppliers require the same set of support activities x. Let the size of vector x (consisting of support activities) be n. Therefore, $N_{s,as}^{SUP} = N_{s,ap}^{SUP} = \ldots = N_{sn}^{SUP} = N_s^{SUP}$.

7. The part price, P_{pi}^{SUP} is the same for all suppliers that parts are procured from (where supplier index, p goes from 1 to N_s^{SUP}) and all the parts are subject to the same annual price change, i.e., $P_{1i}^{SUP} = P_{2i}^{SUP} = \ldots = P_{N_s^{SUP} i}^{SUP} = P_i^{SUP}$.

The following presents the formulation of the analytical part TCO model based on the seven assumptions stated above. Based on assumption 7, the total part procurement cost from (3.11) when multi-sourcing can be simplified to its single sourcing form in Section 3.1.3 which assumes indifferent part prices across suppliers.

$$C_{PROC}(D_s) = \sum_{i=1}^{j} \frac{P_i^{SUP} N_i^{PROC}(D_s)}{(1+r)^i} \tag{6.2}$$

The total part quantity procured from all suppliers in year i is, N_i^{PROC}, which is a function of effective disruption date, D_s when sourcing strategy s is adopted, and annual part usage volume, N_i^{VOL} given by,

$$N_i^{PROC}(D_s) = \begin{cases} N_k^{VOL} & \rightarrow \text{if } i < D_s \\ \left(1 + F_{overbuy}\right) \sum_{k=D_s}^{j} N_k^{VOL} & \rightarrow \text{if } i = D_s \\ 0 & \rightarrow \text{if } i > D_s \end{cases} \tag{6.3}$$

The equation for N_i^{PROC} in (6.3) when $i = D_s$ assumes that a lifetime buy is made (the quantity of which is the sum over the demand volume in all years from D_s to the end of the support life for the part) including a buffer/overbuy, $F_{overbuy}$ as a fraction of the lifetime buy quantity. The effective obsolescence date depends on the sourcing strategy used.[20]

Let $C_{TCO}\left(D_s, B^x, N_{sx}^{SUP}\right)$ be the part TCO for a sourcing strategy s after j years. The part TCO depends on procurement, inventory, support, assembly and field failure costs, and can be rewritten, based on the assumptions above, in terms of disruption date, D_s, learning index for support cost, B_s, and the number of suppliers from which parts are procured, N_s^{SUP}, as shown in (6.3),

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[20] The "effective" obsolescence date of a particular sourcing strategy is the observed obsolescence date as a result of N_s^{SUP} suppliers. For example, as discussed in Chapter 4, the effective obsolescence date of a second sourcing strategy is the later of the obsolescence dates of the two suppliers' parts.

$$C_{TCO}\left(D_s, B, N_s^{SUP}\right) = C_{PROC}\left(D_s\right) + C_{INV}\left(D_s\right) + \left(\sum_{p=1}^{N_s^{SUP}} C_{SUP}\left(D_s\right) p^B\right) + C_{ASY} \tag{6.4}$$

where,

$C_{PROC}(D_s) =$ total procurement cost after *j* years, and is given in (3.11)

$C_{INV}(D_s)$ = total inventory cost after *j* years, and is given in (3.6)

$C_{SUP}(D_s)$ = total support cost after *j* years, and is given in (3.8)

C_{ASY} = total assembly cost after *j* years, and is discussed in Section 3.2.3

D_s = disruption date for sourcing strategy *s*

Section 6.3 applies the analytical part TCO model in the assessment of part TCO and subsequent tradeoff analyses between various part sourcing strategies. The analytical part TCO model is also used to solve for break-even learning indices that indicate the conditions under which a sourcing strategy will be cost-effective.

6.3 Comparison of sourcing strategies

The analytical part TCO model can be used in tradeoff analyses to identify the most cost-effective sourcing strategy. This section discusses a method to utilize the simplified TCO model to estimate the difference in TCO between two sourcing strategies based on sourcing-specific procurement lives. This section also discusses a method to estimate a "break-even" learning index that would be required for a second sourcing strategy (implemented to extend the procurement life of a part) that would result in a TCO equal to that of a single sourcing strategy.

Considering two sourcing strategies, *a* and *b*, the difference in cumulative TCO can be formulated as a function of obsolescence dates and learning indices by,

$$[\Delta C_{TCO}]_{a,b} = \left[C_{TCO\,j}\left(D_a, B_a, N_a^{SUP}\right)\right]_a - \left[C_{TCO\,j}\left(D_b, B_b, N_b^{SUP}\right)\right]_b \tag{6.5}$$

D_a and D_b are the effective obsolescence dates (estimated from effective procurement lives) for parts associated with the two sourcing strategies, *a* and *b* (i.e., two combinations of suppliers).

Comparing TCO of single sourcing strategies

This section compares the TCO between two single sourcing strategies as a function of the obsolescence dates of the single sourced parts. This result quantifies the TCO difference between alternative single source solutions.

For single sourcing, learning index, *B*, is not required (and meaningless) since $N_{\sup_a} = N_{\sup_b} = 1$ in (6.1). Learning indices only apply to sourcing strategies with two or more suppliers. Therefore, the equation for ΔC_{TCO} at year *j* comparing two single sourcing strategies (strategy "*a*" vs. strategy "*b*") under the stated assumptions is,

$$[\Delta C_{TCO}]_{a,b} = [C_{TCO}(D_a)]_a - [C_{TCO}(D_b)]_b$$

where D_a and D_b are obsolescence dates for two comparable single sourcing strategies. Therefore, the difference in TCO after *j* years between two single sourcing strategies can be written as follows,

$$\Delta C_{TCO_j} = [C_{PROC}(D_a) + C_{INV}(D_a) + C_{SUP}(D_a)] - [C_{PROC}(D_b) + C_{INV}(D_b) + C_{SUP}(D_b)]$$

Note, as stated in the assumptions, C_{asy} is constant for both sourcing strategies (*a* and *b*) and is independent of obsolescence date. Therefore, for single sourcing, the difference in TCO for two single sourcing strategies after *j* years is given in (6.6),

$$\Delta C_{TCO} = \Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP} \tag{6.6}$$

where,

$$\Delta C_{PROC} = C_{PROC}(D_a) - C_{PROC}(D_b)$$

$$\Delta C_{INV} = C_{INV}(D_a) - C_{INV}(D_b)$$

$$\Delta C_{SUP} = C_{SUP}(D_a) - C_{SUP}(D_b)$$

Part sourcing TCO tradeoffs (single sourcing vs. second sourcing)

This section compares the TCO of single sourcing (strategy "*a*") versus second sourcing (strategy "*b*") a part. The learning index for strategy "*a*", B_a may be omitted from (6.5) since the learning index for a single sourcing strategy does not apply. Therefore, the learning index of strategy "*b*", B_b constitutes the break-even learning index that is of interest in this tradeoff analysis. The part sourcing tradeoff can be represented by,

$$[\Delta C_{TCO}]_{a,b} = [C_{TCO}(D_a)]_{\mathrm{a}} - \left[C_{TCO}\left(D_b, B_b, N_b^{SUP}\right)\right]_{\mathrm{b}}$$

The resulting equation for ΔC_{TCO} after *j* years for the two sourcing strategies of interest (single vs. second sourcing) under the stated assumptions (derived from the equation (6.4)) is,

$$\Delta C_{TCO} = [C_{PROC}(D_a) + C_{INV}(D_a) + C_{SUP}(D_a)] - \left[C_{PROC}(D_b) + C_{INV}(D_b) + \sum_{p=1}^{2} C_{SUP}(D_b)p^{B_b}\right]$$

where D_{O_a} and D_{O_b} are obsolescence dates when single sourcing and second sourcing respectively. As discussed in Chapter 4, second sourcing offers a redundancy in the supply of parts which means that (in terms of obsolescence) D_b is effectively the later of the two supplier-specific disruption dates. $N_{\sup_a} = 1$ for single sourcing and $N_{\sup_b} = 2$ for second sourcing.

$$\Delta C_{TCO} = [C_{PROC}(D_a) + C_{INV}(D_a) + C_{SUP}(D_a)] - [C_{PROC}(D_b) + C_{INV}(D_b) + C_{SUP}(D_b)(1 + 2^{B_b})]$$

$$\Delta C_{TCO} = [C_{PROC}(D_a) - C_{PROC}(D_b)] + [C_{INV}(D_a) - C_{INV}(D_b)] + [C_{SUP}(D_a) - C_{SUP}(D_b)] - C_{SUP}(D_b)2^{B_b}$$

To identify the learning index, B_b, for which ΔC_{TCO} for the two sourcing strategies is 0 (“break-even” point for the two sourcing strategies), the following equation must be solved for B_b,

$$\Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP} - C_{SUP}(D_b)(2^{B_b}) = 0$$

$$(2)^{B_b} = \frac{\Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP}}{C_{SUP}(D_b)}$$

$$B_b = \log_2\left[\frac{\Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP}}{C_{SUP}(D_b)}\right] \tag{6.7}$$

(or) $B_b = \log_2\left[\dfrac{\Delta C_{TCO}}{C_{SUP}(D_b)}\right]$

This equation allows the learning index at break-even to be calculated based on known effective obsolescence dates and single sourcing costs modeled via the part TCO model.

General form: single sourcing vs. multi-sourcing ("N" suppliers)

To compare a single sourcing case (strategy "*a*" where $N_a^{SUP} = 1$) against a sourcing strategy with N_b^{SUP} suppliers (strategy "*b*" where $N_b^{SUP} > 1$), (6.5) reduces to,

$$\Delta C_{TCO} = \left[C_{PROC}(D_a) + C_{INV}(D_a) + C_{SUP}(D_a)\right] - \left[C_{PROC}(D_b) + C_{INV}(D_b) + \sum_{p=1}^{N_b^{SUP}} C_{SUP}(D_b)\, p^{B_b}\right]$$

$$\begin{aligned}\Delta C_{TCO} = {} & \left[C_{PROC}(D_a) - C_{PROC}(D_b)\right] + \left[C_{INV}(D_a) - C_{INV}(D_b)\right] + \left[C_{SUP}(D_a) - C_{SUP}(D_b)\right] \\ & - C_{SUP}(D_b) \sum_{p=2}^{N_b^{SUP}} (p)^{B_b}\end{aligned}$$

To obtain the break-even learning index, the learning index for sourcing strategy *b* (B_b) must satisfy the following equation where ΔC_{TCO} for the two sourcing strategies is 0.

$$\Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP} - C_{SUP}(D_b) \sum_{p=2}^{N_b^{SUP}} (p)^{B_b} = 0$$

Solving (6.8) for the unknown variable, B_{BE}, we get,

$$\sum_{p=2}^{N_b^{SUP}} (p)^{B_{BE}} = \frac{\Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP}}{C_{SUP}(D_b)} = K_{\left(1, N_b^{SUP}\right)} \tag{6.8}$$

where, B_{BE} is the break-even learning index for sourcing strategy *b*.

