ADVANCING COST-EFFECTIVE READINESS BY IMPROVING THE SUPPLY CHAIN MANAGEMENT OF SPARSE, INTERMITTENTLY-DEMANDED PARTS

DISSERTATION

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For my wife, the most important person in my life…

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Abstract

Many firms generate revenue by successfully operating machines such as welding robots, rental cars, aircraft, hotel rooms, amusement park attractions, etc. It is critical that these revenue-generating machines be operational according to the firm's target or requirement; thus, assuring sustained revenue generation for the firm. Machines can and do fail, and in many cases, restoring the downed machine requires spare part(s), which are typically managed by the supply chain. The scope of this research is on the supply chain management of the very sparse, intermittently-demanded spare parts. These parts are especially difficult to manage because they have little to no lead time demand; thus, modeling via a Poisson process is not viable. The first area of our research develops two new frameworks to improve the supply chain manager's stock policy on these parts. The stock polices are tested via case studies on the A-10C attack aircraft and B1 bomber fleets. Results show the AF could save $10M/year on the A10 and improve support to the B1 without increasing inventory. The second area of our research develops a framework to integrate the supply chain processes that generate these service parts. With the integrated framework, we establish two new forward-looking metrics. We show examples how these forward-looking metrics can advance the supply chain manager's desire to know what proactive decisions to make to improve his/her supply chain for the good of the firm.

Acknowledgments

While at the University of Dayton getting my MS, I had a young, passionate professor for two of the 12 courses. Like many others post 911, I felt a strong urge to do something for our nation and Dr. Chambal was there to introduce me to Rich Moore and company. Dr. C, thanks!

While in Rich Moore's 'shop', I picked up significant knowledge on inventory theory and am very thankful to Rich Moore, Mike Niklas, Bob McCormick, Jeremy Brogdon, Tom Stafford, Bill Morgan, Dr. Kel Utendorf, Joe Price, David Kerns, and Deb Hileman, to name a few...

Seemingly the first week in Rich's shop, I was given Dr. Sherbrooke's (some call the 'father' of RBS) text, which I later had him sign. I have met and been influenced by inventory theory 'giants' including Dr. Sherbrooke, Dr. Jack Muckstadt, Dr. Tom Willemain, Dr. Meyer Kotkin, F Mike Slay, and Dr. TJ O'Malley. Also from LMI, I thank Dr. Brad Silver, Dr. Tovey Bachman, Dr. Dave Peterson, Dr. 'Doc' Doug Blazer, and Dr. Dave Fulk. A special thanks to Dr. Fulk/Dr. Bachman for their motivation and influence on chapters 3/4 (respectively).

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I. Introduction

1.1 **Background – A Firm's Objective**

In general terms, the objective of most firms is to generate a profit. One step deeper, many firms generate revenue by successfully operating 'machines' (i.e. welding robots, rental cars, aircraft, hotel rooms, amusement park attractions, etc.) that produce goods/enable services that the firm sells to the consumer. From here on, the word machine(s), without quotes, will be used in general terms, to describe these types of revenue generating streams.

1.2 **Firm's Management of Revenue Generating Machines**

Revenue generating machines can/do break or become unserviceable, and during these times, the firm may lose all or part of the revenue generating stream. Often, the firm establishes targets to assure a given percent of the revenue generating machines are serviceable [1]. A Markov chain from reliability [2] or queueing [3] theory may be used to model the (state) number, n, of downed machines from a finite population, M; where λ is the failure rate and μ is the repair rate, as shown in Figure 1.

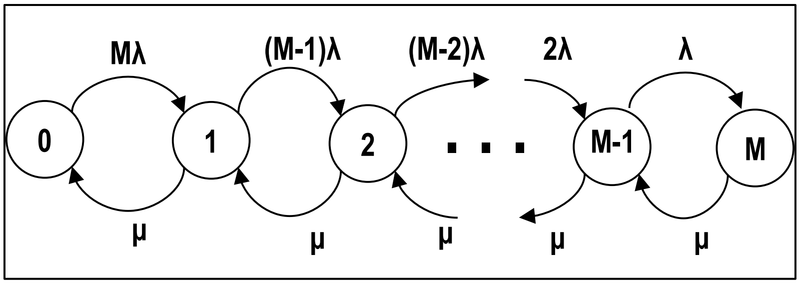

Figure 1: Markov Chain of Finite Population

In most cases, restoring the downed machine requires maintenance actions and often requires a spare part(s). For the Markov chain model shown in Figure 1, the overall repair rate μ is defined as $1/t$ where t is the total time to restore the machine to serviceable condition. The total time to restore often contains sub-segments of time; that is $t=\sum t_i$. For example, one sub-segment might be for maintenance's actual service time, say t_1, and one might be for awaiting spare parts, say t_2 (if a spare part is immediately available, $t_2 = 0$).. The scope of this research is on the management of the spare parts as related to the down time of the revenue generating machine(s).

1.2.1 Supply Chain Management of the Spare Parts

Post initial procurement, management responsibility of spare parts generally belongs to the firm's supply chain, which is not simply purchasing or logistics or warehouse management; rather, it is all of these things. Supply chain management is the integration of all things logistics from customers to suppliers [4]. Formally, supply chain management is defined as "the process of planning, implementing and controlling the efficient, cost-effective flow and storage of raw materials, in-process inventory, finished goods and related information from point-of-origin to point-of-consumption for the purpose of conforming to customer requirements" [5]. Managing spare parts requires the supply chain manager to develop stock policies. Stock policy is typically defined as the firm's answers to basic inventory questions such as [6] [7] [8]:

When do we begin stocking an item?

How much do we stock?

Where do we stock?

The answers to these basic inventory questions result in business rules that provide the supply chain manager's resources with a set of rules for defining engagement.

1.2.2 Stock Policy on Intermittently-Demanded Items

Many parts belonging to revenue generating machines have very low failure rates [9] [10] [7] [11]. This implies that these types of parts will have very little historical demand signals; thus, hard to forecast. These types of parts are typically described as intermittently-demanded items. Over the years, several authors have defined intermittent demand differently, but a good, usable definition from Boylan [8] is: "As a guideline, at least 20% of the time periods should have zero demand for you to count the demand pattern as intermittent".

1.3 **Problem Description, Common Themes and Gaps**

There are many ways to improve the uptime of revenue generating machines, and this research focuses on the awaiting spare parts portion. While themes for the implications of, and management of, spare parts are expanded in chapter two, they are generalized here. This research investigates frameworks to help the supply chain improve its management of the sparse, intermittently-demanded items, because doing so advances the cost-effective readiness of the revenue-generating machine(s).

1.3.1 Common Themes

Reliability theory covers many areas, but relative to this research, it contains availability-based topics. "Availability measures the combined effect of both the failure and the repair process... [2]" As such, it recognizes and includes the contribution of spare parts toward the uptime of the revenue generating machine(s). In this context, reliability desires to understand, to the extent possible, the failure characteristics of the components to assist the firm with spare part inventory management and overall maintenance policies.

Prognostic Health Management (PHM) desires to link the real-world 'stress' environment of the machine's component with the component's designed 'strength'. The goal/benefit of PHM is to monitor, in real or near-real time, the component's health and prompt maintenance when action is needed, including the potential need of a spare part [12]. Many revenue generating machines have both cheap, consumable items and expensive, often reparable, items. The current niche value of PHM lies with improved management of the very expensive components that have attributes that can be quantifiably measured; thus, PHM methods are useful, but limited.

The term intermittent demand goes hand in hand with nearly all research one might pursue in the service parts arena (i.e. revenue generating machines). Croston's seminal paper on intermittent demand [13] shows that typical SES (Simple Exponential Smoothing) leads to positive bias on intermittent items and creates a new method that utilizes two distributions to capture lead time demand: (1) mean time between demands and (2) demand quantity. Croston's method provides a robust framework that can be simultaneously used on both fast-moving and intermittently-demanded items. Increasing the forecast accuracy of intermittent demand continues to be heavily researched [14] [8] [15] [16] [17].

The use of multi-echelon and Readiness-Based Sparing (RBS) models and research of multi-echelon and RBS modeling continues [1] [18] [19]. Many firms have a multi-echelon infrastructure and/or supply chain, by which the spare parts could be stocked at retail (i.e. close proximity to the revenue generating machine) and delivered in time t_1 and/or wholesale (i.e. a centralized warehouse) and delivered in time $t_1 + t_2$. Figure 2 shows a typical, two-level, multi-echelon construct.

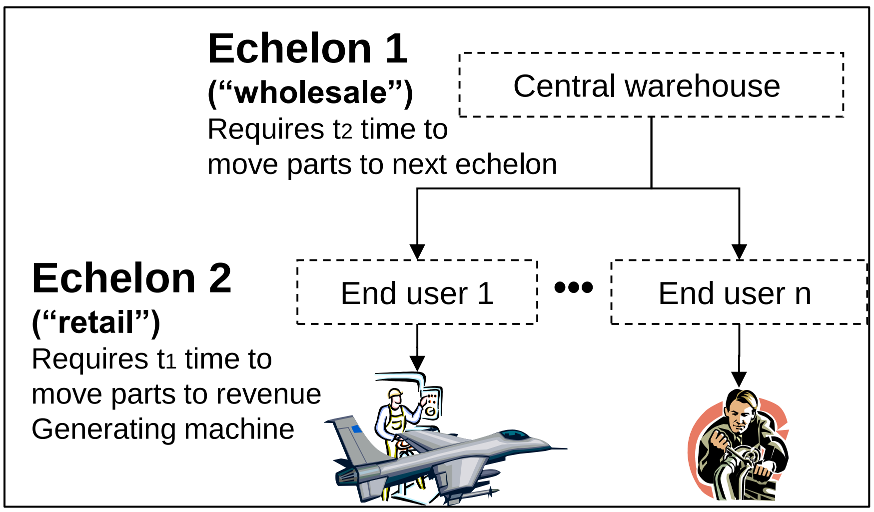

Figure 2: Two-Level Multi-Echelon System

Research on Reverse Logistics (RL), also under the label of Closed Loop Supply Chain (CLSC), appears to be increasing [20] [20] [21]over the last decade. This research area is very important for the revenue generating machine(s) that contain components that can be returned/refurbished, because the time to repair (and repair costs) are likely different from the time to procure (and procurement costs).

Within the supply chain, demand and supply planning areas continue to be researched and at an increased level from 2001-2010 [5]. Demand and supply planning areas contribute to operational availability of the revenue generating machines by including forecasting, spare parts computations (i.e. inventory modeling), stock policies, and order fulfillment actions/management on those parts that belong to the revenue generating machine(s). Also, a significant amount of research continues on various supply chain modeling. However, given the complexity of the supply chain and the current modeling areas, Badole [5] and others [4] [22] [23] show that no single model captures all aspects of the wide range of supply chain processes.

1.3.2 Existing Gaps

Reviewing the above common themes through the lens of this research topic area highlights four Gaps (G), and does so with clear focus.

(G1) Forecasting research on intermittent demand does not contain the extreme values. While there is significant research on intermittent demand within Boylan's [8] definition (20% or more of the intervals without demand), there is little research when intermittent demand is further restricted to those parts which have no demand in 50% or more of the intervals.

(G2) Forecasting research on intermittent demand is limited to lead time demand

(G3) Readiness based sparing models, despite containing multi-echelons, typically exclude components that have a near zero lead time demand; often these are referred to as insurance items via the firm's policy and use heuristics to determine spare parts levels.

(G4) No single model captures all aspects of the wide range of supply chain processes for the supply chain manager

1.4 **Problem Statements & Motivation**

Given the above four gaps, two problem statements naturally follow:

(1) What framework(s) can be developed to optimize stock policy on sparse, intermittently-demanded items; items that had no stock on hand, due to no forecasted lead time demand - yet when needed/demanded caused a revenue generating machine to be down?

(2) What forward-looking framework(s) can be developed to advance the supply chain manager's desire to proactively know what actions to take on sparse, intermittently-demanded items, to prevent a revenue generating machine from going down due to lack of spare parts?

Altay [9] shows that "...down time costs typically run at 100 to 10,000 times the price of the spare parts or service." These are very large ratios. The motivation of this dissertation is to advance cost-effective readiness by improving the supply chain management of sparse, intermittently-demand items.

1.5 **Research Contributions**

We address these problem statements and develop new methodologies; methodologies which link stock policy costs, for the sparse, intermittently-demanded items, to the associated operational benefits of the revenue generating machines.

Additionally, given that status quo supply chain metrics aren't sufficient, we create a new hybrid framework that integrates supply chain processes. This integration occurs within the context of readiness of the supply chain processes to generate parts for the revenue-generating machine. As such, it gives the supply chain manager forward-looking metrics in that it answer's, how ready are my supply chain processes? Inherent within this framework, is that it easily extends to enable cross-cutting analyses; thus, it provides a framework to assist the supply chain manager's desire to advance the supply chain's cost-effectiveness for the firm.

1.5.1 Stock Policy on Sparse, Intermittently-Demanded, Inexpensive Items

In most cases inexpensive items are consumable. Consumable items, as the name implies, are not repaired upon failure because the cost to repair is not justifiable, relative to the cost of new procurement. The down time cost on the revenue generating stream relative to the cost of the consumable item is extremely high. Many times, these consumable items are not stocked anywhere in the network (as spares) because the forecasted lead time demand is zero. Other times, the consumables are not stocked next to the revenue generating machine; rather, at a central warehouse. The first contribution of this research (ref Chapter 3 for more details) develops a new approach, addressing gaps G1, G2 and G3, which improves the supply chain's management of sparse, intermittently-demanded inexpensive items to advance cost-effective readiness.

1.5.2 Stock Policy on Sparse, Intermittently-Demanded Expensive/Reparable Items

Expensive items are often repaired upon failure because the cost to repair is justifiable, relative to the cost of new procurement. The down time cost on the revenue generating stream relative to the cost of the expensive/reparable item is also high, although lower than the previous ratio on inexpensive, consumable items. Like consumables, many times expensive items are not stocked anywhere in the network (as spares) because the forecasted lead time demand is near zero. The second contribution of this research (ref Chapter 4 for more details) develops a new approach, addressing gaps G1, G2 and G3, which improves the supply chain's management of sparse, intermittently-demanded, expensive items to advance cost-effective readiness.

1.5.3 Develop a Framework for Forward Looking Metrics for Supply Chain Manager

When a spare part is needed, often the firm's supply chain can acquire the item more than one way. Stated another way, there are often multiple processes (i.e. paths) that the supply chain manager can invoke to generate parts and get them to the downed revenue-generating machine. For example, the component may be stocked at a central warehouse and merely needs to be shipped to the location of the machine, or may be procured via multiple suppliers, or could be repaired from a previously failed part, or could be taken from another revenue-generating machine (i.e. cannibalized), etc. We leverage the block diagram from reliability theory; let the columns in Figure 3 represent the sparse, intermittently-demanded components needed by the revenue generating machine and let the rows represent the processes (i.e. paths) that the supply chain manager can invoke to generate the parts for the revenue-generating machines.

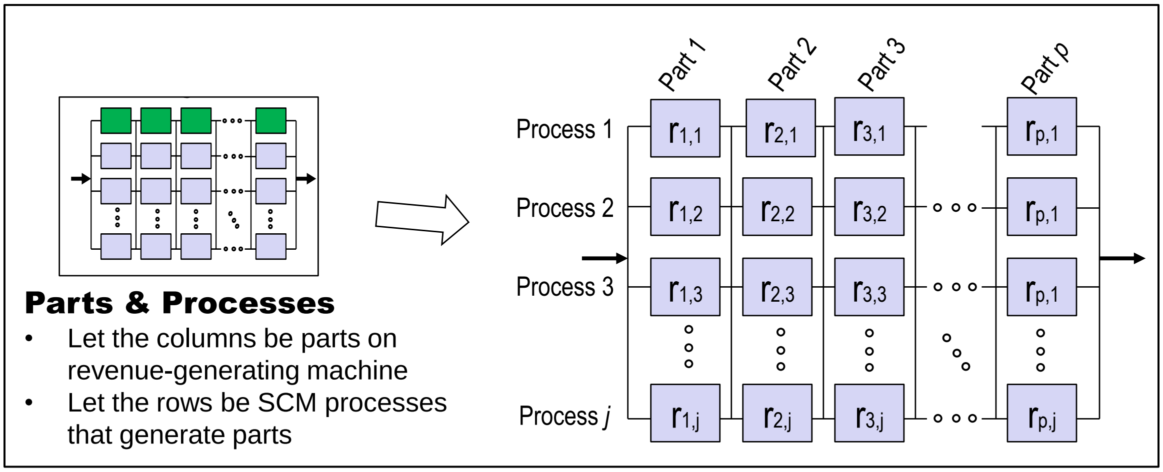

Figure 3: Reliability Block Diagram Representation

Recall from reliability theory, the block diagram indicates the system is a ‘go’ (operating or ready to operate) as long as each column has at least one component operational. In the context of this research, the reliability block diagram is a very useful framework which graphically shows which supply chain processes are ready (and which ones are not ready) to generate the parts for the revenue-generating machines. The third contribution of this research (ref chapter 5 for more details) develops a new approach, addressing gap G4, which establishes supply chain process integration into a framework that provides the supply chain manager with (1) a new, forward-looking metrics that link to the operations of the revenue-generating machines and (2) a methodology to advance his/her desire to make proactive decisions on supply chain processes to advance the firm’s cost-effective readiness.

1.6 **Dissertation Overview**

Chapter 1 provides the foundational background of the research topic, including the motivation for the research, along with problem statements and intended contributions. Chapter 2 contains an overview of the literature reviewed for this dissertation. Additionally, in Chapter 2, we group the reviewed literature into over-arching topics according to their support of our two problem statements (ref 1.4).

Chapter 3 demonstrates how stock policy can be improved on sparse, intermittently-demanded, inexpensive (i.e. consumable) items by taking a different approach, relative to traditional methods. Chapter 4, a natural progression of Chapter 3, continues by advancing the stock policy on the sparse, intermittently-demanded, expensive/reparable items.

Chapter 5 develops a methodology to create forward looking metrics for the supply chain by integrating supply chain processes. The framework (i.e. model) is extended and enables the supply chain manager to make proactive decisions on the supply chain processes that generate the sparse, intermittently-demanded items; thus, advancing the firm’s cost-effective readiness of the revenue generating machine(s).

II. Literature Review

2.1 **Literature Review Framework**

Chapter 2 provides an overview of relevant literature on the research topic. Chapters 3, 4, and 5 each contain additional, context-specific literature reviews. The purpose of this chapter is to show the uniqueness of the research contributions from Chapter 1 in the context of the literature review.

2.2 **Overview of the Literature**

The vast majority of literature is from articles with topics from intermittent demand, inventory modeling, supply chain management, reliability and prognostics, availability, operations of systems, reverse logistics, and closed-loop supply chains. Additionally, there are several thesis/dissertations as well as specialized texts that are relevant to this research.

2.2.1 Topic Relevant Text Books

While several texts are cited throughout the dissertation for analyses uses, three key texts provide specifics. The first is Dr. Sherbrooke's *Optimal Inventory Modeling* [1]; the second is Dr. Jack Muckstadt's *Analysis and Algorithms for Service Parts Supply Chains* [19]; the third is Altay & Litteral's (editors) *Service Parts Management – Demand Forecasting and Inventory Control* [9]. These very specialized texts show the importance of spare parts via their impact on the revenue generating machine and offer methods that link stock policy to the operational availability of the revenue generating machine(s). Related to this research, these three texts contain key assumptions and limitations; thus, also support the existence of the four gaps addressed in this research.

2.2.2 Thesis and Dissertations

Eight thesis and dissertations are reviewed due to their relevance to this research. Kotkin and Kinskie use Readiness-Based Sparing methodology to advance the modeling of spare parts to operational goals of the revenue-generating machines. Burnworth advances the modeling of lateral resupply, which is not addressed by prior readiness-based research. Eaves, Ghodrati, and Varghese all recognize the challenges of intermittent demand in the context of keeping the revenue-generating machines operational. George studies an application that includes a fleet of bicycles using a closed queueing network. These seven Theses and Dissertations link to gaps (G1), (G2), (G3), and (G4). Additionally, Ryan's Thesis progresses the desire of the supply chain manager to have a forward-looking framework to help with proactive decision support, which links to gap (G4). The eight theses/dissertations are shown:

Table 1: Thesis and Dissertations

Year	Title	Author	University
2013	Advancing Forward-Looking Metrics: A Linear Program Optimization and Robust Variable Selection for Change in Stock Levels as a Result of Recurring MICAP Parts	Ryan	Masters - Air Force Institute of Tech.
2012	Stochastic Modeling and Decentralized Control Polocies for Large-scale Vehicle Sharing Systems via Closed Queueing Networks	George	PhD - The Ohio State University
2009	Forecasting Intermittent Demand in Large Scale Inventory System	Varghese	PhD - University of Arkansas
2008	Simulated Multi-Echelon Readiness-Based Inventory Leveling With Lateral Resupply	Burnworth	Masters - Air Force Institute of Tech
2005	Reliability and Operating Environment Based Spare Parts Planning	Ghodrati	PhD - Luleå University of Tech
2002	Forecasting for the ordering and stockholding of consumable spare parts	Eaves	PhD - Lancaster University
1997	An Evaluation of the Budget and Readiness Impacts of Battlegroup Sparing	Kinskie	Naval Post Graduate School
1986	Operating policies for non-stationary two-echelon inventory systems for reparable items	Kotkin	University of Michigan

2.2.3 Articles, Conference Proceedings and Other Publications

Figure 4 contains many publications used to forward this research topic.

		Problem Statement 1						Problem Statement 2				
		Accuracy of Forecast	Cost/Benefits of Stock Policy Mgt	Benefits Linked to Revenue Generating Machine	Forecasting Use: Limited to Lead Time Demand	Length of Forecasting Interval (unconstrained)	Intermittent (and/or Lumpy) Demand	Reverse Logistics and/or Closed Loop Supply Chain	Supply Chain Performance Measures	SC Performance Linked to Revenue Generating Machine	Time Component of Spare Part Delivery to Revenue Generating Machine	Forward Looking Metrics
2009	Syntetos, et al.	x	x		x		x					
2010	Miles											
2011	Nikolopoulos, et al.	x			x		x					
2011	Rossetti & Unlu	x			x		x					
2003	Ghabbar & Friend	x	x	x	x		x					
1972	Croston	x	x				x					
1996	Johnston & Boylan	x	x				x					
1999	Bartezzaghi, et al.	x					x					
2009	Varghese & Rossetti	x					x					
2010	Heaton			x								
1998	Vincent & Tenney			x								
2013	Willemain	x	x	x	x		x					
2012	Lowas & Briggs			x			x					
2005	Syntetos & Boylan	x					x					
2003	Shaw, et al.		x	x								
2011	Pishvaee, et al.		x	x				x	x			
2000	Holmberg								x			
2012	Dersin			x							x	
2003	Kobayashia, et al.			x						x		
2012	San, et al.		x					x		x		
2003	Lendermann, et al.								x			
2013	Deputy Under Secretary: Logistics & Materiel Readiness		x	x	x	x			x	x		
2011	Monnin, et al.			x								
2009	Reymonet, et al											
2011	Shi, et al							x				
2011	Shi, et al.							x				
2007	Tu, et al.			x			x					
2004	Willemain, et al.	x	x		x		x					
2012	Badole, et al.	x	x	x					x	x		
2006	Zeithaml, et al.											x
2005	Campbell, et al.			x						x		
2013	Willemain	x										
2007	Ketchen & Hult								x			x
2014	Fulk		x	x			x			x	x	x
2008	Abbas, et al.											
2008	Cobb & Shenoy											
2006	Boylan & Syntetos	x	x				x		x			
2011	Cattani, et al.		x	x					x		x	
2007	Bachman	x	x	x		x	x		x	x	x	
2005	Boylan & Syntetos	x	x		x		x					
2007	Klassen & Menor								x	x		
1999	Cohen, et al.		x	x	x				x	x	x	
2006	Willemain	x	x				x		x			
2006	Hyndman	x	x				x		x			
2006	Hoover	x	x				x		x			

Figure 4: Articles & Conference Proceedings

2.3 **Literature Linked to Problem Statement #1**

A lack of spare parts is one cause of revenue generating machine(s) being unserviceable. Problem statement #1 (ref section 1.4) focuses on stock policy and management of sparse, intermittently-demanded items because of their impact on the revenue generating machines. Relevant to problem statement #1, the literature covers three over-arching areas: forecasting demand, intermittent (and lumpy) demand, and the benefits of demand forecasting. Additionally, because much of the research in chapter 4 is to extend Bachman's [24] work, which was limited to consumable parts, we characterize his methods and clarify how our research expands, by including reparable parts, which have additional management complexity.

