Using Lead Time Data to Identify Cost Saving Opportunities in an Automotive Supply Chain: Inventory Safety Stock and Trucking Carrier Pool

by

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Abstract

Lead time information from suppliers influences decisions at every level of a supply chain, from sourcing and purchasing, to inventory policies, transportation, and plant design. Large volume, high complexity manufacturers, like those in the automotive industry, collect and store enormous amounts of data, but due to departmental boundaries, out-dated computing systems, and day-to-day priorities, they often do not analyze this valuable information. We analyze lead time data from Nissan on more than 13,000 SKUs and more than 400 suppliers, and apply the analysis to two supply chain and logistics problems: safety stock and transportation fleet sizing, identifying about $10MM of one-time and continuing savings opportunities. In both cases, we similarly are looking at creating a strategic buffer, either in terms of inventory or trailers, to account for variability in lead time.

Much of the academic literature around lead time focuses on complex optimization algorithms, concepts far removed from the reality of Nissan's operations. We bridge the gaps between the rigor of academic analysis to practical application in the automotive industry. Our experiments with heuristic inventory policies to reduce space requirements, holding costs and expedited shipments, as well as our vehicle pooling simulation, should provide valuable transferrable insights. Similarly, our experiences implementing these ideas and processes in a business environment and our observations on organizational structure should inform process change both in automotive and other industries.

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Note on Data

To protect confidential and propriety commercial information, the data presented throughout this thesis has been altered and does not represent Nissan’s data. The dollar values have been rounded and disguised to protect competitive information. This includes all transportation rates, part values, and costs presented throughout the paper. Additionally, Nissan’s logistics and transportation team works with several trucking carriers and third-party logistics providers. To protect privacy, these will be referred to as “Carrier A,” “Carrier B,” and a “3PL.”
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1. Introduction

Lead time information from suppliers influences decisions at every level of a supply chain, from sourcing and purchasing, to inventory policies, transportation, and plant design. Large volume, high complexity manufacturers, like those in the automotive industry, collect and store enormous amounts of data, but due to departmental boundaries, difficult computing systems, and day-to-day priorities, they often do not analyze this valuable information. We look at lead time data from Nissan on more than 13,000 SKUs and more than 400 suppliers, and demonstrate the value of this data in analysis of two supply chain and logistics applications: safety stock and transportation fleet sizing, identifying about $10MM of savings opportunity. In both cases, we similarly are looking at creating a strategic buffer, either in terms of inventory or trailers, to account for variability in lead time.

Much of the academic literature around lead time focuses on complex optimization and programming algorithms, concepts far removed from the reality of Nissan’s operations. We bridge the rigor of academic analysis to practical application in the automotive industry: reducing cost in Nissan’s inbound parts supply chain. Our experiments with heuristic inventory policies to reduce space requirements, holding costs and expedited shipments, as well as vehicle pooling simulation, should provide valuable transferrable insights. Beyond these specific applications we discuss using lead time data to identify and quantify process improvement opportunities. Our experiences implementing processes in a business environment and our observations on organizational structure should inform change management both in automotive and in other industries. Although exact figures are rounded in this thesis to protect confidential commercial information, the methodology is explained in depth.

In this thesis, we first explain the motivation and goals for each part of the study, then introduce the reader to Nissan’s business model and supply chain, and review academic literature before going into depth on our original research and models. Finally, we summarize the lessons learned, immediate cost savings, and additional process improvement opportunities identified.

We found that careful examination of data on variability yields valuable insights into processes across the supply chain. Our results at Nissan demonstrate that reducing non-strategic variability in processes as diverse as setting safety stock and unloading trailers can save companies millions of dollars. We contribute and reinforce two arguments for the academic literature: First, heuristics can significantly improve safety stock, using much simpler calculations than optimization. Second, any analysis of transportation network design must include what takes place after a vehicle has arrived at its destination, because this dwell time can outweigh the entire rest of the transit time in certain applications.
1.1 Project Purposes and Motivation

New product launches, suppliers moving on-site, and changes to manufacturing processes, like increased kitting, have greatly reduced in-plant warehouse space at Nissan's manufacturing plants. As a result, inbound production parts and supplier rack returns have reactively moved to a series of off-site cross docks and warehouses. Adding facilities has increased the complexity of the system, multiplying the number of touch-points for each part and carrier lanes for trucking providers. Nissan is focused on reducing this complexity to reduce total delivered cost (TDC) of its vehicles. Two opportunities they identified at the start of research were:

(1) Optimizing safety stock levels by part, and,

(2) Sizing a common fleet of trailers to replace separate carrier fleets.