Substituting ΔC_{TCO} into equation (6.8), we get,

$$K_{\left(1, N_b^{SUP}\right)} = \left[\frac{\Delta C_{TCO}}{C_{SUP}(D_b)}\right]$$

Equation (6.8) can be solved graphically to find the value of *B* at "break-even", B_{BE} corresponding to ratio[21], *K*, as shown in Figure 6.1.

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[21] Subscripts of ratio, *K*, denote the number of sources being used by the two sourcing strategies being compared.

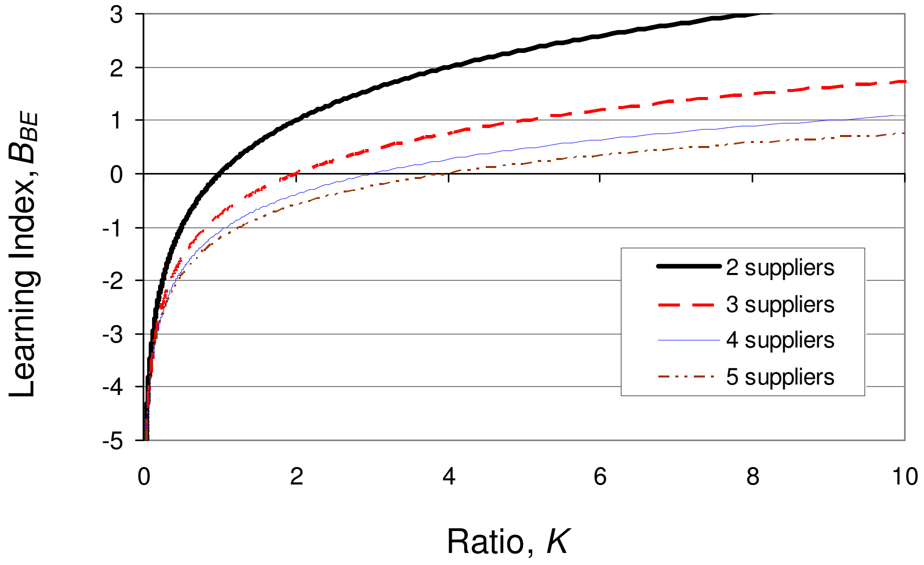


Figure 6.1 – Plot of break-even learning index, B_{BE}, with respect to the ratio, $K = \Delta C_{TCO}/C_{sup}$, at break-even (where TCO of a sourcing strategy with N_b^{SUP} number of suppliers is equal to the TCO of single sourcing).

Therefore, the cost tradeoffs between two sourcing strategies (irrespective of the number of suppliers) can be represented by costs from equivalent single sourcing cases as functions of learning indices and obsolescence dates.

When solving (6.8), the introduction of a logarithm function results in there being real and imaginary solutions for break-even learning index, B_{BE}. For the relationship in (6.7) and (6.8) to provide a real solution, K must be greater than 0. This condition implies that ΔC_{TCO} must be greater than 0. The correlation between learning index, B_{BE} and the bounding limits for support cost, C_{sup} are shown below.

<u>*Case 1:*</u> $C_{SUP}(D_b) \rightarrow 0^+$

$$\lim_{C_{\sup}\to 0^+} B_{BE}\left(C_{SUP}\left(D_b\right)\right) = \infty$$

Case 2: $C_{SUP}(D_b) \to \infty$

$$\lim_{C_{\sup} \to \infty} B_{BE}\left(C_{SUP}(D_b)\right) = -\infty$$

The method to calculate the break-even learning index developed in this section is implemented in examples presented in Section 6.4

6.4 Comparison of analytical and simulation part TCO models (part TCO)

This section presents example cases that compare the analytical and simulation part TCO models. This section will also identify the conditions under which results from the models diverge. Figure 6.2 shows the error in estimating part

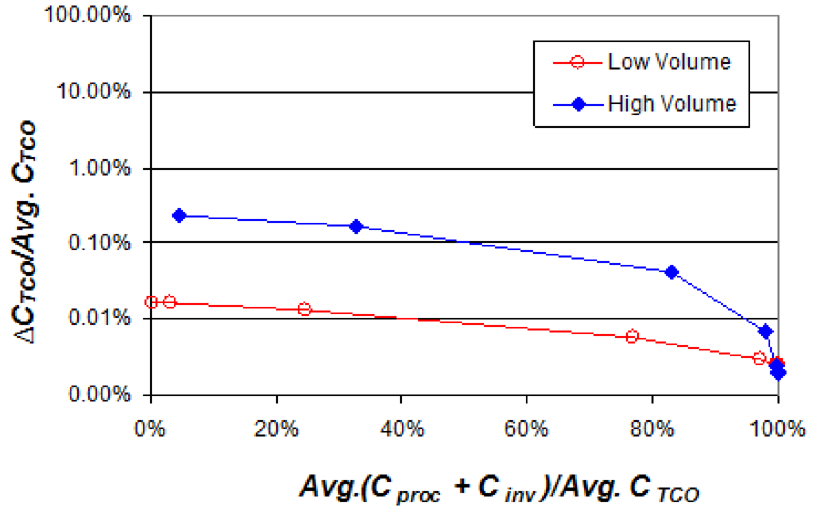


Figure 6.2 – Error between the simulation and analytical part TCO models as difference in TCO (as a fraction of average TCO determined from the simulation and analytical part TCO models), with respect to the average procurement and inventory cost (as fraction of average TCO) for a low volume case (49,752 parts) and a high volume case (49,753,000 parts).

TCO using the simulation and analytical part TCO models for electronic parts. The results in Figure 6.2 show the error as a ratio with respect to average part TCO. The cost difference between the simulation and analytical models is an effect of increasing influence from field failure and assembly cost when part volumes increase. The cost difference, ΔC_{TCO} also increases as the fraction of procurement and inventory cost increases (the independent variable on Figure 6.2) but is negated by the growing average TCO cost in the denominator. The overall model error is also an effect of the total support cost. Both analytical and simulation models estimate support cost in the same way (no difference in the support cost models). When support cost dominates (when procurement and inventory cost is low for example), the total cost error is lower but is amplified by the low average TCO (in the denominator). The maximum observed error is less than 0.23% of part TCO.

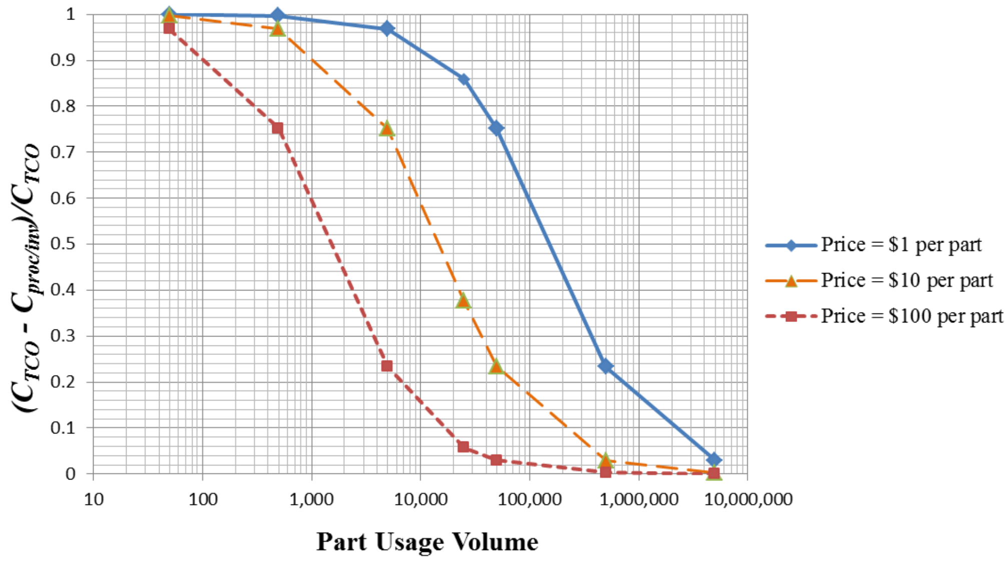


Figure 6.3 – Cost difference (per part site) between part TCO, C_{TCO} and procurement/inventory cost, $C_{proc/inv}$ with respect to total part usage volume after 20 years.

Using the analytical part TCO model, Figure 6.3 shows the difference between part TCO, C_{TCO} and procurement and inventory cost, $C_{proc/inv}$ as a fraction of part TCO with respect to part usage volume. The difference is the error between modeling pure procurement cost and modeling part TCO. Figure 6.3 shows that larger error is observed at lower part usage volumes. The error is attributed to significant cost contributions from support, field failure, inventory, and assembly costs combined. The error diminishes as part volume increases. Figure 6.3 confirms that higher part usage volumes and/or higher part prices increase the relative cost from procurement (fraction of part TCO) thereby, reducing the error between part TCO and procurement cost models. In other words, pure procurement cost models lose accuracy at low part usage volumes justifying the need for part TCO models on which to base part management decisions. This section demonstrates the scale of the error observed between the simulation and analytical part TCO models. Figure 6.2 show application-specific results where error at low volume part usage case is an order of magnitude lower than the error at the high part usage volume case. The level of error is dependent on the cost of procurement relative to the part TCO. Conversely, the level of error can be estimated as the combined cost from support, field failure, and assembly costs.

Section 6.3 presents example cases using the analytical part TCO model to estimate the break-even learning index comparing single sourcing and second sourcing strategies.

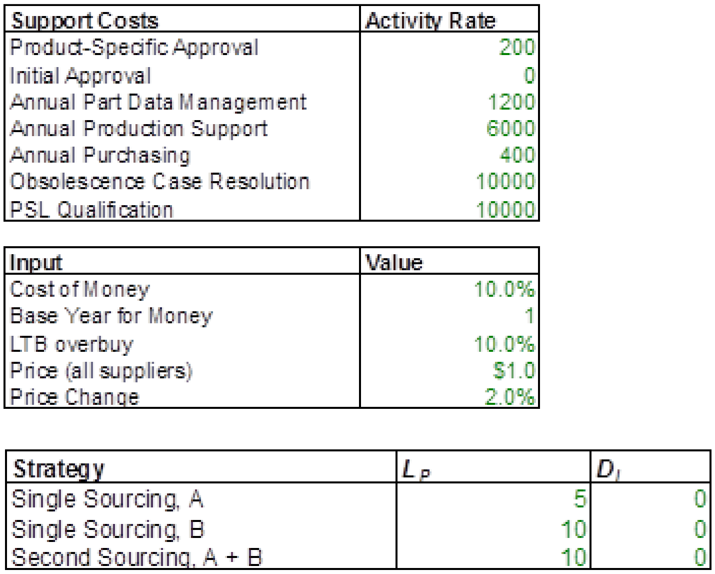
6.5 Implementation of analytical part TCO model (break-even learning index)

The analysis to compare sourcing strategies in Section 6.4 is useful when the parts management organizations are aware of the limitations in their capabilities and their ability to streamline support activities. For example, the analysis provides the organization a means to identify a viable multi-sourcing strategy that requires support cost learning indices, B^x, that are within achievable limits.