2.3.1 Forecasting Demand

It is commonly shown and well understood that forecasting demand for service-parts industries (i.e. parts belonging to revenue generating machines) is challenging [9] [8]; however, the need to do so is great. Altay and Litteral [9] state in chapter 8, "As customers are more demanding with respect to after sales operations and service level agreements put challenging availability targets on equipment uptime, the provision and deployment of service parts becomes of focal interest for many original equipment manufacturers." In this context, when the firm forecasts demand, it does so because of the implications the spare parts are projected to have on the forecasted up-time of the revenue generating machines.

Many firms use time series data as the baseline for forecasting; some adjust the forecast according to planned operational changes of the revenue generating machine(s).

In order to forecast demand, a firm must have policies to (1) define the length of the forecasting interval, (2) the forecasting method, and (3) the number of future time periods to forecast. Literature on the length of the forecast interval, for these types of parts, is scarce. The literature that does include forecast length typically limits the forecasting interval to the length of lead time (for the given part). Additionally, much of the literature relevant to this research limits the number of forecasting time periods to the length of the lead time (for the given part); often referred to as Lead Time Demand (also sometimes called Pipeline) [1] [25].

Given the importance of forecasting demand, it continues to be an area heavily researched, evidenced by the significant amount of reviewed literature that contained the topic of forecast accuracy (ref Figure 4).

2.3.2 Intermittent (and Lumpy) Demand

The term intermittent goes hand in hand with nearly all research one might pursue in the service parts arena. Croston's heavily cited work [13] in 1972 advanced the forecasting accuracy of intermittent demand by providing a single framework that could handle both intermittent demand and non-intermittent demand. Fine-tuning the forecasting of intermittent demand continues by many including articles by Ghobbar and Friend [15], Boylan [8], and Varghese & Rossetti [26]; as well as dissertations by Syntetos, Eaves [27], and Varghese [11].

Croston's seminal paper [13] does not provide a verbal definition of intermittent demand, but it does contain a key example. Using Croston's and Boylan's [8] examples and Boyland's [8] definition of intermittent demand, we show the three views of intermittent demand expressed two ways: (1) the percentage of intervals with zero demand, and (2) average number of intervals between demands. The 2D graphic in Figure 5 allows demand to be viewed as a continuum, from demand in every period (on the far lower-left) to no demands in any period (far upper-right).

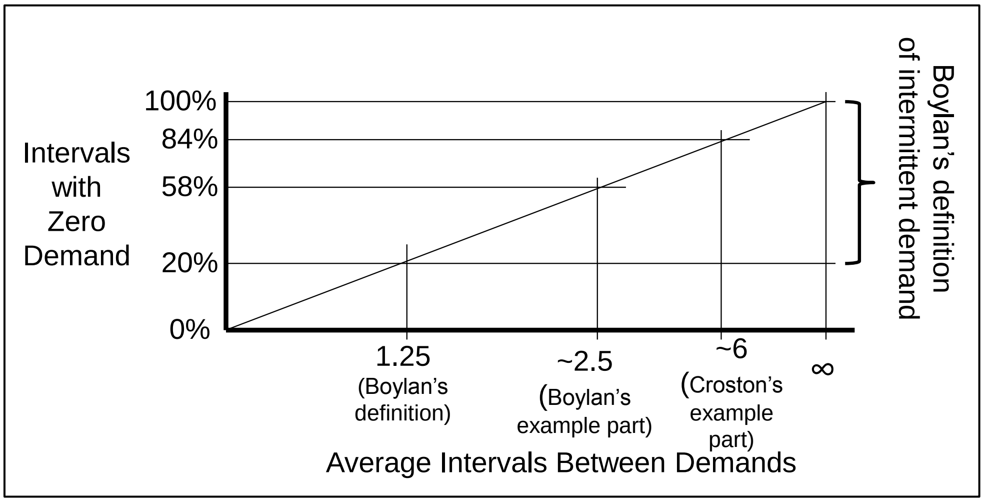

Figure 5: Continuum of Demand

Hadley and Whitin [28] offer a common view on the difficulty of managing intermittent items, "It is especially difficult to obtain accurate values for the usage rate for very low demand spare parts (this includes a majority of the spare parts), items..." As shown in Figure 4, intermittent demand continues to be heavily researched. One key reason is because so many spare parts belonging to the revenue generating machines are defined as intermittent. However, literature on the extreme values of intermittent demand (i.e. ≤ 1 demand over the forecasting interval) is very scarce. This is the area of research undertaken, and the word sparse is inserted in front of intermittent to describe this specific area of research which further restricts intermittent demand to those parts where 50% or more of the intervals contain zero demand.

2.3.3 Benefits of Demand Forecasting

While much literature focuses on forecast accuracy, and understandably so, Johnston and Boylan [10] highlight that the goal isn't necessarily to improve the forecast, rather to support the "stockist's aim of providing good service to the customer". Fully recognizing the presence of uncertainty, Trevor Miles [29] challenges researchers to reflect on supply chain management expectations "...along with the belief among supply chain practitioners that, if we only had enough time and energy, we could describe every phenomenon precisely by a mathematical equation that fully captures causality and consequences."

Much of the literature shows that demand is forecasted to cover the lead time (i.e. lead time demand, pipe or pipeline) [27] [11] [25]. Inventory models use the lead time demand, along with other inputs, and compute the spare parts requirement according to the objective function of the specific inventory model. Two common objective functions are fill rate optimization and expected backorder minimization [1] [18] [19]. It should be noted that minimizing expected backorders (*ebos*) within the inventory model may be for different purposes; two of which are to minimize customer wait time ($cwt = \frac{\sum ebos}{\sum daily\ demand\ rate}$) or maximize operational availability ($A_o = e^{-\frac{ebos}{\#\ machines}}$) [1] of the revenue generating machines (i.e. fleet).

2.3.4 Characterizing Bachman's Work on Consumable Parts

Given the difficulties of managing the very sparse, intermittently demanded parts, often heuristics are created and used to determine stock polices for the supply chain manager to utilize. For the very sparse and sporadic intermittently-demanded parts, Bachman suggests a heuristic called peak demand [24]. The process looks back upon previous time intervals, by part, and establishes the maximum demand amount. The maximum demand is combined with a user-determined group multiplier, which is greater than or equal to zero, and the stock policy reorder point is determined by multiplying the maximum demand and the user-determined multiplier. His work is limited to consumable parts, but case studies on several AF and Navy systems (i.e. machines) show significant improvement possibilities. Chapter 4 expands Bachman's work by adding reparable parts. Reparable parts add significant complexity, including the need to establish a two-tiered stock policy, namely one for repair and one for procurement.

2.4 **Literature Linked to Problem Statement #2**

Recall problem statement #2; what forward-looking framework(s) can be developed to advance the supply chain manager's desire to proactively know what actions to take on the sparse, intermittently-demanded items, to prevent a revenue generating machine from going down due to lack of spare parts? Supply chain management contains many processes [4] as it bridges the firm's entire span between supplier and customer and sometimes back again to the firm (for firms with reverse logistics/closed loop supply chains).

2.4.1 Supply Chain Modeling: Integration and Performance Measures

Badole, Jain, Rathmore & Nepal's article "Research and Opportunities in Supply Chain Modeling: a Review" [5] surveyed 700 supply chain articles across 45 journals. They synthesized the 700 and selected 300 papers to review in greater detail. Their exhaustive review identifies 10 key areas from five categories for future research. Their first four areas (shown below) are included in the framework of the third contribution of this research; thus, addressing Problem Statement #2.

(1) Need for Integrated and Coordinated Supply Chain Modeling

(2) Incorporation of Performance Measures

(3) Implementation of Information Technology

(4) Perishable Products Supply Chain

Holmberg [30] also claims that current measures of supply chain performance are not effective because they lack a system perspective (i.e. for example, don't trade resources between warehousing and transportation). Additionally, he claims that there is a gap between many firms' strategy and the actual measures they take/look at for management review decision support.

Shaw, Meixell & Tuggle [31] recognize the lack of integrated supply chain processes. They show, via an application from the automotive spare parts industry, that integrating knowledge management into the over-arching supply chain process leads to spare parts levels that meet better service levels and without wasting as much stock.

Additionally, Lendermann et al. [32] also recognize the lack of integrated supply chain processes. They show, via an application from the semiconductor industry, that simulation can be used effectively to integrate supply chain processes; thus, providing supply chain managers with a decision support tool.

2.4.2 Reverse Logistics and/or Closed Loop Supply Chain

Many firms have reverse logistics processes; reverse logistics processes can be as simple as returns management programs/policy or as complex as refurbishing non-serviceable assets to reusable/re-saleable condition. Literature on reverse logistics and closed loop supply chains is increasing. The common theme/reason for the increase is that firms are recognizing the importance of reverse logistics, from a long-term financial perspective. Much of the literature contains the network design of the firm's reverse logistics. Another focus area in the literature is on capturing the value of the firm being able to receive the returned goods and refurbish for additional sales to the customer [33]. Readiness Based Sparing (RBS) inventory modelers often refer to these items as reparables [19] [1] and account for return and refurbish time within the computation of expected lead time in order to combine with demand rates to create the lead time demand (i.e. pipeline).

Specific to this research area, however, the literature is very scarce as shown by (1) the lack of reverse logistics articles that also contain intermittent demand and (2) the lack of supply chain management articles that contain intermittent demand and their contribution to revenue generating machine(s).

2.5 **Statement of Original Contribution**

This dissertation seeks to advance the two problem statements (ref 1.4) by addressing gaps (ref 1.3.2) in the literature.

Chapter 3 will introduce a condition-based heuristic that can be used to create improved retail stock policies for the very sparse, inexpensive intermittently-demanded parts. The benefits of the new retail stock policies are then evaluated via a case study on the A-10 fleet of aircraft. Chapter 3 contains some redundancy, especially in the introduction, because it is written to be a stand-alone document.

Chapter 4 is a natural progression of Chapter 3. Chapter 4 will introduce a peak-demand framework that can be used to create improved wholesale stock policies for the very sparse, expensive/reparable intermittently-demanded parts. The benefits of the new wholesale stock policies are then evaluated via a case study on the B-1 fleet of aircraft.

Chapter 5 develops a framework to create forward looking metrics for the supply chain manager by integrating supply chain processes. The framework (i.e. model) is extended to enable the supply chain manager to make proactive decisions on the supply chain processes that generate the sparse, intermittently-demanded items.

III. Condition-Based Stock Policy Heuristic for Very Sparse, Intermittently-Demanded, Inexpensive Parts

3.1 **Introduction: A Firm's Objective and Operating Revenue Generating Machines**

In general terms, the objective of most firms is to generate a profit. One step deeper, many firms generate revenue by successfully operating 'machines' (i.e. welding robots, rental cars, aircraft, hotel rooms, amusement park attractions, etc.) that produce goods/enable services that the firm sells to the consumer. From here on, the word machine(s), without quotes, will be used in general terms, to describe these types of revenue generating streams.

Revenue generating machines can/do break or become unserviceable, and during these times, the firm may lose all or part of the revenue generating stream. Often, the firm establishes operational targets, A_o, to assure a given percent of the revenue generating machines are serviceable.

In most cases, restoring the downed machine requires maintenance action(s) and often requires spare part(s). The average machine down time due to maintenance action(s) is often called Mean Time To Repair (*MTTR*). The average machine down time due to awaiting spare parts is often called Mean Logistics Delay Time (*MLDT*) [2] [34]. Combining *MTTR* and *MLDT* with Mean Time Between Failure (*MTBF*) leads to a commonly used equation for operational availability, A_o [2] [34] [35]

$$Ao = \frac{MTBF}{MTBF + MTTR + MLDT} \tag{1}$$

The scope of this paper, which is focused on improving *MLDT*, is to advance the cost-effective management on a subset of the spare parts, the very sparse, intermittently-demanded, inexpensive ones, by creating a framework to find improved stock policy.

3.1.1 Firm's Supply Chain Management of the Spare Parts

After initial procurement, management responsibility of spare parts generally belongs to the firm's supply chain. The role of the supply chain manager is vast, but the focus of this research is on the cost-effectiveness of the supply chain manager's stock policy. Stock policy is needed to answer basic inventory questions such as [6] [7] [8]:

When do we begin stocking an item?

How much do we stock?

Where do we stock?

Answers to these basic inventory questions result in business rules that provide the supply chain manager's resources with a set of rules that define engagement. The stock policy typically is linked to the firm's operational goals of the revenue generating machines [9] [18] [36] [37] [35] [19] [1] [38].

3.1.2 SCM Stockage Policy on Intermittently-Demanded Items

The term intermittent goes hand in hand with nearly all research one might pursue in the service parts arena. Croston's well-cited 1972 paper [13] does not provide a verbal definition for intermittent, but because it has had such an impact on the forecasting of intermittent demand, it is appropriate to revisit his example; of 180 total time intervals, 29 (16%) had demand while 151 (84%) did not have demand; thus, the average number of intervals between demands is approximately 6 (180 total intervals /29 intervals with demand).

Over the years, several authors have defined intermittent demand; Boylan provides a good, usable definition for intermittent demand: "As a guideline, at least 20% of the time intervals should have zero demand for you to count the demand pattern as intermittent" [8]. The definition of intermittent demand can be expressed two ways; (1) ≥ 20% of the intervals with no demand, and (2) the average number of intervals between demand ≥1.25. Figure 6 shows a 2-demensional (2D) continuum of demand where the first definition of intermittent demand is shown via the vertical axis and the second via the horizontal.

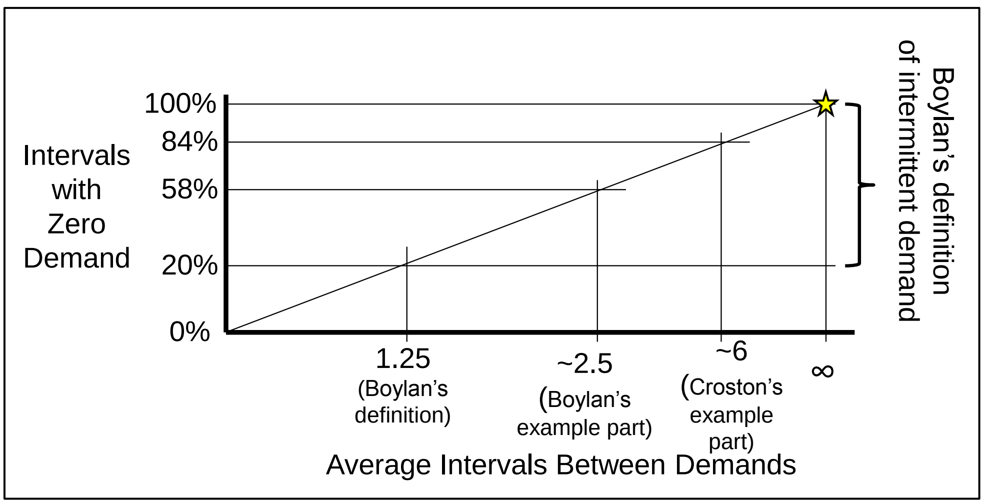

Figure 6: 2D Continuum of Demand; Data Point with No Demand

Plotted in Figure 6 are four key points: (1) a demand continuum - lower left where demand exists in every interval to the upper right where no demand exists in any interval (of the forecasting interval); (2) Boylan's definition of intermittent demand along with (3) Boylan's example part and (4) Croston's example part. A star is shown in the upper, right portion of Figure 6 to show the focus of this research, which is on the very sparse, intermittently-demanded items. These are the items that, effectively, can't be forecasted using time-series methodologies.

3.1.3 Mutli-Echelon Network

Many supply chains operate within a multi-echelon network construct [19] [39] [18]. Shown in Figure 7 is a multi-echelon network with two echelons. Echelon 1 represents a wholesale operation such as a centralized warehouse and echelon 2 represents retail locations. For our research, the retail locations are locations of the revenue-generating machines.

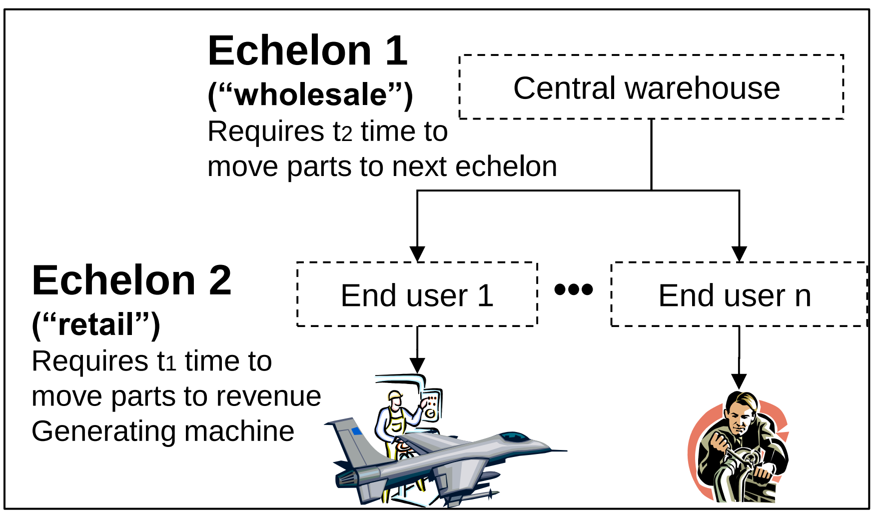

Figure 7: Multi-Echelon Network Design with Two Echelons

3.2 **Problem Description**

Researchers recognize the importance of intermittently-demanded items and their impact to the revenue generating machine(s). Croston's work [13] advanced the forecasting accuracy of intermittent demand by providing a single framework that handles both intermittent demand and non-intermittent demand. Syntetos and Boylan [17] addressed the positive bias that remained in Croston's work. Fine-tuning the forecasting and forecasting accuracy of intermittent demand has been continued by many; Ghobbar and Friend [15], Boylan [8], Boylan & Syntetos [40] , Willemain [41], and Varghese & Rossetti [26]; dissertations by Syntetos, Eaves [27], and Varghese [11] to name a few.

The intermittently-demanded parts of the revenue generating machine often include the full ranges of cost and much of reliability (i.e. *MTBF*), as shown on the horizontal and vertical axis in Figure 8. Of interest to this study is the circle in Figure 8 labeled as set **𝓟**; these are the very sparse, intermittently-demanded, inexpensive items, the focus of this research.

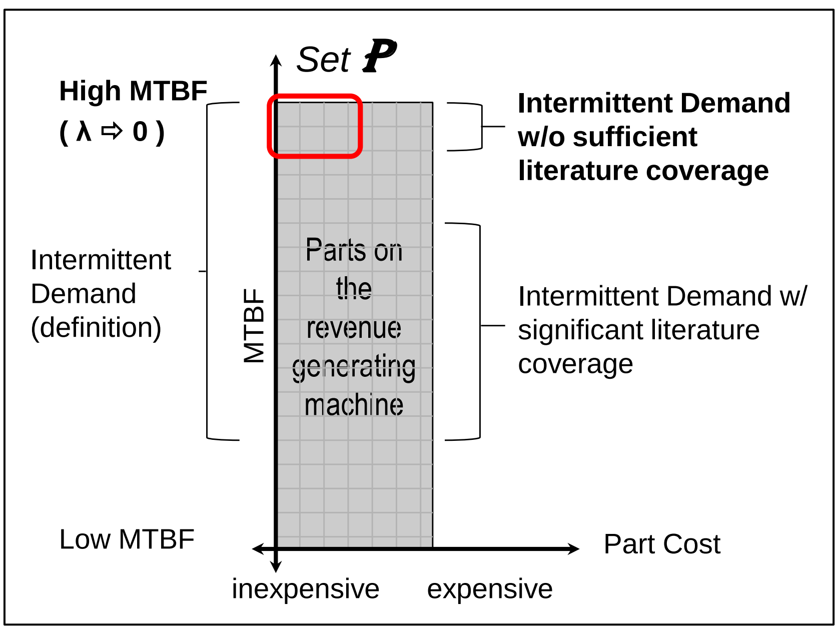

Figure 8: Makeup of Parts on a Revenue Generating Machine

It is common to model many component failures, especially the intermittently-demanded items, as Poisson Processes. As shown in equation (2), λ is the component's failure rate, i is the expected number of failures over a time interval, t, which is typically set to the components lead time. The inventory-modeling application of equation (2) is that it is typically used to establish the distribution of lead time demand [1].

$$P_i(t) = \frac{e^{-\lambda t}(\lambda t)^i}{i!} \tag{2}$$

Equation (2) is not a 'one size fits all' [42] [11], but its use is very common for service parts. Sometimes, especially for inexpensive, consumable parts, order sizes can vary [14] [8]. For the cases where order sizes are larger, a stochastic-based lot size may be added and distributions such as the negative binomial are used to compute lead time demand [25] in place of the Poisson.

Bachman and Willemain go further and show that lead time demand, for a sub-set of the intermittently-demanded parts, doesn't always fit the typically-used distributions (Poisson, negative binomial, etc.); therefore, they don't explicitly estimate the standard parameter(s) for fitting lead time demand into one of the standard distributions. Willemain shows that bootstrapping methods [41] can be used to outperform Croston's method and exponential smoothing. Bachman's method, called NextGen, is proprietary (patent pending), but an empirical test using Defense Logistics Agency (DLA) data produced good results. Bachman and Willemain's methods produce the part's empirical distribution (using historical information from the part) for lead time demand, vice estimating a parameter(s) and fitting it to a standard distribution; both methods advance the intermittent-demand problem on a sub set of the intermittently-demanded items.

3.2.1 Limitations of Computing Lead Time Demand

For the very sparse, intermittently-demanded parts, which this research focuses on, λ is approximately zero; hence, the probability of demanding zero parts over the lead time is, effectively, one. Many firms employ only demand-based stock policies and since lead time demand is determined to be zero, the SCM will not stock these items as spare parts. The implication to the revenue generating machine is that too often, un-forecasted failures occur on these parts, and results in the machine being down/unserviceable somewhere between the supply chain's expedited time and the components full lead time. Altay and Litteral [9] highlight the importance, *"*Customers are usually less concerned about spare part prices than about speed of delivery and availability of service know how, whether on sight or via telephone. The reason is simple: down-time costs typically run at anywhere from 100 to 10,000 times the price of spare parts or service.*"*

3.2.2 The Research Question

The scope of this research is on the inexpensive (i.e. consumables), very sparse intermittently-demanded items which are represented by set **P**, the circle shown in Figure 8. The research question is: what framework can be developed to advance the cost-effectiveness of stock policy on inexpensive, consumable items that have near-zero lead time demand– yet if/when demanded, will likely down the revenue generating machine?

3.3 A New Approach: Designing a Condition-Based Stock Policy Heuristic

We recognize the demand-based approach to stock policy, likely endorsed by the pure mathematicians, is to continue focusing on determining the true, underlying λ and use it within the inventory models, such that spares would naturally be computed by the inventory models. As highlighted in section 3.2, this approach has major challenges that have spanned at least five decades. Due to this persistent challenge, our approach is to seek a condition-based stock policy heuristic for the very sparse intermittently-demanded, inexpensive items.

