Evaluating Inventory Segmentation Strategies for Aftermarket Service Parts in Heavy Industry using Linked Discrete-Event and Monte Carlo Simulations

by

Randolph L. Bradley

Bachelor of Science, Mathematics
Oklahoma State University, Oklahoma, 1984

Master of Business Administration
Oklahoma State University, Oklahoma, 1985

Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degree of

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Signature of Author ........................................

Master of Engineering in Logistics Program, Engineering Systems Division

May 7, 2012

Certified by ....................................................

Jarrod Goentzel
Director, MIT Humanitarian Response Lab
Thesis Supervisor

Accepted by ....................................................

Yossi Sheffi
Elisha Gray II Professor of Engineering Systems
Professor of Civil and Environmental Engineering
Director, Center for Transportation and Logistics
Director and Founder, Master of Engineering in Logistics Program
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ABSTRACT

Heavy industries operate equipment having a long life to generate revenue or perform a mission. These industries must invest in the specialized service parts needed to maintain their equipment, because unlike in other industries such as automotive, there is often no aftermarket supplier. If parts are not on the shelf when needed, equipment sits idle while replacements are manufactured. Stock levels are often set to achieve an off-the-shelf fill rate goal using commercial inventory optimization tools, while supply chain performance is instead measured against a speed of service metric such as order fulfillment lead time, the time from order placement to customer receipt. When some parts are more important than others, and shipping delays are accounted for, there is ostensibly little correlation between these two metrics and setting stock levels devolves into an inefficient and expensive guessing game. This thesis resolves the disconnect between stock levels and service metrics performance by linking an existing discrete-event simulation of warehouse operations to a new Monte Carlo demand categorization and metrics simulation, predicting tomorrow’s supply chain performance from today’s logistics data.

The insights gained here through evaluating an industry representative dataset apply generally to supply chains for aftermarket service parts. The simulation predicts that the stocking policy recommended by a simple strategy for inventory segmentation for consumable parts will not achieve the desired service metrics. An internal review board that meets monthly, and a quarterly customer acquisition policy, each degrade performance by imposing a periodic review policy on stock levels developed assuming a continuous review policy. This thesis compares the simple strategy to a sophisticated strategy for inventory segmentation, using simulation to demonstrate that with the latter, metrics can be achieved in one year, inventory investment lowered 20%, and buys for parts in low annual usage categories automated.

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1 Motivation

Heavy industries operate equipment having a long life to generate revenue or perform a mission. These industries must invest in the specialized service parts needed to maintain their equipment, because unlike automotive parts, there is often no aftermarket supplier. If parts are not on the shelf when needed, equipment sits idle while replacements are manufactured lead time away. Stock levels are often selected to achieve an off-the-shelf fill rate goal using commercial inventory optimization tools, while supply chain performance is instead gaged against a measure of the speed of service such as Order Fulfillment Lead Time (OFLT), the time from order placement to customer receipt. The OFLT metric is analogous to perfect order fulfillment, but within a delivery window that varies based upon priority. Stock levels for service parts in heavy industry are frequently optimized based on fill rate using an industry standard inventory optimization tool. Since these existing tools are neither designed to optimize to nor estimate OFLT, heavy industries cannot predict performance to their desired service metrics.

This thesis tests the hypothesis that OFLT and inventory investment, using a common baseline inventory segmentation strategy for consumable parts, can be improved through an alternate inventory segmentation strategy that groups parts by annual use, or cost times demand.

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Master of Engineering in Logistics (MLOG) masters’ theses are often sponsored by industry partners participating in the Supply Chain Exchange program of the MIT Center for Transportation and Logistics (CTL). This thesis is based a dataset which is representative of aftermarket service parts in heavy industry. Although the dataset does not reflect any specific company, the results are broadly applicable across heavy industry.
Estimating OFLT performance over time, and testing the inventory segmentation strategy hypothesis, will be conducted by linking an existing discrete-event simulation of warehouse operations with a newly developed Monte Carlo demand categorization and metrics simulation. First, the discrete-event warehouse simulation will evaluate orders of varying size for parts which fail according to a Poisson distribution, where time is important because inventory levels vary based on demand for spare parts, and replenishment occurs within the manufacturing lead time of parts which reach their reorder point. This warehouse simulation creates a list of orders which occur over time. Second, the Monte Carlo demand categorization and metrics simulation will review each warehouse order after “rolling the dice” to determine order priority, order size, whether the order is included in the metrics calculation, and shipping delay. Empirical distributions for these random variables will be developed using historical data. The Monte Carlo simulation will use these random draws to categorize each warehouse order and determine the metrics for OFLT, by month.

The linked simulations analyze supply chain data from a representative industry dataset and historical orders placed by operating organizations needing to maintain their equipment over time. Required supply chain data includes the inputs (current on hand, due-in, and backorder inventory position, demand, lead time, price, condemnation rate, and maintenance concept) and outputs (target stock level, reorder point, and reorder quantity) of a commercial inventory optimization. Also required are historical requisition data (part number, order quantity, and date), shipping performance data (days shipping delay by requisition, priority by requisition), performance (as reported within a company), and operational data including equipment delivery schedule and future operating hours by period. After benchmarking the new predictive
simulation models to an existing commercial inventory optimization model by comparing fill rate results, the new models will be used to estimate OFLT over time.

Unlike most supply chain simulation models, which require an extended warm-up period and only estimate steady state conditions, these new models will take into account the existing state of the supply chain, due-in orders with scheduled delivery dates, and optimized stock levels and reorder points in order to estimate OFLT over time, as of the exact date of the data pull. In this manner, these simulations will extend the state of the art by eliminating the warm-up period, thus providing both short-term and long-term predictions of performance to contractual metrics. Further, this thesis demonstrates how complex legacy simulation models can find new life by feeding data to specialized demand categorization simulations which evaluate contemporary metrics.

This thesis will benefit heavy industry in general by predicting future OFLT performance over time, given supply chain uncertainty, providing guidance in (a) setting appropriate stock level goals, and (b) estimating when program performance will achieve contractual goals. This thesis will contribute to academic knowledge by presenting a real world case study demonstrating that an operating supply chain in non-steady state conditions can be effectively evaluated using simulation without a warm up period.

2 Introduction to Aftermarket Service Parts for Heavy Industry

The methodology developed in this thesis for evaluating the relative benefits of competing inventory segmentation strategies is of interest to, and benefits, global users, manufacturers and distributors in heavy industries. Companies in these industries are characterized by:
• High dollar capital investment in critical resources
• Long equipment life-cycle requiring maintenance over time
• Significant investment in inventory of service parts
• Suffering from low utilization of expensive resources

As manufacturers and distributors realize the extent of the aftermarket spend on industrial assets, ranging from 30% to 2000% of original product cost (Forrester Research, 2002), they are starting to focus on efforts to improve the revenue and cost performance of their aftermarket businesses.

This thesis evaluates an industry representative dataset global typical of companies in key heavy industries:

• Utilities (Oil and gas exploration, Power generation)
• Manufacturing and Industrial Equipment (Logging and mining, Construction)
• Semiconductor, Computer and Electronics (Maintenance and service of production and installed equipment)
• Aerospace (Commercial aviation and military platforms)
• Defense (Military services)
• Telecommunications
• Automotive and Transportation (Rail, Shipping)
• Medical Systems (Equipment maintenance)

This study is geared towards improving the strategies used in the planning and replenishment of repair components (hereafter referred to as reparables), and consumable piece parts (hereafter referred to as consumables) in the aftermarket supply chain of these heavy industries. The results of this thesis are intended to improve aftermarket supply chain performance by:
• Lowering total life-cycle cost of ownership of expensive and critical resources
• Lowering inventory investment through optimization in appropriate segments
• Increasing effective use of the equipment heavy industry requires to generate revenue, which increases profits
• Lowering management and IT infrastructure costs by providing cost-effective recommendations for automating inventory segmentation, and for automating buys of specific segments

3 Operational Scenario

Operational Scenario: An industry representative dataset was configured in a single indenture, single echelon network. Single indenture means that while there are separate networks for consumable parts, reparable assemblies, reparable sub-assemblies, and reparable sub-sub-assemblies, each network is optimized individually to a fill rate target. That is, there is no explicit indenture relationship between parent and child parts. Single echelon means that all parts are centrally located at a single wholesale warehouse operated by either a company or a third party logistics (3PL) vendor, and all demand occurs at retail equipment operations.

Equipment Operating Hours: A generic fleet of operating equipment was simulated using a common Bill of Materials (BOM). The current annual operating hours, expected equipment delivery schedule, and expected future equipment operating hours were appropriate for the equipment type.
Consumable and Reparable Parts: Service parts for heavy industry are commonly divided into two groups: the reparable components which are repaired, and the consumable parts which are replaced.

- Repairs of reparable components often involve replacing multiple consumable piece parts, as well as testing, evaluating, reconditioning, refurbishing, and otherwise returning components to a serviceable status in repair shops capable of intermediate level repairs and depots capable of returning parts to like new status. Reparable parts may be optimized to a fill rate target, either as a group or by level of repair, or optimized to an equipment availability target based upon the maintenance indenture structure of the equipment, which specifies the parent-child relationships between parts.

- Consumable parts are simply scrapped, and replaced with new parts. Consumable parts are optimized to a fill rate target, either as a group or within groups specified by an inventory segmentation strategy.

Focus of Thesis: The focus of this thesis is on evaluating inventory segmentation strategies for determining stock levels for consumable parts. While reparable parts are mentioned for completeness, the analysis delves into selecting appropriate strategies for optimizing inventories of consumable parts.

Data Source: The inputs and outputs of a commercial inventory optimization model, selecting the data elements described in Section 1, were extracted on November 2011. Since fleet operating hours increase as additional new equipment is delivered, the target stock levels from the mid-point of the upcoming twelve month period were chosen as being appropriate for supporting the average, steady state demand over this timeframe.
**Inventory Optimization Goals:** Consumable parts were segmented into an A network for parts costing over $2,000 with a 90% fill rate target, and a B network for parts costing $2,000 or less with a 95% fill rate target. The model performs an economic order quantity analysis to balance inventory holding cost with order placement cost, and then selects additional parts until the desired fill rate target is achieved. Further, a business rule was developed to ensure that at least the average pipeline quantity of parts is on hand, which means that the minimum stock level is effectively the average number of parts which will be required during the weighted average lead time across procurement and repair, or enough to ensure a minimum 50% fill rate.

**Inventory:** The starting inventory is the current on hand plus due-in minus backorders from the inventory management system used for warehouse operations. This data is fed to the inventory optimization model daily.

**Initial Starting Conditions:** In order to model the data in the commercial inventory optimization model, which contains daily inventory feeds from the inventory management system, several assumptions were required in order to translate from the static inventory position in the inventory optimization model to the dynamic, time varying inventory position of the simulation. The most important are:

- **Due-In Parts:** For evaluation with the Discrete-Event Warehouse Simulation, due-in parts arrive on the due date specified within the inventory management system.

- **Overdue, or Delinquent, Due-in Parts:** A random offset was assigned to “Overdue Due-In” parts so that they would arrive between the current date and the procurement lead time. An analysis showed that many of these parts were overdue by amounts up to
and exceeding lead time, so randomly assigning the due-in date within this range was deemed appropriate.

- **On Hand but Defective Reparables**: A random offset was assigned to “On Hand Defective” parts so that they would arrive back from repair between 1X and 1.5X the repair lead time. Since most of these parts had yet to be inducted into repair, and since the depot repair capacity might be taxed if all parts were inducted simultaneously, spreading the repair time between one and one and a half times the historical repair time was deemed appropriate.

- **On Hand but Defective Consumables**: These parts were condemned and not modeled, as by default consumables are not repaired. While in some cases limited repairs to consumables are possible, such as turning down a shaft when this can be done within tolerance, this is the exception.

- **Parts on Backorder**: Many inventory optimization models do not recognize negative starting inventory (backorders). When required, backorders were summarily filled when the inventory position was negative. Since sufficient parts were on hand or due-in to fill the backorders in many cases, few inventory positions were non-negative.

**Order Fulfillment Lead Time (OFLT)**: The OFLT metrics that a company might report internally come from an analysis of transactional data contained in an inventory management system; an inventory optimization model itself does not contain sufficient information. For this thesis, OFLT was simulated by developing probability distributions created through analyzing historical (transactional) data from an inventory management system. In fact, the Monte Carlo demand categorization and metrics simulation model discussed later mimics this reporting process.
**Time Period:** Simulations were executed for 761 days spanning December 1\(^{st}\), 2011 through December 31\(^{st}\), 2013. The current inventory position as of November, 2011, was modeled to determine how well these stock levels support simulated demand beginning on December 1\(^{st}\), 2011. Thus, this thesis simulates tomorrow’s supply chain performance based on today’s inventory data by synchronizing the start date of the simulation with extract creation date from the inventory optimization model, which contains daily feeds for inventory data.

### 4 Sources of Supply Chain Uncertainty

Supply chain uncertainty comes from multiple sources. This thesis will consider demand variability and order quantity variability together as *variability of monthly demand*. Acquisition policy will also be considered as *review policy*; that is, whether orders are placed monthly, quarterly, or annually. Other sources of uncertainty, which are candidates for inclusion in future development spirals, are captured for completeness.

*Exogenous uncertainties*, which are not influenced by managerial decisions, include:

- **Demand Variability**: How often equipment service parts require maintenance.
- **Procurement Lead Time Variability**: The time vendors require to fabricate a new part.
- **Order Quantity Variability**: How many parts retail (equipment operators) order from wholesale (the central warehouse).
- **Condemnation Rate Variability**: Whether reparable parts can be fixed to a Ready For Issue (RFI) condition, or are discarded as Beyond Economical Repair (BER).

These uncertainties are *path independent*, because supply chain issues with one part do not impact other parts.
Endogenous uncertainties, which are influenced by managerial decisions, include:

- **Stocking Policy**: The Reorder Point and Reorder Quantity may be set by a number of different models. Safety stock may be added as a buffer against uncertainty in order to achieve a desired level or performance, such as fill rate.

- **Review Policy**: Validating orders for costly investment spares by periodically convening a Spares Requirements Review Board (SRRB) adds a delay in processing orders which either must be added to the procurement lead time of each part, or will degrade supply chain performance.

- **Acquisition Policy**: Whether funding contracts are annual or quarterly, and whether the contracts allocate budget for a fixed quantity of specific part numbers, or general budget to be used flexibly based on random demand.

- **Repair Turnaround Time Variability**: Repair turnaround time is a function of the authorized budget, because in a tight economy not all failed parts are funded for repair. Further, the fill rate goal for consumable piece parts impacts the ability to effect repairs at the depot using piece parts from on hand stock.

In the special case of depot level repair of components, these uncertainties are not path independent, because shortages of “child” piece parts impact the ability to repair the “parent” component, which extends the repair turnaround time of the component, causing a ripple effect in the supply chain. Further, depots will often fabricate parts internally, or at local machine shops, or buy consumable parts outside of formal supply channels, skewing the apparent distribution of demand for child piece parts which are in short supply.
5 Introduction to the Order Fulfillment Lead Time Metric

Fill Rate: The percent of total orders shipped from stock on hand is known as Fill Rate. Backorders are the remaining percent of total orders out of stock. Fill Rate + Backorders = 100% (Fill Rate and Backorders are inversely proportional).

Perfect Order Fulfillment (POF): Perfect Order Fulfillment is the percent of total orders shipped on time and in full.

Order Fulfillment Lead Time (OFLT): A measure of the speed of service, Order Fulfillment Lead Time represents the average time from order placement to customer receipt. As a performance metric, OFLT represents POF within a delivery window. OFLT may be simulated as POF plus shipping delay. OFLT and Backorders are also inversely proportional, but it is not an exact relationship due to variability of demand and order quantity.

Performance Goals: Goals for Order Fulfillment Lead Time metrics, selected to represent notional industry requirements, are described in Table 1.

<table>
<thead>
<tr>
<th>Priority</th>
<th>Performance Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Priority Orders</td>
<td>85% filled in full within 4 days</td>
</tr>
<tr>
<td>Low Priority Orders</td>
<td>90% filled in full within 16 days</td>
</tr>
</tbody>
</table>

Simulation models, described in detail in Section 7.3, will be used to evaluate supply chain metrics over time. The interrelationships between these metrics, as captured through the simulations, are shown in Figure 1. For consumable parts, Fill Rate (orders shipped from stock on hand) is the highest scoring metric, followed by the most stringent Perfect Order Fulfillment (orders shipped on time and in full) metric. Order Fulfillment Lead Time (orders delivered on
time and in full) is essentially POF shifted down due to the impact of shipping delays. The proportion of parts on Backorder (out of stock) is inversely proportional to Fill Rate, and Fill Rate plus Backorders account for 100% of all orders; that is, parts are either in stock (Fill Rate) or out of stock (Backorder).