In both cases, we examine how variability of lead time would affect safety buffer requirements and service level, in terms of both part stock-out and trailer availability. Using the wealth of lead time data provided, we were able to identify cost savings opportunities in these two projects and beyond their scope Nissan’s supply chain. We also discuss implementation risks and the benefits of changing processes at such a large company.

While many studies of variation in manufacturing supply chains focus on demand or the effects of reducing lead time, we conclude that analyzing variation in existing lead time and using this knowledge to create inventory and transportation policies itself can result in significant cost savings. The analysis also helps pinpoint the best opportunities to shorten lead time. Additionally, the tools and processes used are simple to explain and implement, proving that even without fully optimizing a system, there are still significant opportunities for cost savings through small changes.

1.2 Application 1 Background: Safety Stock

Four separate warehouses, some more than thirty minutes away from the plant, supply Nissan's Canton, Mississippi, production lines. During the research period for this project, Nissan was in the initial stages of planning and building a new 1.5 million square foot "mega-warehouse" to be called the Integrated Logistics Center (ILC) to replace the off-site warehouses. The ILC project was undertaken in conjunction with moving the plant towards a "Want-To-Be-Condition" (WTBC) for both manufacturing and supply chain, planning processes the right way in advance rather than reacting to conditions as they occur. One critical aspect of planning for the ILC was calculating how much of each part would be stored in the new warehouse, meaning that safety stock and inventory ordering policies had to be understood and improved.
Nissan uses a fixed order-quantity, continuous-review, future-looking order process in which the system generates an order to suppliers requiring delivery at a set time in the future when the system expects part inventory to fall below the safety stock level (measured in hours of supply). However, suppliers can ship well before this set time, and often do in order to fill trailers. Although they might ship one part late, they could, in the same trailer, have several other shipments due a few days in the future that they happened to have ready on their docks. Additionally, production does not always meet the manufacturing plan, meaning that the demand forecasts the system uses in ordering do not vary normally with actual part usage. Nissan calls this "underbuild" and during the time of this study it ranged, depending on plant and product line, from 0% to more than 20%. Both underbuild and suppliers shipping early contribute to Nissan having more parts on-hand than it needs or expects.

Currently, Nissan does not have a methodological process for determining safety stock level, relying instead on a few people with years of acquired knowledge to determine the number of hours of inventory-on-hand ("float") that the system will use for ordering. We developed a heuristic tool to set safety stock based on lead time, demand, storage space requirements, piece price, part quality, and delivery frequency. Next, we tested this algorithm through two pilot experiments, each with a test group and a control group of parts. The first test included 50 parts, all from one car-line and one delivery dock, over the course of one month. The second test included 500 parts across multiple docks and production lines, also over the course of one month. The thesis analyzes the results and findings from each of these two tests in terms of on-hand inventory and stock-outs requiring expedited freight, extrapolating recommendations for improving inventory systems and illuminating additional areas for improvement in logistics in a complex automotive supply chain. We conclude that moving to the heuristic could immediately save $2.5MM and also identify additional inventory savings from other process improvements.

1.3 Application 2 Background: Grey Trailer Fleet

Nissan uses eight core trucking carriers to bring production parts from suppliers and return the empty metal racks or returnable totes these parts come in back to the suppliers. When a delivery is made, a trailer with parts is "dropped" on the yard of the off-site warehouses or plant to be unloaded at a later time. Once the trailer is unloaded, it is supposed to be reloaded with racks or returnable totes for a specific supplier, although not necessarily the same one, and a different driver will pick it up from the yard and return the racks to the appropriate supplier. Each trucking carrier is assigned to specific lanes and each carrier can only pull trailers it owns. There is variability in unloading times, transit times, and yard processes moving trailers between different off-site warehouses and the plant. The lack of adequate coordination often creates a situation in which, while there are many empty that could be loaded with racks, there are no trailers of the correct carrier for a specific supplier. In this situation, Nissan creates an
expedited shipment to get the racks to the supplier. The annual cost of these expedited shipments was more than $10 million in the last fiscal year.

One potential solution to reduce expedited shipments due to trailer availability problems is to move to a common trailer pool, a so-called "grey" fleet in which any carrier could pull any available trailer. Cost savings from such a move would not only include significant reductions in expedites, but also lower carrier transportation rates because the carriers would not be taking on the risk of supplying trailers.

To understand the cost savings from moving to a common trailer pool, we needed to determine the appropriate size of such a pool. Neither Nissan nor the trucking carriers currently monitor the movement of trailers through the network, so we created a model to simulate Nissan's entire trucking network under several scenarios. We examined sensitivities around transit times and unloading times between actual data and what the planning team thought was reasonable. The thesis discusses how results of this analysis compare to the current trailer pool of Nissan's various carriers; other similar studies of pooling resources when there is variation in timing; and queuing theory. We conclude that the potential savings ($1.4MM) of moving to a grey fleet rest entirely on bringing the process of trailers on the yard into control as well as additional lessons on the effects of transportation scheduling decisions on trailer fleet requirements.

