REDUCING INVENTORY THROUGH SUPPLY CHAIN COORDINATION AND IMPROVED LEAD TIMES

by

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Abstract

In supply chain management, it is commonly held that reducing lead times and minimum order quantities (MOQs) from suppliers can drive down the customer's inventory levels substantially. Customers providing a consumption forecast along with a commitment to a supplier to cover some portion of raw material, work-in-process, and finished goods in exchange for reduced lead times and lower MOQs can support that goal; however, there does not exist a general method for identifying and optimizing the terms of these agreements. Existing literature describes techniques that involve vendor-managed inventory and other lead time reduction strategies, but none exists where the customer manages the ordering and replenishment policies from a vendor stock.

In this thesis, we investigate a method for a company to reduce lead times and inventory level while maintaining or improving their customer service level. To do so, we introduce a new process for the business where a customer identifies the optimal subset of parts with their corresponding lead time and stocking policy trade-offs to drive inventory reductions relative to the existing state. We describe the benefits for both supplier and customer and specifically focus on the investigation of the opportunity for the customer and the appropriate segmentation of suppliers and parts for consideration in a pilot leading to full implantation. We expect this new approach to substantially reduce the inventory at the customer while improving the suppliers' ability to optimize their own manufacturing planning and setup schedules.

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Contents

Abstract .... **iii**
Acknowledgements .... **v**
Contents .... **vii**
List of Figures .... **ix**
List of Tables .... **ix**
Glossary .... **xi**
1 Introduction **1**
1.1 Project Motivation 1
1.2 Problem Statement 2
1.3 Hypothesis 3
1.4 Contributions 3
1.5 Thesis Overview 4
2 Literature Review **5**
2.1 Inventory Policy 5
2.2 Replenishment Lead Time Impacts 6
2.3 The Value of Information and Integration 8
2.4 Collaborative Supply Relationships 11
3 Problem Setting and Business Context **13**
3.1 Manufacturing Process 13
3.1.1 Raw Material 13
3.1.2 Cold Forming and Threading 14
3.1.3 Secondary Processing 15
3.2 Distribution Model 15
3.2.1 Network Design 15
3.2.2 Replenishment Value Stream 17
3.2.3 Inventory Management 21
4 Data Analysis **27**
4.1 Sources 27
4.2 Exploratory Analysis 28
4.2.1 Segmentation 28
4.2.2 COGS Part distribution 30
4.2.3 Actual lead time distributions 30
4.2.4 Safety stock calculations 32
4.2.5 Inventory turnover 34
4.3 Data Summary 35
5 Supply Chain Model **36**
5.1 Factors 36

5.1.1 Customer Demand 36
5.1.2 Inventory Position 38
5.1.3 Order Receipt and Supplier Lead Time 40
5.1.4 Ordering Policies 41
5.2 KPIs 43
6 Model Analysis and Business Opportunity 44
6.1 Theoretical Optima 44
6.2 Realistic Expectation 47
6.2.1 C/D/N Parts 48
6.2.2 APAC 48
6.2.3 Customer-defined sourcing 48
6.2.4 Success factor 49
7 Conclusions and Future Work 51
Bibliography 53

List of Figures

Figure 1. Distribution Network Diagram 17

Figure 2. Diagram of Current Replenishment Process 18

Figure 3. Part Segmentation Comparisons........ 29

Figure 4. Unique Part Distribution by COGS 30

Figure 5. Lead Time Distribution (A+/A/B Parts) 31

Figure 6. Safety Stock Average Days (Percent Lead Time vs Statistical Safety Stock)33

Figure 7. Theoretical Improvement in Inventory 47

Figure 8. Realistic Expectation of Inventory Reduction 50

List of Tables

Table 1. Historical ABC Demand Segmentation 23

Table 2. Historical XYZ Variability Segmentation........ 23

Table 3. Inventory Turnover by Segment 35

Table 4. Theoretical Lead Times by Segment 44

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Glossary

2-bin Kanban system	A visual system used in manufacturing processes where there are two bins of inventory in place and the depletion and removal of a bin serves as a signal to replenish for continued operations.
Crashing cost	The investment (capital or process) necessary to develop incremental improvements in lead time.
Cycle stock	Results from an attempt to order or product in batches instead of one unit at a time. The amount of inventory on hand, at any point, that results from these batches is called cycle stock. (Silver, Pyke, and Thomas 2017, 26)
Economic Order Quantity (EOQ)	The order quantity that minimizes the total costs for a product (usually including the holding costs and ordering costs).
Enterprise Resource Planning (ERP)	Business process management software that allows the company to manage the different aspects of their business, which in our case specifically relates to the inventory processes.
Lagging indicator	An indicator that becomes apparent only after a large shift in the underlying data has taken place.
Leading indicator	An indicator that becomes apparent ahead of a large shift in the underlying data.
Min-max system	An inventory management system where orders are placed to maintain an inventory level between a pre-specified minimum and maximum quantity.
Safety stock	The amount of inventory kept on hand, on the average, to allow for the uncertainty of demand and the uncertainty of supply in the short run (Silver, Pyke, and Thomas 2017, 26)
Service level	A measure of the actual or desired performance of a system where the value indicates the percentage of orders filled with inventory on hand.
Setup wheel	In cold form manufacturing, a process for managing the flow of production as a function of the related tooling required for each part.
Structured query language (SQL)	A programming language for managing and accessing data stored in relational database management systems.

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1 Introduction

1.1 Project Motivation

The company with which I worked is a leading provider of supply chain solutions and engineering support, supplying highly-engineered fasteners and C-Class components (high-volume, low-cost parts including small stampings, hydraulic fittings, machine parts, and consumables) to customers in the North American commercial vehicle market, the global luxury automotive market, the global power generation equipment market, the global agriculture equipment market, and general industrial markets. Although the company manufactures some small portion of the parts they sell, the core of their business is providing upstream consolidation and on-time distribution and delivery of components to their customers to support just-in-time (JIT) manufacturing supply chains. A common rule of thumb that the business uses for their products is that they are typically only one percent of the material costs for these original equipment manufacturers (OEMs), but 50% of the unique parts that go into any given end product.

The original motivation behind this project came as a result of examination of the operating footprint of the business, where it was found that in a facility consolidation scenario, the business would reap limited near-term benefit in terms of facility capacity requirements without materially reducing the overall inventory position of the business. This challenge exists, in part, because most parts in the company's inventory exist in a many-to-one relationship with customers and thus there is limited benefit from the pooling of inventory. As a business with high net working capital (NWC) intensity, the ability to reduce that inventory requirement could substantially increase the value of the business and create opportunities for other uses of the cash.

1.2 Problem Statement

As a distributor, sourcing long lead-time parts and supplying to JIT OEM customers, the company faces a common problem of carrying significant amounts of inventory. They carry more than 80,000 parts globally, sourced from more than 3,000 suppliers, further adding to the complexity of their supply chain and inventory management. Faced with the threat of significant penalties for causing a stock-out on a customer's production line, the company is incentivized to set very high service levels to mitigate this risk. High service levels paired with long lead times very quickly lead to bloated inventory which requires large amounts of physical space and capital to maintain and makes the business less responsive to shifts in demand. The question that this thesis endeavors to solve is the following: how can the company reduce lead times and, subsequently, inventory while maintaining or improving customer service level?

There are myriad challenges for the business that include the high service level requirements and long upstream lead times. In addition to these challenges, the business has historically not engaged in strong relationships with many of their suppliers and has not maintained a healthy flow of information. Instead, they have made discrete purchases only upon receiving a "buy" signal from their replenishment planning system, leaving the suppliers to make their own guesses at future production requirements with no knowledge of the company's inventory levels or recent sales. In recent periods, the company has begun to focus on building healthy, trustful, long-term relationships with their suppliers which include commitments to return business and volume over the long term along with the implementation of better communication processes and data flow. We evaluate how the company might use these developments to improve their inventory position.

1.3 Hypothesis

The hypothesis of this thesis is that through an updated business process and by extending the existing inventory stocking models to better understand tradeoffs, the company might be able to significantly reduce inventory levels as a function of both safety stock and cycle stock while maintaining or improving service levels for their customers. They can accomplish this in practice through a targeted approach by establishing long-term agreements and improving communication with suppliers. This will be possible by identifying the right suppliers and the right parts and entering into agreements where the company provides guarantees of return business, better forecasting, data on stock level and consumption, and accepts some potential responsibility for the suppliers pipeline inventory (raw materials, work in process, and finished goods) as a function of weeks of demand, in exchange for suppliers providing a reduced lead time (ideally no more than transit time for the highest volume parts). This has the potential to benefit both the company and the suppliers by allowing the company to reduce safety stock as a function of the lead time and lead time variability, while providing suppliers the predictability in demand to support their own manufacturing set-up optimization. We will model the long-term benefit of these reduced lead times at an enterprise level and then create a model understanding the impact at the part level.

1.4 Contributions

This thesis makes several contributions from the business and engineering viewpoints. From the business viewpoint, by taking a critical look at the procurement and replenishment systems of a company in an industrial supply chain, we further develop the case for supply chain coordination by way of long-term agreements and improved communication. In this case, the major benefit of the coordination results in reduced lead times and inventory levels. From a technical perspective furthering supply chain management practices, we extend a base stock inventory model to develop a framework for understanding the aggregate benefit of improved lead times in this business. We also develop a model for simulating the replenishment ordering process at the part level to compare tradeoffs between lead time improvement (along with inventory reduction) and the long-term supply agreement liabilities. Within this model, we include the ability to account for customer forecast uncertainty, demand uncertainty, and lead time uncertainty in order to more accurately capture the variability of the process. In bringing together the business case and the technical tools, we present the opportunity to structurally improve systems in the industrial supply chain.

1.5 Thesis Overview

This thesis consists of seven chapters. Having described the problem and the hypothesis of the project in the first chapter, we will describe the literature review and existing approaches to the problem in **Chapter 2**. We will use this chapter to put the project into context relative to the current state of the art. In **Chapter3**, we will provide a detailed overview of the problem setting and the business context. We will briefly examine the manufacturing process before examining the current distribution model which is fundamental to our current state analysis. In **Chapter 4**, we analyze the data relevant to the problem and current systems. In **Chapter 5**, we develop a model for simulating and analyzing the supply chain at the part level and we provide the list of key performance indicators (KPIs) that we will use to evaluate and compare models and results as we apply changes to our model. In **Chapter 6**, we will develop the analysis for the aggregate opportunity presented by the reduced lead times to provide an indication on the potential opportunity from successful implementation.

2 Literature Review

In order to understand the context of this project within the greater body of research on collaborative supply chain relationships and lead time reduction on ordering processes and inventory, we completed an extensive literature review. This set the baseline for the existing body of knowledge relating to the project. For the sake of clarity, we organize the literature review into four sections. The first section, inventory policy, relates to broad inventory management policies. The second section discusses the work to date on the value of improving replenishment lead times. The third section describes the views of other studies regarding the value of information sharing and integration between buyers and suppliers. Lastly, we will review the findings regarding the different collaborative supply relationships.

2.1 Inventory Policy

One of the key works on inventory management which built much of the foundation for inventory systems of the late 20th century was *Decision Systems for Inventory Management & Production Planning* by Edward Silver and Rein Peterson (1985). Much of the inventory policy in existence today has been adapted from this work. Within this text, they develop different inventory control systems for probabilistic demand and lead times, which we use extensively throughout the thesis. The book details four key control systems for single-product inventory management with relatively stable demand. These include continuous review systems like order point, order quantity (s, Q) and order point, order-up-to-level (s, S) systems along with the periodic review, order-up-to-level (R, S) and the (R, s, S) system which is a hybrid of the continuous review, order point, order-up-to-level system and the periodic review, order-up-to-level system. Included in this text also is the development of the safety stock and expected stock on hand calculations for the different policies.