6 Review of the Relevant Literature

Law and Kelton (2003) describe the successful use of simulation to understand large-scale systems, such as “determining ordering policies for an inventory system.” Simulation is the classic approach to studying complex engineered systems.

Given that simulation is the chosen technique for estimating the Order Fulfillment Lead Time metric, this literature review focuses on three areas: (1) application of inventory optimization to
maintenance supply chains, (2) applications of discrete-event simulation to maintenance supply chains, and (3) identifying future research directions for creating additional value in the supply chain through expanding the efficient frontier by increasing the return for a particular level of risk. The last area suggests that the simulation developed for this thesis has enduring value as a tool for evaluating these future supply chain solutions. These references describe recent technical approaches which can enable companies to achieve supply chain metrics tomorrow at lower lifecycle cost than today.

6.1 Optimizing Stocking Policies for Service Parts

The use of multi-echelon inventory optimization for service parts, characterized by low demand probabilities, high cost, and high priority for service characterized by “response time service levels” is described by Cohen, Kleindorfer and Lee (2006); Inventory Optimization Model A referenced in this paper uses this technique. A system approach to setting stock levels for multi-echelon, multi-indenture equipment in fleets of commercial and military aircraft, ships, telecommunications networks, and power plants is described by Sherbrooke (2004), along with distinguishing between the treatment of consumable and reparable parts; Inventory Optimization Model B referenced in this paper uses this technique. Fuerst (1981) describes the classic ABC inventory segmentation analysis from a practitioner’s standpoint. Rossetti and Achlerkar (2004, 2009) discuss techniques for spare parts segmentation, presenting a summary review of the literature on multi-echelon inventory models and clustering approaches to inventory segmentation. McKinsey & Company (2008) notes that service, inventory, and profitability improve when industry implements supply chain segmentation techniques based on product needs and demand patterns. The focus of planning departments also improves.
6.2 Simulating Stocking Policies

Integrating inventory optimization and simulation to analyze supply chain effectiveness is espoused by Ingalls, Cornejo, Methapatara and Sittivijan (2008), noting that “Given a mathematically optimal solution as recommended by optimization, simulation shows how that optimal solution will perform under dynamic conditions.” A modular approach to simulation, in which modules are related based on process, but independent based on coding, is described by Shoaf (1983). The commercially available ExtendSim simulation language is designed to integrate simulation with the supporting data that defines the scenario (Diamond, et al., 2010). The Discrete-Event Warehouse Simulation described in this thesis is based on a library of reusable supply chain modules for evaluating manufacturing schedules, performing inventory analysis, and modeling supply chains that uses ExtendSim as the foundation. Practical methods to verify and validate simulation models are discussed by Sargent (2010); this paper used the techniques of data validity, comparison to other models, face validity, historical data validation, internal validity, parameter variability – sensitivity analysis, and predictive validation in developing and validating linked simulations of aftermarket service parts. Park and Won (2006) apply a statistical process to calculating the minimum number of repetitions of a simulation, also described in Dowling, Skabardonis and Alexiadis (2004) and originally in Banks, Carson, Nelson and Nicol (2001, pp. 414-416).

Skoogh, Michaloski and Bengtsson (2010) recommend automating data collection and processing to integrate supply chain simulation as a daily tool, rather than a single-purpose study; the Extract, Transform and Load (ETL) tool of this paper automates the creation of simulation datasets, based on input data contained in an inventory optimization model, representing a significant step in this direction.
Dorey (2011) provides an overview of standard and incentive contract types, proposes to characterize contract risk by using simulation to map probabilistic cost estimates to profit distributions, and recommends risk-driven contract structures to impose cost sharing and bound cost growth; the Order Fulfillment Lead Time metric discussed in this paper is an example of a speed of service metric that would be attached to a risk-driven service parts contract.

### 6.3 Future Supply Chain Solutions

Maintenance supply chains for heavy industry can be further improved through additional analysis, and numerous studies suggest where to focus attention. First, an approach by Chang, Chou and Huang (2005) to hold back inventory for high priority demand in lieu of filling low priority demand is discussed. Second, a group of studies are reviewed which together offer an exciting combined approach to improving maintenance supply chains that integrates suppliers and customers. Kennedy, Patterson, and Fredendall (2002) characterize spare parts inventories; Ghobbar and Friend (2002) discuss aerospace demand forecasting; Gallego (1995) combines different demand forecasting models with the newsvendor problem; Sheffi (2009) applies the newsvendor problem to coordinate buyers such as heavy industry and sellers such as suppliers; Johnson (2010) coordinates buyers and suppliers with flexible range planning contracts tailored to tiered demand scenarios; Graves (2000) instead favors supplier coordination by specifying lead time and Work In Process (WIP) safety stocks; and discussions with Crane (2012) inspired a new approach combining demand forecasting to identify requirements, the newsvendor model to set contract goals for range planning contracts, and contracting for specific WIP safety stocks to lower lead time. Third, Haydamous (2009) suggests that predictive supplier metrics provide early warning, allowing future supply chain issues to be preempted. These references weave
together a credible approach to extend the efficient frontier past traditional inventory optimization and into supplier management through innovative contracting approaches.

Chang, Chou and Huang (2005) classify demand for spare parts into critical and non-critical demand, depending on the importance of the part in restoring equipment to service. The authors create an inventory model for spare parts in which some of the stock is reserved for critical demand known as (r,r,Q). A procedure is presented to determine the critical level (r), which is set equal to the reorder point (r), and the reorder quantity Q. This model is successfully used to select spare parts for semiconductor fabrication equipment. For heavy industries with multiple classes of supply demand, this method could be used to segregate inventory depending on whether an order is high priority (critical) or low priority (routine).

Kennedy, Patterson, and Fredendall (2002) draw distinctions between retail inventories of parts for sale, WIP manufacturing inventories, and inventories of spare parts for maintenance of equipment. Their paper discusses the peculiar characteristics of spare parts inventories, reviews the literature, and addresses special cases including wear-out items, multi-echelon inventory optimization, obsolete parts, and reparable parts. The special purpose parts models described in this research could be tuned to the part by part fill rate of a global inventory optimization model, thereby offering a method of fine tuning stock levels.

The industry standard technique for estimating future requirements is Simple Exponential Smoothing (SES) with a 10% smoothing constant, in conjunction with applying future operating hours as a causal factor to forecast increasing or decreasing demand, in what is known as a blended forecast. Alternate forecasting techniques may be more appropriate for the characteristics of demand for service parts, or may reduce forecast error. Ghobbar and Friend (2002) evaluate multiple well known techniques for predicting demand for spare parts in airline
fleets, finding the best being the weighted moving average, Holt’s method for forecasting using exponential smoothing with a linear trend, and Croston’s method for low and intermittent demand. The authors then suggest a new model for evaluating forecasting approaches for low and intermittent demand parts based on forecast error. Varghase (2009) reviews forecasting methods for large scale inventory systems with intermittent demand, focusing on spare parts for military equipment. Varghase’s research develops a new technique for forecasting intermittent demand, suggests a new performance measure for evaluating forecasting techniques for inventory systems based on error measures, and creates new forecasting software for selecting the best techniques for inventory systems.

In lecture notes, Gallego (1995) reviews the classic newsvendor problem, which involves sizing a single order that must be placed before observing demand where overage (excess) and underage (shortage) costs exist. The problem is important for items with significant demand uncertainty and large overage and underage costs. Gallego develops the equations used to solve the newsvendor problem with normal, Poisson, lognormal, and worst case demand distributions, which are the demand distributions applicable to high dollar low volume spare parts. The advantages of altering the supply chain to one’s advantage through forecast updates and gaining access to advance demand information are detailed. This research applies to so-called retail locations, which operate heavy equipment and often set stock levels locally; these retail stock allocations are often funded through an annual budgeting process, which is often insufficient to fully fund the desired stock levels. The newsvendor problem, incorporating the appropriate demand distributions, could be applied to stock levels set via an annual budgeting process by assigning overage (inventory holding) and underage (penalty of missing metrics) costs.
Sheffi (2009) notes that when buyers and sellers optimize individually in their own self-interests, profits for the supply chain as a whole are often unnecessarily low. Buy-back contracts, revenue-sharing contracts, and wholesale price contracts offer buyers and sellers incentives to act in the supply chain’s global interest (Sabbaghi, Sheffi and Tsitsiklis, 2011). The classic newsvendor problem is used to highlight the risk associated with mismatched supply and demand. Sabbaghi’s analysis extends the newsvendor problem towards achieving a global optimal solution between buyer and seller via supply contracts.

Johnson (2010) emphasizes that range planning bases inventory plans on a stochastic distribution, or uncertain range, of expected requirements, rather than a single average estimate. Benefits of range planning include improving supply chain performance, increasing operational and financial performance, and lowering risk. A prototype system is developed to value the benefits of range planning. Companies participating in Johnson’s study observed that the move from planning with a single number to an expected range requires changes to a company’s internal processes. Range planning offers an alternative to safety stock in dealing with uncertain demand, which leverages supplier relationships. Johnson’s analysis emphasizes dealing with uncertainty via supplier contracts containing flexible ranges for requirements, and offers guidance for setting appropriate ranges.

Graves (2008) examines the use of strategic inventory placement models to determine the amount and positioning of safety stocks in manufacturing supply chains. The inventory of finished goods can be reduced using safety stock to lower waiting time in manufacturing stages, this lowering overall production lead time. By strategically storing inventory to eliminate bottlenecks in the production process, even with uncertain demand, high services levels can be provided at minimum cost. Hetzel (1993) quantifies the savings potential for placing minimum
safety stocks at manufacturing stages in Eastman Kodak's manufacturing process for the film supply chain. Billington et al. (2004) describe how holding inventory at key steps in the manufacturing chain lowered costs and improved fill rate within Hewlett Packard's Image and Printing Group. Billington's co-author Crane (2012) explained, in a conversation, that he preferred to specify a lead time, which could be loaded into a supplier's Enterprise Resource Planning (ERP) system, and buffer stock at specific levels, which could also be put in a supplier's ERP system. Crane also espoused the value of involving multiple people in model building, to gain consensus and validate assumptions.

Haydamous (2009) notes that predictive metrics provide advance notice of impending business, project, and supplier issues. As applied to the Aerospace & Defense (A&D) industry, they estimate future performance, enabling decision makers to synchronize strategy with expected results. A combination of predictive operational metrics to foretell future problems, and supply chain simulation to evaluate recommended solutions, offers a particularly powerful solution for supply chain execution in heavy industry.

7 Methodology: The Supply Chain Simulation Process

Rapidly integrating multiple supply chain software tools, in order to provide a forward looking analysis of a supply chain, offers companies a competitive advantage: if you can predict the future, you can continue strategies that work and alter those that do not. With an emphasis on melding tools though data cleaning and integration, this thesis developed the capability to seamlessly integrate data analysis, inventory optimization, warehouse simulation, demand categorization and metrics simulation, and supply chain reporting. As the experience simulating service metrics demonstrates, the challenge is to rapidly create different data models, such as
model containing different networks of consumable parts; populate these data models with different data elements, such as (a) current inventory position, (b) target stock levels from a commercial inventory optimization model, or (c) trial stock levels during thesis analysis of alternate stocking policies; and conducting trade studies by simulating metrics in order to compare the scenarios.

The study was conducted in several steps, as shown in Figure 2 and as described below:

- Extracting supply chain data from the November 2011 run of a commercial inventory optimization model (hereafter referred to as Inventory Optimization Model A, or simply Model A) using a commercial Extract, Transform and Load (ETL) software tool.
- Preparing the supply chain data by creating a normalized, common dataset for analysis using a data cleaning and integration software tool of the author’s design. See Section 7.2 for more detail.
- Validating the data extract via automated line count reports, which tally part counts and analytically calculate annual consumption. Comparing these reports to the numbers reported in Inventory Optimization Model A validates the data manipulations and summaries necessary to create an appropriate dataset for simulation.
- Validating the extract by running a second commercial inventory optimization model (hereafter referred to as Inventory Optimization Model B, or simply Model B) in evaluation mode, to evaluate the fill rate that could be achieved with the extracted dataset and the Target Stock Levels (TSLs) from Model A. If both Model A and Model B agree on fill rate, one could conclude that (a) both models perform similarly, and (b) more importantly, that the myriad supply chain parts and data elements were accurately extracted from Model A, manipulated correctly in the data cleaning and integration
system, and successfully loaded to Model B. One could extend this conclusion to infer that an accurate input dataset for the Discrete-Event Warehouse Simulation could be created by the data cleaning and integration system.

- Executing multiple runs of the Discrete-Event Warehouse Simulation model, also referred to as the warehouse simulation. By altering the random number seed on each run, a different view of how typical years might play out was created. See Section 7.3.1 for more detail.

- Validating the starting conditions, using the Inventory Optimization Model B to evaluate the expected fill rate from the current inventory position in an inventory management system.

- Developing a custom Monte Carlo Demand Categorization and Metrics Simulation model, also referred to as the metrics simulation, to visualize supply chain metrics over time. This post processor added probabilistic data, based on an analysis of inventory management system data, for the percentage of time an order counted towards metrics (on metric), the percentage of time a part was ordered as High Priority or Low Priority (based on history), the cumulative probability distribution of shipping delay time, and the cumulative probability distribution of order quantity. See Section 7.3.2 for more detail.
7.1 Commercial Inventory Optimization Models

A strategic inventory optimization model determines what parts to stock based upon the statistical demand forecast of future requirements. Strategic inventory optimization achieves fill rate goals for consumable parts and availability goals for reparable parts at minimum cost. Inventory optimization considers a complex multi-indenture (parent-child relationships between service parts), multi-echelon (multiple levels of maintenance capability) environment across multiple stocking locations supporting a fleet of equipment, which may have varying requirements by operating location.
The most common commercial models are (s,S), or (Order-Point, Order-up-to-Level), inventory models, in which the objective function is to minimize the cost of initial inventory for a given fill rate constraint.

Some models are capable of evaluating the expected performance of a current inventory of spare parts, enabling the data extract and stock level recommendations from a second model to be evaluated independently.

7.2 Data Cleaning and Integration

Data cleaning is a disciplined process, for which the author submitted a patent application (Bradley, 2005), for managing supply chain data from multiple sources, streamlining manual analysis by identifying top drivers, maintaining traceability to the data source, and providing consistent data to multiple software tools. The data cleaned includes procurement lead time, demand, price, repair time, and condemnation rate. Data cleaning decreases the financial risk of misstating requirements by improving the overall mix of spare parts and reducing excess inventories. The tool’s algorithms turn data into a competitive advantage by marrying proprietary design, logistics, and pricing data with customer, supplier, and shipper data. A screen print of the data cleaning and integration tool is shown in Figure 3.
Figure 3 - The Data Cleaning and Integration Tool Provides the Capability to Merge Disparate Sources of Often Conflicting Data, Serving as a Common Source of Supply Chain Data for Inventory Optimization and Simulation Models

Benefits of an integrated data repository strategy include:

- Allowing efficient use of a company’s existing legacy systems by turning them into a source of data to perform investigation, research and analysis. This data can be utilized to forecast, acquire, and allocate spares to support equipment operations.

- Allowing traceability to multiple sources of data with logic to select the “master.”

- Providing a “one stop shop,” or single point of reference, for asset managers to conduct research and analysis.

- Providing a centralized source of supply chain information which consolidates key spares related data from legacy systems into a data repository, and converting data to a common
set of standards. For example, units of measure would be converted from dozen to each, and the currency of unit cost would be converted from pound sterling, known as Great Britain Pound (GBP), to United States Dollar (USD).

- Interfacing with the strategic and tactical inventory models to provide model scenarios and spares data, receiving store stock level recommendations, and providing this data to simulation models for analysis of supply chain metrics.

### 7.3 Simulation

Simulation reduces operational risk for the customer and financial risk for a company by understanding how a strategic inventory optimization will perform during peacetime and surge operations, during deployments, and in other scenarios. Simulation provides an important confidence booster by evaluating the ability of a proposed supply chain to operate with the variable demand seen in real world equipment operations.