This section discusses the comparison of two sourcing strategies in terms of TCO and disruption risk. The example cases will also estimate a break-even learning index subject to a learning index threshold, B_{TH} imposed by the capabilities of the part management organization.

The example problem addressed in this section can be stated as follows:

- Determine the break-even learning index, B_{BE} for second sourcing linear regulators from two possible suppliers: A and B. The inputs for this example are shown in Figure 6.4. The part usage assumed for this case is shown in Figure 5.1.
- For a particular learning index, what is the maximum allowable inventory cost (per part) that makes a second sourcing strategy viable?
- Based on the uncertainty of disruption dates, determine the break-even learning index, B_{BE} for second sourcing linear regulators from three possible suppliers: ON Semiconductor, Analog Devices, and TI. What is the probability that the required break-even learning index, B_{BE}, will exceed a specified learning index threshold, B_{TH}? The parameters for supplier-specific procurement life distributions (Weibull) are shown in Figure 5.1.



Support Costs	Activity Rate
Product-Specific Approval	200
Initial Approval	0
Annual Part Data Management	1200
Annual Production Support	6000
Annual Purchasing	400
Obsolescence Case Resolution	10000
PSL Qualification	10000

Input	Value
Cost of Money	10.0%
Base Year for Money	1
LTB overbuy	10.0%
Price (all suppliers)	\$1.0
Price Change	2.0%

Strategy	L_P	D_I
Single Sourcing, A	5	0
Single Sourcing, B	10	0
Second Sourcing, A + B	10	0

Figure 6.4 – Inputs for the example case discussing the method in Section 6.3 (Lp is the part's effective procurement life and D_I is the part's introduction date).

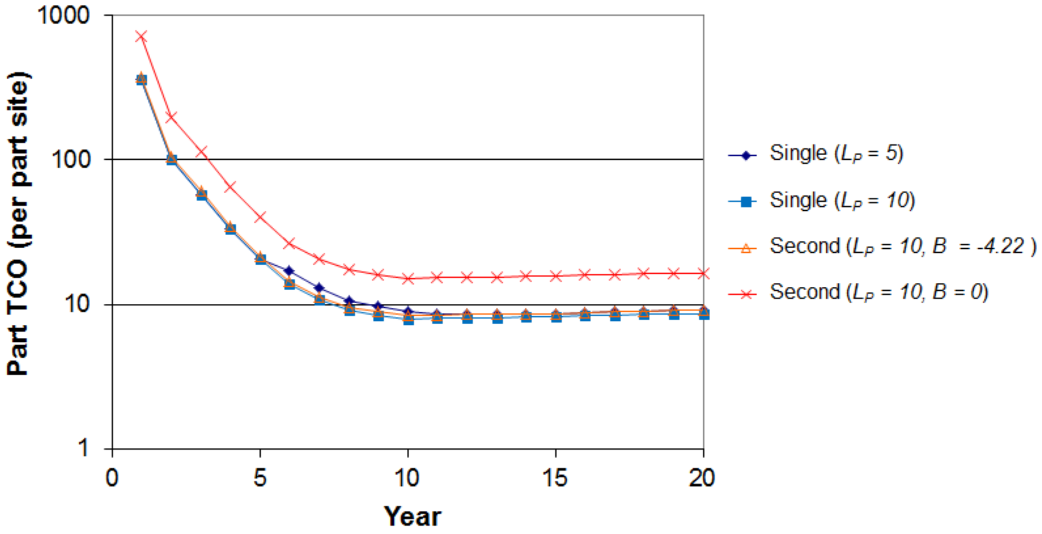


Figure 6.5 – Part TCO (per part site) versus year of support for the example case where inventory cost is $0.1 per part.

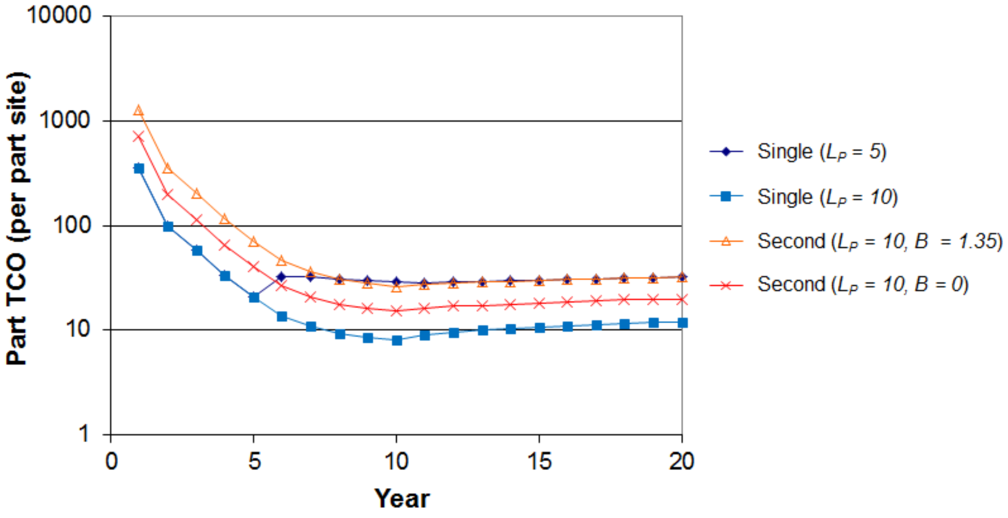


Figure 6.6 – Part TCO (per part site) versus year of support for the example case where inventory cost is $10 per part.

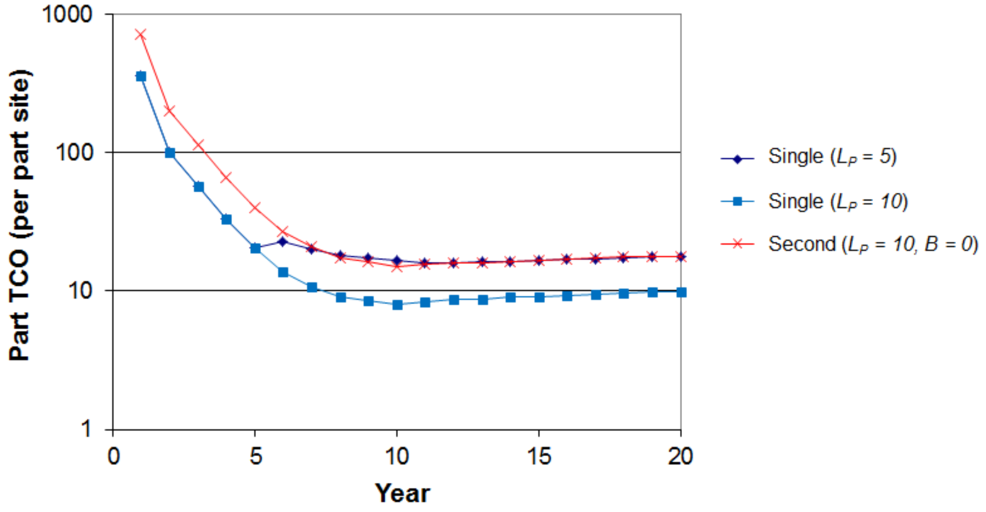


Figure 6.7 – Part TCO (per part site) versus year of support for the example case where learning index, B is 0 (maximum allowable inventory cost is \$3.84 per part).

Figure 6.5 and Figure 6.6 demonstrate the methodology to estimate the break-even learning index for second sourcing using the analytical part TCO model. The figures show the part TCO (per part site) with respect to the year of support (starting at 1). The example cases vary inventory cost for the part presented in Figure 6.4. For a predetermined inventory cost of \$0.1 per part (per year), second sourcing is viable when learning index is $B < -4.22$. Similarly, when inventory cost is \$10 per part (per year), the required learning index for second sourcing to be cost effective is $B < 1.35$.

Consider a learning index threshold, B_{TH} imposed on the part management organization[22]. The learning index threshold, B_{TH} yields the ratio, K_{TH} (derived from (6.8)) and vice versa, as shown below,

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[22] In order to minimize repeated support activities (reduce the ratio K and subsequently total support cost) in multi-sourcing strategies, the part management's goal is to minimize learning index value (where $-\infty < B < \infty$). The learning index may be determined by the level of qualification needed (either

$$K_{TH} = \sum_{p=2}^{N_b^{SUP}} (p)^{B_{TH}}$$

where,

$0 \leq K_{TH} < \infty$ are the feasible boundary conditions for ratio K

K_{TH} = ratio (threshold) of support cost for repeated support activities in sourcing strategy b with respect to support cost in single sourcing strategy a

N_b^{SUP} = number of suppliers in multi-sourcing strategy b

B_{TH} = learning index threshold

p = supplier index

In practice, $B = 0$ ($K_{TH} = 1$ for second sourcing) defines the realistic "worst-case" for learning index since adding suppliers under these conditions requires the complete duplication of support activities when no learning occurs. The following example cases comparing second sourcing to single sourcing assumes $K_{TH} = 1$ ($B_{TH} = 0$). When break-even learning index is $B_{BE} > 0$, second sourcing is always a cost effective option. Figure 6.5 to Figure 6.7 show the second sourcing part TCO (per part site) when $B = 0$. For $B = 0$, the maximum allowable inventory cost is \$3.84 per part (per year) for single sourcing and second sourcing strategies to "break-even" as shown in Figure 6.7.

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based on product regulations or organizational policy) or practical capabilities (i.e., cost of resources used).

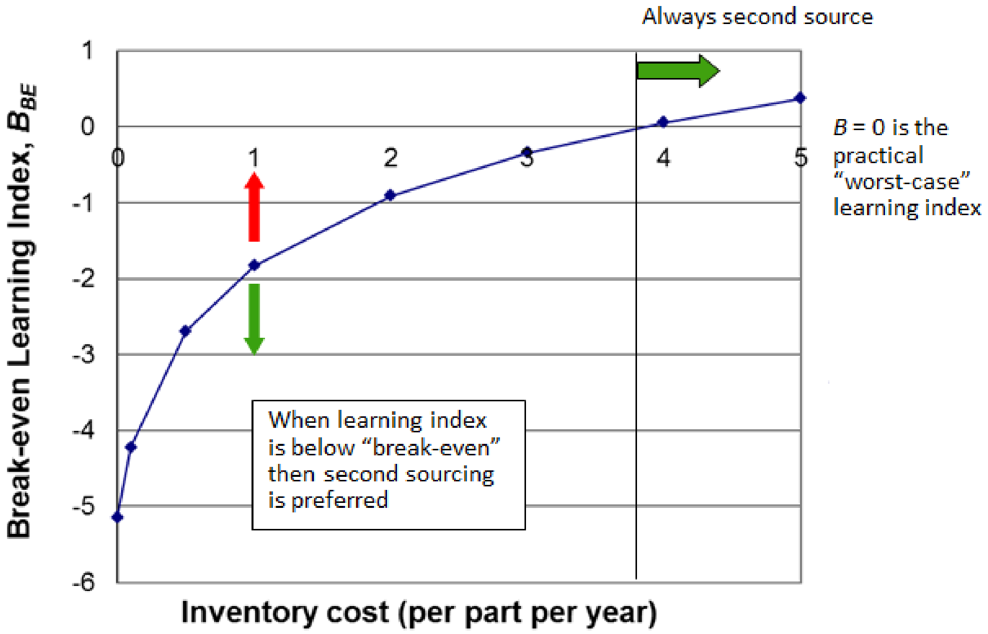

Figure 6.8 – Break-even learning index, B_{BE} versus inventory cost (per part per year) for the low volume example case discussed in Figure 6.4.