Many have extended the foundations from Silver and Peterson to further develop the science of inventory policy. Zhao and Katekis (2006) evaluate a single-product, periodic-review inventory model with minimum order quantities (MOQs) and stochastic demand to characterize the optimal inventory policies. They found that, at the time of their study, there were no studies on multi-period inventory systems with MOQs. Additionally, they find that the optimal policy becomes highly complex with no easily implementable and effective heuristic. As we will develop later, their work on this model with MOQs reinforces the importance of mitigating or eliminating MOQs applied by suppliers for the sake of both simplifying planning and reducing overall inventory.

We also see several studies developing inventory policies for multi-stage and/or multi-product supply chains, as opposed to single-product supply chains (Al-Hawari et al. 2013; Viswanathan 1997). Although we consider the problem at the company to be a single-product supply chain, meaning that, for simplicity of this model, we are evaluating inventory decisions for each part in isolation, we still observe opportunity for extension into multi-product optimization. Even so, inventory policy optimization is out of the scope of this project as it is being undertaken by the business in parallel.

2.2 Replenishment Lead Time Impacts

The motivating feature of this project is the benefit of reducing lead time. Reducing lead time to drive down inventory is not a novel concept, but we spent time reviewing the literature nonetheless to develop a sense for the different approaches that others had taken to reduce lead times and validate the value of this approach. As previous entities have developed through the lean manufacturing and the Toyota Product System (TPS), lead time reduction is an essential element of eliminating waste; however, as a supplier to JIT manufacturers, we wanted to understand the background on reducing lead times as a distributor rather than as the end manufacturer.

At least as far back as 1989 we found quantitative studies on the impact of lead time and lot sizing on inventory levels (Chapman 1989). In this case, the study evaluates the link between an OEM and their suppliers, developing a regression model to explore the relationship between total customer (OEM) inventory levels and related supplier variables. Unsurprisingly, the study develops lot size, lead time, and schedule stability as the key factors affecting inventory. In the discussion of the findings, the study calls out a specific set of suppliers that are presented with stable schedules by the customer, but still maintain larger inventories to maintain adequate service to the JIT customer, much like our case (Chapman 1989, 2004). What the study does not develop is the impact of the longer lead time upstream of the supplier that might drive this increased inventory, which would relate more closely to our scenario. The study concludes with a recommendation that firms implementing JIT might work to educate their own suppliers to prevent counterproductive responses. Although we are not implementing JIT, this recommendation to work with and education suppliers to prevent counterproductive response remains applicable.

There have also been other papers regarding the length and variability of lead time. Liao and Shyu (1991) develop a calculation for the optimal lead time and reorder point pair where the crashing cost is proportional to the length of time being crashed. The term "crashing cost" is used in the sense that a company might pay some cost in terms of overtime, expedited freight, special equipment, etc. that directly reduces the lead time by a proportional amount. Adjacent to lead time reduction, Gerchak and Parlar (1991) develop the value of reducing the variability of lead time, again evaluating the tradeoff between the cost of reducing, or "crashing" the variability and the value of that reduction. Ben-Daya and Raouf (1994) further extend the model of Liao and Shyu, treating both lead time and order quantity as decision variables, suggesting a possible extension where stochastic lead time might be included or introducing lead time as a decision variable into other models. In 2004, Chopra et al. evaluated the distinction between cycle service level and fill rate and the impact of reductions in lead time uncertainty versus reduction in lead time, finding, counter-intuitively, that for cycle service levels above 50% and up to some level, reducing lead time uncertainty can drive an increase in safety stock. This finding appeared particularly when the coefficient of variation was high but emphasized that the focus for items with high variability, the focus should be on reducing lead time directly.

In 2012, Senapati et al. conducted an extensive review of the literature to date, reinforcing from a broad range of research that lead time can be reduced at some crashing cost, driving lower safety stock, reduced loss from stock out, improved service levels, and increased business performance. Li et al (2013) develop a concept known as a liability period or "freshness clause" where a customer becomes liable for goods if they are stored beyond a liability period, studying the impact of differing lengths of liability period. Although focused on the relationship between an OEM-type customer and their supplier in a vendor managed inventory system, the concept might be extended to other buyer-supplier relationships.

2.3 The Value of Information and Integration

In reviewing the literature on inventory reduction in distributed supply chains, one key factor stood out beyond the hard, quantitative values like lead time and order quantities: the value of information sharing. There exist numerous studies and papers on the value of information in the supply chain. One of the areas frequently discussed was the bullwhip effect. Various papers directly address the bullwhip with Baganha and Cohen (1998) developing the stabilizing effect of inventory in a supply chain to overcome the impact of poor information flow. While there may be some benefits to stabilizing flow and mitigating the bullwhip through the inventory, others develop mitigating measures through information flow like developing strategic business partnerships (Hoppe 2001), using early order commitments (X. Zhao, Xie, and Lau 2001), or developing better relationships to overcome coordination risk that results when, among other things, entities do not trust the decisions of their counterparties, even when decision rules are known (Croson et al. 2014).

As technology has progressed over the previous three decades, studies and papers have continually tried to modernize the view on the impact of these changes and the challenges that go with them. Together with the advance in technology and communications capabilities has been the understanding that more firms are winning and losing based on supply chain processes as much as on internal operations processes. There was the development of the "extended enterprise" where a firm might compete based on their internal resources as well as "the entire extended network of suppliers, vendors, buyers, and customer" (Greis and Kasarda 1997, 55). Importantly, in this extended enterprise, not only must goods and services flow, but also information must flow in order to make this enterprise effective. The authors point out that "a key feature of the extended enterprise is the alignment of production activities in a way that both encourages and demands the free exchange of information across organizational boundaries" (60).

Adding detail to the "extended enterprise," Monczka et al. develop success factors in strategic supplier alliances emphasizing the importance of a sense of trust as key, even over formal commitments of time and money (1998, 568, 570). Later, Cao and Zhang (2011) reinforce this finding with another study where the finding is that firms should collaborate with partners to compete and win as an entire chain. Frolich and Westbrook (2001) conduct an empirical analysis of manufacturers' supply integration strategies, finding that higher levels of supply chain integration are associated with higher levels of performance.

Gaverneni (2002) develops simple models to illustrate a means for improving the utilization of information flows in a supply chain by changing operating policies, continuing to reinforce the value of information sharing but also suggesting direct operational changes that might be made. In another quantitative model, Moinzadeh (2002) develops a supply chain with a single product and single supplier, but multiple retailers (with some similarity to this company if we consider different customer manufacturing sites to be multiple retailers). In this model, the supplier has information on the demand and inventory position of the product at each retailer and uses the information for order/replenishment decisions. An interesting finding of this study is that the benefit of the information sharing is greatly diminished when the fixed order quantity, Q, is either very small or very large. The intuition from this finding is that with a very small Q, the ordering frequency is high enough to provide granular detail on the downstream demand, limiting the marginal benefit of the additional information. On the opposite end of that spectrum, with a very large Q, the inventory is already very large, and thus the safety stock improvement driven by the information flow is a small portion of overall cost.

There are several empirical studies to understand the spectrum and the impact of information sharing in supply chains. In a frequently referenced study, Fawcett et al. (2007) evaluate information sharing and supply chain performance along two dimensions, connectivity and willingness, finding that the willingness to share information is equally, if not more important than the connective capability to share the information. Further, Prajogo et al (2012) and Prajogo and Olhager (2012) develop the relationship between supplier integration, long term relationships, and firm performance.

Lastly, Huang and Hung (2018) develop a very interesting distinction between two rolling forecasting mechanisms. Based on a three-echelon supply chain with a customer, a focal or distributor, and a supplier, they compare two information sharing scenarios with a baseline where no forecast information is shared between partners. In one information sharing scenario, each partner only shares their own demand forecast information with the next upstream partner. In the second, both upstream suppliers receive the customer's forecast demand information. The finding is that the focal, or distributor, observes a benefit in both scenarios, but the upstream supplier's benefit is minimal in the first with a significant improvement in the second. This highlights the importance of information sharing across the supply chain in order to drive operational results.

2.4 Collaborative Supply Relationships

The final area of literature reviewed relates to the various types of formal collaborative supply relationships that have been developed and studied over the years. Although we are not proposing these for the company, they provide a framework of the state of the art for these mechanisms. Across the body of knowledge, two sequentially developed collaborative supply chain systems stand out: vendor-managed inventory (VMI) and collaborative planning, forecasting, and replenishment (CPFR).

In a general overview of supplier-retailer collaboration, Sheu et al (2006) develops a model for understanding the social and technical factors contributing to the successful supplier-retailer collaboration, finding eight critical social and technical variables that affect the relationship. In the paper from Olson and Xie (2010), they evaluate the relative benefits and costs of collaborative supply arrangements and develop the conditions for which these systems are appropriate. They evaluate systems including the traditional supply chain, efficient consumer response, vendor-managed inventory (VMI), continuous replenishment, and collaborative planning, forecasting, and replenishment (CPFR), finding in particular that VMI provides benefit to the retailers, but at some cost with the extensions providing better visibility at greater risk. Cao and Zhang (2011) study the results of a survey, finding that in many cases, firms are able to view supply chain collaboration as a positive-sum game, rather than a zero-sum game.

In the paper of Jung et al. (2004), they evaluate by simulation the supply chain environments which achieve the most benefit from the VMI and the shared information. They identify cost reduction when the manufacturer has a high capacity, when the setup cost at the distribution center is low, and when expediting cost at the manufacturer is high. Evaluating the performance outcomes of VMI, Claassen et al (2008) find that VMI leads to three performance outcomes: higher service levels, improved supply chain control and, to a lesser extent, cost reduction. Birim and Sofyalioglu (2017) evaluate VMI systems and find that the balance of benefit between buyers and suppliers is not necessarily symmetrical with more of the benefit going to the buyer. They propose that the buyer-suppler dyad may achieve better balance by implementing some benefit sharing incentive between buyer and supplier.

As the supply chain world has continued to evolve, CPFR became more popular, but like any other system, the configuration of that system varies from company to company. Pamela Danese (2006) describes the six types of collaboration that can be performed to implement CPFR along with the differences in technology and liaison devices across different companies. Extending the original design for implementation of CPFR, Demiray et al (2017) proposes a roadmap for implementation that the authors consider to be more broad and flexible as it is industry-independent, quantitative, flexible, holistic, detailed, and recursive.

Although these specific systems are not necessarily in scope for the project, the continued evolution and development of systems that revolve around buyer-supplier communication only reinforces the importance of information sharing and collaboration for the success of the supply chain.

3 Problem Setting and Business Context

In this chapter, we will describe the manufacturing and distribution processes of the business in detail to provide the overall business context for modeling and implementing collaborative supply relationships with reduced lead times. It includes a qualitative description of the manufacturing process and distribution network, followed by a presentation of the decision rules on which the supply chain team relies for replenishment.

3.1 Manufacturing Process

To better understand the inputs into the company's supply chain and sales, we will discuss the manufacturing process in some detail. Although this company also sells and distributes other low-cost components, here we will discuss cold-headed fasteners which have some of the longest lead times in the business and represent a significant portion of the company's sales. Additionally, the other cold-formed parts in the company's sales book like nuts follow a similar process. Because of the longer lead times, the greater size, and the higher cost, these fasteners present the greatest opportunity to reduce inventory by reducing lead times.

3.1.1 Raw Material

From the perspective of the company as a cold-heading manufacturer and their other cold-heading suppliers, the raw material for their cold-heading process comes in the form of metal wire coil of different materials, grades, and diameters. Each of these different wire coils typically serve as input into a diverse array of production parts. Because of the broad usefulness of these raw coils, manufacturers keep a large enough amount on hand with limited risk for the raw material becoming obsolete. Even if end demand changes for a specific part number, the material, grade, and diameter of the coil can typically be used for other parts as well. We will assume that most suppliers keep enough on hand so that for any given order, even on short notice, the service level of the raw material will effectively be 100%. For this reason, we will exclude the lead time of the raw material acquisition from the calculation of the manufacturing lead time in replenishment orders (as opposed to initial production orders).