3.3.1 Bayesian Beliefs Lead to Condition-Based Stock Policy

We revisit the demand continuum and plot intermittent demand rates on a single notional item for four locations of the revenue generating machine, as shown in Figure 9. In this example, locations 1, 2, and 3 all have historical intermittent demand; that is, all three have positive estimates for λ and thus a computation of lead time demand > 0. Location 4 has no historical demand; that is, the estimate of λ is zero and thus the lead time demand = 0.

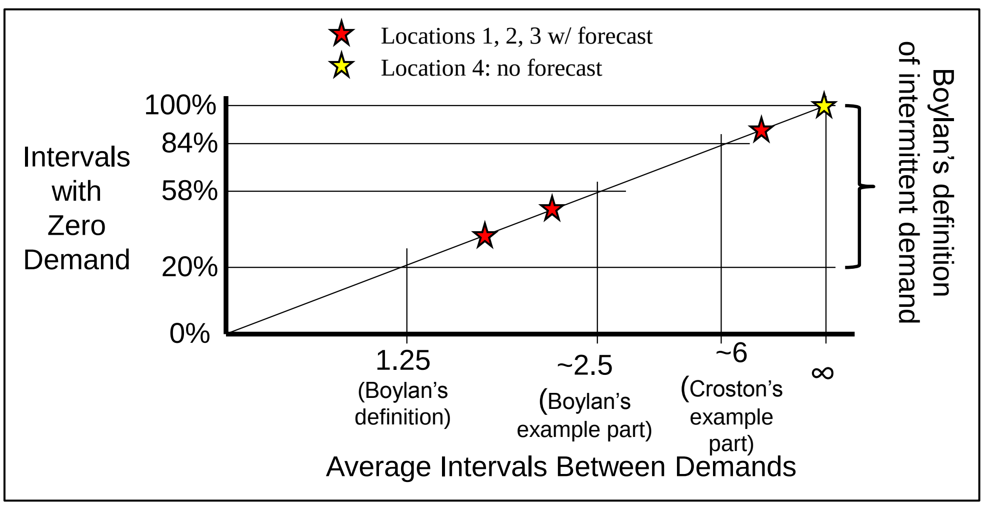

Figure 9: Continuum View of Intermittent Demand at 4 Locations

If location 4 is operating the same machine as locations 1, 2, and 3 (and the operational environments are similar), then it is intuitive that the underlying failure rate at location 4 may not be zero; rather, $\lambda > 0$. Let λ^* be the critical failure rate that drives the inventory model to compute a spare part level greater than or equal to 1. Let $\mathbf{L}$ be the set of locations with revenue-generating machines. As depicted in Figure 9, the cardinality of $\mathbf{L}$ is 4; that is, there are 4 locations of the revenue-generating machine. The conditional-based belief leads to:

$$P\left(\lambda_4 \geq \lambda^* \middle| \lambda_1, \lambda_{2,} \lambda_3 > \lambda^*\right) \geq P(\lambda_4 \geq \lambda^* | \lambda_1 \; or \; \lambda_2 \; or \; \lambda_3 > \lambda^*) \tag{3}$$

Equation (3) implies three beliefs. The first is that $\lambda_4 \neq 0$, despite no historical demand; rather, $\lambda_4 > 0$. Secondly, equation (3) implies that λ_4 may be greater than or equal to λ^*. Thirdly, the likelihood that $\lambda_4 \geq \lambda^*$ increases as the number of other locations with historical demand increases. Narratively, λ_4 is more likely to be greater than λ^* when demand is seen at all three other locations than when demand is seen at only one other location. Equation (3) is for a single part at four locations; we are motivated to generalize. Given set $\mathbf{L}$, let l be an individual location of the revenue-generating machine, $l \in \mathbf{L}$. Let R be the number of locations with historical demand. Let n be an arbitrary number (i.e. a design parameter between 0 and $|\mathbf{L}|$ -1). Let x be a location of the revenue generating machine without historical demand on a given part. This leads to a more general, conditional inequality.

$$P(\lambda_x \geq \lambda^* | R > n + 1) \geq P(\lambda_x \geq \lambda^* | R > n) \tag{4}$$

We seek to validate the merit of equation (4). Given the set $\mathbf{P}$, let p be an individual part, $p \in \mathbf{P}$. Let t be a given time. A Stock Keeping Unit (SKU) is a part/location pairing [7]. Given the set of locations, $\mathbf{L}$, then SKU^t is a $|\mathbf{P}|$ x $|\mathbf{L}|$ matrix where:

$$SKU_{p,l}^t = \{ \begin{matrix} 1, & \text{if location } l \text{ has historical demand for part } p \text{ } at \text{ time } t \\ 0, & \text{otherwise} \end{matrix} \} \tag{5}$$

Let $R_p^t = \sum_L SKU_{p,l}^t$. R_p^t is a row-sum of the matrix; it states how many of the $|\mathbf{L}|$ locations have historical demand on part, *p*, at time, *t*. The elements of matrix SKU^t can be broken into two disjoint sets. Let set $\mathbf{S}^{t'} = \{ (p, l) \mid SKU_{p,l}^t = 1 \}$. This set contains all the SKUs from matrix SKU^t that have historical demands on part, *p*, at time, *t*. Conversely, let set $\mathbf{S}^{t''} = \{ (p, l) \mid SKU_{p,l}^t = 0 \}$. This set contains all the SKUs from matrix SKU^t that do not have historical demand on part, *p*, at time, *t*. Therefore, $\mathbf{S}^{t'} \cap \mathbf{S}^{t''} = \emptyset$; each SKU in matrix SKU^t either has historical demand or does not at time, *t*.

The number of locations with demand, as defined by R_p^t, can be used to produce subsets of $\mathbf{S}^{t'}$ and $\mathbf{S}^{t''}$. Let *n* be some arbitrary value; then set $\mathbf{S}_n^{t'} = \{ (p, l) \in \{\mathbf{S}^{t'}\} \mid R_p^t \geq n \}$. This set contains all the SKUs for those parts that had a specified minimum number of locations with historical demand at time, *t*. Conversely, let set $\mathbf{S}_n^{t''} = \{(p, l) \in \{\mathbf{S}^{t''}\} | (p, .) \in \{\mathbf{S}_n^{t'}\}\}$. This set contains all the SKUs with no demand, given the parts had demand at a minimum number of other locations as recorded in $\mathbf{S}_n^{t'}$. Similarly, $\mathbf{S}_n^{t'} \cap \mathbf{S}_n^{t''} = \emptyset$; for the two reduced sets, the remaining SKUs either have historical demand or do not.

Given the above notation and sets, we can define a term *Hit Rate$_n$* as as:

$$Hit\ Rate_n = \frac{|\mathbf{S}_n^{t''} \cap \mathbf{S}_n^{t+1'}|}{|\mathbf{S}_n^{t''}|} \tag{6}$$

Hit Rate$_n$ in this context is the percentage of predetermined, non-demanded SKUs that get demanded in the following time period. Figure 10 provides a graphical representation of the notation leading up to and used in equation (6).

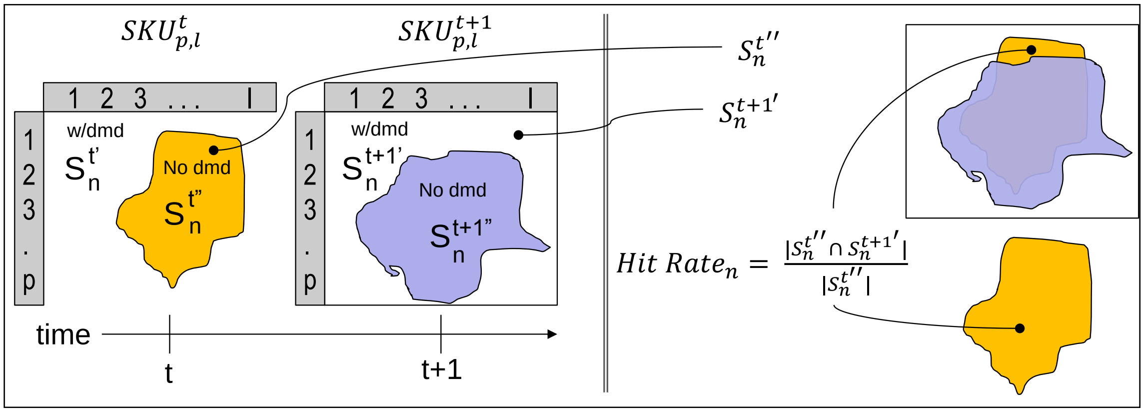

Figure 10: Graphical Representation of Equation (6)

Equation (6) suggests a belief that the likelihood of demand (i.e. failure rate > 0), for SKUs without historical demand, is conditioned upon how many other locations do have demand (signals) on the same parts; this leads to the condition-based inequality:

$$Hit\ Rate_{n+1} \geq \ Hit\ Rate_n \tag{7}$$

3.3.2 Empirical Test to Validate Bayesian Beliefs

An empirical test, using 12 months of actual demand data, is used to test the validity of the proposed inequality in equation (7). For this empirical test, the firm is the US Air Force; the revenue generating machine is the A10C aircraft; the number of intermittently-demanded parts, $|\mathbf{P}|$, is 3,111; the number of locations of machines, $|\mathbf{L}|$, is 12 (i.e. A10C aircraft are at 12 locations); inexpensive parts are defined as costing $1450 or less; parts coded with shelf life implications are excluded (not addressing spoilage); and, parts have been mission coded (i.e. all parts in $\mathbf{P}$ have shut-down implications to the revenue generating machine). The initial data set to build the matrix SKU^t contains 37,332 pairings ($|\mathbf{P}|$ = 3,111 x $|\mathbf{L}|$ = 12) and was provided when time, *t* was 2011.

Setting n = 1 and using t = 2011, sets $\mathbf{S}_1^{2011'}$ and $\mathbf{S}_1^{2011''}$ are determined. Actual demand data was also provided for the following year, that is t = 2012, and set $\mathbf{S}_1^{2012'}$ is determined. Using equation (6), $Hit\ Rate_1\ =\ 10.7\%$. Similarly, setting n = 2 and t = 2011, sets $\mathbf{S}_2^{2011'}$ and $\mathbf{S}_2^{2011''}$ are determined. Updating with t = 2012; set $\mathbf{S}_2^{2012'}$ is also determined. Using equation (6), $Hit\ Rate_2\ =\ 16.5\%$. The empirical results of equation (6) are shown:

$$Hit\ Rate_2 = 16.5\% \geq\ Hit\ Rate_1 = 10.7\% \tag{8}$$

The narrative result of equation (8) is that for all the parts that had demand at one or more locations (at a particular point in time), 10.7% of the SKUs that had no historical demand on those same parts had at least one demand during the next 12 months. Similarly, for all the parts that had demand at two or more locations (at a point in time), 16.5% of the SKUs that had no historical demand on those same parts had at least one demand during the next 12 months. The empirical data supports the Bayesian-belief as shown in equation (8) where n is 1 and 2. Table 2shows the relationship between *Hit Rate* and n for all values of n and further supports the conditional-based beliefs proposed in equations (4) and (7) .

Table 2: *Hit Rates* for Values of *n*

n	*Hit Rate*	$\lvert S_n^{t''} \rvert$	$\lvert S_n^{t''} \cap S_n^{t+1'} \rvert$
1	10.7%	18,137	1,934
2	16.5%	7,822	1,294
3	22.9%	3,282	750
4	28.9%	1,135	328
5	40.2%	378	152
6	49.5%	107	53
7	50.0%	8	4
8	100.0%	2	2
≥ 9	na	-	-

Recall $\mathbf{S}_n^{t''}$ are those SKUs with no historical demand at time, t; the extremities within the definition of intermittent demand (ref section 3.1.2). As such, they are typically not stocked by demand-based stock policies. However, equation (8) and Table 2 show that data from donor locations captured in $\mathbf{S}_n^{t'}$ provides insights on the likelihood that future demand will occur on members of set $\mathbf{S}_n^{t''}$; insights which grow as *n* increases. Thus, the number of users with historical demand, R_p^t, is included as a parameter (i.e. $R_p^t \geq n$) within the condition-based stock policy we seek.

An extreme policy that stocks all the very sparse, intermittently-demanded parts at all locations is likely not cost effective for the firm because a significant amount of capital would be needed to procure the parts. Conversely, an extreme policy to not stock any of the very sparse, intermittently-demanded parts at any location is likely not cost effective for the firm because of high losses of revenue from machine downtime (awaiting parts). To evaluate at and between these two extremes, costs and benefits can be compared such that any stock policy for the very sparse, intermittently-demanded items can be evaluated for cost-effectiveness.

3.3.3 Costs & Benefits of a Stock Policy

The total cost of an individual stock policy is typically comprised of sub-cost elements. For our total cost, we use four sub-cost elements: procurement, holding, transportation, and lost revenue (i.e. machine is down for lack of part). We recognize there are other sub-costs such as spoilage, disposal, salvage, etc., but they are assumed to be small, and not used in this research.

Let PC_{pl} be the procurement cost of part, *p*, from the supplier for location, l. Let HC_{pl} be the holding cost, which is 15% of PC_{pl} per year for this firm. Let TC_{pl} be the expedited transportation cost (to get a spare part to the downed machine), which is $350 per transport action for this firm. Finally, let RC_{pl} be the lost revenue cost, incurred because the machine was down/unserviceable due to the lack of a part, which is an average of $6,238 per downing incident for this firm. The total cost of any individual stock policy containing (|**P**| x |**L**|) SKUs is given by:

$$Cost = \sum_{p=1}^{|\mathbf{P}|} \sum_{l=1}^{|\mathbf{L}|} PC_{pl} + HC_{pl} + TC_{pl} + RC_{pl} \qquad (9)$$

Stock policy determines whether the SKU will be stocked or not. Subsequently, for a given time interval, the SKU will either be demanded or not demanded. Thus, there are four discrete cases as shown in Table 3.

Table 3: Four Discrete Cases of Stocking/Demanding

Case	Description	Stock Policy Cost
1	SKU stocked; subsequent demand	$Cost = PC_{pl} + 0.5\,HC_{pl} + 0 + 0$
2	SKU stocked; no subsequent demand	$Cost = PC_{pl} + HC_{pl} + 0 + 0$
3	SKU not stocked; subsequent demand	$Cost = 0 + 0 + TC_{pl} + RC_{pl}$
4	SKU not stocked; no subsequent demand	$Cost = 0 + 0 + 0 + 0$

For case 1, the policy would proactively stock the SKU; as such, there is a cost to procure the part, PC_{pl}; a cost to hold the part for an assumed 6 months (before demand occurs), $0.5HC_{pl}$; no expediting transportation costs, TC_{pl}, and no lost revenue cost, RC_{pl} (since the part was proactively stocked at the given location). For case 2, the policy would proactively stock the SKU; as such, there is a cost to procure the part, PC_{pl}; a cost to hold the part for the entire year (no demand occurred), HC_{pl} ; no expediting transportation costs, $TC_{pl,}$ and no lost revenue cost, RC_{pl}. For case 3, the policy would not proactively stock the SKU; as such, there are no costs to procure, $PC_{pl,}$ or hold the part, HC_{pl}; because a demand occurs there are expediting transportation costs, TC_{pl}, and lost revenue cost, RC_{pl}. For case 4, the policy would not proactively stock the SKU; as such, there are no costs to procure, $PC_{pl,}$ or hold the part, HC_{pl}; because a demand did not occur, there are no expediting transportation costs, TC_{pl} , and no lost revenue cost, RC_{pl}.

3.3.4 Experiment to Generate Potential Condition-Based Stock Policies

Given the importance of procurement costs, PC_{pl},to equation (9), it is also included as a design factor to consider in the condition-based stock policy. To keep the size of the experiment reasonable, procurement costs were discretized into 10 buckets {\$10.00, \$25.95, \$53.96, \$100.00, \$172.21, \$281.51, \$442.34, \$673.64, \$1,000.00, & \$1,453.04}. The buckets are, by design, not uniform because sampling at smaller intervals, at the lower end of procurement costs, was desired. An expression, $10^{\sqrt{j}}$, used to produce the ten values above by incrementing *j* from 1 to 10.

We fully enumerated a two factor experiment. Given the factors have levels of 11 and 10 respectively; the enumerated space contains 110 discrete stock policies. The proposed condition-based stock policy is a two-parameter pairing, containing the minimum number of locations (with historical demand), R_p^t, and the maximum procurement cost, PC_{pl}. The first two and last two condition-based stock policies from this enumerated space, *K*, are shown along with a narrative in Figure 11.

k = 1, Stock Policy (1, \$10)	‘ Stock SKU if $R_p^{2011} \geq n$ =1 & PC_{pl} $\leq$ \$10.00
k = 2, Stock Policy (1, \$25.95)	‘ Stock SKU if $R_p^{2011} \geq n$=1 & PC_{pl} $\leq$ \$25.95
...	
k = 109, Stock Policy (11, \$1000)	‘ Stock SKU if $R_p^{2011} \geq n$=11 & PC_{pl} $\leq$ \$1000
k = 110, Stock Policy (11, \$1453)	‘ Stock SKU if $R_p^{2011} \geq n$=11 & PC_{pl} $\leq$ \$1,453

Figure 11: |K| = 110 Stock Policies to Test

3.4 **Testing the New Condition-Based Stock Policies**

The focus is on set $\mathbf{S}_1^{2011''}$, which contains 18,137 SKUs without demand in 2011. Of these 18,137 SKUs, 1,934 had at least one demand in 2012, that is $|\mathbf{S}_1^{2011''} \cap \mathbf{S}_1^{2012'}|$ = 1,934. The demand-based policy is to not stock any of these parts at any location; as such, all 1,934 actual demands had implications to the revenue generating machine. Using equation (9), the demand-based stock policy cost the firm \$12.9M. With the demand-based stock policy cost determined, the 110 condition-based stock policies are tested; motivated by the desire to improve the cost-effectiveness of stock policy on these very sparse, intermittently demanded, inexpensive parts.

3.4.1 Pseudo Code to Test Potential New Stock Policies

The following pseudo code describes the methodology used to test the 110 potential new stock policies, including use of equation (9) to determine the cost and benefits of the potential condition-based stock policies.

For n = 1 to |L| ‘ numerical value to compare to R_p^{2011}
 For j = 1 to 10 ‘ runs thru the range of cost buckets to test
  $part\ cost = 10^{\sqrt{j}}$ ‘ numerical value to compare to PC
   For ∀ 18,137 *(p,l)* (SKUs in $\mathbf{S}_1^{2011''}$) ‘ test policy on SKUs with no 2011 demand
    If $PC_{pl} \le part\ cost$ & $R_p^{2011} \ge n$ ‘ policy will stock these SKUs
     If *(p,l)* ∈ $\mathbf{S}^{2012'}$ then ‘ subsequent demand in 2012
      $Cost_1 = Cost_1 + (PC_{pl} + 0.5HC_{pl})$ ‘ case 1
     Else ‘ no subsequent demand in 2012
      $Cost_2 = Cost_2 + (PC_{pl} + HC_{pl})$ ‘ case 2
     End If
    Else ‘ policy will not stocks these SKUs
     If *(p,l)* ∈ $\mathbf{S}^{2012'}$ then ‘ subsequent demand in 2012
      $Cost_3 = Cost_3 + (TC_{pl} + RC_{pl})$ ’ case 3
     Else ‘ no subsequent demand in 2012
      $Cost_4 = 0$ ‘ case 4
     End If
    End If
  $Cost\ (n, j) = \sum_{i=1}^{4} Cost_i$ ‘ record stock policy (min R_p, max PC_{pl}) cost
 Next j
Next n

3.5 **Initial Experimental Results**

As anticipated, as stock policies increase the number of SKU’s proactively stocked, procurement costs, PC_{pl}, and holding costs, HC_{pl}, go up while loss of revenue, RC, and expedited transportation costs, TC_{pl}go down. This occurs when the number of locations R_p^t is small (≤ 2) and the procurement costs PC_{pl} are high (≥ \$1000). The converse is also true; as the stock policies decrease the number of SKU’s proactively stocked, procurement costs, PC_{pl}, and holding costs, PC_{pl}, go down, while loss of revenue, RC_{pl}, and expedited transportation costs, TC_{pl} go up. A contour plot, using common software, of the results is shown in Figure 12. Each dot in the plot resents one of the 110 stock polices that were tested.

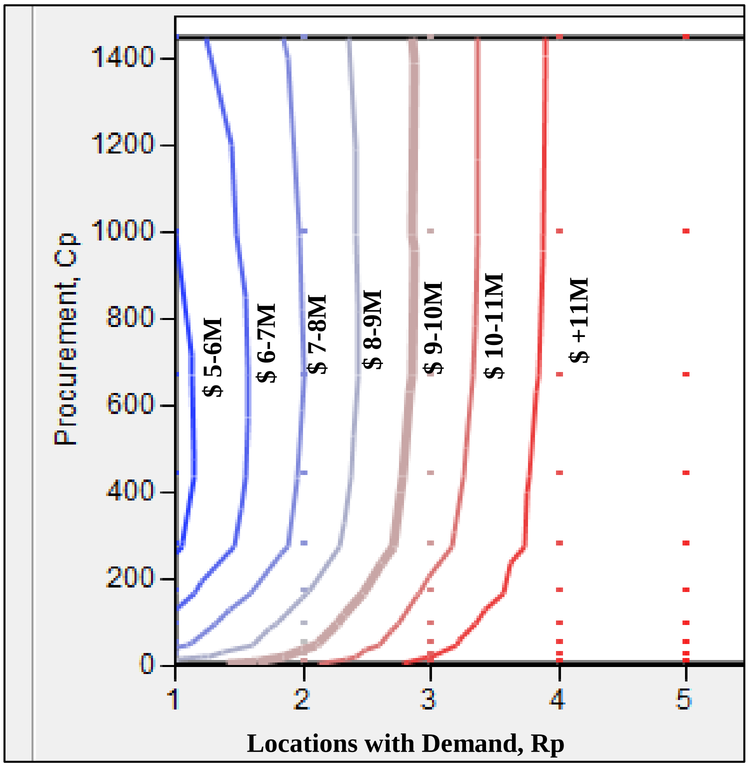

Figure 12: Contour Plot of Case Study Results

As the number of locations, R_p^t, increases to four and above, it is observed that contours do not continue. This region of the area is relatively flat because the costs of those stock policies remain about equal. Looking at each decision provides insights, and highlights the fact that this problem instance is all about very sparse, intermittently-demanded items. As such, there are simply very few parts that have historical demand at four+ locations. In fact, none of the 3,111 parts had demand at 9 or more locations. For this problem instance, any/all new condition-based stock policies where $R_p^t \geq 9$, produce the same cost/benefits as the demand-based stock policy; the demand-based and condition-based stock policies, albeit for completely different reasons, simply don't proactively stock SKUs in advance of demand.

Recall the firm's current policy is to stock none of these 18,137 SKUs, and the demand-based stock policy cost per equation (9) is $12.9M. Following the contour lines in Figure 12 from right to left, each contour represents a change of $-1M. With seven contours, the contour line farthest left represents costs of $5M; cutting the As Is demand-based stock policy cost by $7.9M. Table 4 lists the top 25 cost-effective condition-based stock polices, along with the As Is demand-based stock policy (Appendix A contains the results of all 110 tested condition-based stock policies).

For this problem instance, it is very clear that a condition-based stock policy is much more cost-effective than the As Is demand-based stock policy, which does not stock any of the very sparse, intermittently-demanded items because $\lambda \approx 0$; thus, no lead time demand. Additionally, a condition-based stock policy that recognizes and uses smaller values of R_p^t proactively stocks more SKUs and leads to a more cost-effective policy than the As Is demand-based stock policy, especially when the condition-based stock policy includes the procurement cost, PC_{pl}.