Companies employ simulation models to assist policy designers in creating decision rules for implementing tactical transfer of spares, recovering from asset vulnerabilities, assessing the adequacy of input assumptions, and in making better informed logistics policy decisions. Simulation models provide decision support in the areas of:

- Reducing operational risk through analysis of inventory optimization scenarios.
- Formulating decision rules for transferring spares among stock locations.
- Formulating decision rules for expediting repair, procurement, and shipment of spare parts.
- Predicting equipment performance (logistics availability, issue effectiveness, backorders, and costs) more accurately than possible in inventory optimization models alone.
- Assessing the importance of input assumptions such as part failure and repair time distributions.
- Evaluating complex scenarios for managing individual parts.
- Resolving problems with program metrics and the fact that they often do not appear to optimize system performance.
- Evaluating the likelihood of whether programs are likely to meet performance metrics (such as inventory turns) and financial objectives (such as meeting performance goals) in an uncertain environment.

7.3.1 Discrete-Event Warehouse Simulation
The Discrete-Event Warehouse Simulation uses an existing model written in the ExtendSim language, which was modified to accept a user defined cumulative probability density function describing the order quantity distribution, as mentioned in Section 8.8. Since this thesis used an existing warehouse simulation similar to those described by Diamond, et. al. (2010), the reader is referred to this article for additional details.

7.3.2 Monte Carlo Demand Categorization and Metrics Simulation
The author designed the Monte Carlo Demand Categorization and Metrics Simulation to answer the question, “When will Order Fulfillment Lead Time improve to the desired level of performance?” This new simulation incorporates a statistics module using Student’s t-Test for small sample sizes, Order Fulfillment Lead Time demand categorization and metrics logic, data import utilities, and automated graphing.

The Monte Carlo Demand Categorization and Metrics Simulation is a stand-alone software application which uses Visual Basic for Applications (VBA) and Excel 2010 to run a Monte
Carlo simulation of the probability that a part requisition generated in the Discrete-Event Warehouse Simulation is categorized as “on metric”, the probability a part is ordered as High or Low Priority, and the probabilistic shipping delay. The probabilities are calculated based on historical inventory management system data. This simulation performs a random draw for each requisition, based on the part number, as the model iterates. A flowchart of this categorization is shown in Figure 4.

The Monte Carlo Demand Categorization and Metrics Simulation was created to (a) model the demand categorization logic required to assess Order Fulfillment Lead Time metrics, and (b) to address the most common complaint about simulation, which is that results are cryptic and require an expert to interpret. Simulation can produce so much data that analyzing the results
becomes daunting. The Monte Carlo Demand Categorization and Metrics Simulation allows the non-expert to simply navigate to the Discrete-Event Warehouse Simulation results files, import and prepare the data for post processing, and then run the desired number of repetitions. The most common mistakes are trapped with error handling routines, making the tool stable enough for non-expert use. Elementary help is also available within the tool.

The Monte Carlo Demand Categorization and Metrics Simulation incorporates these features:

- Graphs visualize fill rate and perfect order fulfillment over time.
- A degraders report ranks bad actor parts.
- Defaults allow use on programs which do not use Order Fulfillment Lead Time.
- Source data may be deleted, freezing the model and resulting in a compact and presentation ready set of results for delivery to executives and customers.
- The OFLT metrics charts over time are implemented entirely within code, eliminating the need to manually adjust graph ranges when the data ranges changed.
- File handling utilities enable the simulation to run independently of the Discrete-Event Warehouse Simulation.
- Perfect order fulfillment calculations for consumable parts, which are often ordered in quantity. Reparable parts are often ordered as one (1) part per order, in which case perfect order fulfillment would equal fill rate.
- Fill rate calculations, for use in validating the network fill rate of an inventory optimization model.
7.4 The Sweet Spot for Analysis

Although simulating 761 days of supply chain operations in two hours using the Discrete-Event Warehouse Simulation is relatively fast, multiple simulations are required in order to generate statistics such as confidence intervals over time, and each simulation requires an hour to prepare. Further, each iteration of the Monte Carlo Demand Categorization and Metrics Simulation requires an additional 20 minutes. When evaluating multiple scenarios in a trade study, this can result in hours of simulation analysis. As shown in Figure 5, conceptually there is a trade-off between the additional effort required to run multiple simulations and the corresponding increase in accuracy accrued as the confidence interval decreases with the additional runs. The trade-off is to identify the smallest number of simulation runs necessary to achieve an acceptable level of confidence in the results.

![Figure 5 - Trading Off Increased Accuracy from Additional Iterations of Simulation versus the Increased Time Investment Necessary to Make the Runs](image)

The author met with Prof. Mort Webster, Assistant Professor of Engineering Systems within MIT's Engineering Systems Division, to discuss methods to determine the optimal number of
runs necessary to draw conclusions from very large scale simulations, such as the Discrete-Event Warehouse Simulation (M. Webster, personal communication, December 1, 2011). The solution is to run a number of simulations, recalculating the confidence interval for each additional simulation. When the confidence interval either (a) converges to a steady state value, or (b) reaches an acceptable level of accuracy, the lowest number of iterations has been reached.

7.4.1 Optimal Runs of Monte Carlo Demand Categorization and Metrics Simulation

The Monte Carlo Demand Categorization and Metrics Simulation was executed for 21 iterations of a single run of the Discrete-Event Warehouse Simulation. The metric with the widest variation was OFLT, which conveniently is also the metric of interest in this thesis. Since this metric varies over time, convergence graphs were plotted by month for High Priority Consumables. The monthly graphs showed similar characteristic, with the graphs for May, June, and July 2011 are shown in Figure 6. These graphs all show considerable variation through the twelfth simulation, at which point the confidence interval stabilizes and remains fairly constant as additional runs are incorporated into the Student's t-Test. This demonstrates that beyond 12 runs of the simulation, there is no appreciable gain in fidelity.

Figure 6 - The Sweet Spot for Iterations of the Monte Carlo Demand Categorization and Metrics Simulation is Twelve (12) Runs
The number of runs required for the Monte Carlo Demand Categorization and Metrics Simulation was evaluated first, because this is the model that is also used to evaluate results of the Discrete-Event Warehouse Simulation.

### 7.4.2 Optimal Runs of Discrete-Event Warehouse Simulation

The Discrete-Event Warehouse Simulation was also executed for 21 iterations, varying the distribution of overdue due-in parts which each run, in order to create as much variability in the model as possible. The resulting confidence intervals for High Priority Consumables, using a varying number of simulation runs, are shown in Figure 7, with the confidence interval over time shown above, and individual confidence intervals by month shown below for June and December 2012, and June 2013.

![Figure 7 - The Sweet Spot for Iterations of the Discrete-Event Warehouse Simulation is Four (4) Runs](image)

There is little practical difference between the 80% confidence interval for four simulations at +/- 1.5% and that for 21 simulations at +/- ½%. The percent of transactions falling within the
window for being “on metric” ranges within a remarkable tight 2-3% band, given the variability in demand, order quantity, due-in arrival times for overdue orders, probability of an order being placed “on metric”, high vs. low priority, and variable shipping delay. As the lower charts show, the confidence interval is wide with three simulations, narrows with four simulations at +/- 2-4%, and narrows further to under +/- ½% at 21 simulations. Given the likelihood that procurement lead time will be variable (which was not simulated for this thesis, but is common in industry), or that other endogenous uncertainties which are influenced by managerial decisions will come to pass, a +/- 2-4% confidence interval is as narrow as should be accepted. For this reason, four iterations of the Discrete-Event Warehouse Simulation were chosen as appropriate.

A secondary reason for selecting four iterations was that even though the 64-bit version of Excel 2010 is supposed to be able access the full amount of memory on a desktop computer, for which the author had 12 gigabytes (GB) available, after about 4GB Excel would crash while writing dynamic formulae to cells of the Monte Carlo Demand Categorization and Metrics Simulation. This would occur when processing the fifth output dataset of the Discrete-Event Warehouse Simulation; therefore, needing to process only four iterations of the warehouse simulation was fortuitous indeed.

7.5 Conclusion

The optimal simulation strategy for this thesis is to model the demand transactions from four (4) warehouse simulations, which are subsequently simulated through twelve (12) iterations of the metrics simulation, in order to generate supply chain metrics over time with an acceptable confidence interval. The equates to about eight hours of CPU time to process each of four warehouse simulations at two hours each, with an additional hour required to set up each simulation; and about four hours of CPU time to process each of twelve metrics simulations at
about 20 minutes each, with about an hour required to import the transactional data from the warehouse simulation and incorporate distributions for “on metric”, priority, and shipping delay. This works out to about seventeen (17) hours per scenario, or about two business days.

The approach presented in this section provides a straightforward methodology for determining the number of iterations of any large scale simulation necessary to achieve results that fall within an acceptable level of confidence.

While the author has considerable experience within heavy industry, it should be noted that the data collection and validation, along with discussions to understand nuances in the data, took about two months. For a completely new project in a new industry, data analysis could run significantly longer. Conversely, the author has been able collect data sufficient for inventory optimization in as little as a week on proposals, and surmises that for a simple fill rate or perfect order simulation it might be possible to conduct a simulation of one scenario in as little as another week, contingent upon a clean dataset. This suggests a range for conducting simulation of two weeks to six months, depending on the complexity and number of scenarios, and accessibility and cleanliness of the data source(s). Due to the complexity of extracting data via an Extract, Transform, and Load (ETL) tool, a superior strategy would be to load a common dataset once, based upon the data cleaning and integration tool of Section 7.2, which would then feed multiple models. Articulating the benefits of data management and analytics would make an excellent dissertation topic, for which there is insufficient room in the margins of this master’s thesis, which we will call Bradley’s Latest Theory. Math majors will catch the reference.
8 Data Analysis

Calculating Order Fulfillment Lead Time (OFLT) requires knowing information about each order, which is synonymous with the frequently used term “requisition.” Figure 8 describes the decision flow used to determine, based on this information, whether a specific order counts towards metrics, and if so, whether the metrics were achieved. This information includes characteristics of the order specific to the part number, highlighted in Figure 8 in green:

- What is the repair classification, or category, which either consumable or reparable?

This information also includes characteristics that change order to order, which are highlighted in Figure 8 in red:

- Is the item “on metric”, in which case the order counts towards metrics?
- What is the priority of the order? Is the order high priority, which means that the part is necessary to return equipment to service, or is the order low priority, in which case this is a routine reorder?
- What is the shipping delay, or transportation time, which historically varies order to order?
Figure 8 - Calculating Order Fulfillment Lead Time (OFLT) requires information on the characteristics of the order (in green) and the likelihood of events (in red).

8.1 The Inventory Management System

Inventory in heavy industry is tracked using a commercial inventory management system. An industry representative historical dataset was analyzed, which contained orders from operating locations (retail) to a central warehouse (wholesale) between January 2010 and November 2011, inclusive. The historical order data was analyzed to:

- Determine the probability an order is “on metric” (variable METRIC).
- Assign repair classification as consumable or reparable (variable CONREP).
- Determine the probability that an order was placed as high or low priority (variable HIPRI).
- Determine shipping delay from the central warehouse (wholesale) to the operating location (retail) based on order priority (variable SHIP).
8.2 Shipping Delay

Order Fulfillment Lead Time is essentially a combination of Perfect Order Fulfillment, or whether an order is shipped in full, and shipping delay, or transportation time from the central warehouse (wholesale) to the operating location (retail). Therefore, understanding shipping delay is important to understanding OFLT performance.

Shipping delay, as shown in Figure 9, is defined as customer receipt data (the date that the part was received at the destination where the operational equipment is located, as listed on the shipping document) minus shipping date (the date the part was picked up by the shipper from the central warehouse, as listed on the shipping document). Warehouse delays are excluded from shipping delay. Warehouse delays are defined as warehouse receipt date minus warehouse shipping date, and are generally significant only when the part is out of stock.

![Graph of Average Shipping Delay by Month](image)

Figure 9 - Analysis of Average Shipping Delay by Month Shows Significant Volatility in the Last Six Months

Shipping declined from an average of 4 ½ days in January 2010 to level off between 2 and 2 ½ days from April 2010 through April 2011. Shipping delay then began oscillating towards the end of 2011, which should be further investigated, as these fluctuations cause commensurate swings
in OFLT. The simulation captured this variability by using an empirical distribution of shipping delay based on historical data from January 2010 through December 13, 2011.

8.3 Correlation Analysis (On Metric vs. Off Metric, Consumables vs. Reparables)

A regression analysis was performed to determine whether there were variables that contributed significantly to shipping delay, or transportation time. The variables having predictive power were order status, i.e., was the order placed as “On Metric” or “Off Metric”; and repair classification, i.e., was the order for a consumable or a reparable part, as shown in Table 2. In statistics, the P-Value is the lowest value at which a variable could be considered statistically significant. For “On Metric” and repair classification the P-Values were significant. Parts that were designated “On Metric” had a -1.81 day’s delay coefficient, indicating that these experienced less shipping delay than “Off Metric” parts.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation Coefficient</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order Status (On Metric=1, Off Metric=0)</td>
<td>-1.83</td>
<td>0.04</td>
<td>-44.94</td>
<td>0.00</td>
</tr>
<tr>
<td>Repair Classification (Con=1, Rep=0)</td>
<td>-0.43</td>
<td>0.05</td>
<td>-7.94</td>
<td>0.00</td>
</tr>
</tbody>
</table>

8.4 Order Status: “On Metric” vs. “Off Metric”

Orders that are designated “On Metric” when they are placed count towards metrics. “Off Metric” orders generally support depot maintenance operations. Since “On Metric” orders help explain shipping delay, and only “On Metric” orders count towards OFLT, “Off Metric” orders were filtered from the dataset.
In addition, the probability that an order was “On Metric” was calculated on a part by part basis. As summarized in Table 3, 73% of orders for consumable parts are “On Metric”, along with 79% of orders for reparable parts.

Table 3 - Percentage of Orders Categorized as “On Metric” by Repair Classification

<table>
<thead>
<tr>
<th>Repair Classification</th>
<th>Variable</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumable</td>
<td>METRIC</td>
<td>73%</td>
</tr>
<tr>
<td>Reparable</td>
<td>METRIC</td>
<td>79%</td>
</tr>
</tbody>
</table>

8.5 Repair Classification: Consumables vs. Reparables

There are two kinds of parts: those you cannot fix, or consumables, and those you can fix, or reparable (also referred to as repairable). The repair classification is stored in variable CONREP.

Consumables are usually lower dollar parts for which repair is not practical, parts that cannot be reused for safety reasons, such as certain nuts, bolts, rivets and washers, or parts requiring specialized equipment to repair that is not cost effective to procure based on the part’s failure rate. Reparables are usually more expensive parts for which repairs are cost effective. Reparables may also have a maintenance indenture structure, which means that they have reparable or consumable sub-parts that are replaced in order to effect repairs. An example would be an electronic “black box”, which can be removed and replaced on the equipment, also known as the organizational level of maintenance. The black box itself contains a number of circuit cards that can be individually removed and replaced at a maintenance shop, also known as the intermediate level of maintenance. The circuit card itself might go to a central facility specializing in electronic repairs, or depot, and individual parts, such as consumable power diodes, might be replaced. Thus, consumable parts include the brackets, tires, and bolts that are replaced on equipment, and the parts used to conduct repairs to reparable items.
8.6 High vs. Low Priority Orders

The priority code assigned to a part determines the allowable window for shipping delay before a part is considered delinquent. As shown in Table 4, 27% of orders (requisitions) for consumable parts are placed as high priority, along with 39% of orders for reparable parts.

<table>
<thead>
<tr>
<th>Repair Classification</th>
<th>Variable</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Priority Consumable</td>
<td>HIPRI</td>
<td>27%</td>
</tr>
<tr>
<td>High Priority Reparable</td>
<td>HIPRI</td>
<td>39%</td>
</tr>
</tbody>
</table>

8.7 Shipping Delay by Order Status and Repair Classification

An empirical distribution of shipping delay was created based upon order status (segregating historical order data to “On Metric”) and repair classification (segregating data to consumables), the two variables with the best explanatory power for shipping delay based on the regression analysis. For consumable parts, two empirical distributions were created depending on order priority, which generated the shipping delays (or transportation times) of variable SHIP.

Historical data was categorized by days shipping delay (days transportation time) in order to create a Cumulative Density Function (CDF) for the probability that a shipping delay was 0, 1, 2, 3, 4, 5, 6, 7, 8-10, 11-15, 16, 17-27, or 39+ days. CDF’s were created based on order priority, as shown in Figure 10 for high priority consumables, and Figure 11 for low priority consumables.