If $K_{TH} = 1$, then from (6.8) as applied to second sourcing, we get,

$$\frac{\Delta C_{PROC} + \Delta C_{INV} + \Delta C_{SUP}}{C_{SUP}(D_b)} \geq 1$$

$$\Delta C_{PROC} + \Delta C_{INV} \geq C_{SUP}(D_b) - C_{SUP}(D_b) + C_{SUP}(D_a)$$

$$\Delta C_{PROC} + \Delta C_{INV} \geq C_{SUP}(D_a) \tag{6.9}$$

From (6.9), the key costs that drive the decision to single sourcing or second source the part under the "worst-case" conditions discussed above are the difference in cumulative procurement cost (after *j* years), ΔC_{PROC}, difference in cumulative inventory cost (after *j* years), ΔC_{INV}, and the cumulative cost to support the part (after *j* years), C_{SUP} subject to disruption date, D_a.

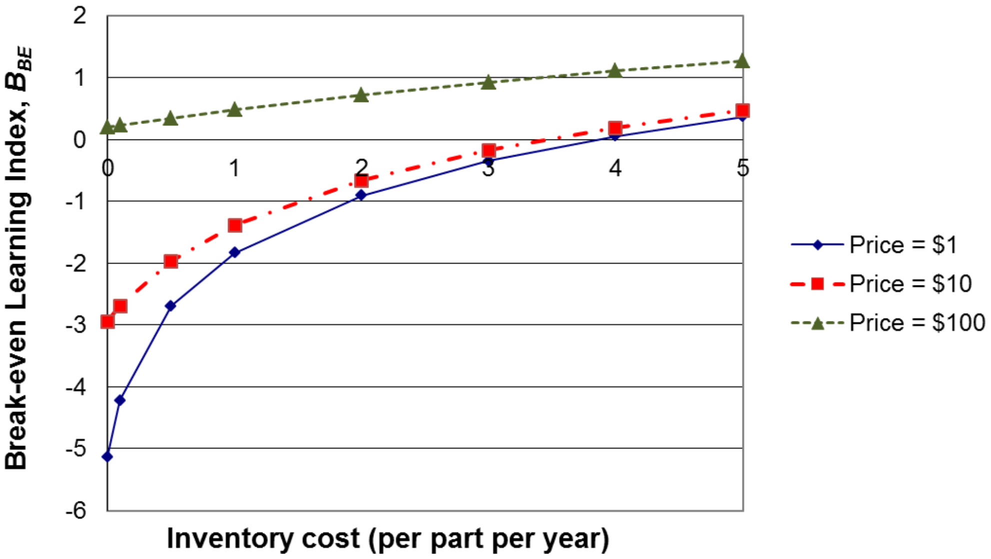

Figure 6.9 – Break-even learning index, B_{BE} versus inventory cost (per part per year) with contour lines of varying procurement price for the low volume example case discussed in Figure 6.4.

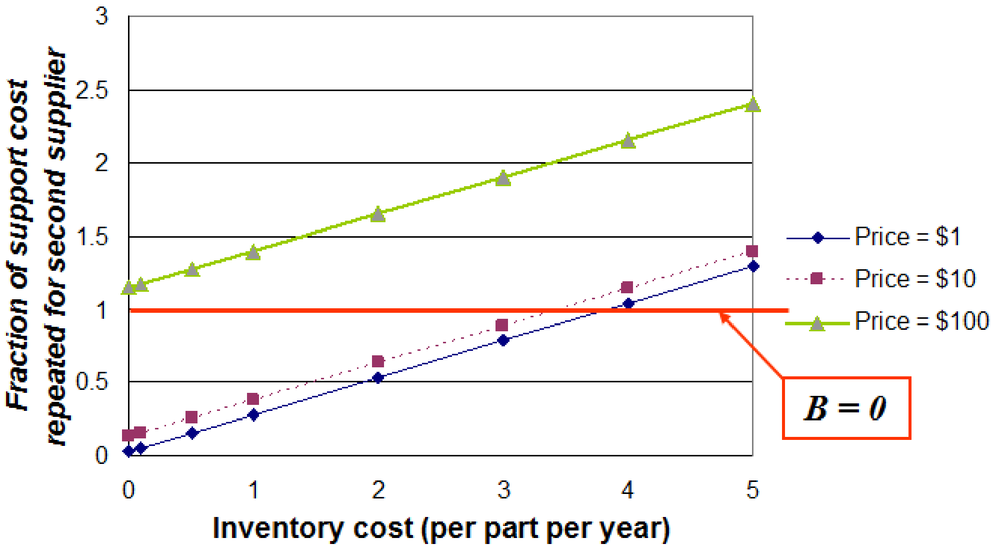

Figure 6.10 – Fraction of support cost repeated for second supplier (with respect to single sourcing support cost) at break-even, K_{BE} vs. inventory cost (per part per year) with contour lines of varying procurement price for the low volume example case discussed in Figure 6.4.

Results from Figure 6.8 to Figure 6.10 show the relationships between break-even learning index and price, inventory, and support costs. Figure 6.8 shows a plot of break-even learning index, B_{BE} vs. inventory cost for a linear regulator part with a procurement price of $1. As inventory cost increases, the decrease in TCO is larger due to extending the effective procurement life from 5 years (single sourcing strategy *a*) to 10 years (second sourcing strategy *b*) thereby increasing the break-even learning index, B_{BE}. For the example case, $B_{BE} > 0$ when inventory cost exceeds $3.83 (per part per year) where second sourcing is the preferred sourcing strategy. Figure 6.9 shows a plot of break-even learning index, B_{BE} versus inventory cost with contours for part price at varying orders of magnitude. Figure 6.9 shows that, when part price is high, cost of money increases the benefit of extending the part's procurement life. When part price is approximately $100 (per part), second sourcing is preferred under all conditions of inventory cost. Similarly, Figure 6.10 shows the relationship between K_{BE} (fraction of support cost repeated for the second supplier with respect to single sourcing support cost at break-even) vs. inventory cost. The given information allows the calculation of an exact break-even learning index that determines the feasibility of a multi-sourcing strategy.

The following are Monte Carlo analyses for uncertain procurement lives in the second sourcing of linear regulators. These case studies deal with break-even learning index from the perspective of uncertain part procurement lives based on discussions from Chapter 4. Figure 6.11 to Figure 6.14 show results for the Monte Carlo analysis for varying inventory costs (linear regulator example case described in Figure 6.4). The results in Figure 6.11 show ratio, K_{BE} comparing single sourcing and second

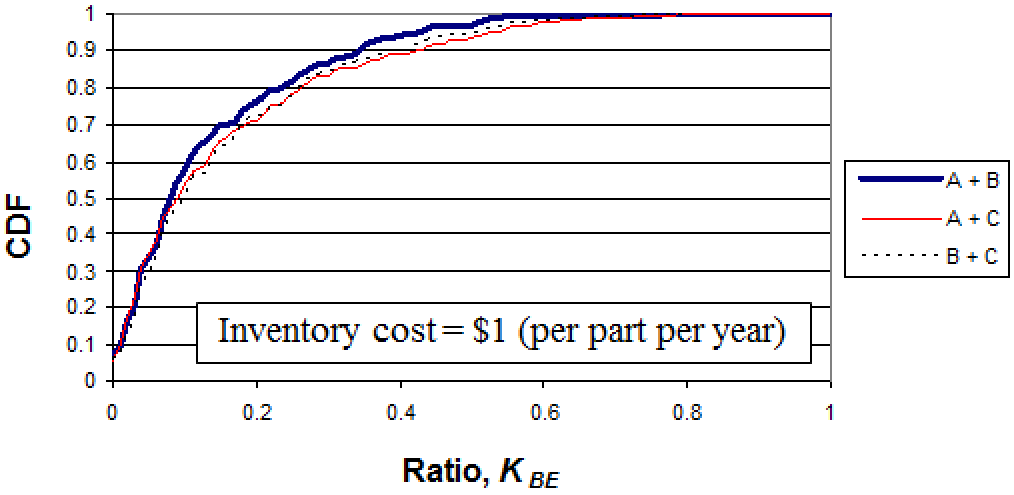

Figure 6.11 – Monte Carlo results for inventory cost of \$1 (per part per year) - probability of occurrence of K_{BE} (CDF).

sourcing strategies obtained using the method described in Section 6.3 for sampled procurement lives of three linear regulator vendors (TI (A), ON Semiconductor (B), and Analog Devices (C)) as discussed in Section 4.2. For each instance of the Monte Carlo sampling, the ratio K_{BE} (and the corresponding break-even learning index, B_{BE}) are calculated between the earliest and the latest disruption dates (i.e., this approach assumes that second sourcing is unbiased towards a particular). The distribution seen in Figure 6.11 is the probability (CDF) of occurrence of K_{BE} between values of 0 and 1.

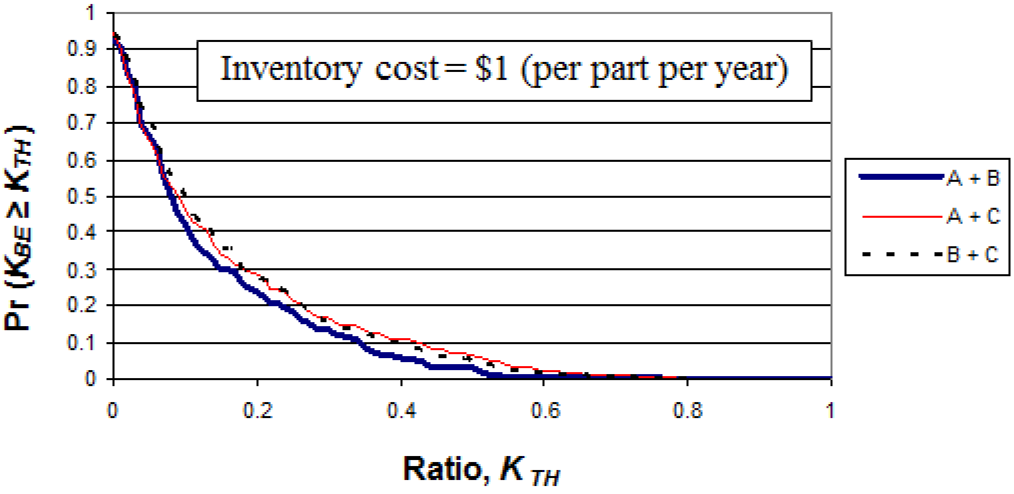

Figure 6.12 – Monte Carlo results for inventory cost of $1 (per part per year) - probability that K_{BE} exceeds K_{TH}.