Table 4: Cost/Benefits of As Is & Top 25 Condition-Based Polices (R_p^t, PC_{pl})

Stock Policy Criteria (minimum Rp, maximum PC)	**SKU's Stocked**		**SKU's Not Stocked**		**Costs of Stock Policy ($)**				
	# SKU's Stocked by Policy	demand on stocked SKU's (next 12 months)	# SKU's Not Stocked by Policy	demand on non stocked SKU's (next 12 months)	*PC* (procurement)	*HC* (holding)	*TC* (expedited transporation)	*RC* (lost revenue)	*Total Cost of Stock Policy*
"As Is" Demand Based	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(1 , 442)	15,872	1,634	2,265	300	2,450,180	183,764	105,000	1,898,400	4,637,344
(1 , 674)	16,766	1,742	1,371	192	3,174,349	238,076	67,200	1,214,976	4,694,601
(1 , 282)	14,824	1,507	3,313	427	1,857,529	139,315	149,450	2,702,056	4,848,350
(1 , 1000)	17,503	1,832	634	102	4,002,001	300,150	35,700	645,456	4,983,308
(1 , 1453)	18,137	1,934	0	0	5,216,033	391,203	-	-	5,607,236
(1 , 172)	13,638	1,308	4,499	626	1,355,708	101,678	219,100	3,961,328	5,637,814
(1 , 100)	12,361	1,139	5,776	795	926,899	69,517	278,250	5,030,760	6,305,426
(1 , 54)	11,403	1,037	6,734	897	738,374	55,378	313,950	5,676,216	6,783,918
(2 , 674)	7,237	1,173	10,900	761	1,749,350	131,201	266,350	4,815,608	6,962,509
(2 , 1000)	7,503	1,223	10,634	711	2,133,791	160,034	248,850	4,499,208	7,041,883
(2 , 442)	6,831	1,097	11,306	837	1,377,105	103,283	292,950	5,296,536	7,069,874
(2 , 1453)	7,822	1,294	10,315	640	2,755,781	206,684	224,000	4,049,920	7,236,385
(2 , 282)	6,384	1,016	11,753	918	1,061,572	79,618	321,300	5,809,104	7,271,594
(1 , 26)	9,909	894	8,228	1,040	550,666	41,300	364,000	6,581,120	7,537,086
(2 , 172)	5,796	869	12,341	1,065	740,536	55,540	372,750	6,739,320	7,908,147
(2 , 100)	5,231	759	12,906	1,175	532,260	39,919	411,250	7,435,400	8,418,829
(1 , 10)	7,719	741	10,418	1,193	427,538	32,065	417,550	7,549,304	8,426,458
(2 , 54)	4,799	689	13,338	1,245	420,302	31,523	435,750	7,878,360	8,765,934
(2 , 26)	4,178	600	13,959	1,334	334,819	25,111	466,900	8,441,552	9,268,382
(3 , 1453)	3,282	750	14,855	1,184	1,272,987	95,474	414,400	7,492,352	9,275,214
(3 , 1000)	3,144	711	14,993	1,223	1,044,900	78,368	428,050	7,739,144	9,290,462
(3 , 674)	2,989	672	15,148	1,262	847,919	63,594	441,700	7,985,936	9,339,149
(3 , 442)	2,807	625	15,330	1,309	699,158	52,437	458,150	8,283,352	9,493,097
(3 , 282)	2,560	571	15,577	1,363	535,436	40,158	477,050	8,625,064	9,677,708
(2 , 10)	3,382	513	14,755	1,421	286,152	21,461	497,350	8,992,088	9,797,051

3.6 **Conclusions and Future Research**

Our framework to find a conditioned-based stock policy for the very sparse, intermittently-demanded, inexpensive parts demonstrates the possibility of a large dividend. Ketchen and Hult remind us that best-value supply chains are agile and have a "strong ability to be proactive as well as responsive to changes." [43]. Using a generalized Bayesian approach, our framework provides a method to identify condition-based policies that would proactively stock some SKUs because doing so advances the cost-effectiveness of the stock policy. The SCM should procure many inexpensive items, in advance of demand, and forward stock them to reduce the down time of revenue-generating machines.

This study leveraged 12 months of actual demand data to capture costs and benefits. It is desirable to expand from one year to two years of actual demand data to evaluate the stock policy, including an annual update to the SKUs that get stocked by the policy. The costs in equation (9) can easily be expanded to include the second year. With the additional data, for example, the framework would capture the reduced $RC_{pl}$and TC_{pl} costs as a result of getting additional demand in the second year, as well as the additional HC_{pl} for those that don't. Furthermore, equation, (9) could be expanded to contain cost elements for salvage and disposal.

3.6.1 Update - Real World Implementation

This paper shows significant merit in determining condition-based stock policy for a subset of parts on the revenue-generating machine; namely, the very sparse, intermittently-demanded, inexpensive items. The merit exits because the Bayesian beliefs associated with equations (4) and (7) are shown to be valid with empirical data.

The same Bayesian beliefs were accepted by AF leadership and the AF stood up a centralized management team in Fiscal Year 2012. This team implemented a condition-based stock policy called Proactive Demand Leveling [44], demonstrating the value of our framework to the operational world.

Our framework can be used to determine condition-based stock policies on the very sparse, intermittently-demanded, inexpensive parts; ultimately, achieving the SCM's desire to improve the cost-effective readiness of the firm's revenue-generating machines.

IV. Improved Stock Policy for Very Sparse, Intermittently-Demanded Reparable Items

4.1 Motivation

The motive behind chapters 3 and 4 is to advance the management of the very sparse, intermittently-demanded parts of the revenue-generating machine. Chapter 3 focuses on the inexpensive/consumable parts. Chapter 4 shifts to the expensive/reparable parts which contain additional challenges:

> "Our interest is the support of systems, and it turns out that the availability of these is dominated by repairable items. These repairable items tend to be expensive, and the demand at a base for any particular item tends to be low. Another reason to pay special attention to repairable spares is that they tend to have longer lead times. If we buy an insufficient quantity, it will take longer to rectify the error" – Sherbrooke [1]

4.2 Introduction

As hinted by Sherbrooke, the expensive parts require two additional 'dimensions' to manage, namely: (1) the repair policy is needed because unserviceable parts can often be repaired to serviceable condition and, (2) the high costs of these parts often shifts the network-based decision where to stock. For clarity, a serviceable asset is a part that is operational and ready to be installed on the revenue-generating machine; an unserviceable asset is a failed part that has been removed from the revenue-generating machine and needs to be repaired before it can be used again. As for the network, shown in Figure 13, the term multi-echelon [19] [39] [18] is typically used to describe the network where a wholesale supply node provides parts to retail demand node(s).

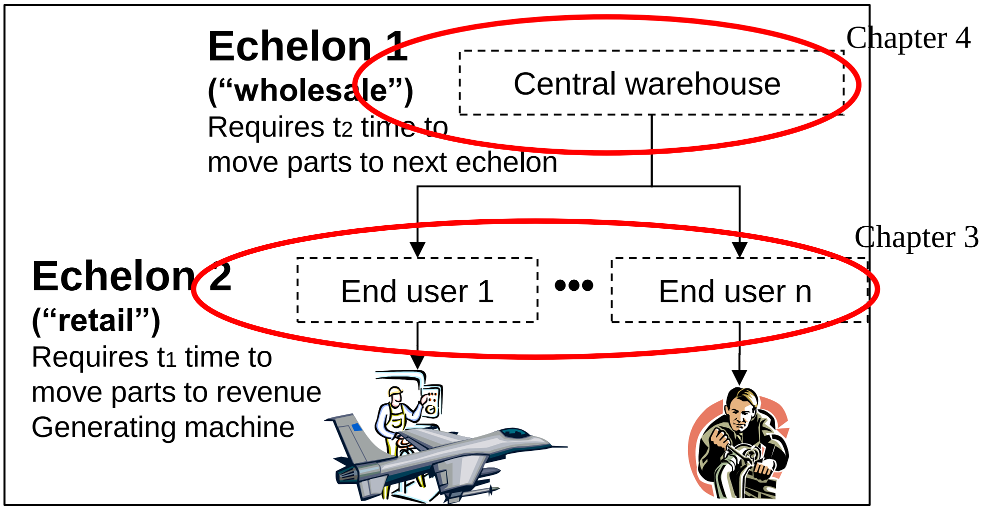

Figure 13: Focus of Chapters 3 & 4 Related to Multi-Echelon Network

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Chapter 3 can be thought of as a retail problem instance because it's attempting to push some of the inexpensive, intermittently-demanded spare parts right next to the revenue-generating machines; thus, avoiding resupply time t_2 from Figure 13. Chapter 4 is primarily a wholesale problem instance where the supply chain manager has the difficult decision: should they stock 0 spare parts, or 1, or more, just to be safe? Also, given these items are reparable, should the supply chain manager repair any/all of the unserviceable part(s) and stock them as serviceable – OR – leave them unserviceable and repair only when needed by a revenue-generating machine?

The intermittently-demanded, expensive parts in our research are parts that (1) are coded as being reparable and (2) have at least 50% of the time intervals with zero demand. We note that our definition of intermittent demand further restricts Boylan's definition [8]. The parts in our research are represented by the set $\mathbf{P}$, shown in Figure 14. For notation clarity, let p be an individual part, $p \in \mathbf{P}$.

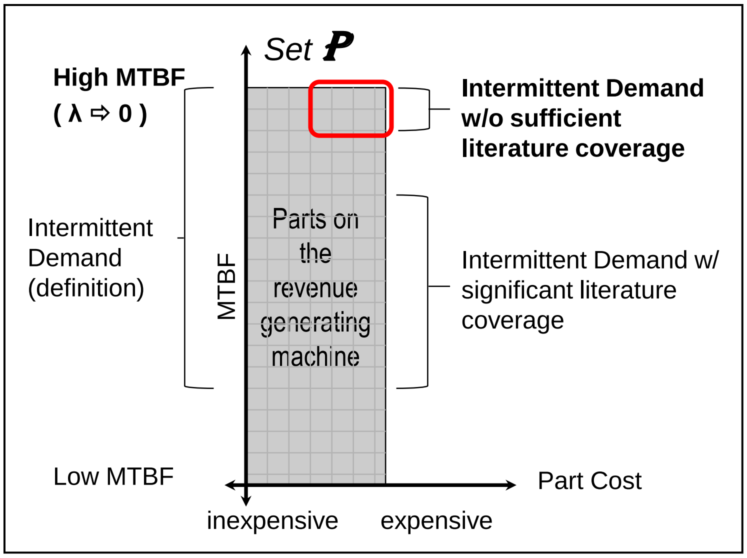


Figure 14: Set **P**, the Parts Included in this Research

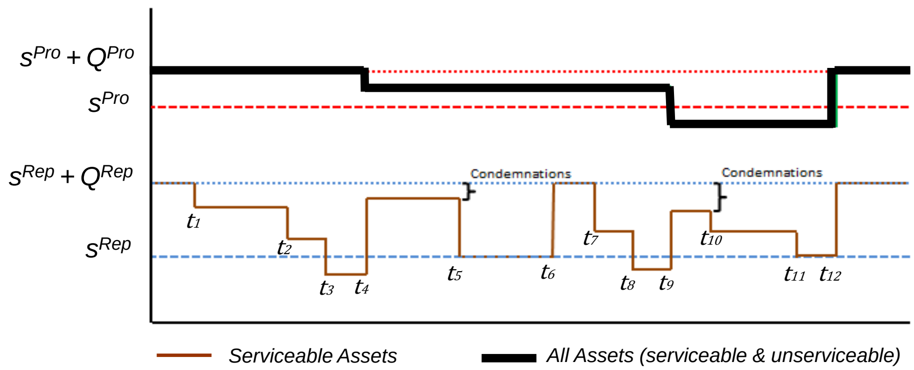
4.2.1 Stock Policy: Complexity of Reparable Parts

Supply chain stock policy is typically defined by a three parameter notation [7] which defines the engagement rules for the supply chain manager's resources. A common, general policy is (*s*, *Q*, *R*), where: *s* defines the reorder point, *Q* defines the replenishment quantity (often Wilson's EOQ), and *R* defines the review period. When the review period is continuous, the *R* is often omitted and the notation contains only two parameters (s, Q).

Using (7, 3, 30) as a repair-only example: every 30 days (i.e. *R*), serviceable on-hand assets are reviewed and if 7 (i.e. *s*) or fewer exist, then an order is placed by the supply chain's repair resources for a quantity of 3 (i.e. *Q*). Two key additional questions arise. (1) What if there are not enough unserviceable assets to repair? (2) What if some/all of the unserviceable parts are beyond repair and must be condemned? Answers to these questions hint at the need to procure additional parts and highlights the natural interaction between repair and procurement stock policies.

To differentiate between the procurement stock policy and the repair stock policy, we use a superscript *Pro* for procure and *Rep* for repair. Thus, the procurement stock policy is defined by (s^{Pro}, Q^{Pro}, R^{Pro}) and the repair stock policy is defined by (s^{Rep}, Q^{Rep}, R^{Rep}). For both the repair and procure processes, it is the reorder point, s, that triggers the supply chain resources to take action, but there is a distinct difference between the two that must be clear. For repair, only serviceable assets are counted and compared to s^{Rep}; however, for the procurement process, all assets (serviceable and unserviceable) are counted and compared to s^{Pro}.

We show an example of this interaction over time, using an asset-based diagram of a notional part via Figure 15. At time t_4, some asset(s) are condemned because they are beyond repair; no procurement action is taken because the procurement reorder point, s^{Pro}, is not yet breached. Again, at time t_9, some asset(s) are condemned because they are beyond repair; however, this time, the procurement reorder point is breached and the supply chain manager's procurement resources engage to procure Q^{Pro} asset(s).



time (t)	event
1, 2, 3	part failure(s) - decrement serviceable assets, increment unserviceable assets
3	breach of repair reorderpoint, s - invoke repair process (to get Q more serviceable assets)
4	part(s) repaired - decrement unserviceable assets, increment serviceable assets
	parts(s) condemned - decrement total assets (sum of serviceable and unserviceable assets)
5	part failure(s) - decrement serviceable assets, increment unserviceable assets
6	part(s) repaired - decrement unserviceable assets, increment serviceable assets
7, 8	part failure(s) - decrement serviceable assets, increment unserviceable assets
8	breach of reorder point, s - invoke repair process (to get Q more serviceable assets)
9	part(s) repaired - decrement unserviceable assets, increment serviceable assets
	parts(s) condemned - decrement total assets (sum of serviceable and unserviceable assets)
	breach of procure reorder point, s - invoke procure process (to get Q more assets)
10, 11	part failure(s) - decrement serviceable assets, increment unserviceable assets
11	breach of repair reorder point, s - invoke repair process to get q more serviceable assets
12	part(s) repaired - decrement unserviceable assets, increment serviceable assets
	part(s) procured - increment total assets

Figure 15: Notional Timeline of Changing Assets and Stock Policy Actions

4.3 The Research Question

The scope of this chapter is to create a framework that can improve stock policies for both procurement (s^{Pro}, Q^{Pro}, R^{Pro}) and repair (s^{Rep}, Q^{Rep}, R^{Rep}). The research question is: what advancements can be made to stock policy on expensive/reparable items that have near-zero lead time demand– yet if/when demanded, will likely down the revenue generating machine for a substantial length of time?

There are several approaches a supply chain manager could use to answer the research question and improve stock policies. We propose one such approach in Section 4.4 and follow up an actual case study in Section 4.5 that uses the proposed approach. Finally, we provide a summary and conclusion in Section 4.6.

4.4 **The Approach to Address the Research Question**

The approach is to construct a framework to extend Bachman's [24] work. For consumable-only intermittently-demanded parts, Bachman's method looks back upon previous time intervals and establishes the maximum demand, by part. The maximum demand is combined with a user-determined multiplier, which is greater than or equal to 0. The reorder point, *s*, is then determined as

$$s = \textit{multiplier} * \text{maximum demand} \tag{10}$$

Bachman shows in [24] that using this method produces improved stock policy for the intermittently-demanded consumable parts managed by the Defense Logistics Agency. We expand on Bachman's work by adding reparable parts, which adds significant complexity. Shown in Figure 16 are demand and condemnation quantities, by part, plotted over a given time interval *t*, which is comprised of *k* intervals. Let the maximum demand for each part, *p*, over *k* intervals be:

$$\max \mathrm{dmd}_p = \max\{\mathrm{demand}_{p,1}, \mathrm{demand}_{p,2}, \dots, \mathrm{demand}_{p,k}\} \tag{11}$$

Similarly, let maximum condemnations be:

$$\max \mathrm{cmd}_p = \max\{\mathrm{condemns}_{p,1}, \mathrm{condemns}_{p,2}, \dots, \mathrm{condemns}_{p,k}\} \tag{12}$$

The maximum demand and maximum condemnations will be used in the development of the procurement and repair stock policies we seek.

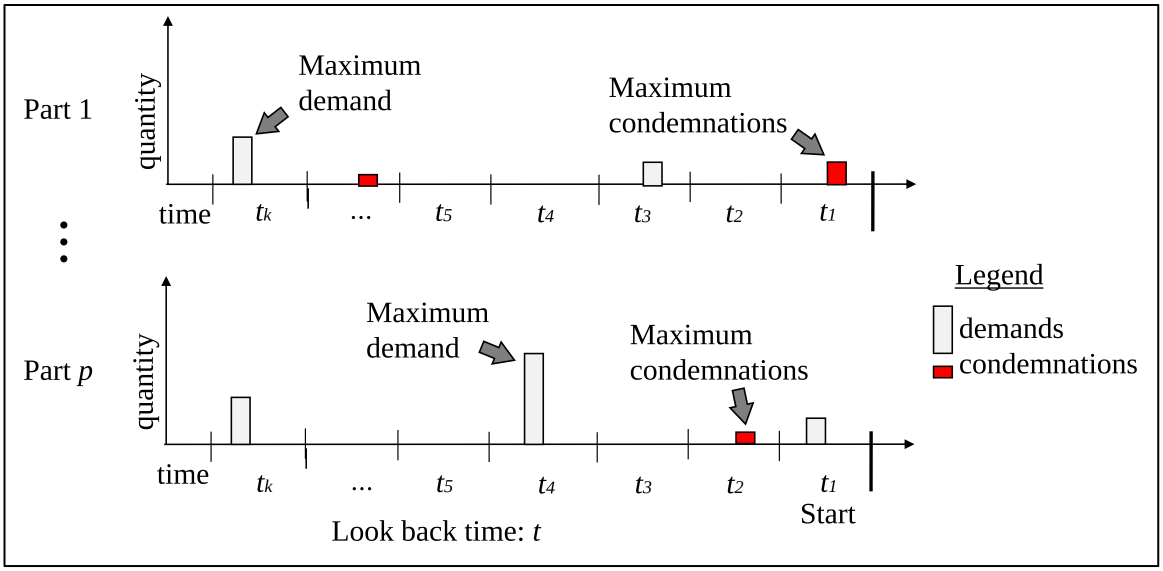


Figure 16: Demand and Condemnations on Two Example Parts

4.4.1 Defining Procurement and Repair Stock Policies

Let $mult_p^{Rep}$ be a user-defined parameter defined by real numbers in the range $[0, \infty)$. Let the reorder point for the repair process, for a given part *p*, be defined as:

$$\mathrm{s}_{\mathrm{p}}^{\mathrm{Rep}} = \max \mathrm{dmd}_p \ * mult_p^{Rep} \tag{13}$$

When this repair multiplier is zero, the repair reorder point is also zero which means the supply chain manager's resources don't take repair actions until there are no serviceable assets. Suppose the multiplier is 3.5 and the maximum demand for a given part is 2, then (13) produces the repair reorder point of 7. Given the common desire for a firm to minimize inventory, the assumption is that very expensive parts to repair will have smaller repair multipliers, relative to the parts that are cheaper to repair.

Similarly, Let $mult_p^{Pro}$ be a user-defined parameter defined by real numbers in the range $[0, \infty)$. Let the reorder point for the procurement process, for a given part *p*, be defined as:

$$\mathrm{s}_{\mathrm{p}}^{\mathrm{Pro}} = (\max \mathrm{dmd}_p + \max \mathrm{cmd}_p) * mult_p^{Pro} \tag{14}$$

When the procurement multiplier is zero, the procurement reorder point is also zero which means the supply chain manager's resources don't take actions to procure assets until no spare assets (serviceable and serviceable) exist. Suppose the multiplier is 1.5, the maximum demand is 4, and the maximum condemnations are 2, then (14) produces the procurement reorder point of 9. Similar to repair, the assumption is that the very expensive parts to procure will have smaller procurement multipliers, relative to the parts that are cheaper to procure.

Equations (13) and (14) show specific repair and procurement multipliers for a given part, *p*. Having a specified repair and procurement multiplier for each part, *p*, could be computationally challenging when $|\mathbf{P}|$ is large, as is the case on many revenue-generating machines [38] [45] [27]. For example, if $|\mathbf{P}|$ = 10,000 then 20,000 values must be determined for the procurement and repair multipliers. On the other end of the spectrum, a single multiplier could be used for repair and procurement for all parts. Using this methodology requires the supply chain manager to determine how many multipliers, or groupings of parts, to use. Bachman [24] suggests a good starting point is four to six groupings; with four groups, break points could be set at 25%, 50%, and 75%; with six groups, break points could be 5%, 25%, 50%, 75%, and 95%.

To complete the stock policies, let $\mathrm{Q}_{\mathrm{p}}^{\mathrm{Pro}}$ and $\mathrm{Q}_{\mathrm{p}}^{\mathrm{Rep}}$ be user-defined parameters defined by positive integers in the range $[0, \infty)$.

4.4.2 Description of the Underlying Decision Variables

Given the need to establish groups for repair and procurement, we partition the parts, p ϵ $\mathbf{P}$, into *n* subsets according to repair cost and *m* subsets according to procurement cost. The partitioning for repair places each part into a disjoint (repair) subset, that is: $p_i \cap p_k = \emptyset\ \forall i \neq k$ and $\bigcup_{i=1}^{n} \mathbf{P}_i = \mathbf{P}$. Similarly, partitioning for procurement places each part into a disjoint (procurement) subset, that is: $p_i \cap p_k = \emptyset\ \forall i \neq k$ and $\bigcup_{j=1}^{m} \mathbf{P}_j = \mathbf{P}$.

Given the partition, then *n*-1 decision variables are needed to identify the break points for the *n* repair groups. Similarly, *m*-1 decision variables are needed to identify the break points for the *m* procurement groups.

Additionally, *n* decision variables we call $mult_i^{Rep}, i = \{1, \dots, n\}$ are needed to determine repair multipliers. Similarly, *m* decision variables we call $mult_j^{Pro}, j = \{1, \dots, m\}$ are required to determine procurement multipliers. Using *m* and *n* in our group notation, the reorder points for out repair and procurement stock policies are defined as:

$$\mathrm{s}_{\mathrm{p}}^{\mathrm{Rep}} = \max \mathrm{dmd}_p * mult_i^{Rep} \quad \forall p \in \mathbf{P}_i, i = \{1, \dots, n\} \tag{15}$$

$$\mathrm{s}_{\mathrm{p}}^{\mathrm{Pro}} = (\max \mathrm{dmd}_p + \max \mathrm{cmd}_p) * mult_j^{Pro}\ \forall p \in \mathbf{P}_j, j = \{1, \dots, m\} \tag{16}$$

In total, as shown in Table 5, 3*n*+3*m* decision variables are required in order to determine the procurement and repair stock policies. Since *m* and *n* can range from 1 to

$|\mathbf{P}|$, the total number of decision variables can range from a minimum of 6 to a maximum of $6|\mathbf{P}|$.