Where days are shown in ranges, based upon the relevant performance categories, the weighted average shipping delay was calculated. The CDF functions as a lookup table: a random number between zero and one is drawn, the computer looks up the cumulative distribution to find the first column exceeding the random number, then reads the corresponding weighted average days shipping delay, which is used within the categorization and metrics simulation.
The average shipping delay is shown in Table 5. If the average shipping delay was used in the simulations, then shipping delay would never impact OFLT metrics. For example, the average shipping delay for high priority consumable parts is below the 4 day threshold for the delivery window. The CDF accounts for shipping delays when simulating OFLT performance, because a certain percentage of shipping times to exceed the threshold.
Table 5 - Average Shipping Delay for High and Low Priority Consumable Parts

<table>
<thead>
<tr>
<th>Repair Classification</th>
<th>Shipping Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Priority Consumable</td>
<td>1.74</td>
</tr>
<tr>
<td>Low Priority Consumable</td>
<td>1.94</td>
</tr>
</tbody>
</table>

8.8 Order Quantity

An empirical distribution for order (requisition) quantity was created for each part, as shown in Figure 12. A Cumulative Density Function (CDF) for each part allows the warehouse simulation to draw a random number between zero and one, and look up the corresponding order quantity. This determines the number of parts for each order, following an adjustment in the model’s demand generator to convert demand based on single order quantity to demand based on variable order quantity.

![Empirical Order Quantity Distribution](image)

Figure 12 - Empirical Order Quantity Distribution by Part, by Mean Operating Hours Between Supply Demand (MOHBSD)

The Mean Operating Hours Between Supply Demand (MOHBSD) are the average equipment operating hours between requests for parts made to central warehouse. This was calculated from data in the industry representative inventory dataset. Operating hours increase over time.
equipment is added to the fleet. MOHBSD was calculated by taking the expected monthly demand six months into the future (the mid-year demand), times 12 months in a year, and dividing the product into the expected annual operating hours over the next 12 months. This created an expected MOHBSD that was then validated against the expected Average Monthly Units for the current month as listed in Inventory Optimization Model A.

Model A contains data on both primary parts, which are the current design configuration actually bought, and alternate parts, which are usually older configurations. In cases where the new configuration is interchangeable with the older configuration, the demand for both primary and alternate parts, as well as inventories, were combined for the simulation in order to simplify the analysis.

8.9 Defaults for Missing Data

Defaults were established to populate missing data, based on an analysis of the historical data. The defaults are withheld to protect the confidentiality of the industry representative dataset.

9 Validation

Substantiating the analysis encompasses both stock level validation and simulation validation. For the stock level validation, the expected fill rate from Inventory Optimization Model A was verified by running Inventory Optimization Model B in evaluation mode and comparing fill rates for both the current inventory position, and for the recommended stock levels. While it is recognized that both models have different inventory optimization engines, the hypothesis is that stocking policies from one model should yield comparable results when evaluated in the other model. This validation exercise also serves as a check against gross errors.
A line replaceable unit (LRU) is a modular component that is designed to be replaced at the operating location of a piece of heavy equipment. For the simulation validation, the target stock levels for LRUs, as specified by Inventory Optimization Model A, were evaluated in both the Discrete-Event Warehouse Simulation and the Monte Carlo Categorization and Metrics Simulation. These tests show that both simulations produce results that are close to the inventory optimization, thus validating (a) the data extract, (b) the demand calculations in the different tools, (c) the ability of the target stock levels to achieve the stated fill rates.

9.1 Known Discrepancies Impacting the Validation

For several reasons, the inventory optimization models and simulation models will start with somewhat different initial fill rates.

The simulation model is designed to spread out the repair times for parts in-repair at the start of the simulation to occur between their repair time and repair time and a half, under the theory that the repair centers probably could not absorb all the failed components coming through the depot simultaneously. Similarly, parts that are due-in but overdue were spread out over their procurement lead time. A key value of simulation is to provide visibility into non-steady state conditions, which provides executives with an understanding of how performance is likely to vary over time.

To estimate the initial fill rate, Inventory Optimization Model A calculates inventory position as parts which are on hand and ready for issue, plus half the parts due-in within the procurement lead time of the part, minus parts on backorder. Parts which are on hand but defective or in repair for reparables are excluded, as these are not ready for issue (RFI) and may or may not actually be able to be repaired.
Inventory optimization Model B was given an inventory position equal to on hand, plus on order, minus due-in, since it is important that the model begin with an accurate inventory count before determining whether additional spares are required.

9.2 Current Inventory Position

The current inventory position for the LRU network should achieve a 61.6% fill rate according to the Model A. Model B achieves a 67.2% fill rate. Considering known discrepancies in the initial inventory calculation between these models, these fill rates were considered sufficiently close.

The LRU network was evaluated with the Discrete-Event Warehouse Simulation, which began with a fill rate in the mid 40% range and quickly surpassed 60% as due-in parts arrived and repairs were completed. Details of the simulation are shown in Figure 13.
Similarly, the Monte Carlo Demand Categorization and Metrics Simulation, which evaluated ten (10) warehouse simulations over twelve (12) replications, started with an average 46.2% fill rate.

9.3 Target Stock Levels

The target stock levels, for the LRU network, should achieve a 90% fill rate according to the Inventory Optimization Model A. Model B achieves an 87.7% fill rate. The LRU network was evaluated with the Discrete-Event Warehouse Simulation, which ended with a 90.1% cumulative fill rate.

Similarly, the Monte Carlo Demand Categorization and Metrics Simulation ended with a 90.9% cumulative fill rate, mirroring the warehouse simulation. The monthly fill rate was also evaluated, which surpassed 90% during June 2013 and maintained this performance over the duration of the ten (10) year simulation run.

9.4 Student's t-Test of Simulated Monthly Fill Rate

A Student's t-Test was run to test the null hypothesis that the mean of the final monthly fill rates for the ten (10) year simulation ending November, 2011 was greater than or equal to the 90% fill rate estimated by Inventory Optimization Model A. The test was run at the 5% significance level, meaning that the null hypothesis is only rejected when it is true 5% of the time; this is termed a Type I error in statistics. The sample values are listed in Table 6, below.
### Table 6 - Simulated Monthly Fill Rate for November, 2021

<table>
<thead>
<tr>
<th>Simulation Number</th>
<th>Monthly Fill Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.914</td>
</tr>
<tr>
<td>2</td>
<td>0.967</td>
</tr>
<tr>
<td>3</td>
<td>0.943</td>
</tr>
<tr>
<td>4</td>
<td>0.896</td>
</tr>
<tr>
<td>5</td>
<td>0.929</td>
</tr>
<tr>
<td>6</td>
<td>0.933</td>
</tr>
<tr>
<td>7</td>
<td>0.956</td>
</tr>
<tr>
<td>8</td>
<td>0.911</td>
</tr>
<tr>
<td>9</td>
<td>0.934</td>
</tr>
<tr>
<td>10</td>
<td>0.976</td>
</tr>
</tbody>
</table>

At a 5% level of significance, there is no reason to reject the null hypothesis that the mean of the simulated monthly fill rates at steady state are equal or greater than 90%. This result confirms the analytic results of Inventory Optimization Model A with the warehouse simulation, or alternately, confirms the warehouse simulation based upon the acceptance of Model A. The statistical analysis is described in Figure 14, below.
**t Test for Hypothesis of the Mean (σ unknown)**  
σ is the standard deviation of the population

<table>
<thead>
<tr>
<th>Data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Hypothesis H₀</td>
<td>μ = 90</td>
</tr>
<tr>
<td>Level of Significance</td>
<td>α = 0.05</td>
</tr>
<tr>
<td>Sample Size n</td>
<td>10</td>
</tr>
<tr>
<td>Sample Mean x</td>
<td>93.6</td>
</tr>
<tr>
<td>Sample Standard Deviation s</td>
<td>2.5</td>
</tr>
</tbody>
</table>

μ is the hypothesized population mean  
A Type I error occurs when the researcher rejects a null hypothesis when it is true. The probability of committing a Type I error is called the significance level, and is often denoted by α.  
n is the sample size  
x is the sample mean  
s is the standard deviation of the sample

Intermediate Calculations

| Standard Error of the Mean | 0.7906 |
| Degrees of Freedom         | 9      |
| **test statistic t**        | 4.5537 |

The standard error (SE) of the sampling distribution  
The degrees of freedom (DF) is equal to the sample size (n) minus one  
The test statistic is a t-score (t) defined by the equation $t = \frac{x - \mu}{SE}$

| Lower-Tail Test (Ho: μ >= 90) |         |
| Lower Critical Value          | -1.8331 |
| **p-value = Probability(t <= 4.5537)** | 0.999 |

<table>
<thead>
<tr>
<th>95.0% Lower (Left) Confidence Interval Value</th>
<th>Population of tail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low (Left)</td>
<td>92.15</td>
</tr>
<tr>
<td>5.0% of values &lt; this #</td>
<td></td>
</tr>
</tbody>
</table>

If the p-value is greater than the significance level of α, we cannot reject the null hypothesis Ho.  
(Source of Descriptions: http://stattrek.com/hypothesis-test/mean.aspx, viewed 21MAR12)  
(Source of t Test Template: St. Louis Community College, Meramec Valley, MO, Summer 2011)

Figure 14 - Student's t-Test for the Null Hypothesis that Simulated Fill Rate is Greater Than or Equal to 90%

### 9.5 Validation to Historically Reported Metrics

The calculations in the Monte Carlo Demand Categorization and Metrics Simulation were validated by loading the model with the actual historical demand experienced from October 2011 through September 2012. The demand history contains a log of each individual transaction (also known as a requisition or order) from retail to wholesale. Each transaction contains part number, order quantity, “On Metric” classification, priority, date the order was placed, date the order was shipped, date the order was received, and destination. This information provides everything necessary to calculate the OFLT metrics, as discussed in Section 8, Data Analysis.

The calculations from the metrics simulation were compared to performance metrics reported within heavy industry. Differences in metrics could be traced to individual transactions for parts for which there was no demand history. The simulations were run with only parts that have
demand, rather than the entire list of parts, in order to keep data sizes and run times manageable.

Intuitively, if a part has no demand history, a simulation based on Mean Operating Hours Between Supply Demand (MOHBSD) will never generate demand. The assumption was made that demand for parts that have never failed in the past will be offset by simulated demand for low demand parts that have failed in the past, but will not fail again.

This validation analysis resulted in an interesting enhancement to the metrics simulation. By loading the period between the start of the current contract and the start of the simulation with historical data, it is possible to (a) graph the transition from actual metrics to simulated metrics, and (b) estimate cumulative statistics precisely, by taking into account the actual results since the start of the contract period.

9.6 Validation Summary

The stock level validation indicates that the target stock levels of Model A achieve the expected fill rate when evaluated in Model B. This serves as a check on the data extract for stock level, demand, lead time, and, for reparable parts, condemnation rate.

The simulation validation of the Discrete-Event Warehouse Simulation and Monte Carlo Categorization and Metrics Simulation evaluated monthly fill rate using Student’s t-Test, and found no reason to reject the null hypothesis that the stock levels from Model A would achieve a fill rate at least as good as the inventory optimization goal.

The analysis of historical data in the Monte Carlo Demand Categorization and Metrics Simulation validates the metrics simulation calculations by showing that when historical data is processed, the Order Fulfillment Lead Time results are the same as those reported formally.
10 Hypothesis

Organizations using heavy equipment (retail) want the parts they order when they need them, and often chose Order Fulfillment Lead Time (OFLT) as the service metric with which to measure response from a central warehouse (wholesale). The following summary recaps the intuition for the relationship between fill rate, perfect order fulfillment, and OFLT:

- **Fill rate** is the percent of parts shipped from stock on hand, i.e., shipping 90 out of 100 items ordered = 90% fill rate
- **Perfect Order Fulfillment (POF)** is the percent of orders shipped “on time and in full,” i.e, shipping 90 out of 100 items ordered = 0% POF
- **Order Fulfillment Lead Time (OFLT)** is essentially POF for parts arriving within a delivery window

**Hypothesis:** This thesis tests the hypothesis that the alternate ABCDE inventory segmentation strategy for consumable parts will outperform the baseline AB strategy when measured on Order Fulfillment Lead Time and inventory investment.

The baseline AB strategy segments inventory on unit cost, and the alternate ABCDE strategy segments inventory on annual use, or annual demand times unit cost, as shown in Table 7. These categories are mutually exclusive and collectively exhaustive, meaning that there are no overlaps across segments, and when all segments are combined they encompass all parts.
Table 7 - The Baseline and Alternate Hypotheses for Inventory Segmentation Strategies for Consumables

<table>
<thead>
<tr>
<th>Baseline AB</th>
<th>Inventory Segmentation Strategy</th>
<th>Alternate ABCDE</th>
<th>Inventory Segmentation Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group on price</td>
<td></td>
<td>Group on annual use</td>
<td></td>
</tr>
<tr>
<td>A: Unit Cost ≤ $2,000</td>
<td></td>
<td>A: Parts 80% Annual Use &amp; Unit Cost &gt; $25</td>
<td></td>
</tr>
<tr>
<td>B: Unit Cost &gt; $2,000</td>
<td></td>
<td>B: Parts 15% Annual Use &amp; Unit Cost &gt; $25</td>
<td></td>
</tr>
<tr>
<td>C: Parts 5% Annual Use &amp; Unit Cost &gt; $25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D: $1 &lt; Unit Cost ≤ $25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E: Unit Cost ≤ $1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

11 Baseline AB Inventory Segmentation Strategy

Inventory segmentation strategies are usually restricted to consumable parts, which are optimized by segment to a fill rate target. Reparable parts are instead optimized to an equipment availability goal. Since the hypothesis compares baseline and alternate inventory segmentation strategies, this thesis will be restricted to consumable parts. The baseline is thus all consumable parts in the representative dataset heavy industry.

The Discrete-Event Warehouse Simulation was run four (4) times for the period from December 1, 2011, through December 31, 2013, or 761 days. Each run used a fresh input dataset, in which due-in parts that were overdue, as well as on hand but defective parts awaiting repair, had their due dates randomly spread out. The Monte Carlo Demand Categorization and Metric Simulation was then run twelve (12) times to evaluate metrics via 90% confidence intervals over time. Historical data for October 2011 and November 2011, representing the first two months of a notional one year contract, was inserted into the metrics simulation before the warehouse simulation results. The confidence interval for the first two months will not show any variation, of course, since this is historical data capturing exactly what occurred, without variability.
Actual data from December 2011 and January 2012 has been reported since the simulations were run, providing an opportunity to compare predicted metrics to actual metrics.

Fluctuations in the confidence interval are attributable to batches of orders arriving within a given month, and the fact that the arrival data for overdue due-in parts is random. The slight dip often seen in the last month of the simulation is attributable to open orders at the end of the simulation, where the arrival date is not known. This has also been seen in reported results, where the previous month’s metrics are updated the following month as open orders close out, adjusting metrics up or down a few percentage points.

11.1 AB Inventory Segmentation on Unit Cost

For the baseline AB inventory segmentation for consumable parts, Segment A was defined as all parts whose unit cost was less than or equal to $2,000, and was optimized to a 95% fill rate target. Segment B was defined as all parts exceeding $2,000, and was optimized to a 90% fill rate target. For each segment, the percentage of annual use (defined as unit cost times annual demand), and the percentage of unique part numbers are shown in Table 8.

<table>
<thead>
<tr>
<th>Segment</th>
<th>% Annual Use</th>
<th>% Part Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Unit Cost ≤ $2,000</td>
<td>37%</td>
<td>92%</td>
</tr>
<tr>
<td>B: Unit Cost &gt; $2,000</td>
<td>63%</td>
<td>8%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Consumable parts for the Segment A and Segment B networks were analyzed by comparing Unit Cost, ranked part by part from lowest to highest on the horizontal axis, to Cumulative Part Count on the vertical axis, as shown in Figure 15. Since an inventory optimization model is designed to select the lowest cost mix of spares required to achieve a given fill rate goal, this means that for
Segment A, $0.01 parts are competing for fill rate "bang for the buck" against $1,689 parts. Aware that some type of skew was occurring, strategic planners created a business rule to ensure that all parts were at least stocked to the Wilson Economic Order Quantity (EOQ) amount, ensuring a minimum 50% fill rate part by part at the central warehouse (wholesale). Is this solution appropriate? Does a better solution exist that provides more value for the customer (retail), as measured by OFLT?