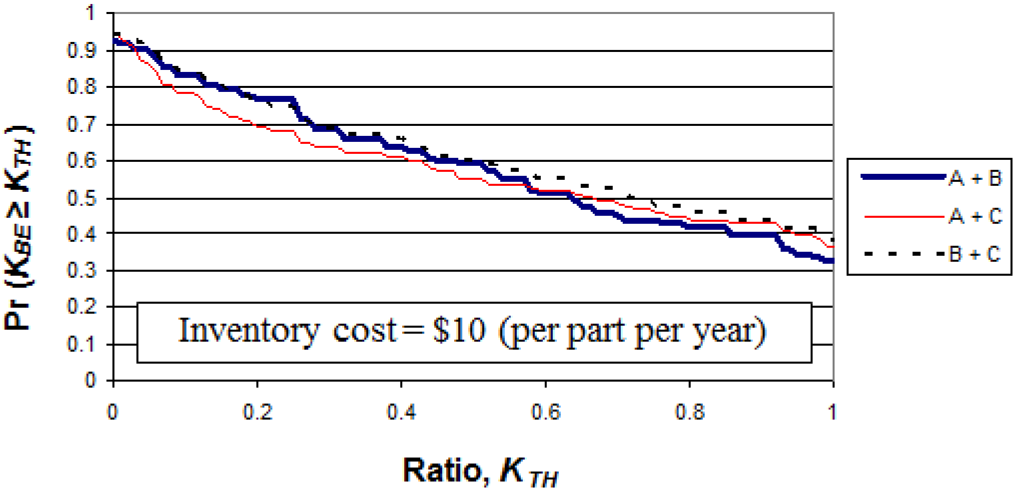

Figure 6.13 – Monte Carlo results for inventory cost of $10 (per part per year) - probability that K_{BE} exceeds K_{TH}.

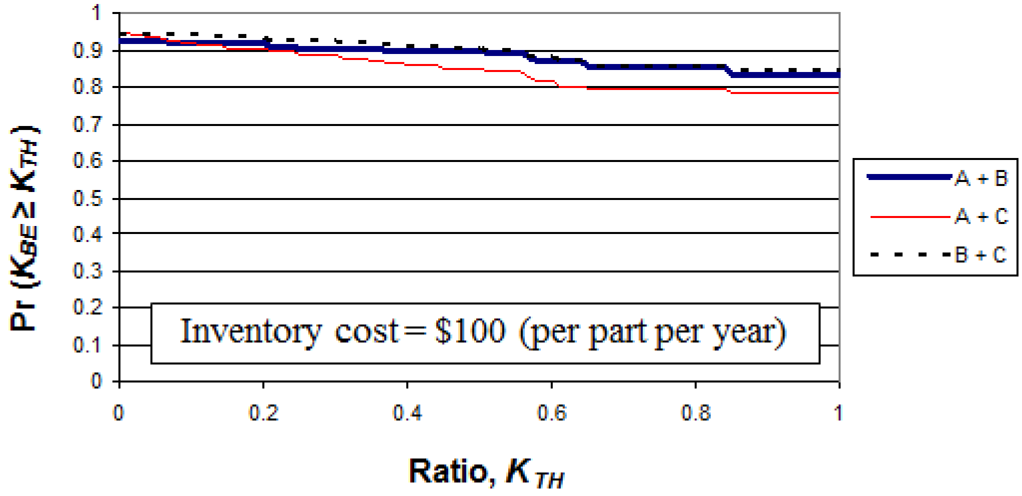

Figure 6.14 – Monte Carlo results for inventory cost of $100 (per part per year) - probability that K_{BE} exceeds K_{TH}.

The results in Figure 6.12 to Figure 6.14 can be interpreted as the probability that K_{BE} exceeds K_{TH} (i.e., $\Pr(K_{TH} \leq K_{BE}) = \Pr(0 \leq x \leq K_{BE})$ where $0 \leq K_{TH} < 1$ for practical applications of this method). The results in Figure 6.12 to 6.14 show that at a specific value of K_{TH} (for example, $K_{TH} = 1$), the probability $\Pr(K_{BE} \geq 1)$ increases as inventory cost (per part per year) increases. Note, in Figure 6.11 to Figure 6.14, $\Pr(K_{BE} = 0)$ is approximately 7% for all three second sourcing strategies. Defining the probability on the y-axis as $\Pr(K_{TH} < K_{BE}) = \Pr(0 \leq x < K_{BE})$ will see a convergence to 1 when K_{TH} on the x-axis approaches zero.

The feasibility of a second sourcing strategy is dependent on K_{TH} which serves as an indicator for the organizations capability to stream-line qualification and support activities for additional suppliers. The results indicate that when the combined cost of procurement and inventory are higher, second sourcing offers greater cost avoidance by extending the part's effective procurement life. Under conditions of high procurement and/or inventory cost, higher values for K_{BE} (B_{BE} values) increase the likelihood that K_{BE} will be greater than K_{TH}. As a corollary to this principle, parts with lower procurement and inventory costs benefit less from extending the effective procurement life and should be single sourced instead.

Chapter 7: Summary and contributions

7.1 Summary

This dissertation presents new life-cycle modeling approaches that quantify risk and enable cost effective part sourcing strategies. The models were specifically developed for application to low-volume, long support life products where sustainment costs may dominate part procurement costs in the decision making process. The models have a general capability to incorporate supply chain disruption likelihoods; specifically, the risk of part obsolescence has been quantified and its impacts on sourcing have been assessed in this dissertation. The method developed quantifies obsolescence risk as "annual expected total cost of ownership (TCO) per part site" modeled by estimating the likelihood of obsolescence and using that likelihood to determine the TCO allowing sourcing strategies to be compared on a life-cycle cost basis. The method is demonstrated for electronic parts in an example case study of linear regulators.

7.2 Conclusions and contributions

Previous treatments of source selection and optimization have focused almost exclusively on procurement costs. While this may be appropriate for high-volume, short support life products, its applicability to low-volume, long support life products is questionable.

This dissertation represents the first known quantitative treatment of sourcing for parts used in low-volume, long support life products, thereby providing strategic decision support for sourcing/risk analysis for systems that must be manufactured and sustained for long periods of time. The methodology and models developed in this dissertation go beyond traditional sourcing models by addressing the cost of qualifying and supporting sources and the risks associated with both individual sources and combinations of sources. This dissertation offers a means to assess the relative importance of effects such as learning by doing, economy-of-scale, and costs to transfer technology to a second source within a thorough part total cost of ownership (TCO) modeling approach.

7.2.1 Contributions to the Understanding of Sourcing

The analysis performed in this dissertation concluded for low-volume, long support life products that:

- Procurement-centric cost models lose accuracy at low part volumes. Instead, part management decisions should rely on part TCO models that account for other life-cycle cost drivers such as support activities, assembly, inventory, and field failures that can contribute to a significant portion of the part TCO.
- This dissertation proposes the use of procurement life as a criterion on which to base the selection of parts and the formulation of part sourcing strategies.
- General conclusions drawn from the analyses performed using the methodology and models developed in this dissertation include:
    - The majority of a part's TCO is attributed to support cost through intensive (and often mandatory) qualification and validation processes. The part usage volume also determines how non-recurring support

costs (incurred when the part is first used within the OEM) are distributed or dissipated over time.

- A part's procurement cost over the part's life cycle is dependent on the part price as well as the part usage volume. The procurement cost must be assessed relative to the part's TCO. For low-value COTS parts that are consumed in low volumes, procurement cost can be a negligible contributor to part TCO (when support cost dominates). Therefore, part price reduction (for example, via competitive pricing) offer negligible benefits in reducing part life cycle cost. When sourcing high-value parts, a tradeoff exists between an increase in support cost (from supplier qualification and support) and reduced procurement cost (through competitive pricing).
- When support cost dominates part TCO, the conditions under which an optimum sourcing strategy exists is dependent on the part management organizations' qualification and support activities as well as the attributes of the supplier from which parts are procured over the part's support life cycle. The use of a second source has been shown to reduce the probability of disruptions at the cost of qualifying and supporting the second supplier.
- When procurement and inventory costs are small contributions to the part's TCO, the cost of qualifying and supporting a second source outweighs the benefits of extending the part's effective procurement life. The use of second sourcing may be constrained by part

    management organizations' ability to stream-line support activities and reduce support costs that are driven by the number of suppliers or sources. As procurement and inventory costs increase (relative to TCO), the benefit of extending the effective procurement life of a part yields larger cost benefits relaxing the target "break-even" learning index.

    - The maximum allowable resources in order to make an alternative multi-sourcing strategy feasible can be represented by the ratio, K_{TH} (as a threshold for an organization's capability to reduce the duplication of support activities) and "break-even" learning index, B_{BE}. When the organization is capable of achieving a learning index below B_{BE}, they are likely to see a benefit from adopting the multi-sourcing strategy. In addition, B_{BE} offers a target learning index in situations where multi-sourcing is required.

- This dissertation established that there is an optimum quantity of products that can use the same part beyond which costs increase. The analysis indicates that the optimum part usage is not volume dependent, but is dependent on the timing of the supply chain disruptions. This example suggests that the risk and timing of supply chain disruptions should be considered as a criterion in product platform design.

7.2.2 Contributions to Modeling and Methodology of Sourcing in Total Cost of Ownership

- Development of a comprehensive total cost of ownership model for electronic part selection and management (no other total cost of ownership models exist for electronic parts). The unique contributions associated with this model include:
    - The model takes a part perspective rather than a product perspective – this view is particularly useful for part selection and management groups at large OEMs that manage the use of parts across multiple products. The model also incorporates "learning by doing" effects in the management of parts which are missing in prior research.
    - The model takes a full life cycle view, not just a view through the manufacturing process. The model is designed for application to long-field life systems (10+ years manufacturing and 20-30 years sustainment).
    - This model allows the quantification of part procurement decisions for systems where the procurement decisions are not driven by part price.
    - The model incorporates the impact of uncertainties on all input quantities.
- Development of sourcing models for inclusion within the part total cost of ownership model

    - These models provide the ability to perform and quantify sourcing tradeoffs for long field life systems. The model is based on fundamental inputs for procurement, inventory, and support cost.
    - Development and application of models for estimating disruption dates and risks.
    - Calculation of support cost via learning indices, *B* (learning by doing) for qualification and support activities in multi-sourcing strategies.
- Development of an analytical model that allows part management organizations determine the feasibility of second sourcing based on internal practices and capabilities.
    - The applicability (accuracy) of the derived analytical model is a function of the Avg. $(C_{proc} + C_{inv})/C_{TCO}$. When this quantity is large the error in the analytical model is small; when it is small, the error for high-volume systems is approximately an order of magnitude larger than for low-volume systems.
    - Support activities are dependent on the number of suppliers and the level of qualification needed for specific suppliers.
- Developed a new procurement life model for electronic part obsolescence.
    - The model can be used as an obsolescence forecasting alternative to current ordinal scale approaches.
    - The model provides a data-driven methodology for determining time-dependent risk of obsolescence.