3.1.2 Cold Forming and Threading

The next step in the manufacturing process is the cold-heading and threading process. These steps are usually completed by a single manufacturer. Depending on the manufacturer's equipment capability, these steps may be completed on a single machine or on separate machines in the same facility. Beyond the initial engineering design work, every production run of a given part requires significant set-up work, in the range of at least two to six hours which, in many cases, is completed with the machine idled for some or all the setup time. As a result, manufacturers typically require large quantities in a production run to make the set-up economical. From the buyer's perspective, these minimum quantities in production translate to minimum order quantities (MOQs); however, there are some opportunities for the manufacturers to make the setup processes more efficient by producing similar or adjacent products in sequence and reducing the overall incremental setup complexity. This efficiency is created by stepping through adjacent products so that each setup is incremental, only changing a fraction of the parameters on any given setup and eventually returning to the "start" of what we will call the "setup wheel." To be the most effective, this does require greater certainty about the future demands across the portfolio of products. We will call the process of working through a series of different adjacent products for minimum setup times "optimizing the setup wheel" for discussion further in the thesis.

Upon completion of these steps, the fasteners have reached their final physical shape and form, although, as discussed below, there is still additional treatment necessary to complete the manufacturing process and make the parts ready for sale and distribution. There are also quality control requirements built into both the manufacturing and distribution processes, but we will exclude them from the scope of the thesis.

3.1.3 Secondary Processing

After the cold forming process, manufacturers next pass the parts through a series of secondary processes necessary to prepare the parts for distribution and installation into end products. These steps ensure the chemical and mechanical integrity of the parts. This step may consist of several different sequential processes, which include heat treating, adding protectant coatings, or adding adhesive patches that eliminate slippage on installation. In some cases, these secondary processes are completed by different companies than the cold forming company due to the equipment requirements for each process with the processes and transitions managed by the cold heading manufacturer. We will not go into greater detail on the mechanical and chemical value of these processes, but we bring it up to address the requirements for these parts to go through multiple steps that each require shipping and processing time which are all drivers of the manufacturing lead time.

3.2 Distribution Model

3.2.1 Network Design

The company's own cold heading manufacturing capability provides a viable alternate source for cold headed fasteners, but the company's primary value proposition in the industrial supply chain is their sourcing and distribution capability. They manage complexity for JIT OEMs by consolidating engineered parts from a diverse supply base with long lead times and delivering them with short required delivery windows. For the company's primary JIT customers, lineside replenishment deliveries are required daily based on signals like that of a 2-bin Kanban system or a min-max stocking strategy, typically with only between four and twelve hours of notice for parts that are included in the stocking agreements. This key requirement from the customers has driven the company's supply chain network design and inventory stocking policies.

Because of the short notice for delivery, the company has built its distribution network so that facilities are located within a short drive to the customer manufacturing facilities, often in the same city or town. Additionally, in most cases, the products are only delivered to a given customer facility from a single company facility (e.g., multiple company facilities do not support the same customer facility). From there, the company consolidates products from their portfolio of suppliers and delivers to customer facilities, supporting each customer site from a single facility. **Figure 1** depicts a conceptual diagram of the existing distribution network in its current state, where many suppliers supply parts to different facilities. In the figure, we see the array of many suppliers delivering to many of the company's facilities on these seven to 14-week lead times, where the parts are consolidated before delivery with less than one days' notice to the customer manufacturing facilities.

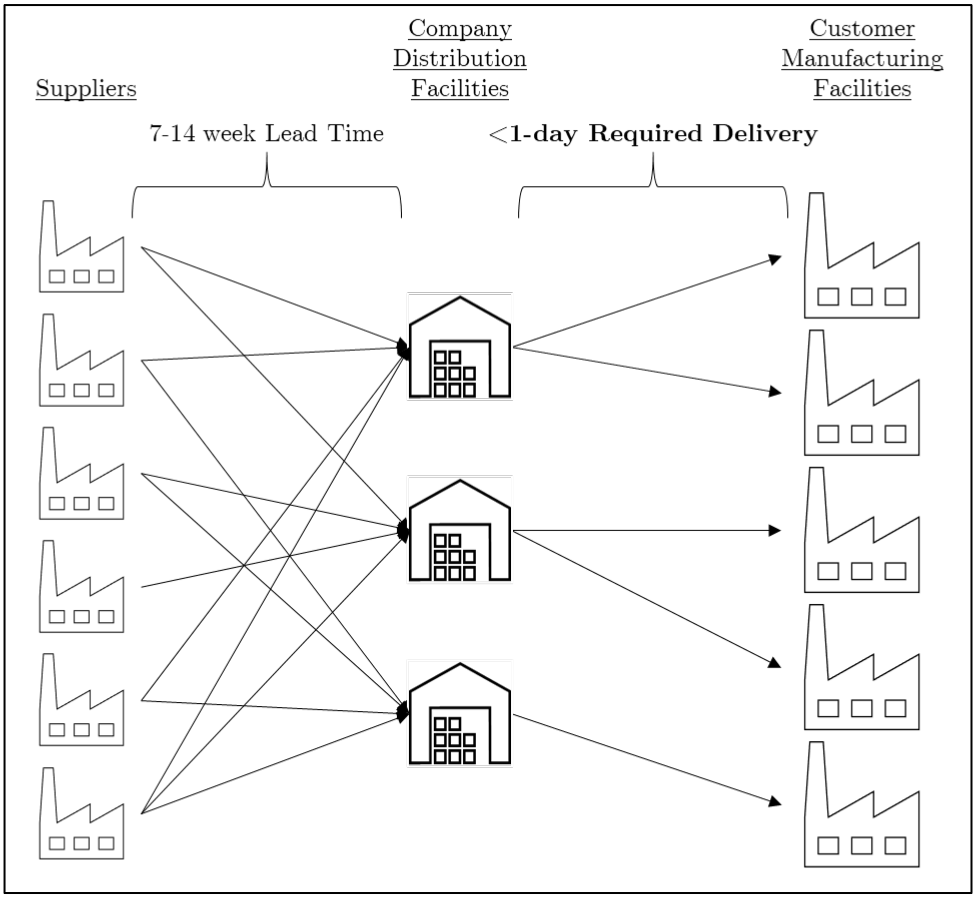

Figure 1. *Distribution Network Diagram*

3.2.2 Replenishment Value Stream

At this point, we will describe the value stream for the replenishment of products that are part of JIT manufacturing in their current state in greater detail. This description will assume that the given parts have already been sourced and gone through all the proper design and engineering approvals for sale to the OEM customer. The initial engineering design and sourcing are out of the scope of this thesis as we are focusing solely on the replenishment process. The diagram in **Figure 2** provides a visual map of the process described here. Additionally, to keep things simple, we will describe relative portions of the process as upstream or downstream, which are both described relative to this company. In the diagram in **Figure 2**, we see that the customer provides two signals to the company: the first is a 3-month rolling production forecast, provided weekly, that goes to the supply chain team to drive their replenishment decisions. The second signal is a daily JIT order that goes to the operations team for immediate fulfillment and delivery. Looking upstream, the only signal sent from the supply chain team to the suppliers is a discrete purchase order when the system drives a replenishment decision. The following sections describe each of these steps in greater detail.

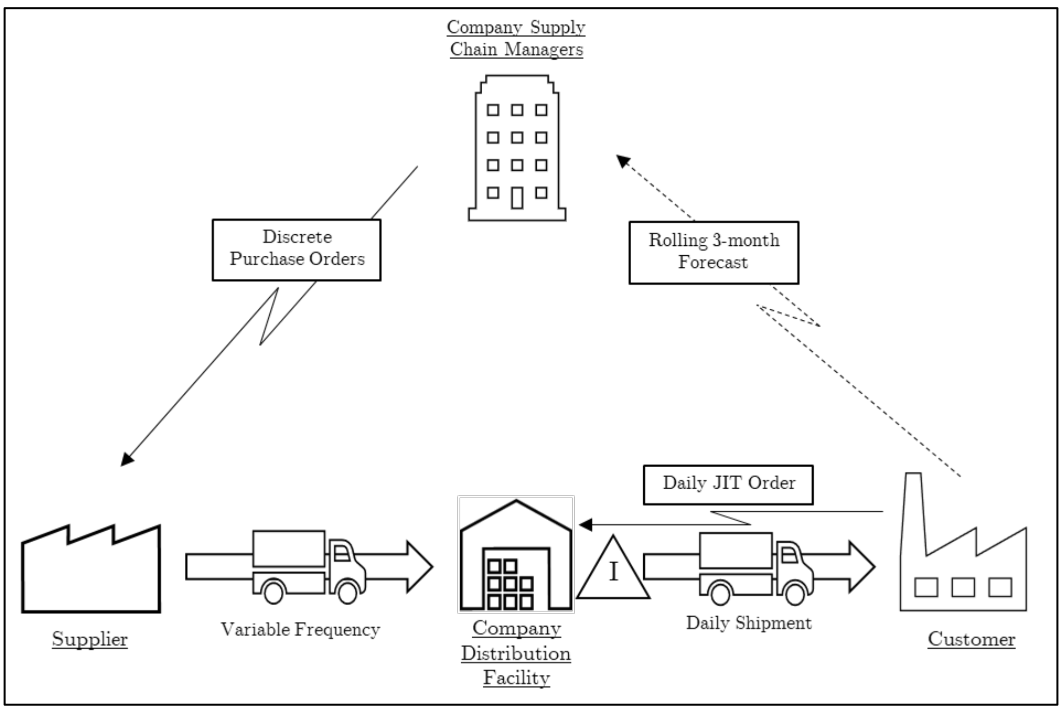

Figure 2. *Diagram of Current Replenishment Process*

3.2.2.1 Customer Facing (Downstream) Process

We will start with the downstream customer providing two pieces of data to the company. The first piece of data is a rolling three-month forecast[1] for consumption of the parts that is drawn from their own production schedule, provided generally on a weekly or semi-monthly basis. Keeping in mind that the forecasts change, but also accounting for the upstream lead time on parts that is frequently longer than the useful forecast, the company's supply chain team places discrete purchase orders when their own material requirements planning (MRP) tool gives a signal that the inventory on hand will fall below the safety stock inside the stated lead time, plus some buffer (usually the review period), taking into account the inventory on hand, the inventory already on order, and the forecasted demand during that time period, which we will call the forecast inventory position.

The other replenishment signal that the customers send to the company is the daily demand signal where demand is signaled as consumption in the previous day, driving a pull system. Although there are several means of tracking the inventory on hand at the customer site and conveying the demand, we will assume that in this case, it is done by having a min-max Kanban system at each assembly station along the customer manufacturing lines. At each of those points, the part racks are designed and labeled with a minimum and maximum number of plastic totes so that there is adequate material on hand to cover the time period before the next delivery from the company to the production lineside with some buffer, but the max is set at such a level to not require excessive amounts of space. At each customer site, an employee (employment varies between the company and customer, depending on the customer) is responsible for walking the line at least daily, if not every shift. This employee looks first to confirm that the number of bins on hand has not fallen below the minimum. Should the number of bins fall below the

[1] Forecast periods vary by customer, but we assume three-month forecast here as a useful baseline representative of most customer forecasts.

minimum with no order already placed, the employee will place an expedited order, which deviates from the process described here. Assuming the number of bins remains above the minimum quantity, the employee then uses a scanner to scan a barcode label for each bin below the maximum quantity currently at that station.

This information, with the assembly station location attached, is consolidated and sent to the company comprising their daily JIT order, at which point the company picks from inventory on hand, packs, and palletizes the parts for delivery lineside. In the company's packing and palletizing process, they organize the bins according to the lineside assembly station so that delivery can be more efficient at the facility. Additionally, although customers do not explicitly send data on their stock of the company's parts on hand, the design of the JIT system and the daily scans do allow the company to infer an approximate level of their inventory on hand at the customer's site.