Table 5: Summary of the Decision Variables

Decision Variable Description	Count
Lookback time	1
Interval size	1
Price breaks (for n buckets of repair)	n-1
Multipliers for repair	n
Quantity for repair	n
Price breaks (for m buckets of procurement)	m-1
Multipliers for procurement	m
Quantity for procurement	m
totals	**3n + 3m**

4.4.3 Multi-objective Functions

The procurement and repair stock policies drive many objectives that have varying levels of importance to the supply chain manager, depending upon the given firm. Four objectives, likely common to many supply chain managers, are: (1) minimize customer wait time, (2) minimize the dollars of inventory to carry, (3) minimize the dollars required to repair unserviceable assets, and (4) minimize the dollars required to procure assets. Given four objectives, one could employ a multi-objective function [46].

$$\begin{aligned} \min y &= (f_1(x), f_2(x), f_3(x), f_4(x)) && \text{‘ multi-objective function} \\ \text{s.t. } & x \in X && \text{‘ decision variables within space} \end{aligned} \tag{17}$$

Not that all of the decision variables are defined, we demonstrate one procedure for optimizing the supply chain mangers decisions based on these variables. In Section 4.5, we apply the approach via a case study. A deterministic simulation is used to calculate the objectives of interest based on choices for the decision variables, then we apply a meta modeling approach to replace the simulation calculations with a less complex function that we then use optimize our objectives.

4.5 **Case Study: 1755 Parts on the B-1**

To test the proposed framework, we perform a case study on reparable parts belonging to the B-1 fleet of aircraft. To establish the parts for set $\mathbf{P}$, we used 20 intervals defined by the 20 quarters of 'look back' data ranging from Oct 2004 – Oct 2009. We include only reparable parts that have sparse intermittent demand, defined by demand in 10 or fewer of the 20 quarterly intervals. This segmentation resulted in 1,755 parts in $\mathbf{P}$. We used the same 20 quarters of data to compute the maximum demand using (11) and maximum condemnations using (12) for each of the 1,755 parts. Lastly, we pulled both repair times and procurement times for the 1,755 parts.

4.5.1 Reducing and Establishing Decision Variables for our Case Study

For our case study, we fix the values on some variables as appropriate for our problem instance. This reduces the number of required decision variables from ($3m + 3n$) to ($m + n$).

The decision variable, t, is set to a 'look back' time of five years and the decision variable for number of intervals is set to 20 quarters. We use uniform splitting (equal number of parts) and established six groupings for repair and six groupings for procurement; thus, $m = n = 6$. Given the desire to have six repair groups with equal numbers of parts, the five (n-1) price breaks for repair are: {$425, $990, $2270, $5625, and $24700}. Given the desire to have six procurement groups with equal numbers of parts, the five (m-1) price breaks for procurement are: {\$685, \$1550, \$4000, \$11305, and \$71675}.

Given our case study is on the very sparse, intermittently-demanded items, and that the USAF employs a repair on demand policy and primarily only procures assets according to condemnations, we fix the values for all six Q^{Rep} and all six Q^{Pro} to one; that is: $Q_{\mathrm{m}}^{\mathrm{Pro}} = Q_{\mathrm{n}}^{\mathrm{Rep}} = 1$. We are then left with 12 decision variables: six decision variables for repair ($mult_1^{Rep}, \ldots, mult_6^{Rep}$) and six decision variables for procurement ($mult_1^{Pro}, \ldots, mult_6^{Pro}$). These decision variables are used in (15) and (16) to determine the reorder portion of the stock policies.

4.5.2 Addressing a Four-Objective Problem: Scalarization Techniques

While multiple criteria problems are challenging, there are multiple modeling techniques used to solve them [46]. One technique, scalarization, has two different methods that can be used: (1) the weighted-sum method, which aggregates the multiple objectives into a single objective to be optimized, and (2) the epsilon constraint method, which retains a single objective to optimize and utilizes the remaining objective(s) as constraints.

An example of the weighted sum modeling method for our problem instance, could be a single (objective) function such as:

$$\min y = \frac{4}{7} CWT + \frac{1}{7} Inventory + \frac{1}{7} repaircost + \frac{1}{7} procurment\ cost) \qquad (18)$$

The weighted sum method can be effectively used when appropriate weights are known a priori. This implies the decision maker or SME has knowledge of all the objectives and ‘pre-builds’ the trade-space into the singularized objective function, such that it can be optimized. The weighted sum method becomes very difficult to use on problem instances that don’t lend themselves to a natural, a priori assignment of the weights. For example, CWT may be critically important to one person or organization within the firm who interfaces with operators of the revenue-generating machines. However, inventory is probably the most important objective to a person or organization within the firm who manages ‘excess’ inventory. Therefore, one person or organization would put an extremely high weight on CWT while another would do the same on inventory. The weighted sum method is a viable

An application of the epsilon constraint modeling method, for our problem instance, could be:

$$\begin{aligned} \min\ & y_1 = CWT \\ \text{s.t. } & Inventory = y_2 \leq \varepsilon_2 \\ & Repair\ Cost\ = y_3 \leq \varepsilon_3 \\ & Procurement\ Cost\ = y_4 \leq \varepsilon_4 \end{aligned} \tag{19}$$

For our research, we use the epsilon constraint method because weightings for the relative values of the responses are not available. Suppose a firm has a limit on how much inventory they want to carry. This limit can be used for ε_2 in (19). The same can be said for repair and procurement costs, ε_3 and ε_4. Even if the firm does not have limits for the constraints, the epsilon constraints can be evaluated at multiple settings within practical, feasible ranges to show decision makers what types of trade-offs can be made between the objectives.

A natural consequence of the USAF's 'on demand' repair operations and limited procurement, as demonstrated with procurement and repair quantities set to 1 (ref 4.5.1 where $Q_{\mathrm{m}}^{\mathrm{Pro}} = Q_{\mathrm{n}}^{\mathrm{Rep}} = 1$), is that any changes to the underlying, steady-state objectives for repair and procurement costs will likely be unchanged. The repair and stock policies we seek to develop, will likely change the inventory and may drive a one-time change to procurement and repair activity and thus impact procurement and repair costs, but following the implementation of the new policies, procurement and repair activity will return to steady state by again operating in 'on demand' mode. Thus, the objectives for procurement and repair costs are not of primary concern within our problem instance. The focus, then, remains on the objectives of customer wait time and dollars of inventory.

Because our motive is to improve upon the current stock policy, we capture and record the current performance. The baseline As Is policy results in $297.6M of inventory and produces a 23.03 day average customer wait time. We can use these as constraints within the epsilon constraint modeling method. The epsilon constraint modeling method requires a known function of the impact of the decision variables on the response. A function is desirable because evaluating a function, or its derivative, at a number of values is typically easier than running experiments for each value [47].

4.5.3 Metamodel Approach

The multi-objective function of (17) may become very large and extremely complex. For our problem instance, 12 decision variables are combined with data from 1,755 parts and computations must be made, over time, to determine the objectives for average dollars of inventory and customer wait time performance. When many factors exist and/or the system is rather complex, deterministic simulation models are a viable approach for the researcher/engineer to arrive at solutions [48]. Additionally, when designed experiments are applied to simulated systems, the data from the experimental design is used to build a metatmodel [48] [49] and the metamodel is used for optimization and building the response surface.

To find procurement and repair policies that advance the cost-effectiveness of the supply chain, our case study focusses on the response surface and finding solutions that improve upon the baseline performance of CWT and inventory. Solution points that are equal to or better than all objectives are called nondominated points [46]. We seek to find nondominated points of CWT and inventory. For our problem instance, nondominated points would require no more than $297.6M of inventory and perform with a customer wait time of 23.06 days or better.

To find advanced stock policies, we use designed experiments to estimate the relationship between CWT, inventory costs, and our decision variables. Figure 17 shows the overview of our approach. The first step is to establish bounds on the 12 decision variables. The second step is to create the metamodel. The third step is to evaluate the adequacy of the metamodel. If the metamodel is not adequate, an improvement to the metamodel is desired, as shown via the feedback arrow in Figure 17. We note that if the metamodel can't be improved, other methods such as the steepest ascent/descent [48] can be used to determine optimal points. Our fourth step is to use the metamodel to produce viable operating points; preferably, nondominated points.

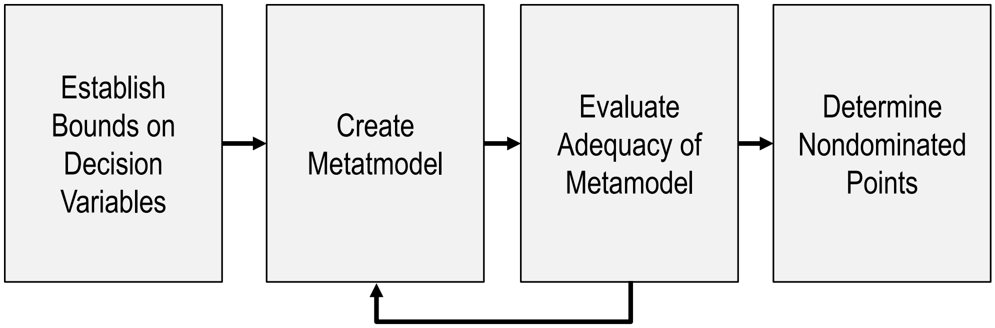


Figure 17: Use of Metamodel in Research

Step 1, Establish Bounds on Decision Variables: Because the 12 decision variables could take on all positive real numbers, we recognize the utility in establishing bounds. Several approaches could be used to limit the decision variables. One common approach is to have them bounded by a subject matter expert. For our problem instance, we establish bounds on the 12 multipliers using underlying limits specific to our problem instance. The six repair multipliers will be bounded by determining the minimum multiplier that results in repairing all unserviceable assets. The six procurement multipliers will be bounded by using the $297.6M inventory baseline. For both the procurement and repair multipliers, we use the bisection method [50]. The bisection method works by finding values above and below a point of interest, and then converges by moving a user-defined step in each iteration until the solution is found.

To find the bounds on the six repair multipliers, all are initially set to zero. Then, one at a time, the individual multipliers are incremented until its value results in a maximum response of inventory. This occurs when all unserviceable assets are repaired. For our problem instance, we begin with a step size of 10, then double each iteration until two iterations in a row produce the same response. We then use the bisection method to find the minimum multiplier that still forces all unserviceable assets to be repaired.

Bounds on the six procurement multipliers are found similarly. We begin with a step size of 10, then double (if under \$297.6M) or cut in half (if under \$297.6M) each iteration until the \$297.6M is breached. Given multipliers above and below the \$297.6M point of interest, we use the bisection method and terminate when the two multipliers (that produce inventory just above and just below the \$297.6M point of interest) are within 2% of each other. The two applications of the bisection method produce bounds on the 12 decision variables as recorded in Table 6.

Table 6: Limits on 12 Decision Variables

Procurement Decision Variables	Repair Decision Variables
$mult_1^{Pro} = [0, 1262]$	$mult_1^{Rep} = [0, 153]$
$mult_2^{Pro} = [0,113]$	$mult_2^{Rep} = [0, 247]$
$mult_3^{Pro} = [0, 31]$	$mult_3^{Rep} = [0, 107]$
$mult_4^{Pro} = [0, 12.8]$	$mult_4^{Rep} = [0, 144]$
$mult_5^{Pro} = [0, 7.5]$	$mult_5^{Rep} = [0, 149]$
$mult_6^{Pro} = [0, 1.77]$	$mult_6^{Rep} = [0, 26]$

<u>Step 2, Create Metamodel</u>: The purpose of the metamodel is to provide a set of equations (one per response) to show how the decision variables impact the response [48] [49]. For our problem, the metamodel will be used to generate an equation for CWT and an equation for inventory. With these equations, we determine optimal settings of the decision variables.

To create our metamodel, we utilize a sphere packing design. A sphere packing design falls under a more generalized design called space filling. Space filling designs are appropriate when deterministic simulation is modeling the underlying system [48].

Space filling designs spread the design points out nearly evenly throughout the region of experimentation. “This is a desirable feature if the experimenter doesn’t know the form of the model that is required, and believes that interesting phenomena are likely to be found in different regions of the experimental space” [48]. The space filling design is appropriate for our problem instance; however, the supply chain manager should choose an experimental design that is appropriate for his/her environment.

The sphere packing design requires high and low values for the decision variables and the number of runs. Collectively, the high/low values and number of runs, determine the experimentation settings, or granularity of the decision variables to test. We set the number of runs to 500. The choice of number of runs is usually linked to cost and the supply chain manager should run as many points as affordability allows. The low values for our decision variables are zero. The high values for our decision variables are the upper bounds per Table 6. We show results of the 500 runs in the scatter plot of Figure 18.

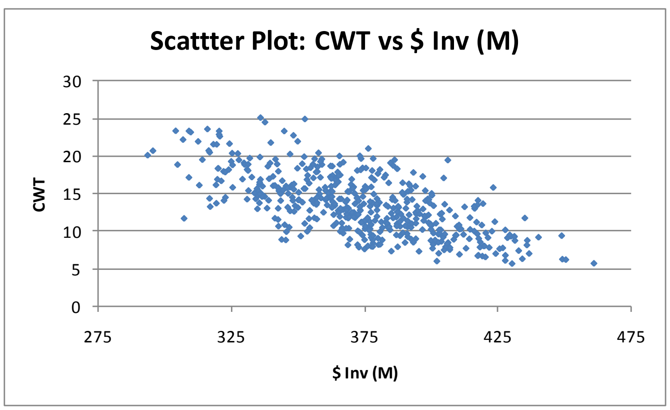


Figure 18: Scatter Plot of 500 Runs

The metamodel will be used capture the response and provide usable information at feasible regions of operation. We build the initial metamodel to estimate 91 terms, comprised of: (1) intercept, (12) main effects, (66) two-way interactions, and (12) main effects squared. A summary of the 91 terms is shown in Table 7.

Table 7: Terms Considered for Metamodel

Count	**Term**	**Notation**
1	Intercept	b
12	Main Effects	$mult_i^{Rep}$, $i = \{1, \dots, 6\}$ & $mult_j^{Pro}$, $j = \{1, \dots, 6\}$
36	2 Way Interactions	$(mult_i^{Rep})(mult_j^{Pro})$, $i, j = \{1, \dots, 6\}$
30	2 Way Interactions	$(mult_j^{Pro})(mult_{j+1}^{Pro})$, $j = \{1, \dots, 5\}$ $(mult_i^{Rep})(mult_{i+1}^{Rep})$, $i = \{1, \dots, 5\}$
12	Square (Main Effects)	$(mult_i^{Rep})^2$, $i = \{1, \dots, 6\}$ $(mult_j^{Pro})^2$, $j = \{1, \dots, 6\}$

Our regression (of CWT and inventory) provides information on the 91 terms being considered for the metamodel (ref Appendix B), including the p values. "The p value is the smallest level of significance that would lead to rejection of the null hypothesis H_o with the given data" [51]. Stated another way, the smaller the p value, the higher the confidence that the term is statistically significant. A given problem instance dictates the threshold that gets placed on the p values and we use 0.1 as our threshold.

For the 66 two-way interactions and 12 squared (main effects) terms, we remove 50 terms that contain p values greater than 0.1 in both CWT and Inventory models. The remaining 41 terms are used in our metamodel for CWT and inventory as shown in Table 8.

Table 8: 41 Coefficients for Metamodel Terms; CWT (left) and $ Inventory (right)

Metamodel: 41 terms				
Term		CWT		Inventory
		Coefficient		Coefficient
Intercept		7.702		376.72
Pro1(0,1262)		-0.01231		12.628
Pro2(0,113)		-0.15678		12.845
Pro3(0,31)		-2.76944		14.136
Pro4(0,12.8)		-0.56819		14.252
Pro5(0,7.5)		-1.10075		13.467
Pro6(0,1.77)		-0.49287		12.646
Rep1(0,153)		-0.08928		0.162
Rep2(0,247)		-0.16399		1.145
Rep3(0,107)		-1.00534		1.781
Rep4(0,144)		-1.27835		2.258
Rep5(0,149)		-1.53897		8.033
Rep6(0,26)		-1.16490		6.724
Pro1*Rep5		0.07792		-0.301
Pro2*Rep2		0.14536		-0.101
Pro2*Rep3		0.14662		0.199
Pro2*Rep5		-0.14318		0.137
Pro2*Rep6		0.15837		-0.256
Pro3*Pro5		-0.10366		0.284
Pro3*Rep3		0.58556		0.333
Pro3*Rep4		0.35365		-0.001
Pro4*Rep1		-0.05202		0.320
Pro4*Rep4		0.07209		0.400
Pro4*Rep5		-0.03112		0.572
Pro5*Rep5		0.06243		0.275
Pro6*Rep1		-0.09822		0.341
Pro6*Rep6		-0.16322		0.215
Rep1*Rep4		-0.05952		0.365
Rep2*Rep3		-0.05598		-0.314
Rep2*Rep4		-0.20436		0.473
Rep5*Rep6		-0.18015		0.137
Pro2*Pro2		-0.04145		1.271
Pro3*Pro3		1.58451		3.319
Pro4*Pro4		-0.12637		3.031
Pro5*Pro5		-0.20897		5.887
Pro6*Pro6		0.14056		2.440
Rep2*Rep2		0.38795		-1.469
Rep3*Rep3		1.31858		-1.548
Rep4*Rep4		1.53335		-2.230
Rep5*Rep5		1.88805		-9.466
Rep6*Rep6		1.52435		-6.643

The sphere packing experiment provides the estimated intercept and coefficients for the 41 terms in our metamodel as shown in Table 8. With the intercepts and coefficients, our metamodel produces the two regression equations in (20) to estimate customer wait time (left side of Table 8) and dollars of inventory (right side of Table 8):

$$\text{CWT} = 7.702 - .01231 mult_1^{Pro}, \ldots, +1.52435(mult_6^{Rep})^2 \tag{20}$$
$$\$\ \text{inv(M)} = 376.72 + 12.628 mult_1^{Pro}, \ldots, -6.643(mult_6^{Rep})^2$$

Step 3, Evaluate Adequacy of Metamodel [49]:

We evaluate accuracy of the metamodel by comparing its predictions with actual values. Figure 19 contains a scatter plot of the residuals and no abnormal patterns are observed. The metamodel is unbiased: 56% of the CWT errors are positive while 45% of the inventory errors are positive. Lastly, the errors are normally distributed with a mean near zero (0.06 for CWT and 0.03 for inventory). Therefore, our metamodel can be used to find potential operating points.

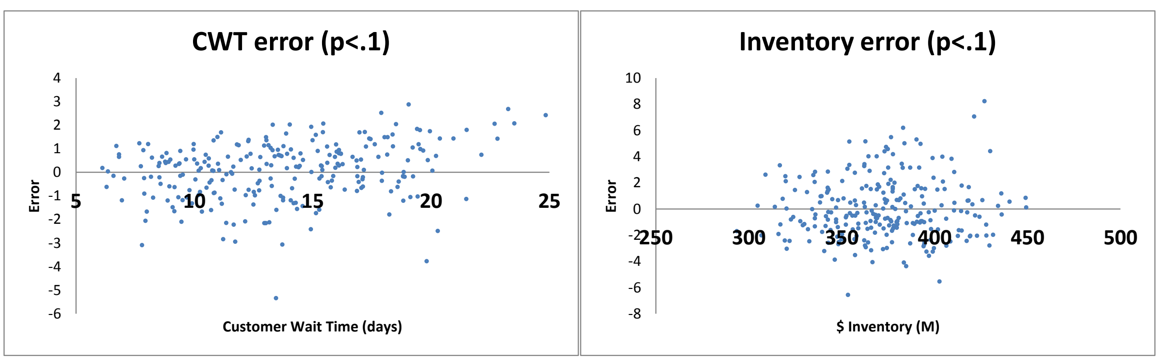


Figure 19: Scatter Plot of Residuals

Step 4, Determine Nondominated Points: To determine nondominated points, we adjust (20) to:

$$\min y_1 = \text{CWT} = 7.702 - .01231 mult_1^{Pro}, \ldots, +1.52435(mult_6^{Rep})^2 \tag{21}$$

$$\text{s.t. } \$\,\text{inv(M)} = 376.72 + 12.628 mult_1^{Pro}, \ldots, -6.643(mult_6^{Rep})^2 \leq e_2$$

We apply (21) six times, one per row of Table 9; each row represents a Pareto-Optimal point [46] that may be a nondominated point. For the six uses of (21), e_2 is set according to the value in the [Epsilon Constraint] column; specifically to {275, 280, 285, 290, 295, and 300}.

Table 9: Simulations to Validate Metamodel

Decision Variables												Epsilon Constraint	Metamodel Responses	
Procurement Multipliers						Repair Multipliers								
Mult1	Mult2	Mult3	Mult4	Mult5	Mult6	Mult1	Mult2	Mult3	Mult4	Mult5	Mult6	$ Inv (M)	$ Inv (M)	CWT
0	0	0	0	0	0	153	0	36	0	0	0	275	275.0002	24.502
0	0	1.20	0	0	0	153	0	99	144	0	0	280	280.0001	19.828
0	0	7.74	0	0.244	0	153	0	80	109	0	0	285	285.0002	17.468
0	0	10.7	0	0.524	0	153	247	85	111	0	0	290	290.0000	15.859
0	0	13.4	0	0.881	0	153	239	81	109	0	1.60	295	294.9999	14.785
0	0	13.6	0	0.908	0	153	235	81	109	4.17	4.14	300	300.0001	13.799

Recall, the baseline contains CWT of 23.06 days with an inventory value of $297.6M. Using design of experiment principles in our case study, we have determined four nondominated points. This suggests that expanding Bachman's work to the very sparse, intermittently-demanded expensive/reparable parts may provide significant dividends to the US-AF, and likely, other firms.

4.6 **Summary and Conclusion**

Our framework validated that much of the US-AF's 'repair on demand' operations are cost-effective as demonstrated with many of the repair and procurement multipliers set to zero to achieve optimality. However, there were cases, especially for groups three and four where the multipliers were greater than zero, which means repairing and procuring some assets and having more serviceable spare parts on the shelf and ready, would be a better policy.

Figure 20 shows the baseline As Is point and eight points from our framework. Six of the eight are nondominated points, that is, they are equal to or better than customer wait times and inventory, relative to the baseline. It is likely that other nondominated points exist. We show six nondominated points which is sufficient for the supply chain manger to effectively see the underlying trade space within the multi-objective problem.

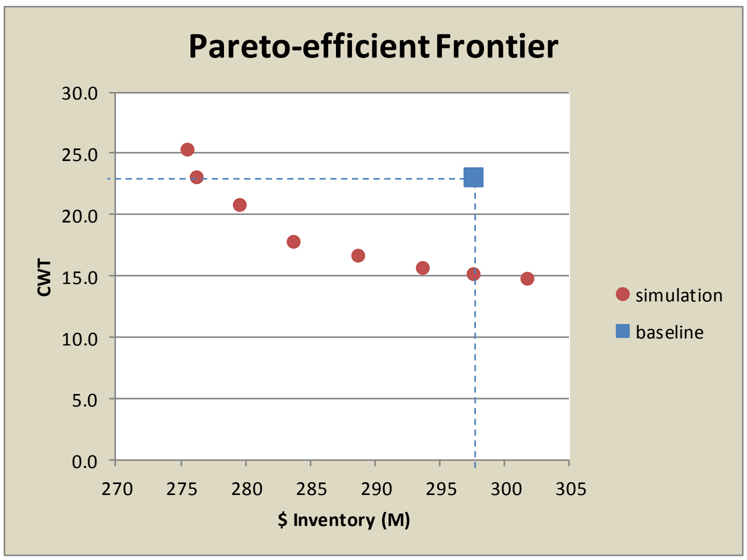


Figure 20: Optimal Solutions: Improving from Baseline

The results, as shown in Figure 20, show that our framework to find an improved stock policy for the very sparse, intermittently-demanded, expensive/reparable parts can produce a large dividend. Ketchen and Hult remind us that best-value supply chains are agile and have a “strong ability to be proactive as well as responsive to changes.” [43]. Expanding on Bachman’s [24] work, which was limited to consumable parts, our framework provides a method to identify procurement and repair policies that reside on the optimal, Pareto-efficient frontier and thus, advance the cost-effectiveness of the stock policy.

Our case study focused on optimally determining 12 ($m+n$ = 6+6) decision variables out of a total of ($3m+3n$) decision variables. Using the 12 decision variables, we were able to find better solutions. Future work could include expanding from 12 decision variables.