7.3 Future work

There are many directions that the current work can be extended such as:

- Use of the models developed in this dissertation within solutions to the newsvendor problem. The model may be extended to solve for optimum lifetime buy quantities based on uncertainty in part demand. The optimization of lifetime buys is yet to be explored from a life cycle perspective. The optimization of lifetime buys has been addressed in prior research; however, the need for assessing the long term impact relative to part TCO offers insight into the allocation of limited resources to address multiple obsolescence issues.
- Use of the model for non-electronic parts. The part TCO model has been calibrated with electronic part data from Ericsson AB. Hence, the data is characteristic of the management of semiconductor parts. The model may also be calibrated and used to assess part management decisions for non-electronic parts in a wide variety of industries (e.g., civil, defense, automotive, medical, HVAC, and aerospace).
- Inventory management through "hoarding". A current issue in the management of long life cycle (low volume) electronics, which is caused, in part, by single sourcing policies is the emergence of excessively long delivery lead-times causing disruptions that are albeit temporary yet recurring throughout the part's life cycle. These so called "allocation" problems (Jorgensen 2011) hit the low-volume manufacturers the hardest because when part suppliers cannot satisfy demand, the low-volume customers go to the

"end of the line" for parts and can experience lead times of 12-18 months or more for parts that are not obsolete. For example, parts bought up by large high-volume OEMs exhaust available commodities causing a back-order for lower-volume purchases. Procured parts may take many months to be delivered to product manufacturers and system sustainers. Therefore, inventory management may be critical to protect against short-term supply chain disruptions for selected parts. This problem is compounded when organizations have chosen to follow "lean inventory" and "just-in-time delivery" management strategies that aim to minimize excess inventory. The trend toward "lean" has been traditionally driven by high inventory cost and limited storage space but variability in lead-times leave organizations susceptible to part unavailability. Future work involves assessing the effects of sourcing and inventory management strategies on the TCO of parts used in long life cycle products to determine when multiple sources should be used and when (and how much) inventory should be held to avoid lead-time problems.

- Treatment of other risks – the methods developed in this dissertation may be expanded to include and combine multiple risk sources for a holistic supply chain risk assessment. Sourcing decisions may be influenced by external factors that may directly or indirectly affect the supply of parts, such as the location of a supplier, management techniques and practices, how the parts are shipped, and the suppliers' customer base. Other sources of risk include natural disasters, political unrest, counterfeiting, bankruptcy, import/export restrictions, etc.

- Development of commodity and part-attribute specific procurement risk indices – risk indices have uses in industry applications which can assist in part and commodity selection decisions. Detailed studies on commodities and part attributes offer insight into long term benefits of certain technologies.
- Assessment of part sourcing decisions when field failure issues dominate part TCO – this dissertation deals with electronic parts that are known to have infrequent field failures. The capacitor and linear regulator case studies assume that field failure cost is negligible relative to part TCO. However, the cost of electronic part failures may be higher when part failures are more frequent (under severe loads and extreme operating conditions) and when warranty periods are long. Future work may include the selection criterion necessary for such parts and the impact on optimum sourcing strategies.
- Apply the tradeoff methodology presented in this dissertation to the multi-sourcing of high-value parts by incorporating existing models (e.g., split-award auctions) in order to capture the reduction in procurement cost through competitive pricing.
- Dynamic sourcing strategies that change over time – perform tradeoff analyses between qualifying a second source up-front or when the disruption occurs (or becomes imminent). The qualification cost of parts from alternate suppliers and possible penalties associated with production delays during the

qualification period are subject to cost of money effects and uncertainty in disruption dates.

Appendix A – Design reuse

The appendix presents examples that discuss and demonstrate the part TCO simulation model's use in Design Reuse case studies for the example surface-mount (SMT) electronic part discussed in Section 3.3. These example cases guide the formulation of simplifying assumptions made in the analytical part TCO model (presented in Chapter 6).

A.1 Design reuse of electronic components subject to long-term supply chain disruptions

In order to support existing products and facilitate the development of new products, electronic systems OEMs maintain databases that consist of hundreds of thousands of electronic parts, (Pecht 2004). Conventional wisdom dictates that the design reuse of components across a family of products generally leads to cost reductions and should be encouraged. If possible, using an existing part that is readily available in a new product design is far more cost effective than pursuing new components. Platform design (design reuse) means that a common platform is reused across a product family, where a platform is a set of common components, modules, or parts, which are shared within a product family, (Meyer and Lehnerd 1997). The concept of platforms is commonly used in the automotive, computer, aircraft and other industries. The potential advantages of multiple products using a common platform include reductions in (Nelson *et al.* 1999): inventory, part proliferation, design lead-time, and the number of different manufacturing (assembly) processes required. The commonality shared across a product platform, class or market segment is referred to as "leveraging" (de Weck *et al.* 2003). Platforms are in essence a policy of component reuse that attempts to take advantage of the economies of scale across a family of products, (de Weck *et al.* 2003). For example, design reuse reduces the number of Product Changes Notices (PCNs) that must be managed.[23] In addition, there are several other advantages of leveraging (or commonizing) electronic parts that include: reductions in part-specific qualification testing, and consolidation of obsolescence resolution and in some cases subsequent lifetime buys.

Although many aspects of platform design have been addressed in the literature, few studies address supply chain issues, and there is little or no treatment of life cycles beyond manufacturing. In addressing design reuse, the model proposed by Huang *et al.* (2005) quantifies platform design benefits by comparing supply chain cost at varying levels of product platform commonality. This is done by assessing the supply chain in its entirety; a supply chain cost and inventory level is calculated at each stage of the supply chain to obtain a total supply chain cost. Su *et al.* (2005) propose a method for calculating the total supply chain cost and customer waiting times to study the performance of mass customization postponement structures (time postponement and form postponement). Huang *et al.* and Su *et al.* provide a complete view of the supply chain from a manufacturing organization's viewpoint, however, these models are insufficient for assessing long-term disruptions during the part's life cycle since they do not account for field failures, support, and manufacturing defects

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[23] An electronic manufacturer announces that their part or the process of fabrication has changed by issuing a PCN. In 2006, over 340,000 PCNs were issued for active and passive electronic parts (Baca 2007) where the changes ranged from modifications to the part marking and delivery packaging, to parametric changes and lead finishes. Over 18% of all the procurable electronic parts will have PCNs issued on them in any given year, (Baca 2007). The change indicated by a PCN on a part used in a particular product may or may not be relevant, but every PCN should be evaluated to determine if action is needed.

that play a role in warranty returns and product reliability decisions (post-manufacturing challenges).

A potential drawback of reusing the same component in multiple products that has been articulated by electronics system manufactures is described by the following scenario: All of your products use (depend on) a common part. An unexpected problem develops with the part. Instead of fighting a fire for one product, you are simultaneously in trouble on every product, i.e., you may have effectively created a “single point of failure” scenario by reusing the part. This situation occurs, for example, when the part becomes obsolete and an acceptable resolution must be found for each of the products that use the part – note, a resolution that is acceptable for one product may not always be acceptable to another. This scenario becomes an issue when there are a specific finite set of resources available to resolve problems across all products, which is often the case after a product enters manufacturing. Those resources cannot address every product simultaneously and as a result manufacturing or support delays occur. It is not the fact that problems with parts occur – they always will, it is not that there are insufficient resources to solve all the problems, it is the timing of the problems – there are insufficient resources to solve all the problems simultaneously. Finite resources (people, equipment, etc.) to address problems becomes an issue when multiple problems or the same problem in multiple products occur concurrently and the resolution to one or more problems or products has to be delayed due to a lack of resources.

A finite resource model has been developed to allow the assessment of cost impacts of a part-specific problem occurring at a future point in time (at a user defined date). The effective finite resource limited cost of resolving a problem *j* quarters after the problem is introduced at date *D* is,

$$C_{FRM_j} = \frac{\left(N_j^R C_{res} + \left(N^{RT} - \sum_{k=1}^{j} N_k^R \right) C_{unres} \right)}{(1+r)^{D+j/4}} \qquad \text{(A.1)}$$

where,

N_j^R = number of problems (products) resolved in quarter *j* (determined from the resolution rate dictated by the available resources)

C_{res} = cost of resolving the problem for one product

N^{RT} = effective total number of full resolutions that have to be done = $1 + (1 - C_o)(N_c - 1)$

C_o = commonality in resolutions (0 = no commonality, 1 = all activities common)

N_c = number of products using the part on the problem date

C_{unres} = cost of unresolved problems/product/quarter

D = problem date

r = after tax discount rate

The cost in (A.1) is included until the problem has been resolved in all products. The model uses the commonality to determine the effective number of full resolutions that have to be done and then performs them as quickly as the finite resources will allow, charging for the resolutions and penalties for unresolved problems as it goes. The model assumes that the problem resolution resources are busy 100% of the time doing something, i.e., no idle time is paid for.

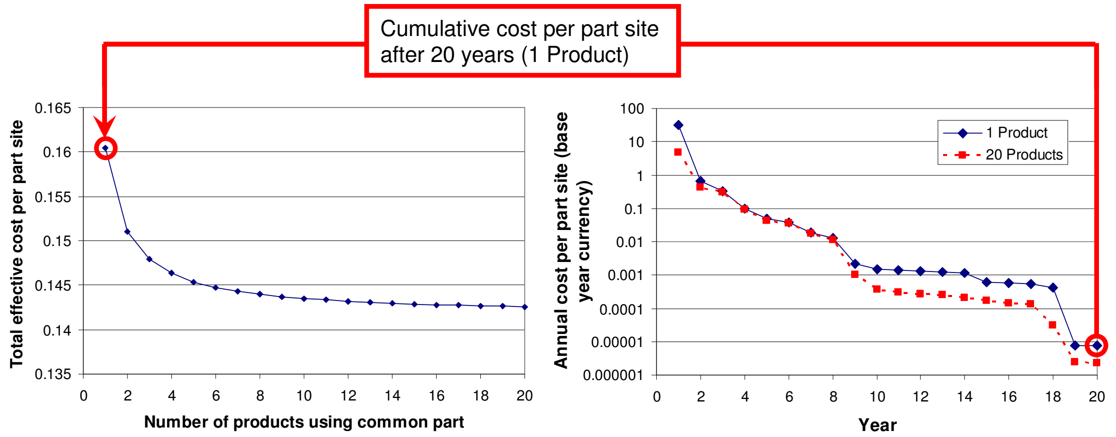

Figure A.1 – (left) 1 to 20 products concurrently using the example part described in Figure 3.2 and 3.3. No finite resource limited problems. (right) annual cost per part site of design reuse in 1 product and 20 products.