3.2.2.2 Supplier-Facing (Upstream) Process

Moving from the downstream, customer-facing side of the system to the upstream, supplier side of the system, we see a different level of information sharing. Whereas the company can see the customer's forecast demand (albeit with variable accuracy), the daily consumption, and an approximate stock on hand for their customers, the only signal that they currently provide to their suppliers are discrete purchase orders, placed at the direction of their MRP. Although suppliers can draw some conclusions from historical purchase orders and plan their production accordingly, they do so at their own risk. The typical supplier reaction to this is to quote a lead time that extends well beyond the actual process times (including transit between secondary processes) of these products. Extending the quoted lead times allows the suppliers to manage their own production schedules more efficiently and reduce the risk incurred by producing prior to receiving an order, although they may still experience some bullwhip effect in their own ordering and production processes. Additionally, suppliers often enforce a minimum order quantity (MOQ) on purchases made in this fashion so that they are able to achieve economies on the set up.

We will assume that these MOQs applied to the company's orders are equal to the suppliers' economic production quantity (EPQ) or some integer multiple thereof. For the lower volume parts which the company sells, the MOQs often far exceed both the economic order quantity (EOQ) and the expected demand over the lead time plus review period, leading to order quantities for the company that are far from economical.

The last element of the supplier process, shipping, is then done on a more variable schedule that depends on completion of the manufacturing process and a transportation structure that the company has designed, but it is also safe to assume that the shipping and transportation design is out of the scope of this project.

3.2.3 Inventory Management

To manage inventory and replenishment planning, the supply chain team at the company uses a hybrid of traditional supply chain logic (specifically as it relates to managing safety stock) and some modified criteria that have arisen as a function of constraints in their existing enterprise resource planning (ERP) system. In order to understand the opportunity presented by improving lead times, it is important to understand the current logic for managing inventory. By understanding this, we can convey the opportunities that relate directly to this new concept and additional adjacent opportunities that may not be proposed as a part of this thesis.

3.2.3.1 Restocking Policies

The first major categorization that the company makes in their inventory management is to assign parts with a "Restock Code" of "Y" or "N". Generally, a "Y" code is assigned to parts that the company is currently selling to customers on a recurring basis with the expectation of continued sales in the future. It is likely that parts with these codes have some forecast sales soon, and, more importantly, will require subsequent replenishment following sales of the current stock to meet future forecasted sales or agreements.

These contrast with the parts that are coded with an "N." N-coded parts are parts that the company sold historically and may have some aftermarket liability for, but those sales are highly uncertain or even unlikely. Therefore, the company may have some remaining stock, but does not sell with enough regularity to restock on depletion of the existing stock and may not even set a safety stock level. In general, a shorter lead time for these parts would benefit the company commercially, but it would not have a significant impact on the company's overall average inventory positions and is not considered as a part of their replenishment planning. Although we will include N-coded parts in the overall inventory levels, we will exclude them from discussion in the lead time reduction opportunity.

3.2.3.2 Demand Segmentation

In keeping with common supply chain practices, the company assigns category or "segmentation" labels to each of the parts that they are actively selling in order to allow customization of inventory management policies where different groups along the spectrum of demand profile should be treated according to different policies. In balancing the trade-off between customizing the management policies for the entire list of parts in their inventory and applying one policy to all parts, the typical approach is to use a small number of segments that are generated and updated as a function of the relative cost of goods sold (COGS) over the previous twelve months. The company has divided their inventory into four segments for parts that are selling actively with a fifth category for parts that are in stock but have not sold in the previous 12 months. Using the standard labeling of A/B/C/D/N the company has assigned the labels along a pareto front using COGS grouped by market region and ranked from largest to smallest according to **Table *1*** below. In the table, we see that the bands are fairly wide and do not follow the more typical pareto curve.

Segment Label	Relative Cumulative COGS Rank (Sorted Largest to Smallest)	Segment Size (% of active parts)
A	0-50%	50%
B	50-80%	30%
C	80-90%	10%
D	90-100%	10%
N	No sales in previous 12 months	

Table 1. *Historical ABC Demand Segmentation*

The company also accounts for the variability of demand, in keeping with common supply chain practice, by assigning X/Y/Z/NoDmd codes, recognizing that variability drives the risks to inventory and policies. The supply chain team updates these codes periodically for aid in making better decisions about the service levels and order policies. These codes are assigned as a function of the Coefficient of Variation (CoV), evaluated by part, by location. Coefficient of variation is calculated by dividing the monthly average demand by the monthly standard deviation of demand as below:

$$CoV = \frac{\sigma_D\ (monthly)}{\mu_D(monthly)}$$

From this calculation, the business has created some thresholds of CoV that they use to assign the X/Y/Z codes, as depicted in **Table *2***, below. The table depicts the CoV values that correspond with each of the segment labels for the products.

Segment Label	CoV (Monthly SD)
NoDmd	No demand in last 12 months
X	$CoV\ <\ 0.3$
Y	$0.3 \leq\ CoV\ \leq\ 0.7$
Z	$0.7 < CoV$

Table 2. *Historical XYZ Variability Segmentation*

Using these different segments, the company assigns different policies to its parts. Although these policies may affect many different aspects of the inventory management for the company, the primary element that is relevant for this thesis is the assignment of different service levels and safety stock policies.

3.2.3.3 Safety Stock Policies

As a result of the legacy ERP system, the company's inventory management policies do not yet follow all of the modern supply chain science policies. the company is undertaking a separate workstream to modernize some of these processes and those updated systems will be able to further enhance the opportunity presented by the reduced lead times, but in this thesis, we will discuss according to the legacy processes. To give a sense for the comparison as we discuss the opportunity, we describe the policy and process for assigning safety stock values to each of the SKUs in the inventory.

The company manages risk of stockout by using margins of safety that are derived from a combination of a safety factor and historical data like either the average demand or standard deviation of demand per some period which are multiplied to derive a safety stock. We will describe the varying processes for determining safety stock over the rest of this section. In large part, the company has assigned the safety factor to parts as a function of the segmentation discussed previously, where the A parts are assigned one service level and the B and C parts each receive a different service level based on the business's overall strategy. Much like the ordering policies, this aids the company in managing inventory levels on the one hand and the risk of stock out on the other hand.

The company manages the safety stock factor one of two ways in the existing system. The first is to include only the average demand over the lead time as the historical input for application of the safety factor. The safety factor is then assigned on a part-by-part basis according to the risk of stockout and the cost of holding the inventory. This calculation is one that the ERP system will do automatically, given the safety factor, so it amounts to some fraction of the average demand during the lead time, calculated as $SS = k\mu_{DL}$where SS is the safety stock, k is the safety factor, and μ_{DL} is the average demand over lead time for the specific part. Fundamentally, adding this safety stock does provide some buffer for variability in either the expected demand or the actual lead time, but the size of the safety buffer does not intrinsically account for the size of the variability for a given part.

Drawing from modern supply chain practice, the company has also begun including variability directly into their safety stock calculations. It is important to note that this calculation is not done automatically and continuously, but is instead updated periodically, in batch by the supply chain team. Because of the manual nature of the process, the team has not applied this to all parts in inventory, but rather to some number of their highest value parts, generally spread across the A and B parts. The company computes the safety factor using a common supply chain management measure of cycle service level (service level for the remainder of the paper). Service level is defined as the probability that there will not be a stockout event within a replenishment cycle (Silver and Peterson 1985). The formulation for the safety stock is calculated as follows, where the first group of formulas relates to the policies of the company and the second set of formulas relates to the historical data observed for the parts and then those two are combined to derive the safety stock:

$$Service\ level = 1 - P[Stockout] = P\left(k < \frac{x_0 - \mu}{\sigma}\right)$$

In this formula, x_0 is the demand in a period. The service level is set by the business, so we will solve for the inverse to find Z which will serve as our safety factor and we will represent with k. The service level is, therefore, the probability that the difference between the demand in a period and the historical average demand divided by the standard deviation of demand is greater than the safety factor, k.

The next group of formulas represent the components of historical data for the parts:

μ_D: average demand (units per week)

σ_D: standard deviation of demand (units per week)

μ_L: average lead time (# of weeks)

σ_L: standard deviation of lead time (# of weeks)

μ_{DL}: average demand over lead time

σ_{DL}: standard deviation of demand over lead time

k: safety factor, derived from inverse of service level

$$\mu_{DL} = \mu_D \mu_L$$

$$\sigma_{DL} = \sqrt{\mu_L \sigma_D^2 + \mu_D^2 \sigma_L^2}$$

Finally, to calculate safety stock, we use the values previously derived to calculate the safety stock level below:

$$SS = k\sigma_{DL}$$

Because the business is undertaking a transition to update their ERP and inventory management which will use this second formula and account for the variability in calculating expected safety stocks, we will also use this method for understanding the "ideal" future state which will drive the goals and the process along the way.

We have used the description of the distribution model and inventory calculations to establish the baseline environment with which we will extend our analysis. In the following chapters we conduct detailed analysis of the inventory data to better understand the quantitative state of the system and the underlying data distributions. In doing so, we gain further insight into the nature of the problem and confirm the opportunity in our hypothesis.

4 Data Analysis

In this chapter, we will discuss the approach that we took to create a quantitative view of the current position. From this current position view, we also created a more simplified model that reflected some approximation of the current state so that we could adjust from the current statement to understand the impact of the changes in key parameters.

4.1 Sources

I extracted the data for this research from the company's ERP system database using Structured Query Language (SQL). Beginning with a query which the supply chain manager had created initially I modified it to extract and display the data in the format that I needed. From the first iteration until the end of the time working with the company, I updated the query and data periodically to capture the data more accurately as I learned more about the systems and the business. This data was formally stored in a Mainframe server which does not store its data in a relational database format, limiting some of the more modern approaches to data management. The company has developed a process for porting the data daily, so that there was a database of near-live data, accessible through the SQL server. The data in this SQL server database truncated the time stamps so that we only had fidelity on data down to the daily level, but because we were generally investigating the process at the more aggregate timeframe like days, weeks, and months, the daily granularity was adequate for the process.

Although over the course of the project we looked at numerous data points and data sources that included time series and daily histories of different inventories, receipts, and sales for different parts in stock, our primary data source was a static aggregate dataset that took a snapshot of each part by location at a single point in time and provided consolidated data on each part. There was a total of 71 columns for the data set, but our analysis only required a subset of those data points. Following our initial collection of the data, we performed an exploratory analysis for the sake of both understanding the fidelity of the data and the overall position of the business.

4.2 Exploratory Analysis

This exploratory data analysis served to help us understand the size of the problem and included some intermediate analysis and manipulation to make the data more useful. Much of this analysis was conducted in Tableau due to its ease of blending and analyzing connected live SQL data sources and static sources like Excel and CSV tables.

4.2.1 Segmentation

As a starting point for completing our exploratory data analysis, we added modified categorical data to improve our perspective of the demand and the inventory. One element of data that we modified was the ABC segmentation. As discussed in Section 3.2.3 above, the company's ERP system tracks the segmentation according thresholds of 50%/80%/90%/100% as a running cumulative percentage of COGS. However, to more closely understand the pareto effect relative to demand, we added two ABC segmentation markers according to a different breakdown in echelons of inventory management.

For the segmentation breakdown, we adjusted the thresholds for the COGS to 80%/95%/99%/100% breakdown. Additionally, although we still considered them as "A" parts, we also applied a tag of "A+" to the first 50% of parts by cumulative COGS which enabled us to identify and adjust the treatment for the fastest moving parts.

We applied the updated thresholds at two different echelons of the business so that we could consider both the location level stocking which related more closely to the customers and demand as well as the national level stocking and demand which might tie in more closely to the sourcing strategy. Because our data set was already divided at the part number-location level, it was simple to rank the parts at each location by COGS and apply the segment labels. Then to capture the segmentation at the regional level (the same level as the original ERP segmentation), we grouped the inventories for the locations back into regions, summing the COGS, and applying the segmentation codes according to those values.