![Figure 15 - Baseline AB Inventory Segmentation for Consumable Parts, Showing Ordered Unit Cost vs. Cumulative Percent Part Count](image)

Reviewing the cumulative count of unique part numbers by dollar value, as shown in Table 9, shows 9% of unique part numbers under $1; 14% of parts between $1 and $25; 25% of parts between $25 and $100; 34% of parts between $100 and $1,000; 15% of parts between $1,000 and $5,000; and 4% of parts over $5,000 accounting for 10% of all part numbers.
Table 9 - Table of Consumable Parts Grouped by Unit Cost for the Baseline AB Inventory Segmentation

<table>
<thead>
<tr>
<th>Unit Cost</th>
<th>Percent of Parts</th>
<th>Cum Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit Cost &lt; 1$</td>
<td>9%</td>
<td>9%</td>
</tr>
<tr>
<td>$1 &lt; Unit Cost ≤ $25</td>
<td>14%</td>
<td>23%</td>
</tr>
<tr>
<td>$25 &lt; Unit Cost ≤ $100</td>
<td>25%</td>
<td>48%</td>
</tr>
<tr>
<td>$100 &lt; Unit Cost ≤ $1,000</td>
<td>34%</td>
<td>81%</td>
</tr>
<tr>
<td>$1,000 &lt; Unit Cost ≤ $5,000</td>
<td>15%</td>
<td>96%</td>
</tr>
<tr>
<td>Unit Cost &gt; $5,000</td>
<td>4%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Is it possible that a different grouping of parts would result in a better quality distribution of spares, as measured by OFLT?

11.2 Inventory Optimization by Segment

Stock levels in each segment were determined by commercial Inventory Optimization Model A, which optimized each segment to the Fill Rate goal shown in Table 10. The column headers have the following definitions:

- **Inventory Segment**: Each segment was optimized as a separate parts network in Inventory Optimization Model A.
- **Description**: The inventory segmentation strategy used to group parts into this segment
- **Fill Rate**: The objective function, or goal, of the inventory optimization model is to select the lowest cost mix of spares based on demand, lead time, unit cost, and (for reparables) condemnation rate subject to the fill rate constraint.
- **Active Part Count**: The percentage of unique part numbers, filtering to parts for which demand has occurred within the time horizon of the industry representative dataset.
- **Inventory Position Value**: The total value (part count times unit cost) of the current inventory (defined as on hand + due-in – backorders).
- **Optimized Stock Level:** The total value of inventory recommended by the inventory optimization model (target stock level times unit cost).

- **Ratio Optimized/Inventory Position:** This column states that the optimal inventory is \(x\%\) of the current inventory. If this number is less than 100%, then there is either excess inventory, or more likely an imbalance of inventory.

- **Annual Usage:** The annual consumption (annual demand * unit cost), where annual demand for reparable parts is multiplied by condemnation rate.

<table>
<thead>
<tr>
<th>Inventory Segment</th>
<th>Description</th>
<th>Fill Rate</th>
<th>Active Part Count</th>
<th>Inventory Position Value</th>
<th>Optimized Stock Level Value</th>
<th>Ratio Optimized/Inventory Position</th>
<th>Annual Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>LRUs</td>
<td>Reparables, Line Replaceable Unit (LRU)</td>
<td>90%</td>
<td>62%</td>
<td>90%</td>
<td>94%</td>
<td>27%</td>
<td>94%</td>
</tr>
<tr>
<td>SRUs</td>
<td>Reparables, Shop Replaceable Unit (SRU)</td>
<td>90%</td>
<td>36%</td>
<td>9%</td>
<td>6%</td>
<td>17%</td>
<td>6%</td>
</tr>
<tr>
<td>SSRUs</td>
<td>Reparables, Sub-SRU</td>
<td>90%</td>
<td>2%</td>
<td>0%</td>
<td>0%</td>
<td>8%</td>
<td>0%</td>
</tr>
<tr>
<td>REPARABLES</td>
<td>All Reparables (LRU+SRU+SSRU)</td>
<td>90%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>26%</td>
<td>100%</td>
</tr>
<tr>
<td>A</td>
<td>Unit Cost &lt;= $2,000</td>
<td>95%</td>
<td>92%</td>
<td>47%</td>
<td>30%</td>
<td>26%</td>
<td>37%</td>
</tr>
<tr>
<td>B</td>
<td>Unit Cost &gt; $2,000</td>
<td>90%</td>
<td>8%</td>
<td>53%</td>
<td>70%</td>
<td>54%</td>
<td>63%</td>
</tr>
<tr>
<td>CONSUMABLES</td>
<td>All Consumables (A+B)</td>
<td>N/A</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>41%</td>
<td>100%</td>
</tr>
</tbody>
</table>

### 11.3 Consumables High Priority OFLT

High priority consumables are referred to as “Hi-Pri Consumables.” The goal is to achieve 85% Order Fulfillment Lead Time (OFLT) within the four day delivery window. As shown in Figure
16, the simulation predicts that performance will dip through mid-April 2012, as due-in parts arrive within their procurement lead time. Performance will then steadily increase through the summer of 2013, when it will level off in the low 80% range. The confidence interval is generally 3-4% wide, a relatively narrow band, which indicates that for a given stocking policy, it should be relatively straightforward to predict performance over time, given the assumptions about variability of demand and assuming that due-in dates are accurate (although the preponderance of delinquent due-in parts suggests otherwise).

Figure 16 - Order Fulfillment Lead Time (OFLT) for Consumables Ordered as High Priority (with 80% Confidence Interval), the Result of a Baseline AB Inventory Segmentation Strategy, Compared to Customer Goal (Straight Line) and Actual Results (Stars *)

Actual OFLT performance (designated with stars *) for December 2011 was 75%, which is just outside the high confidence interval for that month. Actual performance for January 2012 was 86%, far exceeding the expected simulated performance of 72%. Why so far off? A forensic analysis of the demand data revealed that the forecasts used to generate stock levels are biased higher than what was experienced in actual operations. This discrepancy will be explored further.
in Section 13. The key takeaway is that if retail locations operate to schedule, then OFLT metrics will fall short of goals under the current stocking policy for the wholesale warehouse.

A review of the previous period of performance revealed that OFLT for consumable parts ordered as high priority between October 2010 and September 2011 ranged from 53% to 71%.

11.4 Consumables Low Priority OFLT

Low priority consumables are referred to as “Lo-Pri Consumables.” The goal is to achieve 90% OFLT within the 16 day delivery window. As shown in Figure 17, the simulation predicts that performance will dip through mid-June 2012, as due-in parts arrive within their procurement lead time. Performance will then steadily increase through the spring of 2013, where it will level off in the upper 80% range. The confidence interval was generally 3% wide, a relatively narrow band, which indicates that for a given stocking policy, it should be relatively straightforward to predict performance over time.

![Historical Simulated](chart.png)

*Figure 17 - Order Fulfillment Lead Time (OFLT) for Consumables Ordered as Low Priority (with 80% Confidence Interval), the Result of a Baseline AB Inventory Segmentation Strategy, Compared to Customer Goal (Straight Line) and Actual Results (Stars *)
Actual OFLT performance (designated with stars ★) for December 2011 was 84%, and for January 2012 was 83%, exceeding the expected simulated performance of 77% and 76%. As noted previously, the demand forecast was significantly higher than actual demand, resulting in an imbalance of forecast supply (high) to the actual demand (low).

A review of the previous period of performance revealed that OFLT for consumable parts ordered as low priority between October 2010 and September 2011 ranged from 58% to 75%.

11.5 Rightsizing Inventory

For November 2011, stock levels in Inventory Optimization Model A were set to achieve a 95% fill rate for the Segment A network of consumables $2,000 or less. For the Segment B network of consumables over $2,000, stock levels were set to achieve a 90% fill rate. The total inventory investment was only 44% of the current inventory position, as shown in Figure 18. An additional lay-in of new spares, equal to 4% of the current inventory investment, is necessary to achieve these optimal stock levels. Fully 20% of current inventory is excess and can be “burned down” or depleted over the next five (5) years. The remaining inventory, of which 14% is inactive, and 26% has over five years of stock, becomes a candidate for disposal.
Figure 18 - Inventory Summary for Consumables with Stock Levels from Inventory Optimization Model A, using Today's Part Networks based on the Baseline AB Inventory Segmentation on Unit Cost

Efforts to improve Order Fulfillment Lead Time (OFLT) will be compared to this 44% baseline.

11.6 Explaining the Simulated Increase in Service Over Time

*How is the steady increase in service over time in the simulation explained?* As depicted above in Figure 18, the current mix of service parts is not well balanced; in fact, the value of the inactive and excess spares exceeds the value of the optimal spares, as determined by Inventory Optimization Model A. As explained previously in Section 9.2, Model A estimates the fill rate that can be achieved with the current inventory position (shown in Figure 18 as Current Customer Inventory 100%). As explained in Section 9.3, Model A also estimates the fill rate that could be achieved by managing to the optimal target stock levels (shown in Figure 18 as Manage to Optimal Inventory 44%). As shown below in Table 11, the increase in service over time directly follows the increase in fill rate as parts delivered after their Procurement Lead Time arrive in inventory at the central warehouse.
Table 11 - Comparison of Current Inventory Position (Starting) to Optimized Stock Level (Steady State) Fill Rate for Inventory Optimization Models A & B, and for the Simulation

<table>
<thead>
<tr>
<th>Segment</th>
<th>Fill Rate for Segment A: Unit Cost ≤ $2,000</th>
<th>Fill Rate for Segment B: Unit Cost &gt; $2,000</th>
<th>Fill Rate for Segments A &amp; B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model A: Current Inventory Position</td>
<td>73.0%</td>
<td>71.7%</td>
<td></td>
</tr>
<tr>
<td>Model A: Optimized Stock Level</td>
<td>94.9%</td>
<td>90.0%</td>
<td></td>
</tr>
<tr>
<td>Model B: Current Inventory Position</td>
<td>72.9%</td>
<td>71.3%</td>
<td></td>
</tr>
<tr>
<td>Model B: Optimized Stock Level</td>
<td>97.1%</td>
<td>93.5%</td>
<td></td>
</tr>
<tr>
<td>Simulation: Current Inventory Position</td>
<td></td>
<td></td>
<td>79.6%</td>
</tr>
<tr>
<td>Simulation: Optimized Stock Level</td>
<td></td>
<td></td>
<td>93.3%</td>
</tr>
</tbody>
</table>

The value of simulation is to indicate *when* the fill rate goals of the inventory optimization model will be reached, and based on the confidence interval, *how likely* they are to be reached.

A number of factors are likely to cause the simulation to tend to outperform reality, and perhaps an equal number of factors are likely to cause reality to turn out better. These are summarized in Table 12. Section 14 describes the adverse impact on simulated results, assuming a stocking policy with continuous resupply, when actual review policy and actual acquisition policy are considered. The bottom line is that while simulation assumes flawless program execution, flawless program execution can adjust a number of supply chain levers that are not included in the simulation. The net effect is that actual performance may be either better or worse than simulated performance, and much depends on factors within management control.
### Table 12 - Comparison of Factors Influencing both Simulated and Actual Performance

<table>
<thead>
<tr>
<th>Simulation (Model)</th>
<th>Actual Operations (Reality)</th>
<th>Net Effect of Reality on Fill Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parts procured in lead time</td>
<td>Procurement lead time varies</td>
<td>-</td>
</tr>
<tr>
<td>- // -</td>
<td>Can expedite procurement</td>
<td>+</td>
</tr>
<tr>
<td>- // -</td>
<td>Can transfer between operating locations</td>
<td>+</td>
</tr>
<tr>
<td>- // -</td>
<td>Can borrow parts meant for production of new equipment</td>
<td>+</td>
</tr>
<tr>
<td>Continuous Resupply</td>
<td>Spares Requirements Review Board adds 30-day review period</td>
<td>-</td>
</tr>
<tr>
<td>- // -</td>
<td>Acquisition policy adds 90 or 360-day review period</td>
<td>-</td>
</tr>
<tr>
<td>Wholesale experiences bullwhip effect due to</td>
<td>Wholesale experiences bullwhip effect due to variable order quantity</td>
<td>No Change</td>
</tr>
<tr>
<td>variable order quantity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- // -</td>
<td>Wholesale experiences bullwhip effect when operating locations change stock</td>
<td>-</td>
</tr>
<tr>
<td>demands based on operating hour forecast</td>
<td>levels</td>
<td></td>
</tr>
<tr>
<td>Demands based on operating hour forecast</td>
<td>Variability in actual operating hours</td>
<td>+ or -</td>
</tr>
<tr>
<td>- // -</td>
<td>Demands based on manual overrides</td>
<td>+ or -</td>
</tr>
<tr>
<td>Automated buys when reorder point reached</td>
<td>A &amp; B Segments not automated; C, D &amp; E Segments may or may not be automated</td>
<td>-</td>
</tr>
</tbody>
</table>

#### 11.7 Value Proposition from Inventory Optimization

The value proposition for inventory optimization is to reduce inventory investment and increase fill rate. The current inventory position is summarized above in Figure 18; of the current inventory of consumable and reparable parts of 100%, 40% contributes to the optimal provisioning; 20% is excess that can be burned down, or used up without replenishment, within five years; 40% remains excess after five years and becomes candidate for disposal through scrapping or resale, since with a typical 20%-25% annual inventory holding cost it would be more economical to buy any needed parts new after five years; and the obligation for current parts on backorder is negligible. The current inventory position is defined as on hand, plus due-
in, minus backorders. Not shown but of interest to financial analysts is the accompanying accounting view of inventory over time, showing the traditional accounting double ledger with sources of inventory equaling uses of inventory by year. The value proposition chart is based on this accounting view.

It is recommended that a team form to rationalize the current inventory investment, with an eye towards eliminating unneeded inventory in a way that returns the best value for the existing investment. Excess wholesale inventory can be addressed by selling back to the OEM to support new equipment production, resale on the aftermarket, resale via a third part vendor, or scrapping to recoup the cost of raw material and eliminate holding cost by clearing warehouse space.

12 Alternate ABCDE Inventory Segmentation Strategy

Simulation analysis reveals that Order Fulfillment Lead Time metrics are not achievable if the forecast number of operating hours is exceeded, when stock levels are set using the baseline AB inventory segmentation strategy. The obvious question is: "What does heavy industry need to do to achieve their contractual OFLT metrics, how much more money will it cost, and when will goals be reached?"

12.1 An Alternate Inventory Segmentation Strategy

Inventory is ultimately managed on a part by part basis. Review of multiple part inventory systems shows that annual usage, defined as annual demand multiplied by unit cost, follows the Pareto principle: 5% of the parts are responsible for 80% of the annual usage; the next 15% of the parts are responsible for another 15% of usage; and the remaining 80% of the parts are responsible for 20% of the usage. Silver, Pyke, and Peterson (1998) suggest that inventory
should be managed by ABC usage segments, which this thesis abstracts to also encompass DE segments:

- **Class A** parts, with unit cost > $25, should be carefully tracked by asset managers. When it comes time to order replenishment parts, are there existing items in inventory that could be transferred to eliminate an imbalance of inventory between locations? Could the supplier manager and vendor collaborate to reduce lead times? Could the buyer reduce unit cost through competition among suppliers? These parts are candidates for review by a monthly Spares Requirements Review Board (SRRB).

- **Class B** parts, with unit cost > $25, are in the mid-range, and should receive moderate attention, with management by exception rules flagging asset managers when close attention is warranted.

- **Class C** parts, with unit cost > $25, should be managed with simple decision rules. The value of an asset manager’s time in researching stock outs is greater than setting high fill rate goals. These parts should be managed electronically to reorder points and target stock levels, without human intervention.

- **Class D** parts cost between $1 and $25, and should be managed with simple decision rules to high fill rates.

- **Class E** parts cost $1 or less, and should be managed with simple decision rules to very high fill rates.

An ABCDE inventory segmentation strategy will be modeled. The process involves four steps:

- Segment the inventory of consumables into ABC classes.
- Segregate parts with unit cost between $1 and up to $25 inclusive as D class, and with unit cost $1 or less as E class.
- Optimize each class individually to graduated fill rate goals, with A parts receiving the lowest fill rate and being managed closely, and E parts receiving the highest fill rate and being managed automatically.
- Simulate the results to determine whether this alternate mix of parts achieves a higher Order Fulfillment Lead Time than the baseline solution.