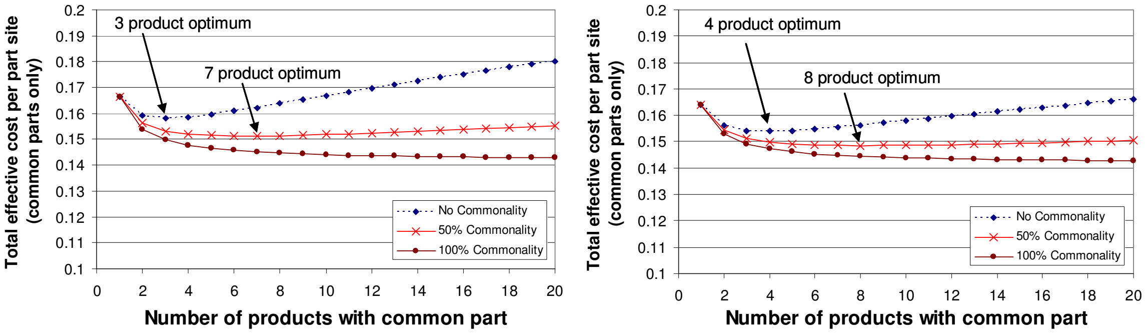

Figure A.2 – 1 to 20 products concurrently using the example part described in Figure 3.2 and 3.3. Problem introduced in year 5 (left) and year 10 (right).

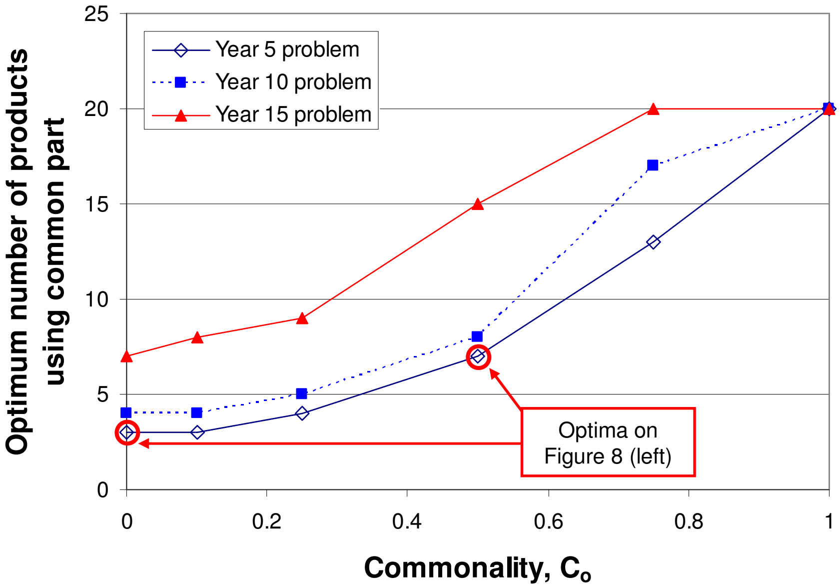

Figure A.3 – Optimum number of products using a common part with respect to problem resolution commonality. Total quantity of each part = 12,910,500.

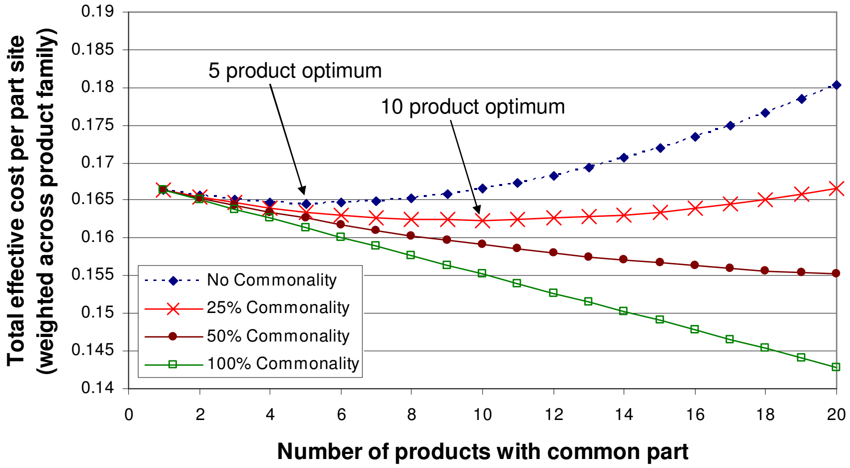

Figure A.4 – Weighted total effective cost per part site of a fixed pool of 20 products. Problem introduced in year 5.

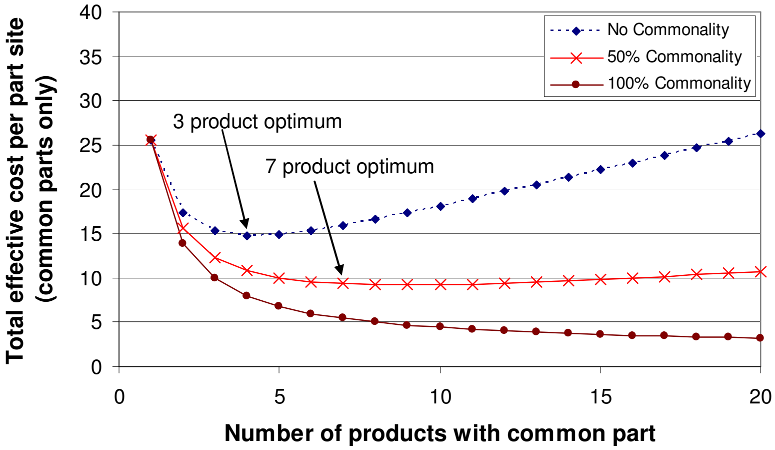

Figure A.5 – 1 to 20 products concurrently using the example part described in Figure 3.2 and 3.3. Problem introduced in year 5, total quantity of each product = 12,910.

We now explore potential design reuse strategies across multiple products of the example part described in Figure 3.2 and 3.3. For simplicity, we have assumed that all the products have the same production schedule i.e., every product in the product family has the same annual part (site) usage per product shown in Figure 3.3. Therefore, the total number of part sites in a product family (i.e., total number of common parts) is calculated by multiplying the annual part site usage per product by the desired level of design reuse. The design reuse examples in this section also assume that the number of products that the part is designed into remains the same throughout the 20 period. If we first consider the case where no problems (that would be finite resource limited) are introduced, the results in Figure A.1 are obtained. As shown on the left side of Figure A.1, as the number of products that use the part increases, the effective cost per part site drops. The effects of "economy of scale" are observed as a greater degree of design reuse helps distribute costs across a larger number of part sites. The right side of Figure A.1 shows a comparison of the annual cost per part site for the 1 and 20 product cases. Nearly all of the difference between the annual costs is support cost (economies of scale are taking effect). Note that Figure A.1 is consistent with a traditional platform design analysis that only considers manufacturing costs.

Now consider the introduction of a disruptive problem whose solution could be limited by finite resources. In this case, we will assume that the problem is not an obsolescence problem since the example part we are considering is forecasted to become obsolete in year 17 and a lifetime buy at that time is already figured into the base model. If a problem is introduced in year 5,[24] the costs as a function of the number of products the part is in are given in Figure A.2 for a range of solution Commonality (*Co*). For one product, the cost is slightly higher (because the year 5 problem has to be resolved) than the results in Figure 6.1. If there is no commonality between products in the solutions to the problem, Figure A.2 indicates that for this example, there is a 3 product optimum usage. As the commonality of problem solutions increases, the size of the optimum product usage increases until 100% commonality results in approximately the solution in Figure A.1.

In Figure A.3, a fixed pool of 20 products exists from which a design reuse strategy for a single part must be implemented. For example, if 5 products use a common part, the remaining 15 products (out of the pool of 20 products) have unique parts of similar characteristics. Contrary to the belief that consolidating common parts

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[24] For the analysis results given here, we have assumed that the cost of the problem resolution in a single product is C_{res} = \$100,000, that we have resources to perform a maximum of one full resolution every 6 months (resolution rate = 0.5 resolutions/quarter), and the cost of unresolved problems is C_{unres} = \$50,000/product/quarter.

in a family of products minimizes cost, a threshold for commonality exists below which an optimum number of products minimizes the total cost of ownership of a predetermined family of products.

The date of the introduced problem and the sensitivity of the results to total volume of part site usage have been explored. Figure A.2 and Figure A.4 show that the optimum number of products to use the part in increases as the date of the problem moves further into the future. For the results in Figures A.1 to A.4, the total volume of parts is 12,910,500 parts per product. If this volume is decreased by a factor of 1,000 to 12,910 parts per product, the effective cost per part site increases substantially (the various non-recurring support costs and the cost of problem resolution at year 5 increase it dramatically), but the optimum number of products to use the part in is the same as the high-volume case, Figure A.5. In finite resource limited problems, it appears that the optimum design reuse strategy is independent of the volume of parts used since problem resolutions are performed at the product level. Note, in the example case used here (a capacitor), the price variation due to volume above a few thousand parts is negligible, but the relationship may be important in more expensive parts.

The example results in this appendix demonstrate that, from a life cycle cost viewpoint, there is an optimum quantity of products that can use the same part beyond which costs increase. The analysis indicates that the optimum part usage is not volume dependent, but is dependent on the timing of the supply chain disruptions. This example suggests that the risk and timing of supply chain disruptions should be considered as a criterion in product platform design.

A.2 Summary and discussions

The design reuse case study results indicate an increasing benefit to greater degrees of design reuse in cases where no long-term supply chain disruptions occur. For finite resource limited problems, an optimum design reuse strategy exists and it is not to reuse the part in as many products as possible. The case study results indicate dependencies between part commonality and timing of a disruption event in determining the optimum design reuse strategy (number of products using a particular part). The optimum is independent of part volume since problem resolutions are performed on the product level.

Appendix B - Part lifetime buy tradeoffs

Part decisions are often trumped by uncertainty in the market. Supply chain changes during the life of a part, both expected and unexpected, require a reaction or resolution. Electronic parts are subject to high-frequency involuntary procurement obsolescence, (Sandborn 2008a). Part obsolescence becomes a problem when a product must be manufactured and/or supported for longer than its constituent parts are available for procurement. Because short manufacturing and support life products such as cell phones and laptop computers dominate the demand for electronic parts, many electronic parts are only procurable from their original manufacturer for a few years and are then discontinued in favor of newer, higher performing parts. For long field life electronic products, such the avionics in airplanes, medical applications, and military systems, it is not uncommon for the majority of the electronic parts to be obsolete and non-procurable before the first instance of the product is fielded, and then the system has to be manufactured and supported for significant amounts of time beyond that. When parts become obsolete and are still required by the system, considerable resources may have to be expended to resolve the problem.

When an electronic part becomes obsolete a range of possible mitigation approaches are possible (Stogdil 1999), but there are usually two viable resolution actions considered if more than a few thousand parts are needed: 1) replace the part with a newer part, or 2) buy enough parts to satisfy your anticipated future needs and store them until they are needed (i.e., lifetime buy), (Feng *et al.* 2007). Replacement of the existing part with a new part carries with it potentially significant costs associated with finding the new part, approving the part for use, possibly qualifying the supplier of the part, and product-specific qualification tests – depending on the product and the role the part plays in the product. Due to prohibitive costs, replacement of an obsolete part with a new part may or may not be viable. In this example, we will only consider lifetime buys.