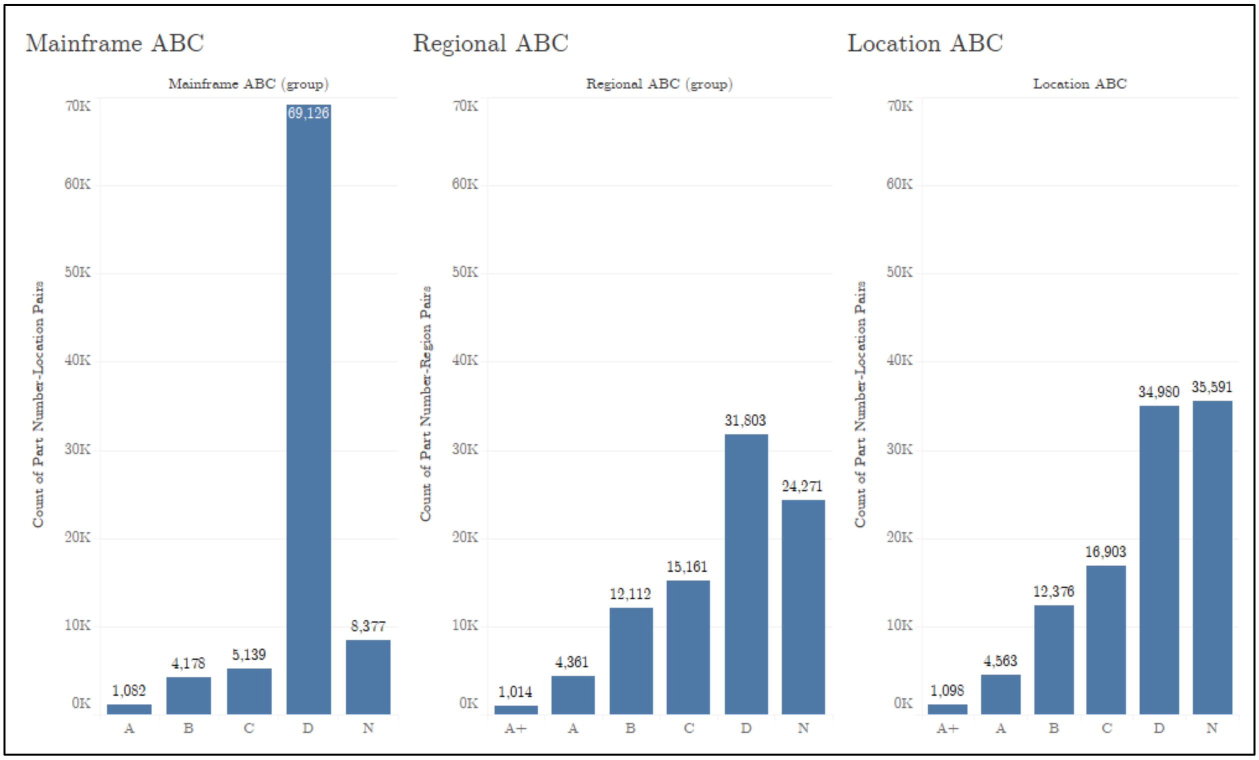

Figure 3*. Part Segmentation Comparisons*

As we can see in **Figure 3** and as one might expect from the breakdown, the "A+" parts have approximately replaced the "A" parts that were calculated by the Mainframe system with approximately 1,000 parts included in each group. We also see the Mainframe "B" parts replaced by our new "A" parts so that the sum of the mainframe "A" and "B" parts is nearly equivalent to the newly calculated "A+" and "A" parts. What we do see is some divergence between the "D" and "N" parts which we might attribute to some discrepancies in the underlying calculation logic, but for this project, we expect to focus primarily on the newly assigned A+/A/B parts, as they have the highest value and the greatest opportunity to materially impact the inventory level quickly.

4.2.2 COGS Part distribution

In the interest of understanding the distribution of COGS value by part, we also evaluated the parts at the part-location level, evaluated the cumulative COGS by part number. Unsurprisingly after comparing to the segmentation chart in **Figure 4**. Unique Part Distribution by COGS, approximately 80% of the COGS (annual spend on parts) occurs on the first 5% of part number-location pairs. **Figure 4**, below, depicts the specific distribution, with the cumulative number of Part Number-Location pairs on the horizontal axis as the corresponding percentage of total COGS on the vertical axis.

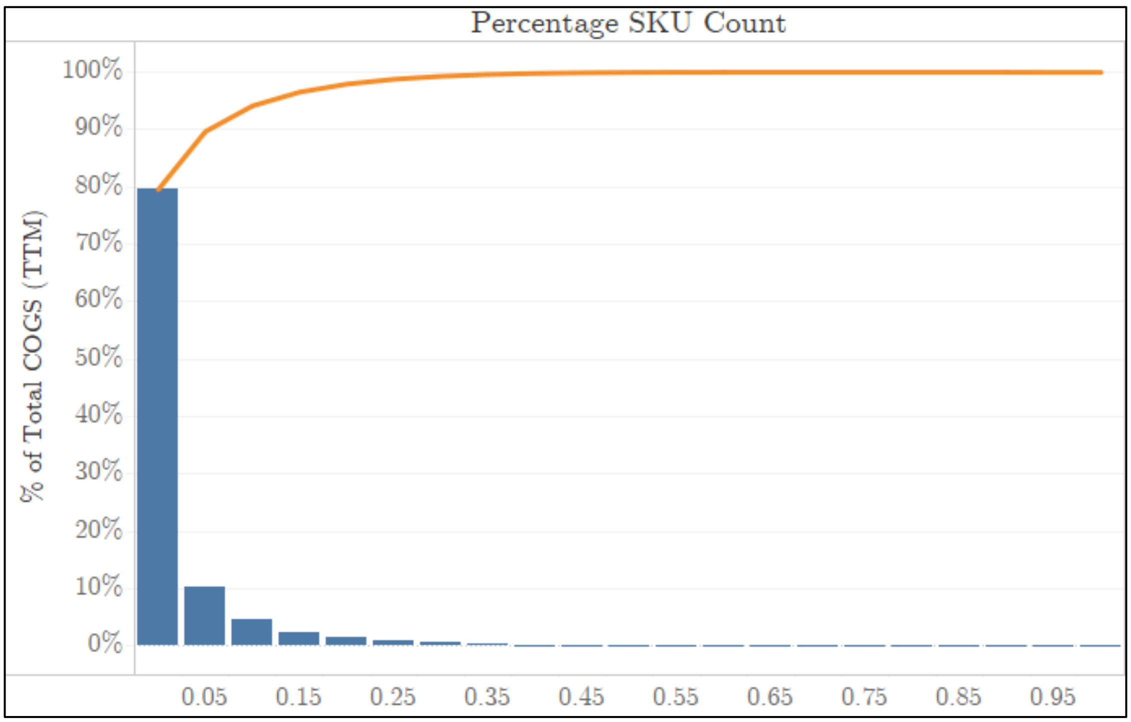

Figure 4. *Unique Part Distribution by COGS*

4.2.3 Actual lead time distributions

In the context of our goal to reduce the lead time for our fastest moving parts down to approximately two weeks, we wanted to understand what the current distribution of lead times was for the company. To collect this information, we used the same dataset discussed previously. Within this dataset, there were some part number-location pairs where the replenishment was received from another location, intra-company, like a hub and spoke model. We removed these from the dataset because our focus is on delivery from suppliers outside the company and those data points would skew the understanding of the problem. We also excluded those parts with the restock code “N” because these parts are not in consideration for the lead time improvement. Lastly, we only included the A+/A/B parts (the first 95% of COGS), because the focus of our initial pilots is on the parts where we can have a sizeable impact relatively quickly.

The lead times that we depict are drawn from historical orders based on the day that the purchase order is placed and the day that the purchase order is received into inventory. Those lead times are averaged for each part number-location combination over the trailing 12 months.

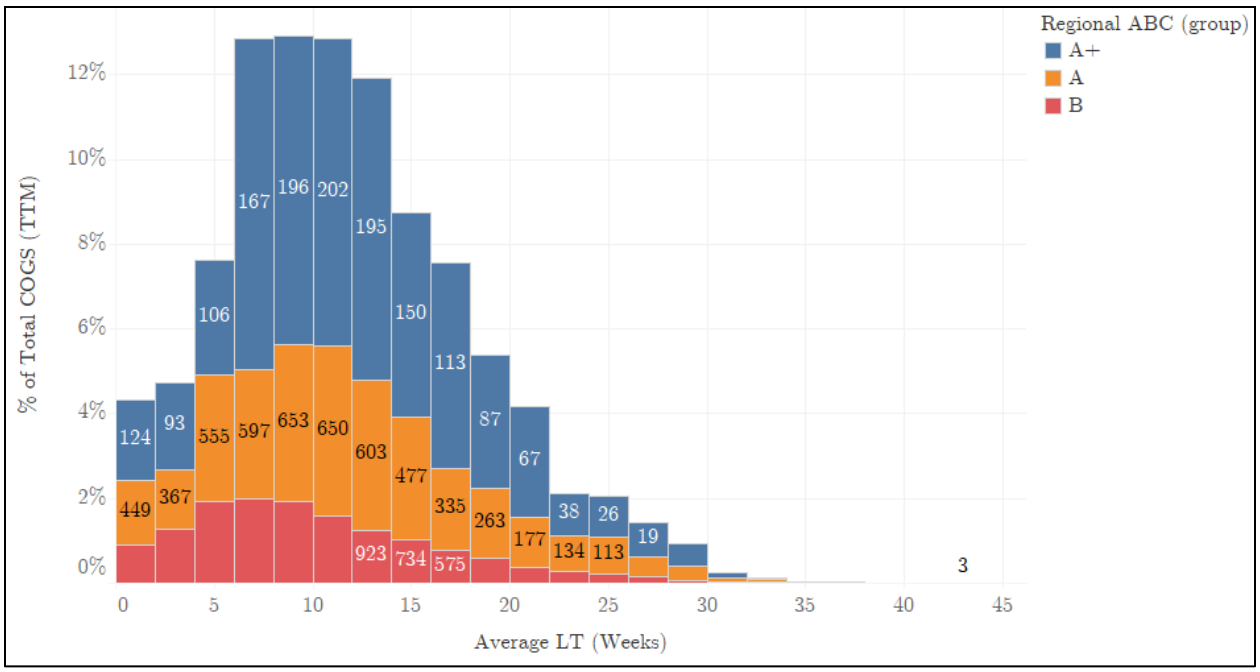

Figure 5. *Lead Time Distribution (A+/A/B Parts)*

In the chart above, it is important to note that the numbers that are displayed on the vertical bars are the number of part number-location pairs of which each category consists, as opposed to a COGS or lead time value. Visually, we see that the modal lead time is between eight and twelve weeks, so immediately, we might deduce that a reduction in lead time to two weeks might both create opportunity, but also remain an attainable goal.

4.2.4 Safety stock calculations

We also looked to see how the current safety stock calculation methods affected the average days of inventory (ADI). As mentioned previously, this distinction is between safety stock calculated as a percentage of demand over lead time in one form and a traditional safety stock calculation as the other. Our unit of measure in this evaluation is the ADI where the current safety stock is based on the system parameters rather than the on-hand value and the COGS is based on the average daily sales over the trailing twelve months, or TTM. We calculate for each part number-location combination in the inventory as follows:

$$ADI = \frac{Current\ Safety\ Stock\ (USD)}{Average\ Daily\ COGS,\ TTM\ (USD)}$$

This value is representative of the number of days it would take to sell through the entire safety stock according to the average demand over the trailing twelve months (TTM), using the assigned system value for safety stock rather than the actual quantities on hand at the time the analysis was completed. All these safety stock calculations are completed at the current supplier lead times, rather than the future state lead times This calculation is important to represent the system parameters and give a measure of the desired safety factor rather than the actual inventory.