Specifically, we observe that the repair multipliers for groups three and four are larger, relative to the other groups. This could mean that if groups three and four were further split (i.e. a total of 8 groups), a better solution may exist. With eight groups for m and n, our problem would expand from 12 to 16 decision variables.

Lastly, this case study focusses on 1,755 expensive/reparable, very sparse, intermittently-demanded parts on a single revenue generating machine. Future work could also expand by adding parts from other revenue-generating machines to assure the B-1 results apply to other fleets; thus, establishing an enterprise value for the improved procurement and repair stock policies.

4.6.1 Update - Real World Implementation Considerations

This paper shows significant merit in expanding Bachman's work to the expensive/reparable parts on the revenue-generating machine. The underlying merit was accepted by AF leadership and we have been tasked to expand to all AF-managed expensive/reparable, very sparse, intermittently-demanded parts. Our results will be combined with implementation costs (IT upgrades, changes to policies & procedures, etc.) such that an enterprise cost analysis can be created and provided to AF leadership for implementation direction.

V. Advancing Forward Looking Metrics on the Very Sparse, Intermittently-Demanded Items

5.1 Introduction: SCM of Short Supply and Impact on Revenue-Generating Machine

"Many organizations fall into the trap of simply reacting and expediting when shortages occur." - Huber [52]

Huber points out that many supply chain managers make common mistakes in service-parts management. His above quote is in reference to the mistake, "Inability to Effectively Deal with Short Supply Situations" [52]. Supply Chain Managers will always find themselves in short supply of serviceable parts for a multitude of reasons including: spikes in demand (caused by degraded parts reliability and/or changes to the operational environment); unforeseen quality issues; suppliers delivering orders late; or, as is the case of this research, a single demand on the non-stocked, very sparse, intermittently-demanded item. It is neither feasible nor optimal for a supply chain to stock all parts at all locations of the revenue-generating machines; managing the supply chain processes that generate parts, especially while in short-supply is critically important to the operational up-time of the revenue generating machines [18] [35] [39] [1] [19].

5.1.1 SCM Value in Integrated Knowledge of SC Processes & Need for Metrics

The Supply Chain Management Institute (SCMI) features eight key processes [4]: Customer Relationship Management, Supplier Relationship Management, Customer Service Management, Demand Management, Order Fulfillment, Manufacturing Flow Management, Product Development and Commercialization, and Returns Management.

Given these eight processes, SCMI's framework keys on the need to successfully manage them and the complex networks associated with them in order for the firm to be successful. Lambert states [4], "In this emerging competitive environment, the ultimate success of the business will depend on management's ability to integrate the companies intricate network of business relationships."

Badole's [5] comprehensive survey of 700 supply chain modeling papers identified two gaps with relevance to this research. First, "While there is an abundance of SC management literature, it is realized that research at the inter-organizational level is less prevalent...the objective of SCM is to integrate all the firms in the value chain..." Second, "Performance measures and metrics are essential for effectively managing logistics operations...Performance measures provide the information necessary for decision-making and actions. However, it is observed that the recent literature encompasses only traditional performance measures such as cost, quality, efficiency, and responsiveness. Few researchers have proposed new performance measures and metrics that reflect the changes in markets and enterprise environments..."

5.1.2 Multiple Processes to Generate Parts for Revenue-Generating Machine

Many supply chains have multiple methods, or processes, to generate the short-supply part for the downed revenue generating machine. For example, the supply chain manager may have more than one supplier to procure the part, or may be able to manufacture the part, or may have some ability to re-manufacture (i.e. repair/refurbish) the part, or may have some engineering-disposition process to continue using the part in a degraded capacity (perhaps limiting the revenue-generation capability of the machine), etc.

These discrete supply chain processes are generally well known, perhaps a little deeper within the supply chain manager's organization, and understood to follow standard processing times. Stated another way, knowledge exists that describes these standard processing times via probability distributions such as: process X_1 follows a normal distribution defined by $N(\mu, \sigma)$; process X_2 follows a lognormal distribution defined by $ln(\mu, \sigma)$; ... ; process X_n follows the exponential distribution defined by λ. While empirical data likely exists to sufficiently describe these supply chain standard processing times, distributions may also be effectively elicited and used [53]. With the processes defined by a distribution, then each process has an expected Standard Processing Time (SPT) for a given part. In order for the supply chain manager to make effective decisions for the firm, the or she must have integrated knowledge of their processes, including the probability distributions that describe the processes and the current likelihood that the processes are immediately postured to begin generating the part(s), if invoked by the supply chain manager.

5.2 **The Research Question**

The optimal stock policy will not stock all the very sparse, intermittently-demanded parts at all locations of the revenue-generating machine. For those not stocked by policy, a primary concern is the expected backorder time needed to resolve a short supply situation. Backorder time is critical because it represents a portion of the total down time of the firm's revenue-generating machine(s) [35] [2]. Given that the supply chain manager owns the processes by which parts are generated for the revenue-generating machine; the two-part research question is: (1) are the supply chain processes currently ready (i.e. operational) to generate part(s) and, (2) what is the expected time for the processes to generate the part(s). To answer these questions, we develop a forward-looking, integrated framework to advance the supply chain manager's desire to know what proactive actions to take on the processes that generate these very sparse, intermittently demanded items. Doing so will improve the firm's cost-effective readiness of the revenue-generating machines.

5.3 A Proposed Framework

Given the desire to integrate supply chain processes, we develop a framework that can include all the relevant supply chain processes and all the relevant, very sparse, intermittently-demanded items; items that upon being in short supply, would down the revenue generating machine for a significant amount of time.

5.3.1 Reliability Block Diagram

If we replace the word processes with the word paths, and the word parts with components, we can use block diagrams from reliability theory [2]. Let $\mathbf{P}$ be the set of the very sparse, intermittently-demanded, expensive/reparable parts on the revenue-generating machine and let p be an individual part, $p \in \mathbf{P}$. Let $\mathbf{J}$ be the set of supply chain processes that generate the parts in set $\mathbf{P}$ and let j be an individual process, $j \in \mathbf{J}$. As shown in Figure 21, we construct the reliability block diagram where the columns represent the very sparse, intermittently-demanded parts and the rows represent the supply chain processes that generate parts for the revenue-generating machine. Within the standard reliability diagram, each $r_{p\,j}$ block would have a numerical value between 0 and 1; that is, it indicates the expected reliability of component *p*,*j* expressed as a probability of being operationally ready.

Our application of the reliability block diagram to the very sparse intermittently-demanded problem is that each $r_{p,\,j}$ quantifies the confidence, or likelihood, that process *j* is currently postured to generate part *p* within a user-defined desired process time, should the process be invoked by the supply chain manager. In this context, when $r_{p,\,j} = 1$, the supply chain manager has full confidence that he/she could immediately invoke process *j* to generate part *p* for the revenue generating machine within the desired process time. Conversely, when $r_{p,j} = 0$, the supply chain manager would not be able to invoke process *j* to generate part *p* for the revenue generating machine. This model enables a process-centric view (of the supply chain processes) by looking across each row *j* as well as a parts-centric view by looking down each column *p*.

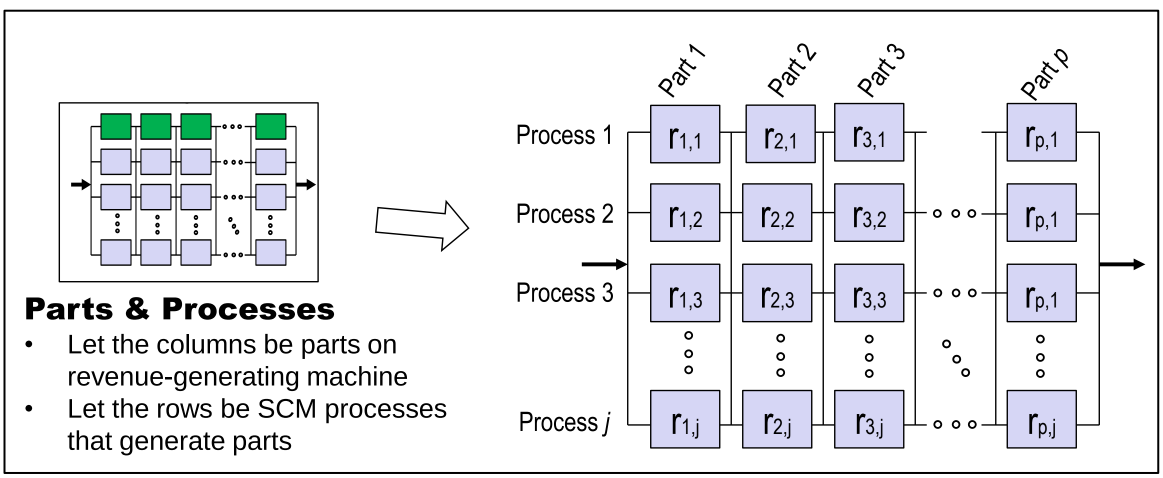


Figure 21: Reliability Block Diagram as an Integrated Framework

Given the $r_{p,j}$ values in a given column, let R_p be the overall reliability of the j supply processes to generate the specific part, p. In this context, R_p quantifies the net effective reliability of the combined processes for the supply chain manager. There are multiple ways to define R_p. We show two ways and include the concept of operations that would dictate which definition is appropriate for use.

Many firms operate where a single process is invoked to generate the part for the revenue-generating machine. Of the processes to choose from, the supply chain manager desires to invoke the 'best', or most reliable process. Thus, for the firms that use this concept of operations, R_p can be defined as:

$$R_p = max\{r_{p,1},\ r_{p,2},\ \ldots, r_{p,j}\} \tag{22}$$

For the firms that have a concept of operations to invoke two or more processes simultaneously to generate the part, we use parallel configurations from reliability theory [2]. In order to use this definition for R_p the processes must be sufficiently independent. The parallel configuration contains redundancy, which increases the reliability of the system. For the firms that would invoke k of the j supply chain processes simultaneously, R_p can be defined as:

$$R_p = 1 - \prod_{j=1}^{k} (1 - r_{p,j}) \tag{23}$$

The supply chain manager would use either (22) or (23) to define R_p according to their concept of operation. R_p provides an aggregated, systems-view confidence, for each part p that the supply chain is readily postured to generate the part for the revenue-generating machine within the desired process time. The R_p reliability values provide the supply chain manager with valuable insights for the parts-centric view. See 5.4.3 for specifics on how these reliabilities/confidences can be used for management insight.

The supply chain manager is also concerned with the expected amount of time needed, collectively by the j processes, to generate part p for the revenue-generating machine. The reliability block diagram does not easily allow us to model this time-based insight; thus, we also develop a framework for the supply chain manager to capture the expected processing time for each of the parts p. A bipartite graph provides this utility and we show how $r_{p,j}$ reliability scores can be generated and become the common link between the reliability block diagram and bipartite graph.

5.3.2 A Hybrid Framework: Relating a Bipartite Graph to a Reliability Block Diagram

A common objective function of the transportation problem is to minimize the total transportation costs to move a required amount of entities from the network's supply nodes to its demand nodes. The transportation model often utilizes a bipartite graph construct. Bipartite graphs possess two special properties that general graphs do not. In order for a graph to be bipartite: (1) all X nodes (vertices) must be partitioned into one of two subsets, say $\mathbf{X}^1$ and $\mathbf{X}^2$; (2) no arcs (edges) can join nodes within a given subset. Because arcs can only join nodes from set $\mathbf{X}^1$ to nodes in set $\mathbf{X}^2$ in bipartite constructs, they can be readily used to model the transportation of entities from (supply) nodes in $\mathbf{X}^1$ to (demand) nodes in $\mathbf{X}^2$.

For our problem instance, let the first subset of nodes be $\mathbf{J}_p$. This subset contains all the supply chain processes from the reliability block diagram for a given part p. Let the second subset be **L** and let *l* be an individual location of the revenue-generating machine, $l \in \mathbf{L}$. Let $PPT_{p,j}$ represent the pre-processing time needed by the supply chain resources, before process *j* can begin generating part *p*. Let DPT_p be a user-defined time that quantifies the supply chain managers desired process time to generate part *p* for the revenue-generating machine. Let $SPT_{p,j}$ represent the expected standard processing time needed by the supply chain resources for process *j* to generate part *p*. Let $t_{p,j,l} = PPT_{p,j} + SPT_{p,j}$ be the total expected processing time, which starts when the supply chain manager decides to invoke process *j* and stops when the revenue-generating machine at location *l* receives part *p*. For our problem example, cost is time. As shown in Figure 22, arcs labeled as $t_{p,j,l}$ connect the (supply) nodes of set $\mathbf{J}_p$ with (demand) nodes in set **L**; thus, a bipartite construct of the transportation problem.

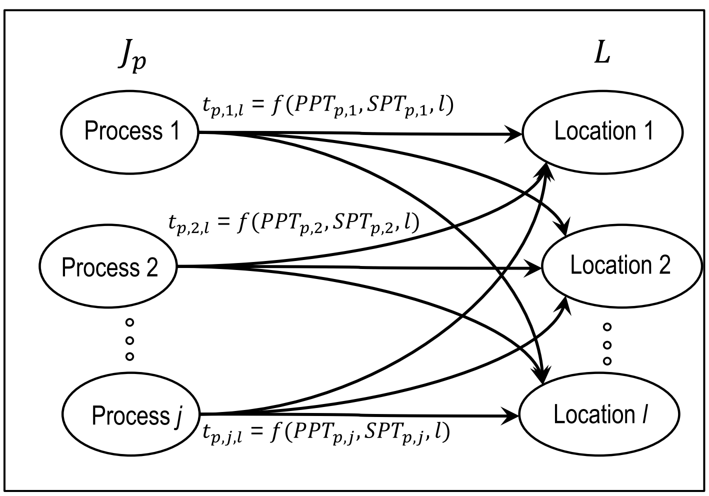


Figure 22: Hybrid Model: Bipartite Graph Related to Reliability Block Diagram

We seek to find the supply process, for each part *p*, that can resupply the revenue-generating machine with the cheapest cost. A standard formulation of the minimum unit-flow cost for part *p* is [54]:

$$
\begin{aligned}
&\min z_p = \textstyle\sum_{j \in J_p} \sum_{l \in L} t_{p,j,l} x_{p,j,l} && \text{‘Minimize flow costs} \\
&\text{s.t. } \textstyle\sum_{j \in J_p} s_{p,j} = d_{l,p} \forall l \in L && \text{‘Balanced flow of supply, } s\text{, \& demand, } d \\
&\quad x_{p,j,l} \geq 0 \; \forall \; x_{p,j,l} && \text{‘Non negativity}
\end{aligned} \tag{24}
$$

In general, all the supply chain processes can generate parts for all locations of the revenue-generating machines. Without a loss of generality, we assume only one unit of flow is demanded/needed across the processes and for a single location of the revenue-generating machine. Our assumptions are founded in the fact that our problem instance is on the very sparse, intermittently-demanded items. The likelihood of needing multiple parts from multiple supply chain processes for multiple locations of the revenue-generating machine, during a short time interval, is assumed to be zero. Incorporating these assumptions into our problem, our objective function can be simplified and revised with adjusted notation as:

$$\min z_p = \min\{ t_{p,1}, t_{p,2}, \dots, t_{p,j}\} \tag{25}$$

The assumptions, valid for our problem instance, greatly simplify the objective function. However, it is worth noting that the Operational run-time, *O(...)* for (24) features algorithms that solve the minimum cost flow problem, a generalized version of the bipartite construct, within polynomial time [55]. Thus, even very large subsets of $\mathbf{J}_p$ and $\mathbf{L}$, with large cardinality can be solved efficiently with polynomial time algorithms.

Our hybrid design relates the bipartite graph to the reliability block diagram. When the supply chain manager has full confidence that a given process, following a distribution defined by the standard processing time, is sufficiently ready to generate a part in an amount of time less than or equal to the desired processing time, then the process reliability score is 1. However, if the supply chain manager's organization has current knowledge that suggests a process is not ready to generate part within the desired processing time, then the process reliability score is less than 1. Sometimes, a delay exists before a supply chain process can begin. These pre-processing delays have implications to the reliability scores. Effectively, the pre-processing time shifts the standard processing time to the right; thus, as pre-processing time increases, the reliability score decreases. Let the reliability score $r_{p,j}$ be defined by:

$$r_{p,j} = P\left(t < DPT_p - PPT_{p,j} \middle| SPT_{p,j}\right) \tag{26}$$

A graphical representation of (26) is shown in Figure 23 using three examples. The top row for each example shows the probability that process *j* will generate part *p*, within the desired processing time when there are no pre-processing delays. The bottom row highlights the impact that pre-processing delays have on reducing the reliability scores. Example A shows the case where the desired processing time falls on the right tail of a given process' standard distribution time; example B the median. Example C shows the impact when the pre-processing delay is very large (i.e. Big *M* notation [56]) meaning the process can't start for the foreseeable future, resulting in a reliability score of zero.

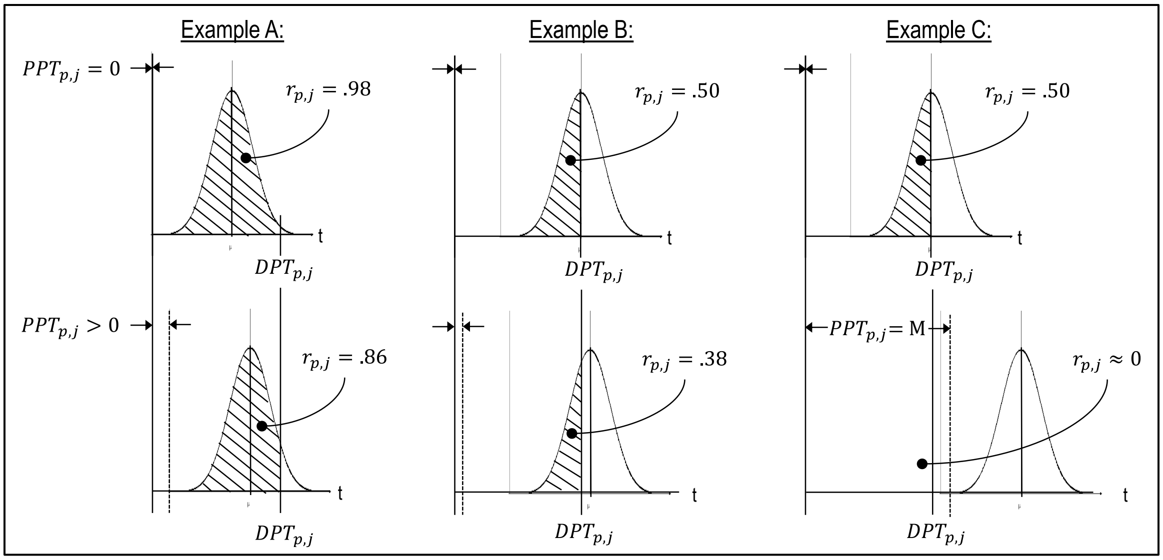


Figure 23: Representation of Reliability Scores of eq (26)

We now show an example of how this integrated framework can be used to advance the supply chain manager's desire to proactively know what actions to consider taking to improve the firm's cost-effective readiness of the revenue-generating machines.

5.4 **Notional Example Using the new Framework**

Without a loss of generality, we limit the example to five parts and four SCM processes. Granted, every firm does not have the same supply chain processes, nor does our framework require all the same processes. The framework needs data for: (1) desired processing times, by part, (2) standard processing times, by part and process, and (3) pre-processing delay times, by part and process. These data elements can come from multiple sources ranging from empirical data to elicitation from subject matter experts [53].

The first supply chain process in our notional example is lateral resupply which contains the logistics of moving a serviceable part from one location in the firm's network to the location of a downed revenue-generating machine. The second process is primary procurement and contains the logistics of purchasing the part from the primary source of supply. The third process, also procurement, contains the same as the above, but from a secondary source of supply. The fourth process is in-house repair and contains the logistics of re-manufacturing an unserviceable asset back to serviceable status.

5.4.1 Data Requirements for the Hybrid Model

As stated in 5.4, every firm does not have/need the same data to describe the supply chain processes, nor does our framework require it. For our example, we use information from SMEs and show how it can be used to generate the $r_{p,j}$ scores. Our intent is that our notional examples are generalized sufficiently such that the concepts can be utilized for any firm that has supply chain processes that generate parts for the revenue-generating machine. For our example, the firm's desired processing time is no more than 120 days, for all parts; that is, $DPT_p \leq 120\ \forall p$. Additionally, Table 10 contains notional firm data covering the five parts and four processes used in our example.

Table 10: Notional Firm Data from SMEs for 5-Parts and 4-SCM Processes

Current SME Data for Sparse, Intermittently-Demanded Parts						
SCM Process	Description	Parts				
		1	2	3	4	5
Lateral Resupply	On Hand Assets	N	N	Y	Y	N
	Location (US or non US)			US	non US	
Primary Procurement	Procurement source known	Y	Y	Y	N	Y
	Contract in place	Y	N	N	N	Y
Secondary Procurement	Procurement source known	N	N	Y	Y	N
	Contract in place			Y	N	
Repair	Unserviceable assets exists to repair	Y	Y	Y	N	Y
	Available Capacity	Y	N	N	Y	Y
	Piece parts available	N	N	Y	Y	Y

In order to determine the pre-processing time delays for the lateral resupply process, key condition-based information must be known and utilized. Specifically: (1) are serviceable part(s) available and (2) if so, where are they, within the firm's network? We use a piece-wise function to establish the values of $PPT_{p,1}$ for the lateral resupply process, extracted from the firm's data in Table 10.

If an asset exists at a location within the US, then the infrastructure is in place to transport the asset without delay. If the asset exists outside the US, then a one-day delay is added to account for the reduced infrastructure to pick and pack the asset, as well as reduced pickup and delivery schedules. When asset don't exist, they can't be laterally resupplied. The Big M is used to assure the given process can't be invoked to fill the demand.

$$PPT_{p,1} = \left\{ \begin{array}{ll} 0, & \text{If On Hand Assets} = \text{Y}, \text{Location} = \text{US} \\ 1, & \text{If On Hand Assets} = \text{Y}, \text{Location} = \text{non US} \\ M, & \text{If On Hand Assets} = \text{N} \end{array} \right\} \tag{27}$$

For demonstration purposes, the supply chain manager's organization provides notional data that shows the standard processing time for lateral resupply follows a normal distribution $N(7.2, 2.1)$. We use (26) and (27) and summarize the impact of PPT in Table 11, culminating into two key process indicators (KPIs) for the supply chain manager, shown in bold font; (1) $t_{p,1}$ values which are used on the arcs of the bipartite graph and (2) $r_{p,1}$ reliability scores which are used in the reliability block diagram.

Table 11: $t_{p,j}$ and $r_{p,j}$ Scores for the Lateral Resupply Process (i.e. j=1)

Lateral Resupply Process $SPT_{p,1}$ follows $N(7.2, 2.1)$ ∀ p	Part p				
	1	2	3	4	5
$PPT_{p,1}$	M	M	0	1	M
E($SPT_{p,1}$)	7.2	7.2	7.2	7.2	7.2
$\boldsymbol{t_{p,1}}$	**M**	**M**	**7.2**	**8.2**	**M**
$DPT_{p,1}$	120	120	120	120	120
$\boldsymbol{r_{p,1}}$	**0.000**	**0.000**	**1.000**	**1.000**	**0.000**

For the procurement processes (primary, j=2; secondary, j=3), the two key pieces of information are: (1) is there a procurement source and (2) is a contract currently in place? We use a piece-wise function to establish the values of $PPT_{p,2}$ and $PPT_{p,3}$ for the primary and secondary procurement processes, extracted from the firm's data in Table 10.