B.1 Lifetime buy analysis – buffer size analysis using part TCO

The following is a very simple lifetime buy analysis that demonstrates the quantification of the value associated with the selection of parts with different years to obsolescence. This analysis does not address prediction or optimization of lifetime buy quantities (i.e., the newsvendor problem), which are out of the scope of this analysis.[25] This treatment is only a simple exercise of the part TCO model used to demonstrate the impacts of varying the buffer sizes on lifetime buys.

In order to include the costs of lifetime buys, the number of years to obsolescence (*YTO*) of the part must be determined,

$$YTO = \left(1 - \frac{L}{6}\right) T_{PL} \tag{B.1}$$

where,

L = lifecode for the part in year 0, L =1 (introduction), 2 (growth), 3 (maturity), 4 (decline), 5 (phase out), and 6 (obsolete), (ANSI/EIA 1997,

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[25] The electronic part lifetime buy problem differs from the classical newsvendor problem in several significant ways (Sandborn, 2011). First, for electronic part lifetime buys, a "must support" assumption has to be made that is not present in simple newsvendor problems, i.e,, you cannot choose not to support the product, i.e., you are not allowed to fail to fulfill the demand and therefore you must pay the penalty to purchase extra parts from the broker if you run out (the newsvendor is not required to do this). Another, more significant assumption that is implicitly made in the classical newsvendor problem is that there is no time dependence. In the case of lifetime buys for electronic parts the cost of money (non-zero discount rate) and the cost of holding parts in inventory are significant cost contributors that cannot be ignored.

Sherwood 2000). Commercially available databases provide lifecodes for electronic parts.

T_{PL} = total procurement lifespan (Sandborn *et al.* 2010) of a particular part type in years. Length of time the part was or will be procurable from its original source.

When the year of obsolescence occurs, a procurement of the remaining parts needed to manufacture and support all the products (plus an overbuy quantity called a "buffer" that represents the purchase of more parts than the demand forecast) happens prior to the supplier's discontinuance of the part at that year's part price. In subsequent years the cost of procuring parts becomes zero, but the cost of inventory for the lifetime buy of parts must be included.

In the case of a lifetime buy, the organization incurs an additional cost in the event of part obsolescence that is included in the support cost model as an obsolescence resolution cost C_{or}. An increase in procurement cost is seen during the

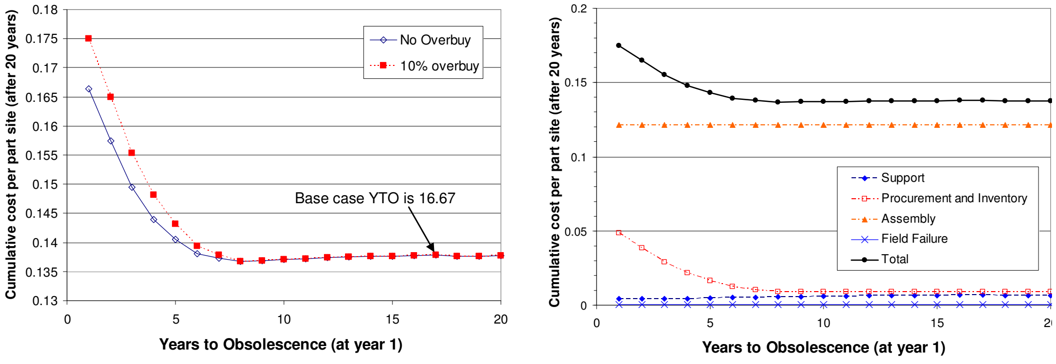

Figure B.1 – Cumulative cost per part site as a function of part procurement life (*YTO*) for (left) 0% and 10% overbuy on lifetime buys, and (right) 10% overbuy with respect to cost category.

year of obsolescence as a result of the lifetime buy purchase followed by annual inventory costs for every subsequent year until the stored parts are either completely consumed or disposed of. During the year of obsolescence, a lower support cost is incurred since only a single purchase order is placed when a lifetime buy is made. In Figure B.1, we see that parts with shorter *YTO*s (parts that start closer to their obsolescence date) tend to incur higher procurement cost (larger life time buy quantities with larger overbuys must be bought) and inventory cost (parts remain in inventory/storage for longer).[26] This conclusion assumes that the total inventory quantity is not limited due to constraints imposed by the warehouse or storage facility (or budget). Figure B.1 clearly shows the magnitude of the value of choosing parts that have longer *YTO*s over shorter *YTO*s. Consider a part that is identical to the SMT capacitor example part (shown in Section 3.3) in all aspects except with a procurement price that is 20% less ($0.012 per part) and *YTO* of 3 years (instead of 16.7 years) at introduction. This alternative part incurs a total effective cost per part site of $0.15; that is $0.012 more than the base case result after 20 years due to its earlier obsolescence.

Feng *et al*. (2007) suggests that a lifetime buy made for many years is likely to suffer from large uncertainty in forecasted part consumption. Variations in storage quantities may also occur as a result of part pilfering (stored parts being misplaced, lost or used by unassigned products) and inventory mismanagement. The additional overbuy parts (as a percentage of the required lifetime buy quantity) are stored to reduce the risk of unexpectedly depleting the inventory, a scenario that would incur

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[26] Note, the higher procurement cost for smaller *YTO* is also due to cost of money, i.e., even without considering deflation in the part costs, one would rather buy the parts in the future than today due to a non-zero discount rate.

high penalty costs. The case shown in this section assumes that the predicted lifetime buy quantity is sufficient to sustain all products using the part and any inventory cost incurred is due to residual parts (unused parts from lifetime buy including the overbuy) remaining in storage. This model does not account for penalties incurred by prematurely depleting the inventory as described earlier. Models that estimate the lifetime buy quantity and cost (inclusive of penalties) can be found in Bradley and Guerrero (2009) and Feng *et al*. (2007).

A Product Change Notice (PCN) issued with sufficient warning prior to an obsolescence event enables a lifetime buy to be made. But this is not always the case, some obsolescence events occur as unexpected long-term supply chain disruptions for which no warning is provided. Such disruptions incur cost that is dependent on the design reuse and require product-level resolution activities.

B.2 Summary and discussions

The lifetime buy case study confirms that the total cost of ownership of a part increases when parts with early obsolescence dates are chosen when the obsolescence event is resolved using a lifetime buy purchase. Choosing higher procurement price parts that have obsolescence dates that are further in the future may be preferable to choosing less expensive parts that will be obsolete sooner.

Appendix C - Supplier-specific obsolescence likelihood (numerical method)

The method to estimate the likelihood of obsolescence described in Section 4.2 offers a way to generate right-censored supplier-specific obsolescence likelihoods. However, there are some challenges in applying an MLE method to supplier-specific data. For instance, a dataset of part obsolescence information sorted by suppliers leads to: 1) variability in the size of the datasets, 2) variability in the completeness of the information (i.e., the number of non-obsolete parts affects the confidence interval of the estimated distribution), and 3) each supplier-specific dataset may have unique characteristics of procurement life distributions that cannot be captured by a Weibull fit alone. To reduce error, a frequentist approach can be adopted as an alternative to the method described in Section 4.2.

A custom procurement life distribution can be generated numerically from raw supplier-specific data by following the procedure described below and shown in Figure C.1:

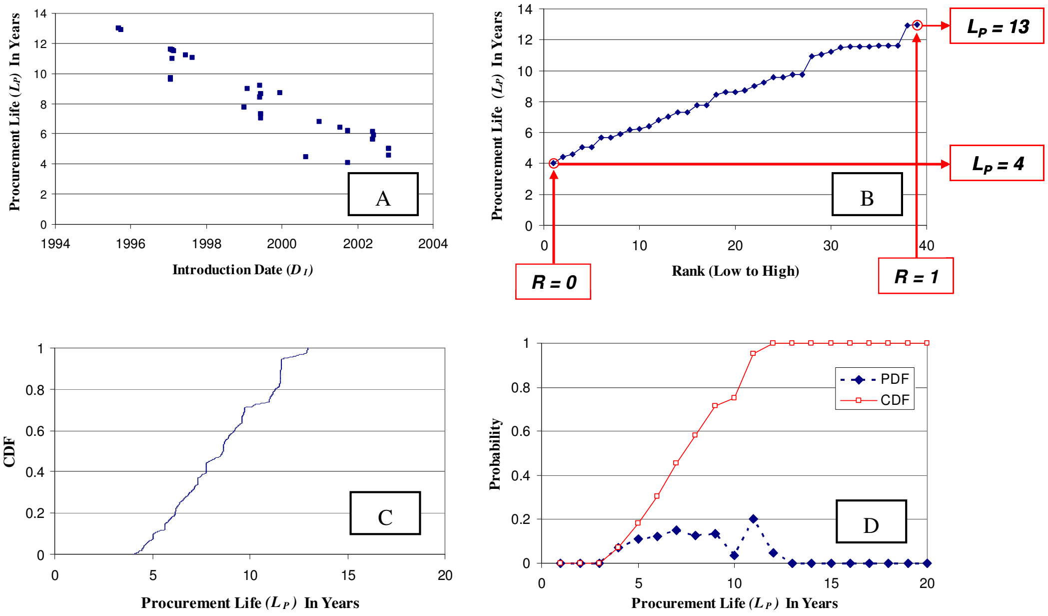

Figure C.1 – Steps in the process of generating a custom CDF/PDF from supplier-specific procurement life data for linear regulators (ON Semiconductor): (A) raw obsolescence data (B) ordered procurement life data (C) CDF of obsolescence from sampled procurement life data for a population size of $N = 1000$ (D) PDF and CDF of obsolescence risk likelihood over time calculated at one year intervals.

1. Sort the supplier-specific data in order of increasing procurement life (i.e., rank data points from low to high procurement life). The set of ordered procurement life data points defines the custom distribution of procurement life of the raw dataset.
2. Generate a set of N random numbers between 0 and 1, $R = \{R_1, R_2, R_3 \dots R_N\}$, from a uniform distribution.
3. Correlate the values in R to the ordered procurement life data to get a sampled population (of size N) of L_P. For example, if R_X is a subset of R:
   - $R_X = 0$ corresponds to the smallest procurement life value
   - $R_X = 1$ corresponds to the largest procurement life value

- Interpolate for L_P when R_X falls between procurement life data points

Note: The custom numerical distribution, like most parametric fits, evolves over time as more data is accumulated.

The numerical method presented in this section discusses how to generate uncensored supplier-specific obsolescence likelihoods. A means to compute a right-censored distribution based on the numerical method does not exist and is an area of future research studies. For this reason, example cases presented in this dissertation utilize the MLE method instead of the numerical method to generate supplier-specific obsolescence likelihoods.

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