One additional change will be made to the baseline: the business rule that ensures that each part is stocked to a minimum of 50% fill rate is no longer necessary, as the inventory segmentation strategy will eliminate the bias that occurs when penny piece parts such as nuts, bolts, rivets, and washers compete against thousand dollar machined parts to achieve fill rate goals.

12.2 ABCDE Inventory Segmentation on Annual Usage

An ABCDE inventory segmentation was conducted by first grouping parts into ABC segments, and then breaking out parts costing between $25 and $100 as Segment D, and parts costing $1 or less as Segment E. Results are summarized in Table 13, showing the segment, percent of annual use, and percent of total unique part numbers.
Table 13 - Alternate ABCDE Inventory Segmentation for Consumable Parts, Segmenting Consumable Parts on Annual Usage.

<table>
<thead>
<tr>
<th>Segment</th>
<th>% Annual Use</th>
<th>% Part Count</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A:</strong> 80% Annual Use &amp; Unit Cost &gt; $25</td>
<td>79%</td>
<td>7%</td>
</tr>
<tr>
<td><strong>B:</strong> 15% Annual Use &amp; Unit Cost &gt; $25</td>
<td>14%</td>
<td>14%</td>
</tr>
<tr>
<td><strong>C:</strong> 5% Annual Use &amp; Unit Cost &gt; $25</td>
<td>4%</td>
<td>42%</td>
</tr>
<tr>
<td><strong>D:</strong> $1 &lt; Unit Cost ≤ $25</td>
<td>3%</td>
<td>30%</td>
</tr>
<tr>
<td><strong>E:</strong> Unit Cost ≤ $1</td>
<td>0%</td>
<td>7%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

As expected, 7% of the unique part numbers are in Segment A and are responsible for 79% of the annual usage; 14% of the parts are in Segment B and are responsible for 14% of the annual usage; and the remaining 79% of the parts are in Segments CDE and are responsible for the remaining 7% of annual usage. Interestingly, 30% of all unique part numbers are in Segment D class and 7% are Segment E.

Results are summarized graphically in Figure 19, showing cumulative annual usage vs. cumulative percent part count.
12.3 Inventory Optimization by Segment

Each class of parts was optimized in a separate network using commercial Inventory Optimization Model B, as shown in Figure 20. The A class parts were optimized to a 90% fill rate goal; the B class to a 92% goal; and the CDE classes to a 99% goal. While other fill rate goals are certainly possible, this was thought to be a reasonable initial goal for the evaluation. It was recognized that if the Order Fulfillment Lead Time goals were not achieved by the simulation, it would be necessary to conduct additional iterations of the process until a satisfactory solution was achieved.
 Inventory optimization uses a "greedy algorithm" to select the lowest cost quantity and mix of parts achieving fill rate constraint.

Referring to Figure 20, the upper cyan curve represents fill rate. As fill rate increases, the cost of achieving that fill rate begins to increase exponentially, especially with the high dollar A and B class parts. The middle magenta curve that starts high and decreases represents the average days delay, or awaiting parts time: as fill rate increases, the time spent waiting for parts decreases commensurately. The lower yellow curve represents availability, which in this case has no real meaning. If the each type of operating equipment were modeled with an indentured parts breakdown, the availability curve would indicate "maintenance availability"; that is, the equipment availability that could be achieved if the only delays were due to maintenance parts and the actually hands on maintenance repair time was ignored.

The results of the inventory optimization for consumable parts are summarized in Table 14. The value of the current inventory of consumable parts is benchmarked to 100%. The value of the optimal inventory drops to 36% of the current inventory investment with the alternate ABCDE strategy, as compared to 44% with the baseline AB strategy, which was unexpected given the
inventory investment curves of Figure 20, which show significantly increasing inventory investment as fill rate increases. Note that 41% with the baseline AB strategy in Table 10 becomes 44% in the inventory analysis of Figure 18, after correcting discrepancies in the baseline dataset where consumable parts were included in the reparable segments and vice versa. The decrease from 44% of baseline to 36% of baseline represents a 20% reduction in inventory investment.

Table 14 - Summary of Segments for Consumable Parts using an Alternate ABCDE Inventory Segmentation Strategy; the Alternate ABCDE Inventory Investment is 20% Lower than the Baseline AB Inventory Investment

<table>
<thead>
<tr>
<th>Inventory Segment</th>
<th>Description</th>
<th>Fill Rate</th>
<th>Active Part Count</th>
<th>Inventory Position Value</th>
<th>Optimized Stock Level Value</th>
<th>Ratio Optimized/Inventory Position</th>
<th>Annual Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>80% Annual Use &amp; Unit Cost &gt; $25</td>
<td>90%</td>
<td>7%</td>
<td>65%</td>
<td>66%</td>
<td>36%</td>
<td>79%</td>
</tr>
<tr>
<td>B</td>
<td>15% Annual Use &amp; Unit Cost &gt; $25</td>
<td>92%</td>
<td>14%</td>
<td>21%</td>
<td>17%</td>
<td>29%</td>
<td>14%</td>
</tr>
<tr>
<td>C</td>
<td>5% Annual Use &amp; Unit Cost &gt; $25</td>
<td>99%</td>
<td>41%</td>
<td>10%</td>
<td>10%</td>
<td>38%</td>
<td>4%</td>
</tr>
<tr>
<td>D*</td>
<td>$1 &lt; Unit Cost &lt;= $25</td>
<td>99%</td>
<td>30%</td>
<td>4%</td>
<td>6%</td>
<td>54%</td>
<td>3%</td>
</tr>
<tr>
<td>E*</td>
<td>$1 &lt;= Unit Cost</td>
<td>99%</td>
<td>7%</td>
<td>0%</td>
<td>0%</td>
<td>83%</td>
<td>0%</td>
</tr>
<tr>
<td>ABCDE</td>
<td>Consumables</td>
<td>97%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>36%</td>
<td>100%</td>
</tr>
</tbody>
</table>

*Create ABC categories, and then break out D & E separately

12.4 Consumables High Priority OFLT

Simulation results for high priority consumable parts indicates that by August 2013, the average Order Fulfillment Lead Time will cross the 85% threshold, achieving goals. Given the confidence interval, shown in Figure 21, this is about a 50% chance of success, significantly better than the baseline, which fails to meet metrics, as shown in Figure 16. Of course, the stocking policy of continuous versus periodic resupply must also be addressed to create a complete solution. Given the 20% reduction investment, another iteration setting Segment A
parts at 92% fill rate and Segment B parts at 95% should be evaluated. In addition, the appropriate delay due to the Spares Requirements Review Board (SRRB), and the customer acquisition policy, must also be added to the procurement lead time.

Figure 21 - Stocking Consumable Parts based on New Target Stock Levels, the Result of an Alternate ABCDE Inventory Segmentation Strategy, Achieves the Desired Order Fulfillment Lead Time Metrics for High Priority Consumables by August 2013 on Average

*Must also address stocking policy: continuous resupply vs. periodic resupply

12.5 Consumables Low Priority OFLT

Simulation results for low priority consumable parts indicate that by May 2013, the average Order Fulfillment Lead Time will handily cross the 90% threshold, achieving goals. The lower band of the 90% confidence level is above the 90% goal line, as shown in Figure 22, indicating that with good program execution, this service metric is eminently achievable. In comparison with the baseline results shown in Figure 17, which fail to meet goals, the results of the inventory segmentation policy are clearly superior.
Stocking Consumable Parts based on New Target Stock Levels, the Result of an Alternate ABCDE Inventory Segmentation Strategy, Achieves the Desired Order Fulfillment Lead Time Metrics for Low Priority Consumables by May 2013

*Must also address stocking policy: continuous resupply vs. periodic resupply

12.6 Rightsizing Inventory

The bottom line results for the inventory segmentation strategy are summarized in Figure 23, which shows that managing to an investment of only 36% of the existing inventory can achieve Order Fulfillment Lead Time metrics. Further, 19% of current inventory is can be “burned down,” or consumed, over the next five (5) years. An additional 59% of inactive and slow moving inventory is targeted for excess.
Figure 23 - Inventory Summary for Consumables with Stock Levels from Inventory Optimization Model B, using Tomorrow’s Part Networks based on the Alternate ABCDE Inventory Segmentation on Annual Usage. Note that the Optimal Inventory Investment is 20% Lower than the Baseline AB Inventory Investment.

The conclusion is clear: for this representative heavy industry dataset, investment in consumable parts can be lowered by 20%, and fill rate increased sufficiently to achieve Order Fulfillment Lead Time (OFLT) metrics, by implementing a straightforward ABCDE inventory segmentation strategy. For heavy industry in general, the choice of inventory segmentation strategy has significant implications for investment and service level. To address the disconnect between fill rate based inventory optimization and service metrics which incorporate response time, supply chain simulation bridges the chasm.

As explained in Section 14, achieving these results also requires that management address the impact of the monthly Spares Requirements Review Board (SRRB) meetings by accounting for this one month review time. Further, management must align acquisition policy with stocking policy in order to manage a healthy supply chain.
13 Forecast Accuracy

The research organization Gartner, Inc., found in a 2009 survey of executives that forecast accuracy and demand variability are the top challenges to reaching supply chain goals. The survey results are summarized in Figure 24 (SCDigest Editorial Staff, 2009). Heavy industry is not alone in having issues with forecast accuracy.

![Demand Predictability and Cost Control Remain Key Challenges to Achieving Supply Chain Objectives](image)

Figure 24 - 2009 Gartner, Inc., Survey of Companies' Biggest Challenges to Achieving Supply Chain Objectives Identifies Forecast Accuracy as the Number One Challenge (SCDigest Editorial Staff, 2009)

13.1 Comparing Forecast Demand to Actual Demand

Forecasts for January 2012 were compared to the actual demand for spare parts. The average monthly forecast from Inventory Optimization Model A, the corresponding average monthly forecast from a comparison report, and the actual average monthly demand from the comparison
report, are shown in Table 15. Differences between Model A and the comparison report are not significant.

Table 15- Comparison of Forecast Demand vs. Actual Demand for January 2012

<table>
<thead>
<tr>
<th>Inventory Segment</th>
<th>Lines</th>
<th>Average Monthly Forecast (Model A)</th>
<th>Average Monthly Forecast/ Estimate (Report)</th>
<th>Average Monthly Demand/ Actual (Report)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reparable LRU</td>
<td>413</td>
<td>177.02</td>
<td>178.66</td>
<td>193.75</td>
</tr>
<tr>
<td>Reparable SRU</td>
<td>240</td>
<td>54.54</td>
<td>57.71</td>
<td>24.13</td>
</tr>
<tr>
<td>Reparable SSRU</td>
<td>11</td>
<td>1.98</td>
<td>1.98</td>
<td>0.38</td>
</tr>
<tr>
<td>REPARABLES</td>
<td>664</td>
<td>233.54</td>
<td>238.35</td>
<td>218.25</td>
</tr>
<tr>
<td>Unit Cost &gt; $2,000</td>
<td>1,033</td>
<td>452.96</td>
<td>452.96</td>
<td>440.71</td>
</tr>
<tr>
<td>Unit Cost ≤ $2,000</td>
<td>12,906</td>
<td>41,565.99</td>
<td>41,565.99</td>
<td>24,810.67</td>
</tr>
<tr>
<td>CONSUMABLES</td>
<td>13,939</td>
<td>42,018.95</td>
<td>42,018.95</td>
<td>25,251.38</td>
</tr>
<tr>
<td>TOTAL</td>
<td>14,603</td>
<td>42,252.49</td>
<td>42,257.30</td>
<td>25,469.63</td>
</tr>
</tbody>
</table>

The comparison report was used as the basis for determining the forecast accuracy metrics in Table 16, because it conveniently contained both the forecast and the actual demand for each part. This table shows the Mean Deviation (MD), Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE). Statistics were calculated for each part network, where reparables are an aggregation of LRU, SRU, and SSRU; and consumables are an aggregation of parts > $2,000 and parts ≤ $2,000. The findings are significant: for reparables, ignoring SSRUs, which contains less than one dozen active parts, MAPE is 13% for LRUs and 9% for SRUs, relatively good for high dollar, low demand service parts. The MPE, which measures forecast bias (over- or under-forecasting), is -6% and -5% respectively, showing that actual demand is slightly less than the forecast. For consumables, MAPE is 17% for parts > $2,000 and 38% for parts ≤ $2,000, and MPE is -10% and -33% respectively, showing a significant over-forecast. This explains why
simulated OFLT for January 2012, which assumes that the higher forecast is accurate, was lower than actual OFLT, which is based on the lower actual demand. A high forecast (more spares) and lower demand (fewer requirements) results in high OFLT metrics.

Table 16 - Forecast Accuracy for January 2012 using MD, MAD, RMSE, MPE, and MAPE

<table>
<thead>
<tr>
<th>Measure of Forecast Error</th>
<th>All Parts</th>
<th>Reparable LRUs</th>
<th>Reparable SRUs</th>
<th>Reparable SSRUs</th>
<th>Consumables &gt; $2,000</th>
<th>Consumables ≤ $2,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>n (Observations)</td>
<td>14,736</td>
<td>413</td>
<td>240</td>
<td>11</td>
<td>1,033</td>
<td>12,906</td>
</tr>
<tr>
<td>MD</td>
<td>(1.14)</td>
<td>0.04</td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.01)</td>
<td>(1.30)</td>
</tr>
<tr>
<td>MAD</td>
<td>1.60</td>
<td>0.07</td>
<td>0.16</td>
<td>0.15</td>
<td>0.11</td>
<td>1.81</td>
</tr>
<tr>
<td>RMSE</td>
<td>16.21</td>
<td>0.23</td>
<td>0.55</td>
<td>0.48</td>
<td>0.37</td>
<td>17.32</td>
</tr>
<tr>
<td>MPE</td>
<td>-31%</td>
<td>-6%</td>
<td>-5%</td>
<td>-39%</td>
<td>-10%</td>
<td>-33%</td>
</tr>
<tr>
<td>MAPE</td>
<td>36%</td>
<td>13%</td>
<td>9%</td>
<td>39%</td>
<td>17%</td>
<td>38%</td>
</tr>
</tbody>
</table>

13.2 Analysis

While Inventory Optimization Model A has an automated forecasting engine, either (a) the manual override for depot requirements, (b) error introduced by the operating hour forecast, or (c) both resulted in a bias towards over-forecasting. The inventory optimization model stocks inventory based on the higher expected number of demands per operating hour, rather than the lower actual number of demands per operating hour. As a consequence, the simulation will consistently underestimate actual performance because the simulation expects to be consuming parts at the higher forecast rate per operating hour, while actual performance benefits from the relatively higher stock levels due to the manual override for depot requirements.

As noted in Section 11.3 for high priority consumable parts, and Section 11.4 for low priority, a review of the previous period of performance revealed that OFLT for high priority orders placed between October 2010 and September 2011 ranged from 53% to 71%, and for low priority from 58% to 75%. As both metrics were trending down over the final three months, analysis of
historical performance would not predict a significant near term improvement. For both periods, a manual override for depot requirements was in place. Confounding this comparison, however, the collection of unique part numbers decreased between periods of performance.

The baseline AB strategy which optimizes stock levels to 44% of original inventory, and the alternate ABCDE strategy which optimizes stock levels to 36%, are consistent because both base stock levels on predicted future operating hours and use the same estimate of demands per part number per operating hour.

13.3 Recommendations

The forecast behind the manual override to generate depot demand, based upon the piece part replacement rates for certain repair parts, should be verified. It should be noted that the wholesale central warehouse is obligated to manage service parts to achieve metrics based on the retail forecast of monthly operating hours; thus, if the depot is repairing fewer components than operating hours would warrant (a) a higher manual override may be justified, and (b) the depot may be repairing insufficient components to maintain pipeline inventory. Collaborative Planning, Forecasting, and Replenishment (CPFR) should also be considered to reduce the “bullwhip effect” between the relatively stable operating location (retail) demand and the fluctuating central warehouse (wholesale) demand.

14 Acquisition Policy

Acquisition policy will be modeled by assuming that an inventory optimization model has been run using a continuous review policy model, but that funding cycles are monthly, quarterly, or annual, resulting in a de facto periodic review policy. This occurs when a monthly Spares Requirements Review Board (SRRB) validates buys for spare parts, inserting a one month delay
time in the acquisition process. This also occurs when funding is approved by part number and quantity during a quarterly or annual budgeting process. A disconnect in the supply chain occurs when heavy industry uses a traditional Order-Point, Order-up-to-Level Model, instead of the Periodic Review Model that these delays necessitate. Curves of the resulting fill rate, perfect order fulfillment, and Order Fulfillment Lead Time from a continuous (s,S) stocking policy versus a periodic (R, s, S) stocking policy will be evaluated. Although not considered in this thesis, as a further refinement stockout cost could be included as the theoretical value of lost performance incentive, often referred to in industry as incentive fee.