If a procurement source exists and a contract is already in place, then the part can be requisitioned without delay. However, if a contract is not in place, then 30 days is used to account for the pre-processing delay that is incurred before the part can be requisitioned. Additionally, 60 days are used to account for the supply chain manager identifying a procurement source; thus, 90 days are used to account for the pre-processing delay when a procurement source and contract are both needed before the part can be requisitioned.

$$PPT_{p,2} = PPT_{p,3} = \left\{\begin{array}{ll} 0, & \text{if Procurement Source} = \text{Y, Contract in Place} = \text{Y} \\ 30, & \text{if Procurement Source} = \text{Y, Contract in Place} = \text{N} \\ 90, & \text{if Procurement Source} = \text{N} \end{array}\right\} \quad (28)$$

The supply chain manager's organization provides notional empirical data for the standard processing times for procurement. The primary procurement process follows the normal distribution with parameters N(150, 40) and secondary procurement has parameters N(180, 60). We use (26)and (28) and summarize the impact of PPT on processes 2 and 3 in Table 12, culminating into two key process indicators (KPIs) for the supply chain manager, shown in bold font; (1) $t_{p,2}$ and $t_{p,3}$ values which are used on the arcs of the bipartite graph and (2) $r_{p,2}$ and $r_{p,3}$ reliability scores which are used in the reliability block diagram

Table 12: $t_{p,j}$ and $r_{p,j}$ Scores for Procurement Processes (i.e. j=2, 3)

Primary Procurement Process $SPT_{p,2}$ follows N (150, 40) ∀ p	Part p				
	1	2	3	4	5
$PPT_{p,2}$	0	30	30	90	0
E($SPT_{p,2}$)	150	150	150	150	150
$\boldsymbol{t_{p,2}}$	**150**	**180**	**180**	**240**	**150**
$DPT_{p,2}$	120	120	120	120	120
$\boldsymbol{r_{p,2}}$	**0.227**	**0.067**	**0.067**	**0.001**	**0.227**

Secondary Procurement Process $SPT_{p,3}$ follows N (180, 60) ∀ p	Part p				
	1	2	3	4	5
$PPT_{p,3}$	90	90	0	30	90
E($SPT_{p,3}$)	180	180	180	180	180
$\boldsymbol{t_{p,3}}$	**270**	**270**	**180**	**210**	**270**
$DPT_{p,3}$	120	120	120	120	120
$\boldsymbol{r_{p,3}}$	**0.006**	**0.006**	**0.159**	**0.067**	**0.006**

For the repair process, we use a three-tier data stream. Specifically: (1) does the repair facility currently have unserviceable asset(s) that can be repaired, (2) does the repair facility currently have sufficient capacity, and (3) does the repair facility currently have the piece-parts (i.e. sub-assemblies and components) available for the repair? The piece-wise function for the repair process is given in (29).

If an asset exists (to be repaired), maintenance has current capacity, and piece-parts are available, then the unserviceable part can be repaired without delay. If an asset exists (to be repaired), piece-parts are available, but maintenance does not currently have capacity, then 10 days are used to account for the pre-processing delay that is incurred before maintenance can begin repairing the part. If an asset exists (to be repaired), maintenance has current capacity, but piece-parts are not available, then 45 days are used to account for the pre-processing delay that is incurred before maintenance can begin repairing the part. If an asset exists (to be repaired), but maintenance does not currently have capacity, and the piece-parts are not available, then 50 days are used to account for the pre-processing delay that is incurred before maintenance can begin repairing the part. Lastly, when assets don't exist (to be repaired), the Big M is used to assure the given repair process can't be invoked to fill the demand.

$$PPT_{p,4} = \left\{ \begin{array}{ll} 0, & \text{if Assets} = \text{Y, Capacity} = \text{Y, Piece Parts} = \text{Y} \\ 10, & \text{if Assets} = \text{Y, Capacity} = \text{N, Piece Parts} = \text{Y} \\ 45, & \text{if Assets} = \text{Y, Capacity} = \text{Y, Piece Parts} = \text{N} \\ 50, & \text{if Assets} = \text{Y, Capacity} = \text{N, Piece Parts} = \text{N} \\ \text{M}, & \text{if Assets} = \text{N} \end{array} \right\} \tag{29}$$

The supply chain manager's organization provides notional empirical data that shows the standard processing time for the repair process follows a lognormal distribution *ln N*(4.26, 0.46). We use (26) and (29) summarize the impact of PPT on process 4 in Table 13, culminating into two key process indicators (KPIs) for the supply chain manager, shown in bold font; (1) $t_{p,4}$ values which are used on the arcs of the bipartite graph and (2) $r_{p,4}$ reliability scores which are used in the reliability block diagram.

Table 13: $t_{p,4}$ and $r_{p,4}$ Scores for In-House Repair Process

In House Repair Process $SPT_{p,4}$ follows ln(4.26, 0.46) ∀ p	Part p				
	1	2	3	4	5
$PPT_{p,4}$	45	50	10	M	0
$E(SPT_{p,4})$	80	80	80	80	80
$\boldsymbol{t_{p,4}}$	**125**	**130**	**90**	**M**	**80**
$DPT_{p,4}$	120	120	120	120	120
$\boldsymbol{r_{p,4}}$	**0.550**	**0.490**	**0.831**	**0.000**	**0.874**

5.4.2 Solving the Hybrid Model

With (26), we compute all $r_{p,j}$ scores and summarize the results in Figure 24. With (23), we compute the R_p values for the five parts: $R_1 = .654$, $R_2 = .527$, $R_3 = 1$, $R_4 = 1$, and $R_5 = .903$. To explain these numbers to a supply chain manager we use part 1 as an example. If part 1 is immediately needed and the supply chain manager invokes all the processes at his/her disposal in an effort to generate part 1, there is a 65.4% chance that the supply chain could deliver part 1 to the operators of the revenue-generating machine(s) within the desired processing time of 120 days; reference section 0 for more details on supply chain management's use of this information.

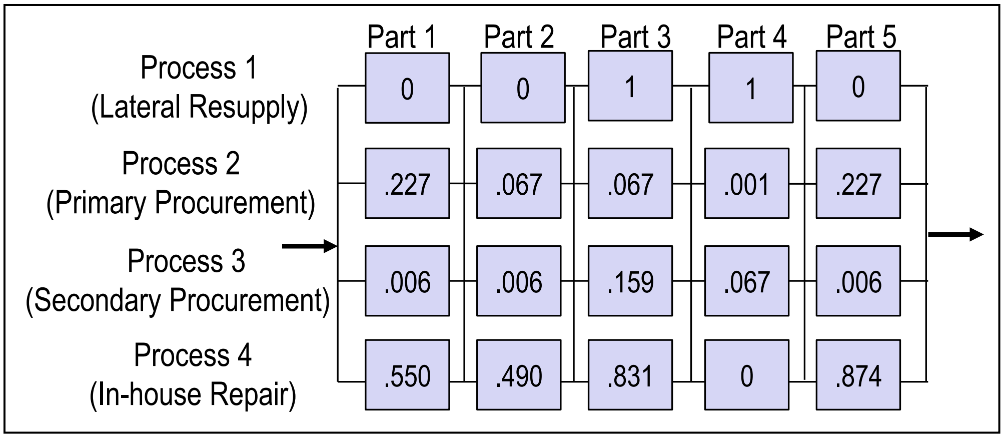


Figure 24: $r_{p,j}$ Scores for Notional Example

We compute all $t_{p,j}$ values, the expected resupply times using the supply chain manager's data for standard processing times and pre-processing delay times. Figure 25 shows the four $t_{p,j}$ values within the bipartite graph construct, for part 1. By quick inspection, we see the fastest resupply process is repair, requiring 125 days.

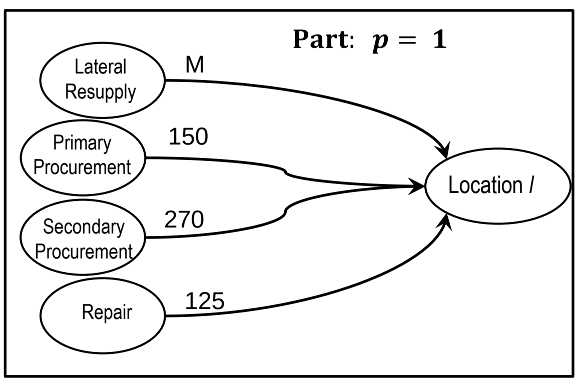


Figure 25: Bipartite Graph of Part 1

With (25), we compute the objective function for each of the five parts: min $z_1 = 125$, min $z_2 = 130$, min $z_3 = 7.2$, min $z_4 = 8.2$, and min $z_5 = 80$ and summarize the results in Table 14.

Table 14: All $t_{p,j}$ & min z_p Times for all 5 Parts

	parts				
processes	p = 1	p = 2	p = 3	p = 4	p = 4
j = 1	M	M	7.2	8.2	M
j = 2	150	180	180	240	150
j = 3	270	270	180	210	270
j = 4	125	130	90	M	80
min $\boldsymbol{z_p}$	**125**	**130**	**7.2**	**8.2**	**80**

The five solutions are shown in the bottom row of Table 14. The implications to the revenue-generating machine is that when a demand does eventually occur on these parts, our solution provides the likely down time of the revenue-generating machine, in days, caused by the lack of spare parts. For example, if a demand occurred today on part 3, the supply chain manager expects to need 7.2 days to resupply the part to the downed revenue-generating machine. Similarly, the supply chain manager expects to need 130 days to resupply part 2.

Management Insights from the Hybrid Model

"In most major corporations, functional managers are rewarded for behavior that is not customer friendly or shareholder friendly. This is because the metrics used focus on functional performance…not on customer value or shareholder value." – Lambert [4]

Many supply chain managers use fill rate as their key, customer-facing metric [4] [52]. Fill rate, typically defined by the count of filled orders divided by the count of total orders, can fall short in two areas: (1) it's a historic measure, and (2) it's not ideal for operators of the revenue-generating machines.

Because fill rate is defined by data from events that have occurred in the past, it can be described as a rear-looking metric. Rear-looking metrics dominate Firm's metrics portfolios because they are easy to compute (by definition, data already exists) and generally, are easy to understand. Rear-looking metrics may be plotted via time series data and forecasting can be utilized. With the forecast, the manager will add his/her intuition to make business decisions for the firm. Firms, however, desire to have forward-looking metrics [57] [58]; frameworks that deliver forward-looking metrics enable the firm's analytical capability to advance from descriptive (limited to quantifying what happened) to predictive (business insights into what will likely happen).

Fill rate also falls short because it does not directly measure, and may not even correlate very well to, the revenue-generating machine's uptime, which is likely the most important metric to the end customer. For example, if a supply chain has a fill rate of 90%, is that good performance for the firm? The operator of the revenue-generating machine(s) would likely say that it depends on the time duration required to satisfy the last 10%; stated another way, the supply chain's management of backorder time while in short supply.

Our hybrid framework utilizes current supply chain information and provides the supply chain manager with two forward-looking metrics: (1) **SCM Reliability** (using R_p from the reliability block diagram**),** and (2) **SCM Expected Resupply Time** (using $\min z_p$ from the bipartite graph). Additionally, with our hybrid framework, the supply chain manager has the ability to perform 'what if' analyses that enable his/her desire to make proactive decisions on his/her processes to advance the over-arching cost-effectiveness for the firm.

5.4.3 SCM Reliability: A new Forward-Looking Metric Using R_p

Recall from 5.3.1 that R_p provides the supply chain manager with an aggregated, systems-view confidence, for each part p that the SC is postured and ready to generate the part for the revenue-generating machine within the desired processing time. The supply chain's readiness is fully described by the distribution of all $|\mathbf{P}|$ values of R_p. Generally, parameters of an underlying distribution are determined and the parameter of primary interest is used as a single-value metric. The most frequently used is the arithmetic mean. Because we would not assume that the underlying distribution of R_p is uni-modal or symmetrical, the geometric mean ($\sqrt[|\mathbf{P}|]{R_1 R_2 R_3 \dots R_i}$) , $i = \{1, \dots, p\}$) , median, or simple minimums/maximums, are also viable options for the SCM to define the **SCM Reliability** metric. If all values for R_i are equal, the arithmetic and geometric means are equal. With varying values of R_i, the geometric mean is less than the arithmetic mean. This distinction is very valuable and useful, especially when low values of R_i may be critical to the operations of the revenue-generating machines; a single R_i value of zero reduces the geometric mean to zero. For our example problem with five parts, the arithmetic mean is .817, the geometric mean is .792, and the median is .903. The supply chain manager should define the **SCM Reliability** metric as appropriate for the firm.

To continue with our example, we use the median, so our **SCM Reliability** metric has a value of .903 (90.3%), using a desired processing time of 120 days. The desired processing time, which could be firm directed, should be an agreed-upon expectation between the supply chain manager and the operator of the machine(s). Establishing an agreed-upon desired processing time implies successful integration of five key management areas from the Supply Chain Management Institute [4]; specifically, Customer Relationship Management, Customer Service Management, Demand Management, Order Fulfillment, and Manufacturing Flow Management. Our framework can also be used to show the relationship between the new forward-looking metric, **SCM Reliability**, and potential values for the desired processing time, as shown in Figure 26.

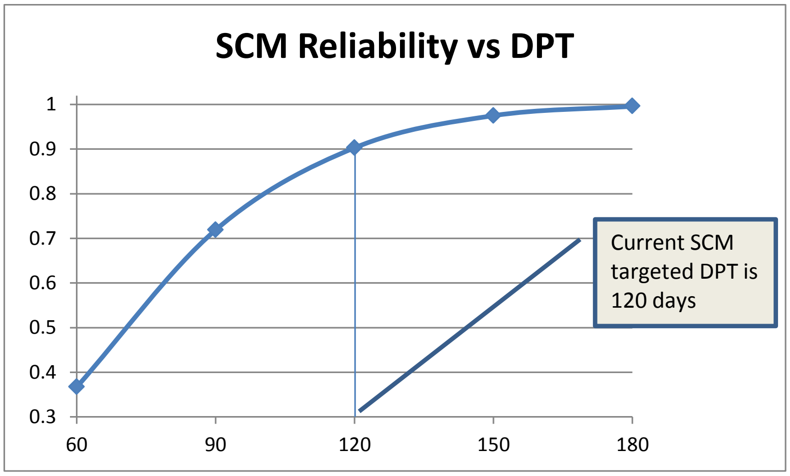


Figure 26: Relationship between Supply Chain Reliability and DPT

The relationship can be used to help or the supply chain manager and operator of the revenue-generating machines establish an agreed-upon target for desired processing time; thus, helps promote a common understanding across the firm of supply chain expectations.

5.4.4 SCM Expected Resupply: A new Forward-Looking Metric Using min z_p

By design, our **SCM Reliability** metric, from the reliability block diagram, requires a desired processing time. In the event a desired processing time can't be easily determined, we are motivated to provide another new, forward-looking metric; one that is independent of the desired processing time.

Recall from 5.3.1 that the min z_p from the bipartite graph provides the supply chain manager with the minimum resupply time (i.e. fastest process), for each part *p*. Just as with our **SCM Reliability** metric, the arithmetic mean, geometric mean, median, minimum/maximum are also viable options for the SCM to define the **SCM Expected Resupply** metric. For our example problem with five parts, the arithmetic mean is 70.1, the geometric mean is 37.8, and the median is 80. The supply chain manager should define the **SCM Expected Resupply** metric as appropriate for the firm. However, we note that caution should be used if considering the geometric mean. For example, if a single part has an extremely fast resupply time (i.e. min z_p approaching zero), the geometric mean will return a small metric and may be overly optimistic. We also note that if all parts are not equal, a weighting method can be used to fine-tune both the arithmetic and geometric means.

To continue with our example, we use the arithmetic mean, so our **SCM Expected Resupply** metric has a value of 70.1. The **SCM Expected Resupply** metric provides the supply chain manager with a forward-looking view of how fast (measured in days) the supply chain processes can resupply the part(s), if invoked. Stated another way, the **SCM Expected Resupply** metric provides an estimate of resolving "tomorrow's short-supply scenarios." The supply chain manager would record the **SCM Expected Resupply** metric on a recurring basis and compare to the previous value(s) and/or a targeted value.

Next we show how our framework is used to advance the supply chain manager's desire to know what proactive actions to take on the processes that generate these very sparse, intermittently demanded items. Doing so would improve the firm's cost-effective readiness of the revenue-generating machines.

5.4.5 Quantifying Process Improvement with Two New SCM Metrics

Recall, the **SCM Reliability** metric for our example is 90.1%. Suppose the targeted **SCM Reliability** is 91%; where/how does the SCM look for areas to improve, such that the 91% target can be achieved? Similarly, suppose the **SCM Expected Resupply** metric decreased by a large amount relative to the last time interval; where/how does the supply chain manager look for areas to improve, such that the metric will return to the baseline? There are multiple ways our framework can be used; we offer two examples: (1) for the **SCM Reliability** metric, which ties to the firm having a desired processing time, and (2) the **SCM Expected Resupply** metric, which is independent of desired processing time. In both cases, our framework enables the supply chain manager to perform process-integrated analyses, via the standard processing times and current constraints via pre-processing delays.

We show two examples where the supply chain manager would evaluate process improvement initiatives using (26). Recall the standard processing time for in-house repair is *ln N*(4.26, 0.46) and when combined with the 120-day desired processing time, produces reliability-block diagram values of: $r_{1,4} = .55, r_{2,4} = .49, r_{3,4} = .83, r_{4,4} = 0, r_{5,4} = .87$. Suppose the supply chain manager, seeking an improvement to in-house repair, is given an external quote that will improve the in-house repair process by ~two days. Is this supply chain process improvement good for the firm? Will the customer, operator of the revenue-generating machines, see an improvement in supply performance? To answer, we run the new standard processing times, for in-house repair, thru our reliability framework of (26) and return: $r_{1,4} = .58, r_{2,4} = .52, r_{3,4} = .85, r_{4,4} = 0, r_{5,4} = .89$. As a result of implementing the process improvement initiative, the new **SCM Reliability** metric would increase from 90.3% to 91.5%..

We also use (25) to run the new standard processing times thru our bipartite graph construct and return new expected resupply times: min $z_1 = 123$, min $z_2 = 128$, min $z_3 = 7.2$, min $z_4 = 8.2$, and min $z_5 = 78$. The net effect is that the new **SCM Expected Resupply** metric would improve from 70.1 days to a faster time of 68.9 days.

The examples show how the hybrid framework can be used to evaluate the impact of a process improvement initiative, which would reduce the standard processing times associated with the in-house repair process. A similar approach can be used for any process, or combinations of processes, as well as quantifying the impact of eliminating the constraints that are intrinsically part of delays behind the pre-processing times.

Given implementation costs for supply chain process improvement initiatives, they can be combined with our integrated framework; thus, enabling the supply chain manager to make proactive decisions on the processes that generate these very sparse, intermittently demanded items, to advance the firm's cost-effective readiness of the revenue-generating machines.

5.5 **Conclusion and Future Research**

We generate reliability scores for all pairings of (1) service parts on the revenue-generating machine(s) and (2) the processes that generate those parts. With the reliability scores, we create a hybrid model that relates a bipartite graph with a reliability block diagram.

The reliability block model is used to provide the supply chain manager with insights that quantify how ready his/her supply chain processes are to generate parts for the revenue-generating machine. With the reliability block diagram, we use two ways to define R_p, the net effect of the supply chain processes to generate each of the service parts. The first way, equation (22), is to use the maximum reliability of the processes to quantify the net impact of all processes for the given part. The second way, equation (23), is to use the parallel configuration and model *k* of the supply chain processes. This method assumes that the *k* processes, for the given part, are sufficiently independent.

For the supply chain's that use this concept of operations, a natural follow-on would be to incorporate costs of the supply chain processes such that a reliability-cost curve could be created. To highlight this research area, suppose $r_{p,4} = .875, r_{p,2} = .500, r_{p,3} = .375, r_{5,1} = 0.100$ and assume the costs are: \$75 for process 4 (repair), \$150 for process 2 (primary procurement), \$155 for process 3 (secondary procurement), and \$25 for process 1 (lateral resupply). Using these costs and equation (23) to compute reliability R_p for the parallel configuration, we have for part *p*:

Part p	Processes			
	j = 4	*j* = 2	*j* = 3	*j* = 1
r_{pj}	0.875	0.5	0.375	0.1
cost	75	150	155	25
Total Cost ($)	**75**	**225**	**380**	**405**
Total Reliability	**0.875**	**0.938**	**0.961**	**0.965**

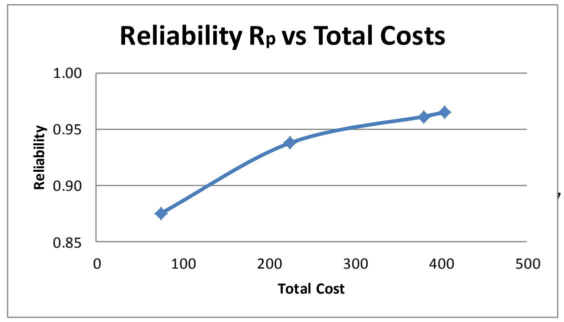


Figure 27: Reliability R_p vs Total Costs to simultaneously invoke *k* SC Processes

This framework can assist the supply chain manager decide which supply chain processes should be included; that is to help define the *k* processes that should be invoked simultaneously for the cost-effective readiness of the revenue-generating machine(s). Additionally, other areas of reliability theory, such as applying a hazard function, might be useful in the modeling of supply chain processes being ready to generate the service part(s) for the revenue-generating machine(s).

The bipartite graph construct is used to provide the supply chain manager with insights to quantify future short supply durations. The new hybrid framework advances supply chain modeling development in at least four areas (1) current supply chain posture, from a parts-centric view, (2) current supply chain posture, from a process-centric view, (3) capability to evaluate trade space of supply chain processes and process improvement initiatives, and (4) two new, forward-looking performance metrics, providing the supply chain manager with insights into supply chain's reliability and expected time in short supply; both important to the operator of the revenue-generating machine(s).

Using the hybrid framework, we show an example, using five parts and four processes. While the example is very small, algorithms exist that solve our model (transportation problem using a bipartite construct) within polynomial time. As such, scaling to actual problems with thousands of parts and dozens of processes is feasible.

Ketchen and Hult remind us that best-value supply chains are agile and have a "strong ability to be proactive as well as responsive to changes." [43]. Additionally, Klassen [22] highlights that when supply chain managers evaluate processes trade space, they should not lose sight of the customer and associated supply chain lead times. Our proposed framework addressed both of these key points.

We developed a forward-looking, integrated framework, designed to advance the supply chain manager's desire to know what proactive actions to take on the processes that generate these very sparse, intermittently demanded items. Additionally, we have created two, new forward-looking metrics that are customer-focused. This framework can be used by the supply chain manager to improve the firm's cost-effective readiness of the revenue-generating machines.

VI. Summary and Conclusions

This dissertation has made several original contributions to the field of operations research. The contributions fall in the domain of supply chain management. The author believes these contributions can be immediately adopted and implemented by the supply chain manager whose responsibility for the firm is to generate sparse, intermittently-demanded parts to assure the revenue-generating machine(s) are sufficiently operational for the firm or customer of the firm.

In chapter 3, we develop a condition-based stock policy of value to the supply chain manager by determining which inexpensive parts should be stocked at retail locations (i.e. close to the revenue-generating machines). The underlying principle is that a location of the revenue-generating machine, that has no historical demand, can benefit by using the positive demand signals from other locations of the revenue-generating machine, and thus determining a spare parts level in advance of the demand.

We perform experiments to determine various condition-based stock policies and test them in a case study that included over 3,000 parts on 12 locations of a revenue-generating machine within the USAF. Our research finds condition-based stock policies that are shown to be more cost-effective than the baseline As Is with the best being at half the cost.

The same Bayesian beliefs of our research were accepted by AF leadership and the AF stood up a centralized management team in Fiscal Year 2012. This team implemented a condition-based stock policy called Proactive Demand Leveling (PDL) [44], demonstrating the value of our framework to the operational world.

In chapter 4, we investigated expansions to Bachman's [24] work that had been limited to the inexpensive, consumable item population. The largest expansion, in the context of this research, is accounting for parts that get repaired, rather than condemned, when they fail and are removed from the revenue-generating machine.