In **Figure 6** below, we have created a depiction of the distribution of safety stock ADI according to the different regional ABC segmentation on the rows and the variability of demand in the columns. Then within those we have charted each of the ADI for the parts managed by percent lead time on the left and the statistical safety stock on the right. Unsurprisingly, we see that, except for the A+ parts, the ADI remains relatively constant across the XYZ categories because it is not accounting for the variability of the demand. Additionally, we see that when looking at the safety stock ADI for the parts that are calculated statistically, the ADI increase as the variability increases from X to Y to Z because this calculation is considering the variabilities.

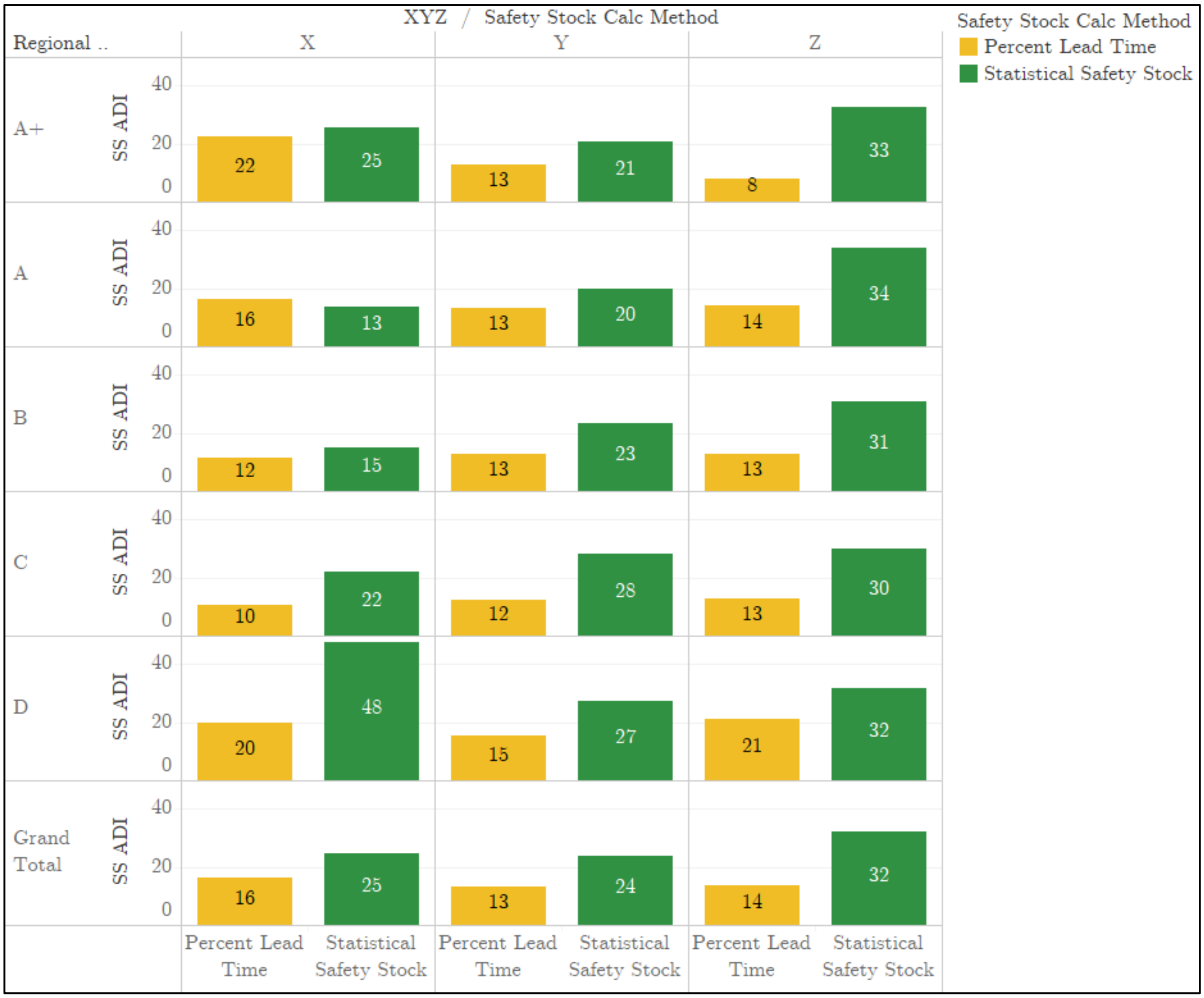

Figure 6. *Safety Stock Average Days (Percent Lead Time vs Statistical Safety Stock)*

A major takeaway from this is that as the business shifts to applying statistical safety stock calculations to more of their parts, they might actually expect the ADI for safety stock to increase if they do not reduce the corresponding service levels, although we might also infer that the business is providing higher cycle service levels with the statistical safety stocks.

4.2.5 Inventory turnover

We also investigated the inventory turnover as a measure of the effectiveness of converting inventories into sales. Although a lagging indicator, this measure is a common indicator used in business to measure inventory management. We take this measure here at the aggregate business level, but we will use the measure in the future, possibly at the part level to measure and compare the effectiveness of the lead time reduction initiatives. In this calculation, we again filter out those parts that are replenished from within the company (like hub-and-spoke) because we are not interested in the impact of lead time reduction for intra-company transfers. We also filter out those parts for which we have calculated no demand over the trailing twelve months.

To calculate inventory turnover, we will use the COGS over the trailing twelve months, but then for inventory we will use the "average" inventory on hand over the previous three months. We use this "average" calculation which is calculated by taking the inventory close-out at the end of the previous two months along with the inventory on hand at the time the report was pulled. Due to limitations in the ERP system, we are unable to achieve a more granular data point. We use a shorter time period so that we can begin to see the impact of changes relatively quickly and not be weighted by the previous year's worth of inventory policies. At the same time, because of the cyclical nature of ordering and sales, a single snapshot in time will not be indicative of the average inventory policy. The company's ERP system does not have the ability to track inventory on hand with any higher granularity than monthly and so we must use this as our best approximate indicator. So, to calculate inventory turnover, we use the formula below:

$$Inventory\ Turnover\ (Turns) = \frac{COGS\ (TTM)}{Avg\ Inv\ (L3M)}$$

The implied meaning of this inventory calculation is that the turnover is the number of times the entire inventory on hand is replaced over the course of a year due to sales. For further clarity of the inventory turnover, we divided the parts by both ABC segments as well as by XYZ segments. We make several observations in **Table 3** that confirm what we would generally expect: the overall turnover decreases from higher to lower as we move across the segments from the higher COGS parts (A+) to the lower COGS parts (D), and also the inventory turnover decreases as variability increases moving from low variability (X) parts to high variability (Z) parts as more inventory is kept on hand to mitigate variability.

	XYZ			
Regional ABC (group)	X	Y	Z	Grand Total
A+	6.06	4.65	2.35	5.46
A	3.48	2.73	2.03	3.01
B	2.18	1.95	1.58	1.97
C	0.95	1.19	0.83	1.02
D	0.28	0.53	0.43	0.37
Grand Total	3.88	2.53	1.63	3.11

Table 3. *Inventory Turnover by Segment*

4.3 Data Summary

Having evaluated the available data and taken a snapshot of the current state, we have reached a point where we might develop a model for future state of the business (the "size of the prize"). We might also use this data to create a model for stress testing the impact that different policies might have at the part level.

5 Supply Chain Model

5.1 Factors

In order to better understand the size of the opportunity, we developed a model that would approximately depict the system so that we could make hypothetical changes to variables and observe the impact. Our model starts from the last step in the process (from our perspective), which is the lineside delivery to our JIT OEM and works its way back upstream to our suppliers. We model the system this way because customer demand drives all our supply chain decisions in our facilities and even further upstream. As discussed previously, we use the JIT OEM customers as the typical customer for this model because they comprise the bulk of the demand for the business. In building the model, we effectively build the flow depicted in **Figure 2** into a quantitative model as it might appear for a single part, focused solely on the signals and flow of material.

5.1.1 Customer Demand

Because we are only focusing on our fastest moving A+/A/B parts, we have modeled the customer demand with a normal distribution derived from historical data, as opposed to the Poisson distribution which we might use for slower moving parts. While we observe some seasonality of demand that results from production schedules, for the purpose of studying the effect of improved lead times, we believe that it is more conservative to apply a normal distribution based on annual demand. Additionally, although the deliveries to JIT customers are generally daily, we have aggregated the demand into weekly demand in order to make the demand function comparable to our lead time functions.

In modeling a specific part, we use the average weekly demand and the standard deviation of demand for the previous 12 months as inputs into our normal distribution, modeled as follows:

$$Demand: \sim \mathcal{N}(\mu_{D(weekly)}, \sigma_{D(weekly)})$$

In simulation, quantities pulled at random from this distribution provide the input that drives the outcomes of the inventory positions and decisions for the business.

While the customer demand and subsequent sales occur as a result of the normal distribution, the external input that drives the business ordering decisions is the customer forecast. Most customers provide a "firm" forecast that extends some number of weeks into the future and approximates what they believe they will produce (e.g. what they will demand from us) for each of those weeks. Although it may adjust week over week, it should usually remain close to what the "actual" production or demand will be in that period. Beyond that number of weeks of the "firm" forecast, the customers may still provide a production number, but it will typically be a much more naïve number like the average forecast production of the preceding *n*-periods or the average production over the previous 12 months or some other simplistic forecast that may not be at all representative of their actual production. It is important to note that, for long lead time parts, the production forecast received from the customer may not be firm until well inside of the upstream ordering lead time, meaning orders are placed on information that may be far from the reality of demand.

Lastly, customers' own production forecasts, even though considered "firm", will not equal their actual production. For this reason, we add an accuracy figure to the customer forecast for our own modeling. We use a typical measure of forecast accuracy evaluation, the mean absolute percentage error (MAPE) as our key measure, although for easier explanation, we subtract the MAPE value from one or 100% and call it the percent accuracy. So, for example, with a MAPE of 15%, we would have a forecast accuracy of 85%. In simulation, working backwards from the normal distribution of demand, we would assume that the forecast value is a uniform plus or minus 15% of the actual demand. Although it might be the case that customers apply some bias to their forecast, habitually forecasting that they will produce more or less than they do, we will assume that there is no forecast bias in our creation of this simulation model. So, the formulation of the actual and forecast demand is as follows:

D_i^A: simulated actual demand in period i.

D_i^F: simulated forecast demand for period i.

ϵ_i: forecast error in period i.

$MAPE$: mean absolute percentage error.

$$\epsilon_i = D_i^A - D_i^F$$

$$D_i^A \overset{iid}{\sim} \mathcal{N}(\mu_{D(weekly)}, \sigma_{D(weekly)})$$

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|\epsilon_i|}{D_i^A}}{n}$$

$$D_i^F = D_i^A + \epsilon_i \text{ where } \epsilon_i^{iid} \sim \mathcal{U}(-MAPE, +MAPE) \cdot D_i^A$$

5.1.2 Inventory Position

Subsequently, working our way upstream from customer demand, we will track our overall inventory position according to three elements: the quantity on backorder, the quantity on hand, and the quantity on order. The quantity on backorder occurs as a cumulative function of the amount by which the company stocks out in a given period before the replenishment occurs. The backorder quantity keeps track of the parts that are claimed for the priority demand on receipt of a replenishment shipment. We will describe the calculations for two of the relevant elements of the inventory position, backorder and on-hand, in the formulas that follow[2]:

OH_i^B: quantity on-hand at the beginning of period, i.

OH_i^E: quantity on-hand at the end of period, i.

[2] We depict use simplified notation to depict the equation $\max\{x, 0\}$ as $(x)^+$, and similarly, we depict the equation $\min\{x, 0\}$ as $(x)^-$. This is useful in those situations where we cannot have non-negative or non-positive numbers.