14.1 Continuous Resupply and Inventory Optimization

When inventory drops to or below reorder point, an order is placed up to target stock level. This is known as an Order-Point, Order-up-to-Level Model (s,S) model. The continuous resupply case is modeled by evaluating an (s,S) model under continuous review conditions.

14.2 Periodic Resupply and Acquisition Policy

By not including review and/or funding cycles in the spares calculations, heavy industry may be under-sparing programs. With a periodic review model, the appropriate review lead time would be added to the calculation of lead time: for an annual funding cycle, 12 months, or for a quarterly funding cycle, 3 months. This is known as a Periodic-Review, Order-Point, Order-Up-to-Level Model (R, s, S). The impact of these acquisition policies will be evaluated by simulating an (s,S) model under periodic review conditions.

14.3 Adjustments to Warehouse Simulation

The Discrete-Event Warehouse Simulation checks inventory levels on a user specified time interval. Working with the model developers, the core code for the “cycle check” was expanded
to include options for a 90-day delay between resupply, and a 360-day delay. This custom version of the warehouse simulation was then compiled and used for the ensuing evaluations.

14.4 Fill Rate

Fill rate for the continuous resupply case, which is the baseline case considered in this thesis, is based on the target stock levels determined by Inventory Optimization Model A. Fill rate for the 30, 90, and 360-day periodic resupply cases is based on stocking to the same target stock levels but imposing a 30, 90 or 360-day delay between reorders. This simulates the impact of a monthly Spares Requirements Review Board, a quarterly funding cycle, or an annual funding cycle.

As shown in Figure 25, the continuous resupply curve represents the best case scenario, where an order up to target stock level is placed as soon as reorder point is reached. The fill rate goal was arbitrarily set to 90%, as only Order Fulfillment Lead Time is measured contractually. This curve represents all parts in the industry representative dataset: reparables and consumables, "on metric" or "off metric". With a 30-day periodic resupply, the fill rate drops marginally in 2013 as parts on order at the start of the simulation arrive on time, but new orders placed when inventory levels fall to reorder point incur the additional 30-day delay. With a 90-day periodic resupply, the fill rate curve shows a saw tooth curve when the additional 90-day delay occurs, and progressively goes out of balance. With a 360-day periodic resupply, the fill rate curve degrades significantly, showing that the supply chain is unsustainable. *Current performance reflects the impact of imposing periodic buys on a supply chain designed for continuous buys, as demonstrated by these simulations.*
Figure 25 - The Impact of Stocking Policy upon Fill Rate

The distinctions between the stocking policies are summarized as:

- **Continuous Resupply**: The stock levels set by the inventory optimization model assume continuous resupply.

- **30-Day Periodic Resupply**: Imposing a Spares Requirements Review Board which meets monthly effectively results in a 30-day resupply period.

- **90-Day Periodic Resupply**: An acquisition policy which funds purchases quarterly effectively results in a 90-day resupply period.

- **360-Day Periodic Resupply**: An acquisition policy which funds purchases annually effectively results in a 360-day resupply period.

14.5 Perfect Order Fulfillment

Perfect order fulfillment for the continuous resupply, and 30, 60, and 90-day periodic resupply cases, is shown in Figure 26. The perfect order fulfillment goal was arbitrarily set to 90%, as only Order Fulfillment Lead Time is measured as a service metric. Interestingly, the monthly Spares Requirements Review Board only drops performance a few percentage points. The effect
of the 90 and 360-day acquisition policies is more dramatic, with both policies resulting in an unsustainable supply chain over time.

Figure 26 - The Impact of Stocking Policy upon Perfect Order Fulfillment

14.6 Continuous, 30, 60 and 90-Day Periodic Resupply for High Priority Consumables

The key to understanding the impact of the review period and acquisition policy is realizing their effect on Order Fulfillment Lead Time metrics. Since inventory segmentation strategies are commonly applied to consumable parts only, reparable parts will not be evaluated. For High Priority consumable parts, as shown in Figure 27, the 30-day Spares Requirements Review Board imposes about a five percentage point penalty on Order Fulfillment Lead Time, enough to cause an organization to continuously fail to achieve metrics. The 90-day delay incurred from a quarterly acquisition policy drops performance another few percent, and the 360-day delay incurred from an annual acquisition policy degrades significantly.
Figure 27 - The Impact of Stocking Policy upon Order Fulfillment Lead Time for High Priority Consumables

14.7 Continuous, 30, 60 and 90-Day Periodic Resupply for Low Priority Consumables

For Low Priority consumable parts, as shown in Figure 28, the 30-day Spares Requirements Review Board imposes about a three to four percentage point penalty on Order Fulfillment Lead Time, also enough to cause a company to continuously fail to achieve metrics. The 90 day delay incurred from a quarterly acquisition policy drops performance another three to four percent, and the 360-day delay incurred from an annual acquisition policy again degrades significantly.
14.8 Recommendations

Stocking policy and acquisition policy go hand in hand. A continuous review stocking policy is appropriate for a flexible contract that funds purchases when stock levels fall to reorder points. Quarterly or annual funding cycles result in a periodic resupply contract. In this case, the stocking policy must be changed from continuous review (with frequent buys to stock level) to periodic review (with quarterly or annual buys to stock level), requiring that the appropriate review period be added to the procurement lead time. The spares recommended by the inventory optimization model increase as review period increases.

Acquisition Policy: The preferred stocking policy should be in concert with the acquisition policy. For example, given an annual funding cycle, heavy industry should stock to a twelve (12) month periodic review policy. Since this requires a larger capital expense for initial spares, due to the added twelve (12) months of pipeline inventory, a company instead should develop a financial business case for changing acquisition policy to (a) fund the “plus up” to achieve optimal stock levels, and (b) allow a funding vehicle for flexible continuous expenditures.
**Review Policy:** Heavy industry should automate routine orders for low dollar parts. The current Spares Requirements Review Board should only validate high dollar orders, and in particular should focus on reviewing orders that are outside of the recommendations of the inventory optimization model, such as asset manager overrides. For these parts, the cost of an additional month’s inventory should be weighed against the value of an independent round of confirmation, which imposes a one month delay on placing orders. The procurement lead time for these parts should have the additional month’s delay time added, in order to convert from the current continuous review policy to the de facto periodic review policy.

**15 Conclusions and Recommendations**

Drawing inferences from the representative heavy industry dataset, organizations which stock service parts can lower inventory investment in consumable parts as much as 20% and increase performance on speed of service metrics such as Order Fulfillment Lead Time through an inventory segmentation strategy, but must be cognizant that acquisition policy will impact results. Further gains are possible through supply chain automation.

Heavy industry’s stocking policy (a continuous review policy set in the inventory optimization model), review policy (a monthly Spares Requirements Review Board), and acquisition policy (funding approved quarterly by executives) must be aligned to avoid significantly disrupting the ability to achieve OFLT goals. The review period (one month for the Spares Requirements Review Board plus three months if executives fund plus-ups to target stock levels quarterly) must be added to the procurement lead time, increasing safety stock levels.

Heavy industry can achieve metrics through an inventory segmentation strategy. Inventory segmentation based on supply chain classes taught at MIT shows that categorizing consumable
parts into an ABCDE network enables OFLT goals to be achieved in a little over a year while reducing inventory investment. These financial projections exclude increases in safety stocks to account for review boards, acquisition policy, and review period.

Organizations should automate management of parts in the CDE categories in order to both eliminate the burden of asset management overhead and eliminate the safety stock required by the review period. Organizations should also consider authorizing a flexible funding pool to eliminate the need to add three additional months’ of safety stock in order to compensate for the quarterly funding cycle.

The following recommendations describe straightforward solutions for achieving supply chain metrics, lower inventory investment, lowering asset management costs, and gaining consensus for implementation. The result will be a win-win-win solution for heavy industry (achieve metrics, increase incentive fee, and increase stakeholder value through lowered inventory investment), asset managers (focus on analysis of critical A and B parts, while buys for CDE parts are automated), and customers (the maintainers receiving the parts they need to service an organization’s heavy equipment, and the operators using the equipment to generate revenue or perform a mission).

15.1 Inventory Segmentation Lowers Inventory Investment and Increases Metrics

The target stock levels for the alternate ABCDE inventory segmentation strategy, determined with Inventory Optimization Model B, should be validated using company standard inventory Model A. Two sets of inventory optimization goals should be evaluated, as shown in Table 17. Case #1 is the baseline case evaluated using Model B, which achieves OFLT goals. Case #2 would allow added leeway due to warehouse delays, and should be considered if the added cost of inventory and corresponding increases in fill rate and simulated OFLT are an attractive mix.
Table 17 - Recommended Fill Rate Goals for Inventory Segmentation

<table>
<thead>
<tr>
<th>Parts Network</th>
<th>Case #1 ABCDE Fill Rate</th>
<th>Case #2 ABCDE Fill Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A:</strong> 80% of Annual Use &amp; Unit Cost &gt; $25</td>
<td>90%</td>
<td>92%</td>
</tr>
<tr>
<td><strong>B:</strong> 15% of Annual Use &amp; Unit Cost &gt; $25</td>
<td>92%</td>
<td>95%</td>
</tr>
<tr>
<td><strong>C:</strong> 5% of Annual Use &amp; Unit Cost &gt; $25</td>
<td>95%</td>
<td>99%</td>
</tr>
<tr>
<td><strong>D:</strong> $1 &lt; Unit Cost ≤ $25</td>
<td>99%</td>
<td>99%</td>
</tr>
<tr>
<td><strong>E:</strong> Unit Cost ≤ $1</td>
<td>99%</td>
<td>99%</td>
</tr>
</tbody>
</table>

As shown in Table 9, while 14% of all consumables by part count are D parts and 9% E parts, 25% of parts have a unit price between $25 and $100. It might make sense to evaluate on addition mix of parts, as shown in Table 18. These four scenarios should be evaluated by (a) comparing the part-by-part fill rates and considering whether the program considers it acceptable to stock the parts with a low fill rate parts at the recommended levels, and (b) by evaluating the simulated metrics.

Table 18 - Recommended Fill Rate Goals for Alternate Inventory Segmentation Trade Study

<table>
<thead>
<tr>
<th>Parts Network</th>
<th>Case #1 ABCDEF Fill Rate</th>
<th>Case #2 ABCDEF Fill Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A:</strong> 80% of Annual Use &amp; Unit Cost &gt; $25</td>
<td>90%</td>
<td>92%</td>
</tr>
<tr>
<td><strong>B:</strong> 15% of Annual Use &amp; Unit Cost &gt; $25</td>
<td>92%</td>
<td>95%</td>
</tr>
<tr>
<td><strong>C:</strong> 5% of Annual Use &amp; Unit Cost &gt; $25</td>
<td>95%</td>
<td>99%</td>
</tr>
<tr>
<td><strong>D:</strong> $25 &lt; Unit Cost ≤ $100</td>
<td>99%</td>
<td>99%</td>
</tr>
<tr>
<td><strong>E:</strong> $1 &lt; Unit Cost ≤ $25</td>
<td>99%</td>
<td>99%</td>
</tr>
<tr>
<td><strong>F:</strong> Unit Cost ≤ $1</td>
<td>99%</td>
<td>99%</td>
</tr>
</tbody>
</table>

For parts which the inventory optimization model chooses not to stock, the reorder point should be set to -1, indicating that an order should only be placed with the part goes on backorder. The reorder quantity should be set to the Economic Order Quantity (EOQ) using the Wilson EOQ model, as when an order is placed, it should be done in the most economic fashion. An added business rule to cap the order at five (5) years of demand may also be implemented.
The representative industry dataset of November, 2011, should be used for these scenarios, because that provides a point of comparison to the simulations conducted in this thesis. Once the management team selects the scenario offering the best tradeoff between inventory investment and OFLT metrics, the current dataset should be used to determine the new target stock levels. The recommendations are summarized in Figure 29, below.

<table>
<thead>
<tr>
<th>Summary of Recommendations for Validating Inventory Segmentation Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Problem:</strong> How to instill confidence in inventory segmentation?</td>
</tr>
<tr>
<td><strong>Solution:</strong> Validate the inventory segmentation strategy in Inventory Optimization Model A</td>
</tr>
<tr>
<td>- Duplicate ABCDE analysis</td>
</tr>
<tr>
<td>- Consider alternate grouping categories (Case#3) fill rates (Cases #2 &amp; 4)</td>
</tr>
<tr>
<td>- Set ROP = -1, ROQ = EOQ for non-stocked parts</td>
</tr>
<tr>
<td>- Use November 2011 dataset as baseline</td>
</tr>
<tr>
<td><strong>Result:</strong> Clear understanding of costs and benefits</td>
</tr>
</tbody>
</table>

Figure 29 - Summary of Recommendations for Validating Inventory Segmentation Strategy

15.2 Acquisition Policy Drives Resupply Period

The business policies in the inventory optimization model, which govern how stock levels are set, and the business policies with which the program is managed, which govern program execution, must be synchronized. Otherwise, as depicted in Section 14, the acquisition policy will result in an unstable and unmanageable supply chain. For parts subject to review at a monthly Spares Requirements Review Board, an additional month administrative delay must be added to the procurement lead time. For parts subject to quarterly or annual acquisition funding, and additional 90 or 360 days must be added to the procurement lead time. These additional administrative delays change the inventory management policy from a continuous review policy to a periodic review policy. The recommendations are summarized in Figure 30, below.
Summary of Recommendations for Incorporating Acquisition Policy

- **Problem:** Acquisition policy and Inventory Optimization Strategy Misaligned
- **Solution:** Spare for periodic review, not continuous review
  - Add resupply period to Procurement Lead Time
  - Spares Requirements Review Board (SRRB): + 30 days
  - Quarterly Funding: + 90 days
  - Annual Funding: + 360 days
- **Result:** Engender a conversation between company and customer that aligns acquisition goals, and within a company about the tradeoff between safety stock and internal review policy

Figure 30 - Summary of Recommendations for Incorporating Acquisition Policy

### 15.3 Recommended Spare Parts List (RSPL)

A comparison between simulated orders and actual orders revealed that there were a number of instances where retail operating locations were ordering parts which had either no recent demand, or were first time orders. It is also possible that orders are being placed for parts not belonging to the heavy equipment in the baseline inventory optimization. One problem is that there is no reason to ever stock inventory for parts which are not expected to fail. A second problem is that with small part population (12% of all unique part numbers are reparables, and 88% are consumables), a few orders for “zero demand” or “first time orders” will skew the results for parts “on metric”. Within the reparable parts group, for example, 94% of active (with demand) parts are in the LRU network, 6% of active reparable parts are in the SRU network, and with under a dozen parts 0% of active reparable parts are in the SSRU network.

There are two obvious solutions. The first is to set higher fill rate goals in the inventory optimization model, to create buffer for absorbing the impact of stock outs on these outlier parts. This is an expensive proposition. The second is to gain consensus on a defined parts list, concurring that parts off the list will be ordered procurement lead time away if low priority, and
expedited at an additional charge if high priority. The recommendations are summarized in Figure 31, below.

Summary of Recommendations for Recommended Spare Parts List (RSPL)

- **Problem:** No demand history
  - Retail ordering “zero demand” parts (no demand history)
  - Retail ordering parts not in inventory optimization model (first time orders)
  - Orders for “zero demand” parts, plus first time orders, skew metrics with small part populations
- **Solution:** Defined parts list
  - Propose that a defined list of parts over n demands per year be “on metric” with others available lead time away
  - Propose that a list of parts, defined at the customers’ prerogative, be “on metric” with others available lead time away
  - This strategy acknowledges that *inventorying parts with no historical demand is unprofitable to stock at wholesale, unaffordable for the customer at retail*
- **Result:** No surprises, no excuses

Figure 31 - Summary of Recommendations for Recommended Spare Parts List (RSPL)

15.4 **Align Asset Manager, Buyer, and Supplier Manager Incentives**

When incentives are aligned, asset managers will make decisions that lower inventory investment, buyers will acquire the recommended part quantities, and workarounds like an “asset manager checkbook” which seeks to reign in asset manager spending will become unnecessary.