We formulate this research as a multi-objective problem and apply operations-research techniques from design of experiments and response surface methods. We determine the Pareto-efficient frontier (i.e. trade space) between the two top-tiered objectives: dollars of inventory to carry and customer wait time.

We perform a case study of 1,755 expensive/reparable parts on the B-1 fleet of aircraft in the USAF. The research within our case study finds procurement and repair polices that are more optimal than the As Is policies.

Given the stock policy improvements in Chapters 3 & 4, in Chapter 5 we design a hybrid framework that integrates supply chain processes. The new framework models supply chain reliability using a block diagram and models resupply times using a bipartite graph construct. The reliability block diagram provides the supply chain manager with a method to capture how ready his/her processes are to generate parts for the revenue-generating machine. The supply chain manager can look across the rows of the reliability block diagram and get insights into his/her processes and down the columns to get insights into how the processes coordinate/combine to generate the parts. Each process/part combination has a reliability score and with the reliability scores, we model the supply chain's resupply time, by part, using the utility of a bipartite graph.

With the integrated reliability block diagram and bipartite graphs, we show how new, forward-looking metrics, with links to the operators of the revenue-generating machines, are created and provide two examples. Embedded within this hybrid framework is the enabling of cross-cutting analyses. With the new framework, a supply chain manager can easily perform ‘what if’ analyses to see if/how process improvements/initiatives would impact the supply chain’s performance.

The author believes these research areas cover the four gaps uncovered during the literature review. As such, the research advances the body of operations research knowledge, under the domain of supply chain management. Our research provides the supply chain manager with usable, analytics to help advance, for the firm, the cost-effective readiness of the revenue-generating machines.

Appendix A: Results of Stock Policy

Stock Policy Criteria (minimum # donors, maximum unit price) (min Rp. max Cp)	SKU's Stocked		SKU's Not Stocked		Costs of Stock Policy ($)				
	# SKU's Stocked by Policy	demand on stocked SKU's (next 12 months)	# SKU's Not Stocked by Policy	demand on non stocked SKU's (next 12 months)	$\sum Cp$ (procurement)	$\sum Ch$ (holding)	$\sum Ct$ (expedited transporation)	$\sum Cr$ (lost revenue)	*Total Cost*
As Is	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(1 , 442)	15,872	1,634	2,265	300	2,450,180	183,764	105,000	1,898,400	4,637,344
(1 , 674)	16,766	1,742	1,371	192	3,174,349	238,076	67,200	1,214,976	4,694,601
(1 , 282)	14,824	1,507	3,313	427	1,857,529	139,315	149,450	2,702,056	4,848,350
(1 , 1000)	17,503	1,832	634	102	4,002,001	300,150	35,700	645,456	4,983,308
(1 , 1453)	18,137	1,934	0	0	5,216,033	391,203	-	-	5,607,236
(1 , 172)	13,638	1,308	4,499	626	1,355,708	101,678	219,100	3,961,328	5,637,814
(1 , 100)	12,361	1,139	5,776	795	926,899	69,517	278,250	5,030,760	6,305,426
(1 , 54)	11,403	1,037	6,734	897	738,374	55,378	313,950	5,676,216	6,783,918
(2 , 674)	7,237	1,173	10,900	761	1,749,350	131,201	266,350	4,815,608	6,962,509
(2 , 1000)	7,503	1,223	10,634	711	2,133,791	160,034	248,850	4,499,208	7,041,883
(2 , 442)	6,831	1,097	11,306	837	1,377,105	103,283	292,950	5,296,536	7,069,874
(2 , 1453)	7,822	1,294	10,315	640	2,755,781	206,684	224,000	4,049,920	7,236,385
(2 , 282)	6,384	1,016	11,753	918	1,061,572	79,618	321,300	5,809,104	7,271,594
(1 , 26)	9,909	894	8,228	1,040	550,666	41,300	364,000	6,581,120	7,537,086
(2 , 172)	5,796	869	12,341	1,065	740,536	55,540	372,750	6,739,320	7,908,147
(2 , 100)	5,231	759	12,906	1,175	532,260	39,919	411,250	7,435,400	8,418,829
(1 , 10)	7,719	741	10,418	1,193	427,538	32,065	417,550	7,549,304	8,426,458
(2 , 54)	4,799	689	13,338	1,245	420,302	31,523	435,750	7,878,360	8,765,934
(2 , 26)	4,178	600	13,959	1,334	334,819	25,111	466,900	8,441,552	9,268,382
(3 , 1453)	3,282	750	14,855	1,184	1,272,987	95,474	414,400	7,492,352	9,275,214
(3 , 1000)	3,144	711	14,993	1,223	1,044,900	78,368	428,050	7,739,144	9,290,462
(3 , 674)	2,989	672	15,148	1,262	847,919	63,594	441,700	7,985,936	9,339,149
(3 , 442)	2,807	625	15,330	1,309	699,158	52,437	458,150	8,283,352	9,493,097
(3 , 282)	2,560	571	15,577	1,363	535,436	40,158	477,050	8,625,064	9,677,708
(2 , 10)	3,382	513	14,755	1,421	286,152	21,461	497,350	8,992,088	9,797,051
(3 , 172)	2,232	468	15,905	1,466	363,279	27,246	513,100	9,276,848	10,180,473
(3 , 100)	1,961	395	16,176	1,539	247,365	18,552	538,650	9,738,792	10,543,359
(3 , 54)	1,763	353	16,374	1,581	196,028	14,702	553,350	10,004,568	10,768,648
(3 , 26)	1,575	314	16,562	1,620	164,944	12,371	567,000	10,251,360	10,995,674
(4 , 1453)	1,135	328	17,002	1,606	426,251	31,969	562,100	10,162,768	11,183,088
(4 , 1000)	1,074	310	17,063	1,624	343,174	25,738	568,400	10,276,672	11,213,984
(4 , 674)	995	285	17,142	1,649	260,520	19,539	577,150	10,434,872	11,292,081
(3 , 10)	1,279	263	16,858	1,671	145,008	10,876	584,850	10,574,088	11,314,821
(4 , 442)	937	262	17,200	1,672	221,297	16,597	585,200	10,580,416	11,403,510
(4 , 282)	849	241	17,288	1,693	152,401	11,430	592,550	10,713,304	11,469,685
(4 , 172)	788	216	17,349	1,718	125,862	9,440	601,300	10,871,504	11,608,106
(4 , 100)	691	181	17,446	1,753	97,005	7,275	613,550	11,092,984	11,810,814
(4 , 54)	633	164	17,504	1,770	84,376	6,328	619,500	11,200,560	11,910,764
(4 , 26)	582	153	17,555	1,781	72,256	5,419	623,350	11,270,168	11,971,193
(5 , 1453)	378	152	17,759	1,782	165,044	12,378	623,700	11,276,496	12,077,618
(4 , 10)	496	134	17,641	1,800	66,172	4,963	630,000	11,390,400	12,091,535
(5 , 1000)	354	142	17,783	1,792	131,825	9,887	627,200	11,339,776	12,108,687
(5 , 674)	329	131	17,808	1,803	109,735	8,230	631,050	11,409,384	12,158,399
(5 , 442)	290	118	17,847	1,816	85,849	6,439	635,600	11,491,648	12,219,536
(5 , 282)	260	108	17,877	1,826	58,649	4,399	639,100	11,554,928	12,257,076
(5 , 172)	239	98	17,898	1,836	48,558	3,642	642,600	11,618,208	12,313,008
(5 , 100)	207	82	17,930	1,852	39,827	2,987	648,200	11,719,456	12,410,470

(5 , 54)	190	73	17,947	1,861	36,448	2,734	651,350	11,776,408	12,466,940
(5 , 26)	178	67	17,959	1,867	32,903	2,468	653,450	11,814,376	12,503,196
(5 , 10)	150	61	17,987	1,873	31,413	2,356	655,550	11,852,344	12,541,663
(6 , 1453)	107	53	18,030	1,881	55,839	4,188	658,350	11,902,968	12,621,345
(6 , 1000)	101	49	18,036	1,885	45,286	3,396	659,750	11,928,280	12,636,712
(6 , 674)	97	46	18,040	1,888	42,329	3,175	660,800	11,947,264	12,653,568
(6 , 442)	83	39	18,054	1,895	32,160	2,412	663,250	11,991,560	12,689,382
(6 , 282)	75	36	18,062	1,898	25,245	1,893	664,300	12,010,544	12,701,982
(6 , 172)	65	31	18,072	1,903	20,591	1,544	666,050	12,042,184	12,730,370
(6 , 100)	60	29	18,077	1,905	19,366	1,452	666,750	12,054,840	12,742,409
(6 , 54)	59	28	18,078	1,906	19,184	1,439	667,100	12,061,168	12,748,890
(6 , 26)	58	27	18,079	1,907	19,075	1,431	667,450	12,067,496	12,755,452
(6 , 10)	51	25	18,086	1,909	18,603	1,395	668,150	12,080,152	12,768,301
(7 , 674)	8	4	18,129	1,930	4,668	350	675,500	12,213,040	12,893,559
(7 , 1000)	8	4	18,129	1,930	4,668	350	675,500	12,213,040	12,893,559
(7 , 1453)	8	4	18,129	1,930	4,668	350	675,500	12,213,040	12,893,559
(7 , 282)	7	3	18,130	1,931	4,205	315	675,850	12,219,368	12,899,739
(7 , 442)	7	3	18,130	1,931	4,205	315	675,850	12,219,368	12,899,739
(8 , 674)	2	2	18,135	1,932	673	50	676,200	12,225,696	12,902,620
(8 , 1000)	2	2	18,135	1,932	673	50	676,200	12,225,696	12,902,620
(8 , 1453)	2	2	18,135	1,932	673	50	676,200	12,225,696	12,902,620
(7 , 10)	4	2	18,133	1,932	2,663	200	676,200	12,225,696	12,904,759
(7 , 26)	4	2	18,133	1,932	2,663	200	676,200	12,225,696	12,904,759
(7 , 54)	4	2	18,133	1,932	2,663	200	676,200	12,225,696	12,904,759
(7 , 100)	4	2	18,133	1,932	2,663	200	676,200	12,225,696	12,904,759
(7 , 172)	4	2	18,133	1,932	2,663	200	676,200	12,225,696	12,904,759
(8 , 10)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(8 , 26)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(8 , 54)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(8 , 100)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(8 , 172)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(8 , 282)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(8 , 442)	1	1	18,136	1,933	210	16	676,550	12,232,024	12,908,800
(9 , 10)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 26)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 54)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 100)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 172)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 282)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 442)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 674)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 1000)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(9 , 1453)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 10)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 26)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 54)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 100)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 172)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 282)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 442)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 674)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 1000)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(10 , 1453)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 10)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 26)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 54)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 100)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 172)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 282)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 442)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 674)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 1000)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252
(11 , 1453)	0	0	18,137	1,934	-	-	676,900	12,238,352	12,915,252

Appendix B: 91 Terms Considered in Metamodel

All 91 Terms (main effects, two-way interactions, squared main effects)								
terms to remove when p < .1		additional terms to remove when reduced p < .05						
Term	Estimate	Std Error	t Ratio	Prpb > |t|	Estimate	Std Error	t Ratio	Prpb > |t|
Intercept	7.600161	0.536355	14.17003	2.31E-37	376.8358	1.049577	359.0358	0
Pro1(0,1262)	0.002186	0.068261	0.032029	0.974465	12.61415	0.133578	94.43292	7.85E-280
Pro2(0,113)	-0.15421	0.069008	-2.23472	0.025975	12.83183	0.135039	95.02295	6.86E-281
Pro3(0,31)	-2.78116	0.067899	-40.9605	8.09E-147	14.16294	0.132869	106.5934	1.65E-300
Pro4(0,12.8)	-0.56115	0.068488	-8.19335	3.29E-15	14.25167	0.134022	106.3382	4.26E-300
Pro5(0,7.5)	-1.09184	0.068086	-16.0361	3.00E-45	13.46378	0.133237	101.0517	2.27E-291
Pro6(0,1.77)	-0.50561	0.068391	-7.39296	8.18E-13	12.6518	0.133832	94.53459	5.15E-280
Rep1(0,153)	-0.08331	0.069037	-1.20672	0.228238	0.155335	0.135096	1.149813	0.250893
Rep2(0,247)	-0.16382	0.06817	-2.40307	0.016703	1.144045	0.1334	8.576045	2.05E-16
Rep3(0,107)	-1.00708	0.068497	-14.7025	1.38E-39	1.788114	0.13404	13.34015	5.88E-34
Rep4(0,144)	-1.26875	0.068842	-18.4298	1.18E-55	2.227391	0.134716	16.53399	2.15E-47
Rep5(0,149)	-1.53813	0.069271	-22.2046	3.02E-72	8.036803	0.135554	59.2885	6.26E-203
Rep6(0,26)	-1.17379	0.068237	-17.2016	2.75E-50	6.723568	0.133532	50.35179	2.08E-177
Pro1*Pro2	-0.00889	0.081167	-0.10956	0.912813	-0.0114	0.158833	-0.07175	0.942834
Pro1*Pro3	0.017001	0.079029	0.215122	0.82978	-0.01361	0.154649	-0.088	0.929919
Pro1*Pro4	0.052808	0.080014	0.65999	0.509632	0.12082	0.156576	0.771636	0.440775
Pro1*Pro5	0.019137	0.079809	0.239785	0.810617	-0.03237	0.156176	-0.20726	0.835913
Pro1*Pro6	0.029662	0.079739	0.371995	0.710089	-0.11634	0.156039	-0.7456	0.456338
Pro1*Rep1	-0.02232	0.080307	-0.2779	0.781229	-0.11317	0.157151	-0.72015	0.471845
Pro1*Rep2	-0.00809	0.079793	-0.10136	0.919316	0.036462	0.156146	0.233511	0.815482
Pro1*Rep3	0.036407	0.08046	0.452486	0.651159	-0.04525	0.15745	-0.28739	0.77396
Pro1*Rep4	0.01599	0.080599	0.19839	0.842838	0.077007	0.157723	0.488243	0.625639
Pro1*Rep5	0.073876	0.080892	0.913263	0.361642	-0.31103	0.158296	-1.96484	0.050109
Pro1*Rep6	0.061303	0.08163	0.750992	0.453089	0.026465	0.159738	0.16568	0.868491
Pro2*Pro3	0.050735	0.081035	0.626085	0.531608	0.018881	0.158576	0.119066	0.905281
Pro2*Pro4	0.002783	0.082077	0.033906	0.972968	-0.14568	0.160614	-0.90702	0.36493
Pro2*Pro5	-0.09913	0.081267	-1.21986	0.223221	0.10859	0.159028	0.682836	0.495097
Pro2*Pro6	-0.03031	0.08196	-0.36987	0.711668	0.129387	0.160385	0.806729	0.420291
Pro2*Rep1	0.085871	0.08145	1.054288	0.292374	-0.11532	0.159387	-0.72353	0.469769
Pro2*Rep2	0.147251	0.080042	1.839667	0.066542	-0.10231	0.156632	-0.65316	0.514019
Pro2*Rep3	0.133828	0.080831	1.655663	0.098557	0.23437	0.158175	1.481713	0.139187
Pro2*Rep4	0.07539	0.08096	0.931202	0.352299	-0.0185	0.158429	-0.11677	0.9071
Pro2*Rep5	-0.15576	0.080948	-1.92422	0.05502	0.121672	0.158405	0.768104	0.442869
Pro2*Rep6	0.160591	0.081957	1.959455	0.050738	-0.25899	0.160379	-1.61485	0.107114
Pro3*Pro4	0.035797	0.080079	0.44702	0.655097	-0.1662	0.156705	-1.06058	0.289505
Pro3*Pro5	-0.11431	0.078755	-1.45149	0.147409	0.322796	0.154114	2.094526	0.036828
Pro3*Pro6	0.064889	0.08024	0.808689	0.419164	0.176944	0.157019	1.126891	0.260449
Pro3*Rep1	-0.00604	0.07946	-0.07595	0.939495	-0.12482	0.155494	-0.80274	0.422593
Pro3*Rep2	0.127591	0.079076	1.613533	0.1074	-0.09894	0.154741	-0.63941	0.522915
Pro3*Rep3	0.571768	0.079859	7.159754	3.78E-12	0.344916	0.156273	2.207138	0.027859
Pro3*Rep4	0.345058	0.080133	4.306061	2.08E-05	-0.01243	0.15681	-0.0793	0.936835
Pro3*Rep5	-0.09045	0.081115	-1.11509	0.265465	-0.09694	0.158732	-0.61069	0.541744
Pro3*Rep6	-0.05139	0.080083	-0.64168	0.521443	0.041001	0.156712	0.261633	0.793736
Pro4*Pro5	0.006035	0.08004	0.075398	0.939935	0.080146	0.156628	0.511699	0.609138
Pro4*Pro6	0.001107	0.08153	0.013579	0.989173	-0.0326	0.159544	-0.20432	0.838208
Pro4*Rep1	-0.05303	0.080446	-0.65925	0.510104	0.325532	0.157422	2.067888	0.039279
Pro4*Rep2	0.036658	0.079072	0.463606	0.643177	0.051872	0.154734	0.335236	0.737619
Pro4*Rep3	0.047911	0.080846	0.592619	0.553764	-0.09112	0.158205	-0.57598	0.564944
Pro4*Rep4	0.059166	0.081714	0.724067	0.469439	0.408494	0.159903	2.554634	0.010991
Pro4*Rep5	-0.03911	0.081823	-0.47801	0.632901	0.574074	0.160116	3.58536	0.000377
Pro4*Rep6	0.108969	0.08063	1.351461	0.177295	-0.09695	0.157783	-0.61446	0.539251
Pro5*Pro6	0.090178	0.079798	1.130075	0.259107	-0.14496	0.156155	-0.92831	0.353797
Pro5*Rep1	0.069852	0.080399	0.868825	0.385453	0.010271	0.15733	0.065282	0.947981
Pro5*Rep2	0.067053	0.079272	0.845854	0.398129	-0.17936	0.155125	-1.15621	0.248269
Pro5*Rep3	-0.00892	0.080242	-0.11117	0.91154	0.073077	0.157024	0.465387	0.641902
Pro5*Rep4	-0.04721	0.080449	-0.58681	0.557652	0.130623	0.157429	0.829729	0.407176
Pro5*Rep5	0.06632	0.080068	0.828296	0.407986	0.266866	0.156683	1.703217	0.089287
Pro5*Rep6	-0.0673	0.080279	-0.83829	0.402356	-0.04422	0.157095	-0.28149	0.778475
Pro6*Rep1	-0.09541	0.08102	-1.17757	0.239652	0.322661	0.158545	2.035137	0.042481
Pro6*Rep2	0.053419	0.080209	0.665996	0.505789	-0.13639	0.156958	-0.86897	0.385375
Pro6*Rep3	-0.02475	0.081342	-0.30432	0.761038	0.062086	0.159175	0.390051	0.696702
Pro6*Rep4	0.06427	0.080615	0.797251	0.425768	-0.03343	0.157753	-0.21191	0.832285
Pro6*Rep5	0.06315	0.081498	0.774872	0.438863	0.093618	0.159481	0.587018	0.557516
Pro6*Rep6	-0.16888	0.0806	-2.09533	0.036756	0.222016	0.157724	1.407624	0.160002
Rep1*Rep2	-0.07173	0.080512	-0.89089	0.37351	-0.03583	0.157551	-0.22739	0.82023
Rep1*Rep3	-0.03487	0.080785	-0.43162	0.666244	-0.04694	0.158085	-0.2969	0.766695
Rep1*Rep4	-0.06193	0.080767	-0.76677	0.443663	0.388791	0.158051	2.459911	0.01431
Rep1*Rep5	-0.08812	0.080933	-1.08875	0.276906	-0.01309	0.158376	-0.08267	0.934154
Rep1*Rep6	0.033716	0.081375	0.414329	0.678851	-0.18779	0.15924	-1.17931	0.23896
Rep2*Rep3	-0.04845	0.079439	-0.60995	0.542232	-0.31553	0.155452	-2.02975	0.043028
Rep2*Rep4	-0.20294	0.080116	-2.5331	0.011679	0.481979	0.156776	3.074306	0.002251
Rep2*Rep5	0.029675	0.079481	0.37336	0.709074	0.053611	0.155533	0.344692	0.730503
Rep2*Rep6	0.025829	0.080636	0.320312	0.748896	-0.09188	0.157794	-0.58226	0.560715
Rep3*Rep4	-0.04113	0.080692	-0.50975	0.6105	0.04393	0.157904	0.278205	0.780996
Rep3*Rep5	-0.07605	0.080224	-0.94791	0.343734	0.064135	0.156988	0.408537	0.683093
Rep3*Rep6	0.007387	0.081559	0.090567	0.927881	0.113983	0.1596	0.714182	0.475522
Rep4*Rep5	-0.0413	0.08108	-0.50938	0.610764	0.043406	0.158663	0.273577	0.784548
Rep4*Rep6	-0.09205	0.080141	-1.14856	0.251408	0.040853	0.156826	0.260497	0.794612
Rep5*Rep6	-0.1654	0.081644	-2.02593	0.043421	0.122159	0.159767	0.76461	0.444945
Pro1*Pro1	-0.18402	0.176325	-1.04363	0.297273	0.409591	0.345045	1.187068	0.23589
Pro2*Pro2	-0.0058	0.169059	-0.0343	0.972652	1.223177	0.330827	3.697329	0.000248
Pro3*Pro3	1.584498	0.174002	9.106203	3.82E-18	3.291327	0.3405	9.666168	4.82E-20
Pro4*Pro4	-0.06518	0.167333	-0.38949	0.697114	2.986836	0.32745	9.121508	3.40E-18
Pro5*Pro5	-0.24223	0.169184	-1.43174	0.152982	5.916323	0.331071	17.87028	3.33E-53
Pro6*Pro6	0.170615	0.168491	1.012606	0.311847	2.380759	0.329716	7.220637	2.54E-12
Rep1*Rep1	0.174791	0.170648	1.024278	0.306309	-0.35367	0.333936	-1.05911	0.290177
Rep2*Rep2	0.356426	0.169641	2.101055	0.036248	-1.46151	0.331967	-4.40258	1.37E-05
Rep3*Rep3	1.3574	0.164626	8.245362	2.27E-15	-1.48961	0.322152	-4.62395	5.06E-06
Rep4*Rep4	1.556627	0.165152	9.425439	3.22E-19	-2.24745	0.323181	-6.95415	1.41E-11
Rep5*Rep5	1.901052	0.164544	11.55348	6.50E-27	-9.55247	0.321991	-29.6669	5.25E-104
Rep6*Rep6	1.541653	0.171443	8.992202	9.11E-18	-6.69348	0.335493	-19.9512	2.42E-62

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13. SUPPLEMENTARY NOTES

14. ABSTRACT

Many firms generate revenue by successfully operating machines such as welding robots, rental cars, aircraft, hotel rooms, amusement park attractions, etc. It is critical that these revenue-generating machines be operational according to the firm's target or requirement; thus, assuring sustained revenue generation for the firm. Machines can and do fail, and in many cases, restoring the downed machine requires spare part(s), which are typically managed by the supply chain. The scope of this research is on the supply chain management of the very sparse, intermittently-demanded spare parts. These parts are especially difficult to manage because they have little to no lead time demand; thus, modeling via a Poisson process is not viable. The first area of our research develops two new frameworks to improve the supply chain manager's stock policy on these parts. The stock polices are tested via case studies on the A-10C attack aircraft and B1 bomber fleets. Results show the AF could save $10M/year on the A10 and improve support to the B1 without increasing inventory. The second area of our research develops a framework to integrate the supply chain processes that generate these service parts. With the integrated framework, we establish two new forward-looking metrics. We show examples how these forward-looking metrics can advance the supply chain manager's desire to know what proactive decisions to make to improve his/her supply chain for the good of the firm.

15. SUBJECT TERMS

Intermittent Demand, Sporadic Demand, Cost-Effective Readiness, Supply Chain Management

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