1.4 Project Goals

The goal of this project is to use existing, but previously unexamined, data on lead time variation to realize cost savings for Nissan. The analysis shows two valuable applications of careful study of transit times from suppliers and how long trailers stay on the yard before being unloaded, aspects of the supply chain with significant variability that directly impacts the bottom line, but which get little attention. Beyond the research goals of looking at operations theories in a live automotive manufacturing environment, we hoped to create tools and outputs that were immediately helpful to Nissan.

In the case of the safety stock analysis, we demonstrated that the tool we created would save inventory holding cost, minimize required storage space, and reduce expedites. It also needed to be robust enough to use across Nissan's North American plants, not just for case specific to one location. Finally, the algorithm needed to be adaptable depending on changes in transportation routing and plant manufacturing conditions (underbuild) and simultaneously be easy to understand without a background in statistics / operations research or even in basic operations management theory.

For the grey trailer fleet, the primary output was determining the right number of trailers Nissan should lease to optimize for cost savings: too many trailers, and the lease becomes prohibitively expensive, and too few, the company has to pay for expensive expedited freight. In the course of analyzing the
transportation network to determine this number of trailers, we also identified several other opportunities for cost savings.

1.5 Project Approach and Methodology

At the start of the research period at Nissan, it was essential to understand how the supply chain group worked and how the logistics and transportation teams interacted with the inventory and material handling teams. For both parts of the project, we needed to become familiar with the processes and people who act within the current state system, from 3PL providers who manage the off-site warehouses to the trucking carriers, to the inventory analysts who enter safety stock in hours into the mainframe computer system.

We observed and recorded specific processes to gain insights into larger trends and spent significant time in the off-site warehouses, watching trailers unloaded from the suppliers and reloaded with rack returns.

Once we began to understand the scope of each task, we began collecting data on lead time and demand by part number and supplier. For lead time, we examined the last six months of orders and were able to pull from Nissan's systems the exact times that shipments left a supplier, arrived on the Nissan yard, and were unloaded. For demand, we could look at the plant's build schedule by part, as well as look at historical levels of underbuild (when the plant does not produce the planned number of cars).

When we scrutinized the data, we realized that the amount of data collected on lead time was previously unanalyzed and quite valuable. In contrast, the demand data was not as robust because it was difficult to correlate underbuild with actual numbers of parts used. After reading the relevant literature and studying the theory, we worked to apply these theories to Nissan's data. For the safety stock tool, we were able to perform two tests to validate the algorithm, collecting original research on heuristic safety stock success in the automotive environment.

1.6 Thesis Overview

After providing an introduction to Nissan North America's business and supply chain network, we review the relevant academic literature and explain the management challenges of implementing these sorts of changes in a large and complex organization. Next, this thesis will describe in detail the lead time data collected and opportunities identified based on the data alone. We discuss our proposed safety stock heuristic, including quantitative analysis of the current state, as well as qualitative commentary gleaned from conversations with the employees on the ground. We explain the algorithm we created and present analyses and conclusions from each of the two pilot tests we performed. Finally, we show the use of the lead time data in our model of Nissan's transportation network and its application to vehicle fleet sizing.
The thesis concludes with ideas of other applications in the automotive industry and transferable lessons to other industries.

2. Nissan North America Supply Chain

2.1 Company Background

Nissan North America (NNA) manufactures and distributes cars, trucks, SUVs, and light commercial vehicles under the Nissan and Infiniti brands. It is a subsidiary of Nissan Motor Ltd (NML), the publicly-traded Japanese auto maker, headquartered in Yokohama. Nissan and French auto maker Renault have a cross-ownership alliance and shared CEO, Carlos Ghosn. Nissan is the sixth largest automaker by vehicle sales volume in the US, with an 8% market share in 2013, behind GM, Ford, Chrysler, Toyota, and Honda (“Auto Sales - Markets Data Center -WSJ.com,” 2014).