What does an inventory optimization model do? The model selects the lowest cost mix of parts that achieve a fill rate goal, when fill rate is the optimization goal. Conversely, what else does an inventory optimization model do? It determines which parts one should be willing to run short on, because stocking them does not add value to the program. How are asset managers incentivized? By not running out of parts. As a result, asset managers are incentivized to stock up on the very parts the inventory optimization model deems it best to run out of! This contributes in bloated inventories of slow moving parts, as seen previously in Figure 23.
To ward off this tendency, innovations such as an “asset manager checkbook” have been developed to keep asset managers from exceeding their annual budget for replenishment spares early in the year. A better solution would be to incentivize asset managers to “manage to plan”, that is, to manage the inventory of parts they are responsible for within the optimal stock levels recommended by a company’s inventory optimization model. Under this scheme, as long as an asset manager kept the inventory position of the parts under their control within the recommended reorder point and target stock level, they would achieve the highest possible performance rating. The result of aligning incentives will be synchronization between optimal target stock levels and the parts ordered for delivery to the central warehouse.

This alignment of incentives must extend to the buyers, who are responsible for placing orders with suppliers based on asset manager decisions. As buyers are incentivized to lower acquisition costs, there is currently an incentive for them to make quantity buys in order to get lower unit costs, again resulting in bloated inventories of parts which a company should not be stocking.

Creating an integrated team comprised of the strategic planner who runs the inventory optimization model monthly, the asset managers who make tactical decisions day-to-day, the buyers to place orders with suppliers, and the supplier managers who have the business relation with suppliers will enable companies to break through silos, improve financial performance, and ultimately run a healthier supply chain. First, however, management must align performance incentives across these functions. The recommendations are summarized in Figure 32, below.
**Summary of Recommendations for Aligning Incentives**

- **Problem:** Performance incentives encourage wrong behavior
  - Asset manager performance based on not running out of stock
    - Inventory optimization recommends what to stock, and conversely what willing to run out of
    - Asset managers thus incentivized to ignore target stock levels and “buy high when they run low”
  - Buyer performance based on lowering unit cost
    - Buyers incentivized to make quantity buys
- **Solution:** Align performance goals
  - Asset managers: manage to recommended stock levels
  - Buyers: buy to asset manager recommendations
- **Result:** Supply chain synchronization
  - Aligning compensation with supply chain strategy will significantly reduce inventory and holding costs

---

**15.5 Supply Chain Automation**

Using an existing feature of many inventory management systems, consumable parts in the CDE classes should be set on “autobuy,” so that when the inventory position drops to or below reorder point, a new buy is made up to the target stock level. For low cost parts in the CDE classes, it is less expensive to order automatically than to waste resources evaluating a trivial order. Manual review inserts an administrative delay which requires additional safety stock and causes delays in placing orders and, as a result, contributes to missing metrics. The recommendations are summarized in Figure 33, below.
Summary of Recommendations for Supply Chain Automation

- **Problem:** Excessive asset management costs
- **Solution:** Intelligent automation using an inventory segmentation strategy
  - Place consumables CDE categories on auto buy
  - Leverage IT to automate processing and reduce administrative lead time
  - Automation reduces asset manager workload
    - Eliminating resupply period lowers safety stock
    - More expensive to run out than to overstock
  - Evaluate whether to place B category on auto buy
    - Closely manage A category
    - Focus asset management on high dollar parts
    - Rather that ordering parts individually, group buys by commodity code or supplier
    - Aligns asset managers, buyers, and suppliers
    - Monthly buys lower workload for asset managers and suppliers
- **Result:** *Increase the analysis, reduce the paralysis!*
  - Lower asset manager workload, allowing redeployment to other programs
  - Asset managers can proactively analyze rather than reactively fight fires
  - Eliminate Spares Requirements Review Board (SRRB) delay for CDE class parts
  - Create a more cost effective solution for customer

With success automating orders for CDE class parts, companies should investigate whether to extend automation to the B class parts.

Companies should also explore the benefits of grouping buys by commodity code, which categorizes parts by manufacturing process, and supplier. For parts subject to a monthly Spares Requirements Review Board, there is no reason not to group each month’s orders. This will enable buyers to place a consolidated order with their suppliers, rather than dribbling piecemeal orders throughout the month, resulting in efficiencies of scale and increasing a company’s bargaining power.

By lowering asset management workload, enabling asset managers to focus their analysis where it adds the highest value, and eliminating the requirement for additional safety stock to cover
administrative lead time, companies will increase performance metrics and increase value to their customers, whether internal to the organization or external.

15.6 Gain Consensus, Implement, and Achieve Supply Chain Health

Changing behavior in a complex organization requires executive leadership to set the course, and employee ownership of the new direction. By evaluating the recommendations in the same inventory optimization model used for program execution, by conducting a thorough peer-to-peer review of the results with the technical staff and Subject Matter Experts (SMEs), by reviewing the recommendations with the operating locations (retail) who require the parts, and ultimately by tracking actual progress against the simulated predictions, consensus for implementing an inventory segmentation strategy (and buy-in that it is indeed the right strategy) can be secured. The recommendations are summarized in Figure 34, below.

<table>
<thead>
<tr>
<th>Summary of Recommendations for Consensus Building</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Problem:</strong> Leading successful change management</td>
</tr>
<tr>
<td><strong>Solution:</strong> Secure consensus to implement recommendations</td>
</tr>
<tr>
<td>o Evaluate new stock levels with warehouse and metrics simulations</td>
</tr>
<tr>
<td>o Peer-to-peer technical review with SMEs</td>
</tr>
<tr>
<td>o Gain customer (retail) buy-in and confidence</td>
</tr>
<tr>
<td>o Track actual progress to simulated goals</td>
</tr>
<tr>
<td><strong>Result:</strong> Execute a healthy program and achieve metrics</td>
</tr>
</tbody>
</table>

Figure 34 - Summary of Recommendations for Consensus Building

15.7 Final Thoughts

Segmenting inventory into classes based on usage, aligning inventory policy with acquisition policy, automating replenishment for low usage parts, establishing a Recommended Spare Parts List, aligning performance incentives for asset managers, and gaining the consensus needed to implement these recommendations will enable heavy industry to manage healthy spares chains
which achieve performance metrics and sustain the operating equipment which the organization relies upon to generate revenue or perform a mission. By analyzing historical supply data, rebalancing stock levels with an inventory segmentation strategy, and simulating the results, this thesis demonstrates that heavy industry can achieve service metrics such as Order Fulfillment Lead Time, reduce the overhead of asset management, and lower inventory investment. The result is a win-win-win for heavy industry, asset managers, and customers.
16 Bibliography


17 Author Biography

RANDOLPH BRADLEY is a degree candidate for Master of Engineering in Logistics and Supply Chain Management (MLOG, 2012) at the Massachusetts Institute of Technology, U.S.A. As a Technical Fellow within the Supply Chain Management organization of The Boeing Company’s Defense, Space & Security business, his primary role is to enable the transition from successful proposal strategy to flawless program execution, focusing on delivering value across a spectrum of supply chain business opportunities. He is experienced with requirements definition to provide focused solutions, statistical demand forecasting to estimate future requirements, strategic inventory optimization to minimize investment, simulation to reduce risk and predict performance over time, tactical asset management to enable efficient daily operations, and inventory management to warehouse assets. His email addresses are Randolph.L.Bradley@Boeing.com, art2part@mit.edu, and soon art2part@alum.mit.edu.
18 Appendix A - Model Formulation and Problem Description

The objective function of each of the inventory optimization models used in this thesis, when optimizing consumable parts subject to an inventory segmentation strategy, is to minimize inventory investment for a given fill rate. The inputs to this model include the operational scenario (number of equipment, by equipment model; operating hours by month; operating locations; repair hierarchy), part level data (part number, manufacturer’s code, nomenclature, price, mean operating hours between demand, condemnation rate for reparable parts, repair turnaround time for reparable parts, procurement lead time), and part and location level data (inventory on hand, due-in, and on backorder). The outputs of this model include stock level recommendations by part and by location (target stock level and reorder point).

The Discrete-Event Warehouse Simulation analyses the inputs and outputs of the inventory optimization model in order to predict fill rate over time, as orders are placed to bring low starting stock levels up to the recommended target stock levels, and excess inventory is used up, or “burned down”, over time. Orders are delivered in the fixed procurement lead time of each part, and demand is variable based on the monthly equipment operating hours. Of the dozens of input and output tables of this simulation, the only table required for calculating the Order Fulfillment Lead Time (OFLT) metrics is the one containing the list of transactions from the operating locations (retail), to the central warehouse (wholesale), representing heavy industry.

The inventory optimization model adjusts target stock levels by month, as equipment is added to the fleet and as the monthly operating tempo changes. The Discrete-Event Warehouse Simulation models a single set of stock levels and reorder points. A baseline scenario was developed by taking the number of equipment and annualized operating hours for the middle of the first twelve months of the inventory optimization model. Since the monthly operating hours
did not fluctuate significantly during the 761 day period being simulated, these were kept as is. This is the baseline steady state scenario for the Discrete-Event Warehouse Simulation.

The Monte Carlo Demand Categorization and Metrics Simulation utilizes the decision variables shown in Table 19. The variable in green is used for demand categorization, and is specific to the part requisition. Variables in red are Monte Carlo variables which change with each iteration.

Table 19: Decision variables for the Monte Carlo Demand Categorization and Metrics Simulation

From the Discrete-Event Warehouse Simulation Model, for Part $i$

- $Close\_Date_i$: The date and time of that the requisition is filled from inventory in the wholesale warehouse, excluding shipping delay
- $Days\_to\_Fulfill_i$: $Requisition\_Date_i - Close\_Date_i$
- $Needed\_Q_i$: Quantity needed/ordered
- $Released\_Q\_SR\_No\_Delay_i$: Quantity released to fulfill the supply requisition with no delay (the order was satisfied from on hand inventory)
- $Requisition\_Q_i$: Requisition Quantity, which is based on an empirical order quantity distribution, in integer parts
- $Requisition\_Date_i$: The date and time of the requisition placed from retail to wholesale
- $Supply_i$: Unique reference number/part number

From the Inventory Optimization Model, for Part $i$ or classification $class$

- $metric\_bst_i$: Percent of requisition categorized as “on metric”, where “on metric” requisitions are defined as counting towards metrics
- $conrep\_bst_i$: Repair classification, or category, which is either consumable or reparable
- $hipri\_bst_i$: Percent of requisitions ordered as high priority
Empirical shipping delay distribution, in whole days, for requisitions ordered as high priority, where class is either consumable or reparable

Empirical shipping delay distribution, in whole days, for requisitions ordered as low priority, where class is either consumable or reparable

The Monte Carlo simulation uses internal Excel functions to calculate the expected outcome for each iteration, based on the input probabilities or empirical distributions, as shown in Table 20.

Table 20: Calculations performed by the Monte Carlo Demand Categorization and Metrics Simulation, for Part $i$ or classification class

<table>
<thead>
<tr>
<th>Calculation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calculation 1</td>
<td>Is requisition categorized as “on metric”? ($metric_{bsti}$)</td>
</tr>
<tr>
<td>Calculation 2</td>
<td>Is repair classification, or category, consumable or reparable? ($conrep_{bsti}$)</td>
</tr>
<tr>
<td>Calculation 3</td>
<td>Is the requisition being ordered as high priority? ($hipri_{bsti}$)</td>
</tr>
<tr>
<td>Calculation 4</td>
<td>What is the shipping delay, in days? ($shiphi_{bst_class}$ or $shiplo_{bst_class}$, depending on Calculation 3)</td>
</tr>
<tr>
<td>Calculation 5</td>
<td>What are the average days delay? ($Days_{to_Fulfill_i}$ + Calculation 4)</td>
</tr>
</tbody>
</table>

The Monte Carlo simulation then uses internal Excel function to categorize each requisition, as shown later in Figure 35. A series of Excel DSUM functions, which sum the numbers in a table matching specified conditions, are used to categorize metrics by month. By using Student’s t-test for small sample sizes, upper and lower confidence intervals are generated. By using Excel’s internal graphing capabilities, charts of metrics over time, with confidence intervals, are created. Wrapping a Visual Basic for Applications (VBA) program around this methodology allows the Monte Carlo simulation to loop over requisition data from 1 to $j$ Discrete-Event Warehouse Simulations, with 1 to $k$ Monte Carlo Demand Categorization and Metrics Simulations, and graph the results for a number of metrics, including fill rate, perfect order
fulfillment, Order Fulfillment Lead Time, and number of backordered requisitions outstanding, as shown in Table 21.

Table 21: Demand categorization performed by the Monte Carlo Demand Categorization and Metrics Simulation, for Part i

<table>
<thead>
<tr>
<th>On Metric</th>
<th>Does the requisition count towards metrics? (Yes if Calculation 1 is true)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hi-Group</td>
<td>Average days delay group if the requisition was ordered as High Priority (grouped as A=1-4 days, B=5-7 days, C=8-10 days, D=11-15 Days, E=16+ days, based on Calculation 4 only)</td>
</tr>
<tr>
<td>Lo-Group</td>
<td>Average days delay group if the requisition was ordered as Low Priority (grouped as A=1-16 days, B=17-27 days, C=28-38 days, D=39+ days, based on Calculation 4 only)</td>
</tr>
<tr>
<td>Category</td>
<td>Is repair classification, or category, consumable or reparable? (Calculation 2)</td>
</tr>
<tr>
<td>Priority</td>
<td>Was the requisition ordered as high priority? (Calculation 3)</td>
</tr>
<tr>
<td>Requisition Q</td>
<td>Requisition Quantity (Requisition Q)</td>
</tr>
<tr>
<td>Released Q SR No Delay</td>
<td>Quantity released to fulfill the supply requisition with no delay (Released Q SR No Delay)</td>
</tr>
<tr>
<td>Fill Rate</td>
<td>Was requisition filled from on hand inventory? (Yes if Requisition Q = Released Q SR No Delay)</td>
</tr>
<tr>
<td>Days On BO</td>
<td>Number of days requisition was on backorder, if backordered? (Days to Fulfill, rounded down by one day to compensate for date and time inconsistencies)</td>
</tr>
<tr>
<td>Req Month</td>
<td>Month and year of requisition (Requisition Date)</td>
</tr>
<tr>
<td>Close Date</td>
<td>The date the requisition was closed out by the military service (year, month of Close Date)</td>
</tr>
</tbody>
</table>

This approach offers several advantages for modeling. First, the existing warehouse simulation required only minor adjustments to (a) incorporate an empirical order quantity distribution, and (b) allow for periodic resupply. Second, the new demand categorization simulation was based on
only one table from the warehouse simulation, allowing (a) the entire table to be imported as an input, simplifying the link between the simulations, (b) providing traceability during model development to the exact source data from the simulation, and (c) allowing the warehouse simulation graph of cumulative fill rate, a standard model output, to be compared to analogous graph from the metrics simulation, offering an expedient validation of the basic categorization and graphing of the second simulation. This process is shown in Table 22.

Table 22: Methodology for calculating supply chain metrics using linked simulations

| Loop over 1 to \( j \) runs of the Monte Carlo Demand Categorization and Metrics Simulation |
| Loop over 1 to \( k \) runs (transaction lists) of the Discrete-Event Warehouse Simulation |
| Loop over 1 to 1 requisitions for part \( i \) |
| Calculate confidence interval using Student’s t-Test for \( k \) runs of the Warehouse Simulation |
| Create charts of metrics over time, with confidence interval |

The process for simulating Order Fulfillment Lead Time follows the flowchart show in Figure 35, which describes the decision flow used to determine whether a specific order counts towards metrics, and if so, whether the metrics were achieved.

- Execute \( n \) runs of the Warehouse Simulation to create a list of orders, or requisitions
- Import the list(s) of requisitions into the Metrics Simulation
- Execute \( m \) runs of the Discrete-Event Warehouse Simulation Model
- Determine whether the requisition counts toward metrics based on characteristic of the order, which is specific to the part number and is highlighted in Figure 35 in green:
  - What is the repair classification, or category, which either consumable or reparable
- Categorize the requisition based on characteristics which change order to order, which are highlighted in Figure 35 in red:
- Is the item “on metric”, in which case the order counts towards metrics?
- What is the priority of the order? High priority indicates that the part is necessary to return equipment to service, and low priority indicates a routine reorder.
- What is the shipping delay, which historically varies order to order?

- Calculate confidence interval using Student’s t-Test for $n$ Warehouse Simulation runs.
- Graph charts of service metrics over time.

**Figure 35 - Calculating Order Fulfillment Lead Time (OFLT) requires information on the order (in green) and probabilistic information on the likelihood of events (in red)**