AFS_i: quantity available for sale in period, i.

R_i^A: actual quantity received in period, i.

SO_i: quantity stocked out in period, i.

BO_i: quantity on backorder at the end of period, i.

$$OH_i^B = OH_{i-1}^E$$

$$AFS_i = \left(OH_i^B + R_i^A + BO_{i-1}\right)^+$$

$$SO_i = \left(AFS_i - D_i^A\right)^-$$

$$OH_i^E = \left(AFS_i - D_i^A\right)^+$$

$$BO_i = BO_{i-1} + OH_i^B + R_i^A - AFS_i + SO_i$$

Additionally, we keep track of the available for sale quantities according to two artificial divisions that do not affect the actual inventory on hand or the service levels but help us to understand how the different parameters like lead times, cycle service levels, and order policies affect our inventory position along different levels. Those two divisions are the cycle stock and the safety stock. With the safety stock serving as our buffer to account for variable demand and variable lead times, we would expect to sell units out of the safety stock on occasion but will largely hold it as a buffer. So, we will calculate the safety stock parameter as discussed in Section 3.2.3, and then the safety stock in any given period will be the lesser of the available for sale and the safety stock parameter. Mathematically, the calculation appears as follows:

$$SS_i = \min\{AFS_i, SS\} \text{ where } SS = k\sigma_{DL}$$

Subsequently, the cycle stock for any given period is calculated as any inventory above the safety stock, recognizing that for any given period this value will vary according to receipts and sales, appearing like a sawtooth above the buffer of safety stock. Mathematically, we calculate cycle stock below:

$$CS_i = (AFS_i - SS_i)^+$$

Then, for comparison of different policies and variable inputs, we will find the average cycle stock over time, $\overline{CS}$, along with the calculated safety stock parameter, SS.

5.1.3 Order Receipt and Supplier Lead Time

The previous section dealt with modeling inventory management between receipt of goods and sales to the customer. Continuing to work upstream, we will also describe and depict the ordering and inbound flow of parts. Much like we simplified stochastic demand with a normal distribution, we also simplify stochastic lead time with a normal distribution from which we will draw randomly sampled lead times. In modeling these lead times to recreate the process according to existing parameters, we will use historical average lead time and standard deviation of lead time in weeks over the previous 12 months. Then when we look to evaluate the ordering with a new set of stochastic lead times, we will assume that the standard deviation of those lead times declines. To adjust the standard deviation in a reasonable manner, we will assume that the standard deviation of lead time decreased at the same rate of the decrease in average lead time so that the coefficient of variation remains the same. As discussed before, the formula for the coefficient of variation appears as follows:

$$CoV_{LT} = \frac{\sigma_{LT}(weeks)}{\mu_{LT}(weeks)}$$

To apply the stochastic variation to the lead times, we will assume that orders are placed according to the average historical lead time with this stochastic distribution. Mathematically, an order placed in a given week will appear as follows:

$$LT_i = \max\{1, \mu_{LT} - \sigma_{LT}, LT_i^S\} \text{ where } LT_i^{S} \overset{iid}{\sim} \mathcal{N}\big(\mu_{LT}(weeks), \sigma_{LT}(weeks)\big)$$

It is worth noting that in this model, the formula for LT_i applies a max value for lead time for orders placed in any given week, accounting for the unlikelihood of observing a lead time less than a week. We also assume that it is very unlikely that a lead time of greater than one standard deviation below the mean lead time is observed without any extraordinary circumstances like expedites or special orders that are out of the scope of this model.

To model the actual receipts in a given period, we will use the following notation and formulation, building up the notations addressed previously:

i, j: week number in simulation

LT_i: randomly selected lead time for order placed in week, i according to formulation above

RP_i: expected order receipt period for order placed in period, i.

R_j^A: actual quantity received in period, j.

Q_i: quantity ordered in period, i.

$$R_j^A = \sum_{i=0}^{j-1} Q_i \text{ where } RP_i = j$$

5.1.4 Ordering Policies

Finally, we develop the underlying inventory decisions and order policies that drive the orders and the inventory position as a function of the downstream demand. In this formulation, we aim to model the ordering decisions as they occur in practice in the business, rather than according to academic inventory decision systems, although we will do our best to make connections where applicable to these decision systems.

The ordering process could be considered a hybrid of the typical (s, Q)[3] and the (R, s, S)[4] order policies and the process occurs as follows: a buyer who is responsible for placing replenishment orders for a given part looks at a system that displays the forecasted inventory on hand for the upcoming 52 weeks, where the forecasted inventory on hand is a function of current inventory and forecasted demand each week along with forecasted receipts each week. The buyer specifically reviews the part within the lead time plus the review period for the part, checking to confirm that the forecast inventory on hand will

[3] The order point, order quantity (s, Q) system assumes a continuous review, where as soon as the inventory position drops to the reorder point or lower an order for Q units is placed (Silver and Peterson 1985, 214).
[4] The (R, s, S) system is one where every R units of time, the buyer checks the inventory position, placing an order large enough to raise the inventory position to S if the current position is at or below the reorder point, s (Silver and Peterson 1985, 215).

not fall below the order point. When the buyer sees that the part is forecasted to fall below the order point in a future week beyond the lead time but inside the lead time plus the review period, the buyer places an order. The quantity in that order is the maximum of three values, the minimum order quantity, the economic order quantity, or the difference between the current inventory position and the order-up-to quantity.

We derive the quantitative model for this as a function of the forecast demand and the starting inventory positions. The variables included in this formulation that have not been previously discussed are as follows:

Q_i: quantity ordered in period, i.

MOQ: minimum order quantity (dictated by supplier).

EOQ: economic order quantity, which is the efficient order quantity for minimizing total cost of holding inventory and the transaction/transportation costs of individual orders.

R_i^F: forecasted quantity received in period, i.

D_i^F: forecasted quantity demanded for period, i.

R: review period or time between reviews, in weeks.

s: reorder point.

S: order-up-to-level.

$$s = \mu_{DL} + k\sigma_{DL}$$

$$S = \mu_{DL+R} + k\sigma_{DL+R}$$

$$If\ OH_i^B + \sum_{i}^{i+LT}(R_i^F - D_i^F) < s, then\ order\ Q\ where\ Q = \max\{MOQ, EOQ, S - s\}$$

Typically, it would be ideal to order according to the economic order quantity; however, in the current state of the system, we are constrained by MOQs imposed by the suppliers to support their own economic production quantities. There will be an overall benefit of the project that occurs as a result of working collaboratively with suppliers to remove the MOQs. In developing the part-level supply chain model, we have included the MOQ to understand the effect that they have on the ordering policies and inventory.

5.2 KPIs

In order to make useful comparisons between the different ordering and inventory systems in both the simulated and the actual processes, we have identified a subset of the overall metrics to serve as our key performance indicators (KPIs) for comparing systems. It will be important to have KPIs that indicate when we are succeeding at our goals to reduce inventory, but at the same time, we should include KPIs that will provide warning that we are incurring additional risk.

The following list is our subset of KPIs that we believe will provide the most utility in measuring the system:

- Average cycle stock on hand (Qty / USD / ADOH) – indicative of the overall order sizes and frequency
- Safety stock parameter (Qty / USD / ADOH)
- Inventory turnover – lagging indicator that provides a measure of efficiency in managing inventory
- Number of stockout weeks – useful in simulation to confirm the risk matches the service level. Harder to measure in practice due to expedites and other factors.

After creating the tools to evaluate the current system in aggregate and also simulate the system at the individual part level, we proceed to apply the changes of the new opportunity to the aggregate collection of parts in play and then some sensitivity analysis as stress testing through the simulation model.

6 Model Analysis and Business Opportunity

As we have discussed previously, after creating tools to adequately understand and replicate the system in its current state, our next step is to apply the benefits to gain an understanding of the theoretical opportunity presented by a reduction in lead time for our highest volume parts. We develop the aggregate model to understand the "size of the prize," and whether it will be worth the effort for the business to undertake the project.

6.1 Theoretical Optima

In measuring the aggregate opportunity, we approach it through a two-step process. First, we calculate what our theoretical inventory level might be if we were able to achieve improved lead times for all parts according to their segments and subsequently order only enough parts each week to cover the demand over that lead time with a safety stock that is driven by the lead time and variability in place for a buffer. For example, for all our A+ parts, which are the first 50% of COGS in the business, we apply a 1-week lead time. Although these lead times may not be realistic across all parts and all suppliers, the calculation provides a goal to work toward and an understand of what could be under ideal conditions. **Table *4***, below, depicts the theoretical lead times that we apply by each of the regional part segments.

Regional Part Segment	Theoretical Lead Time (weeks)
A+	1
A	2
B	4
C	8
D	12

Table 4. *Theoretical Lead Times by Segment*

We effectively use the same calculations as we described in **Section 3.2.3**, modifying it with new values to understand the theoretical outcome. We arrive at the average theoretical inventory value in US Dollars, which for the sake of proprietary information, we will convey here as a percentage of the current average inventory value. The mathematical formulation of the inventory is as follows:

c_m: landed unit purchase cost for part, m

C_m: cost of all parts on hand for part, m

$\overline{OH}_m$: average inventory quantity on hand for part, m

$\overline{CS}_m$: average cycle stock quantity on hand for part, m.

SS_m: safety stock level for part, m

Q_m: order quantity for part, m

$L_m(ABC)$: assigned lead time in weeks for part, m, as a function of the part's assigned regional ABC segment

$\mu_{D,m}$: average demand for part, m, in weeks

$\sigma_{D,m}$: standard deviation of demand for part, m, in weeks

$\mu_{L,m}$: average historical lead time for part, m, in weeks

$\sigma_{L,m}$: standard deviation of historical lead time for part, m, in weeks

$\sigma'_{L,m}$: updated standard deviation for new assigned lead time resulting from historical CoV of lead time, for part, m, in weeks

$\sigma_{DL,m}$: standard deviation of demand over lead time for part, m

$CoV_{L,m}$: coefficient of variation for lead time for part, m

k: safety factor, derived from inverse of service level

$$CoV_L = \frac{\sigma_L}{\mu_L}$$

$$\sigma_L' = CoV_L \cdot L(ABC)$$

$$\sigma_{DL} = \sqrt{L \cdot \sigma_D^2 + \mu_D^2 \cdot \sigma'^2_L}$$

$$SS = k\sigma_{DL}$$

$$Q = \mu_D L$$

$$\overline{CS} = \frac{Q}{2}$$

$$\overline{OH} = SS + \overline{CS}$$

$$C_m = \overline{OH}_m \cdot c_m$$

$$Total\ Average\ Value\ of\ Inventory\ On\ Hand = \sum_{m=0}^{N} C_m$$

Using Tableau and Excel for study and visualization, we are then able to subdivide the inventories appropriately for evaluations of different criteria and divisions. The chart, in **Figure 7**, below, depicts the theoretical improvement in inventory that might be achieved through implementation of this reduced lead time initiative. The chart is arranged by depicting the inventory as a percentage of the current total average inventory on hand, broken down by global region and demand segment. Within each region, the bar on the left side depicts the current position as a percentage of the current total average inventory. On the right side, the bar depicts the theoretical inventory level as a percentage of the current total average inventory. We see that, in each of the regions, this initiative, fully implemented, could reduce the average inventory on hand by more than half.

Achieving this theoretical outcome is far from easy, and so, to create a more realistic picture of the size of the opportunity, we evaluated a modified version of the opportunity by applying assumptions about the feasibility of the opportunity and filtering

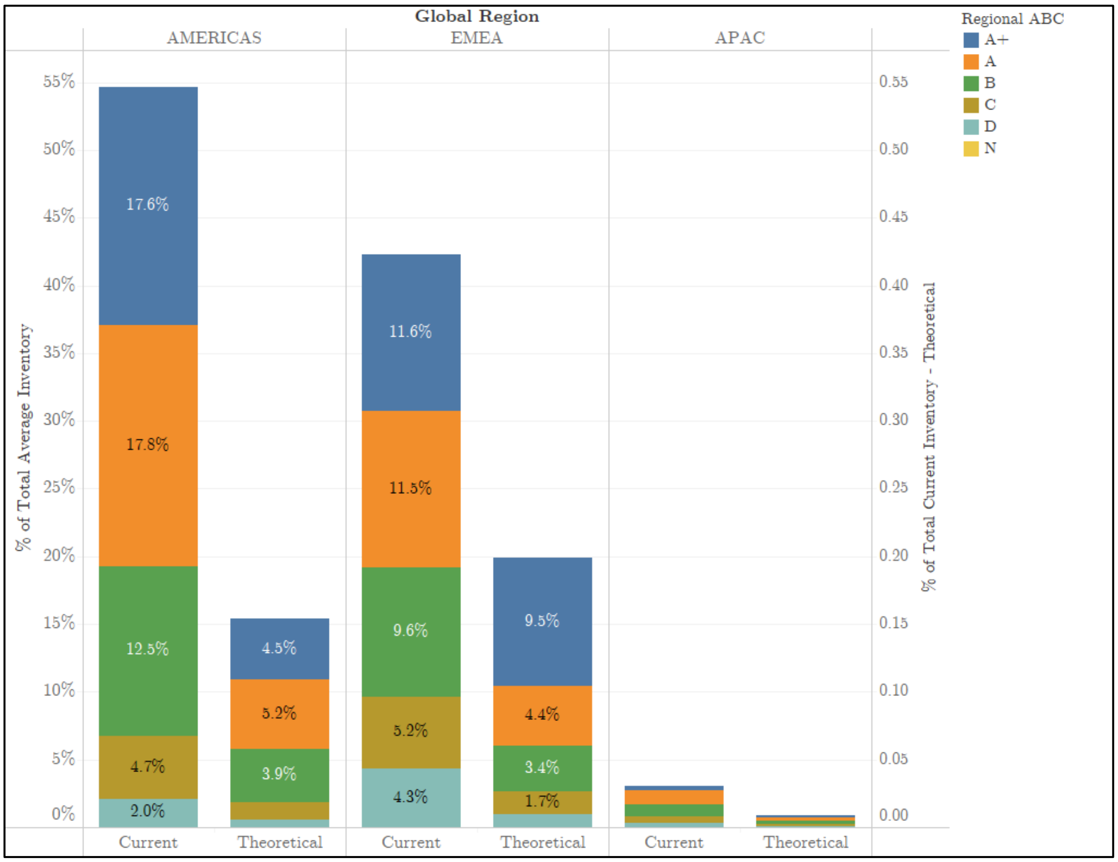

Figure 7. *Theoretical Improvement in Inventory*

out the parts for which we know cannot achieve the improved lead times in the near term.

6.2 Realistic Expectation

Extending beyond a theoretical outcome where we have complete success achieving reduced lead times according to the part segment, we will now apply the set of more realistic filters to get a better understanding of what is in the realm of possible. It is important to note that the business is undertaking other supply chain initiatives in parallel that will also benefit the business, but for the sake of this project, we have attempted to isolate the benefit of the lead time improvements. In applying the filters for the realistic outcome, we hope to set an achievable near-term target.

6.2.1 C/D/N Parts

The first filter we apply is to the parts that are tagged with C/D/N segmentation labels. The N parts are the most important for exclusion from the project because they do not have recurring demand and therefore average inventory will not be reduced easily simply through lead time reduction but should be evaluated for other inventory reduction strategies out of the scope of this project. C and D parts are excluded from this project because, in aggregate, they contribute less than 18% of the average inventory on hand but comprise approximately 45% of the part numbers in inventory. Because of the part-by-part and supplier-by-supplier nature of implementation, these parts are not good parts for implementation of this initiative. In some cases, C and D parts may be included as a part of supplier agreements, but we will not explicitly pursue parts in those categories.

6.2.2 APAC

Although the business sells products and maintains inventory in the Asia-Pacific, or APAC, region, it is a relatively small inventory position (less than 5% of total average inventory). Additionally, as a function of such a small presence in APAC, the opportunities to build trusting relationships and implement new inventory management systems are both fewer and less fruitful. With a similar rationale to the C/D parts, we will exclude the entirety of the parts from the lead time reduction project.

6.2.3 Customer-defined sourcing

One challenge that the company faces in their position sourcing and distributing engineered parts for the OEMs is that the OEMs may maintain pre-existing or favorable, volume-driven sourcing agreements with some of their component manufacturers. Given the scale of some of these OEMs, they may feel that they achieve more favorable pricing terms for some parts than the company can provide with their own volumes, and so in some cases the choice of component manufacturer and terms of contracts are prescribed by the customer. As the company continues to improve their own sourcing processes and terms, they may positively affect the economics of these decisions for their customers, but for the time being we exclude these parts that are explicitly sourced by the customers from the benefit of the project.

6.2.4 Success factor

The final factor which we applied that was less explicit than the first three was a more arbitrary factor which we labeled as the "implementation completion assumption." This factor assumed that even after excluding the parts that we did not expect success, we would still not achieve complete success in implementation. While the previous filters were applied at the part number-level, this success factor is applied in a broad fashion across every part that remains in consideration after the previous filters.

For example, if we successfully enter agreement for reduced lead times with a supplier, we may expect to reduce our average inventory on hand for an individual part from \$100 to \$60; however, because we have tempered the optimism with this success factor which we will say is 85% in this example, our estimate will be that we will only improve our inventory position by \$34 to \$66 instead of \$40. This allows us to think critically and examine the sensitivity of the implementation success.

Like the presentation in the previous section, we also created a chart to understand the opportunity graphically in **Figure 8**, below. We have also divided the inventory bars into the different global regions, but we have added a grand total calculation to more clearly understand the business impact. What we see is that this improved business design has the opportunity to reduce the inventory by 37% to 63% of its current position in the coming years. As expected, we do not see any direct reduction in our C, D, or N parts, nor do we see any change in our inventory position in APAC. What we do see is that the largest opportunity for improvement comes from the improvement in lead times for our A parts.

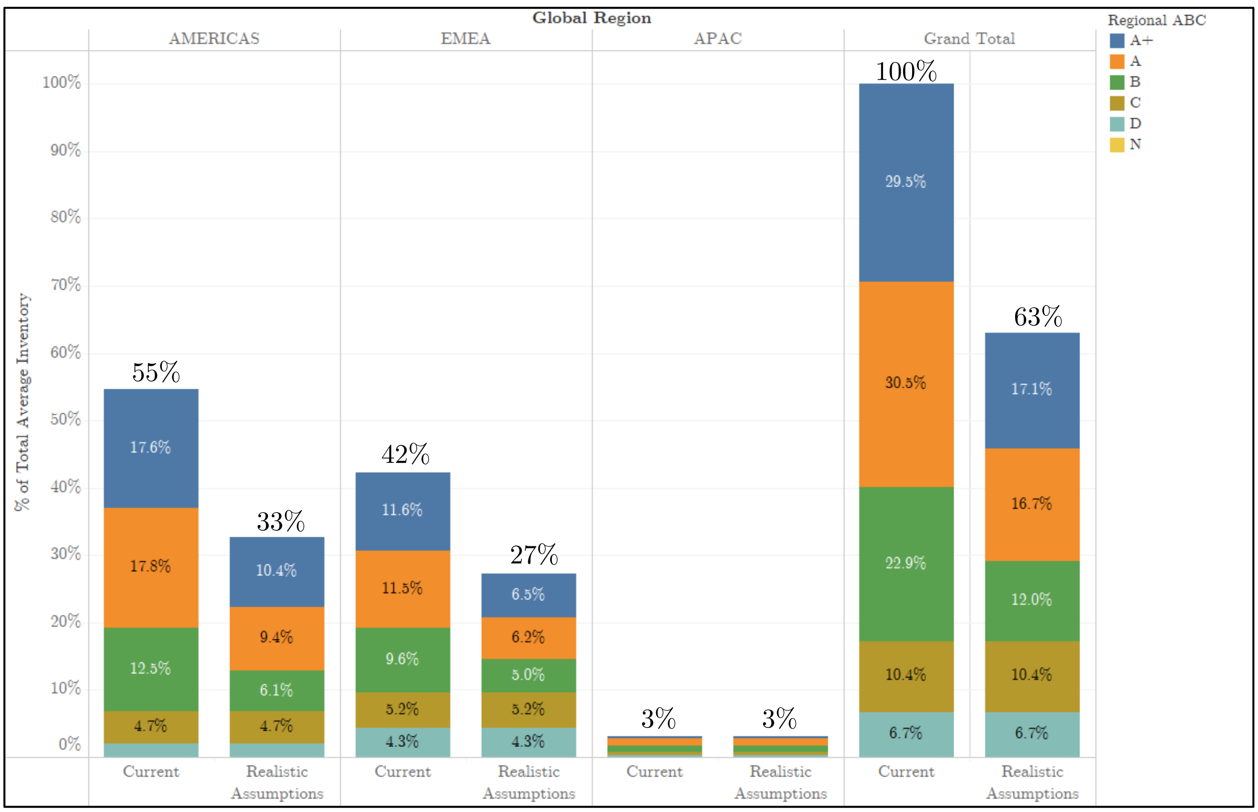

Figure 8. *Realistic Expectation of Inventory Reduction*

7 Conclusions and Future Work

In this thesis and through our time with this company, we worked to answer the question: how can the company reduce lead times and, subsequently, inventory while maintaining or improving customer service levels? We found that there are myriad challenges involved in the business of acting as a supply chain solution, especially when sourcing parts with long lead times and delivering under short deadlines. Even so, we found that the opportunity exists to improve processes and relationships with suppliers to positively affect lead times and subsequently inventory positions. We described the process and modeled the supply chain both at the part level and in aggregate, to drive the business case and to evaluate the tradeoffs between lead times, inventory positions, and commercial risk.

There are many opportunities to extend the analysis completed to date. The model does not yet account for the opportunity to "expedite our way to a service level." In other words, it does not allow for exogenous factors that structurally change the timings of orders. Additionally, there does not yet exist a model for determining the optimal trade-off between the company's liability for unpurchased parts and lead time reduction offered by the supplier. This could be modeled through some extension of the crashing cost where the liability corresponds to the optimal lead time improvement as a function of the crashing cost. Also, the company has already begun to investigate models of consignment from their suppliers, and this could be further modeled to understand the impact of the reduction of lead time effectively to zero. Along with these, there may also exist opportunities to further investigate implementation of some of the collaborative supply relationships discussed in the literature review, like vendor-managed inventory (VMI) or collaborative planning, forecasting, and replenishment (CPFR).

The work completed to date has just been the start of a major transformation in the business model of this business. It presents the opportunity to structurally change the underlying business model of this distribution business that has been unfortunately trapped between the demands of their customers for near-immediate delivery on the one hand and the suppliers on the other hand who have systems in place that include delivering with long lead times for their own protection and benefit. Although the transformation will require significant work to implement across the entire book of parts, there is a reasonable opportunity to capture a large amount of the total possible benefit quickly by prioritizing the implementation candidate suppliers and parts and taking advantage of the fact that there is a subset of parts for which a reduction in lead time can drive outsized reductions in average inventory. Additionally, it will be critical for the success of this project that the company embraces the cross functional nature of the project and develops the appropriate systems and process to ensure continued success.

Lead time reduction is one of the most powerful tools at the company's disposal for inventory reduction, but it will require continued investment in long-term relationships that include trust and willingness to share information to compete and win as a supply chain. These systems will improve the service level that the company provides, and it will improve the overall responsiveness across the supply chain. By reducing these lead times and inventories, the company will become structurally more competitive as they free up working capital, reduce storage requirements, and minimize the risk of obsolescence of their parts.

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