In North America, Nissan operates three non-unionized manufacturing facilities: vehicle stamping and assembly plants in Smyrna, Tennessee and Canton, Mississippi, and a powertrain plant in Decherd, Tennessee. The Smyrna plant started production in 1983 and currently produces the Nissan Altima, Nissan Maxima, Nissan Pathfinder, Nissan LEAF, Nissan Rogue, and the Infiniti QX60. The Canton plant started production twenty years later in 2003 and focuses on larger SUVs, trucks, and vans. At the time of research, in addition to the Nissan Altima and the Nissan Sentra, it produces the Nissan Armada, the Nissan Titan, the Nissan NV commercial vehicle, the Nissan Frontier, and the Nissan Xterra. Total production from these two plants is about 1,000,000 vehicles annually, split about 550,000 from Smyrna, and 450,000 from Canton (“Plant Fact Sheets - Nissan Online Newsroom,” 2014). Nissan is focused on improving quality at the Canton Plant by minimizing inventory losses and rework.

When Carlos Ghosn took the lead at Nissan in 1999, the company rebounded from near bankruptcy to the most profitable large automotive company in the world in just eighteen months. Ghosn is known for dramatic cost savings and using cross-functional teams between different divisions to identify opportunities for improvement (Ghosn, Carlos, 2006; Yoshino & Egawa, 2006).

One of Nissan's key near-term strategic goals is to build vehicles where it sells them (Gagnier, 2013; Saia, 2013b) (Gagnier, 2013; Saia, 2013b). Like other Japanese automakers, in recent years, it has struggled with exchange rates and maintaining profitable growth (Dawson & Takahashi, 2012). Therefore, it has been introducing more and more vehicle lines to its US plants, increasing their complexity in terms of both number of parts and number of suppliers. Simultaneously, it is working to bring its suppliers closer to its US plants, decreasing lead times and transit costs (Saia, 2013a). While 15
outside analysts question whether these changes will work within Nissan's corporate culture and model, this study focuses on strategies to mitigate the effects of added complexity through better supply chain and operations planning, while continuing to save costs (Harner, 2013). The increase in new model launches and therefore increase in part SKUs, suppliers, and transportation routes is essential to understanding the motivation for this project.

2.2 Supply Chain Overview

The three North American plants are supplied by more than 400 suppliers in North America as well as NML Japan and other international suppliers. Domestic suppliers (as categorized by Nissan, includes Canada but not Mexico) are mostly located either near the plants in the middle south or in traditional automotive areas like Michigan or Indiana. However, parts arrive by truck from suppliers as far away as California, Texas, and New England, meaning that these parts have very different lead time profiles than other parts. Supplier selection, price negotiating, and purchasing is done by the Renault - Nissan Purchasing Organization (RNPO), one of the collaborations between Nissan and Renault to leverage economies of scale. Supplier selection and lot sizing, although relevant to lead time analysis of supply chains, are out of scope of this project.

Figure 1 Nissan North American Supply Base

From a transportation perspective, about 85% of parts both by SKU and by volume come from US and Canadian suppliers by truck for the assembly plants. It is these parts specifically that we are concerned with in this study. For the Decherd powertrain plant, the proportion from Japan is higher.
Nissan outsources the design of the trucking network to a third-party logistics company (called A 3PL in this thesis), which uses daily shipment volumes by supplier (in square feet) to optimize each origin-destination lane (Supplier A to Canton Plant, Supplier A to Smyrna Plant, Supplier B to Decherd Plant, for example) into daily frequencies. Most routes are direct between the supplier and the plant, but some are "Milk Runs," meaning the trucking carrier goes to more than one supplier before returning to the plant.

The highest volume suppliers could have as many as 18 dedicated 53' truckloads per day, while others would have as few as one per week. About 10% of inbound shipments are Milk Runs rather than directly from a single supplier. Additionally, Nissan consolidates shipments from multiple suppliers at cross-docks in Michigan and Indiana as well as breaking apart shipments from a single supplier destined for multiple plants at a "break-out" center in Smyrna. Engines move in direct shipments between the Decherd powertrain plant and the Smyrna and Canton assembly plants, and some stamping parts are shipped between Smyrna and Canton. About 320 trailers enter and leave the Canton plant each day. Nissan uses eight core trucking carriers (designated in this thesis as Carriers A through H) who bid on each of these lanes. Changes to the transportation network created by a 3PL are out of the scope of this project, although significant opportunities were identified based on the data collected.

Nissan's mainframe MRP system looks ahead at the plant build schedule and releases orders to suppliers to deliver at a specific date and time so that the inventory on hand never falls below the safety stock level. The quantity ordered is predetermined by the standard packaging size, or "Unit Load" size. Similar to many automotive companies, Nissan has a few specific package sizes and the number of parts in this Unit Load varies by the size of part and how many fit in that container. The suppliers are then responsible for loading parts onto the trucks in order for them to arrive at Nissan by the delivery date and time. There are no penalties for delivering early, and Nissan has instituted several initiatives to improve trailer utilization. Therefore, suppliers will often "fill-up-the-truck," delivering shipments days before they are due. In the instance a shipment is going to be late, Nissan can order an "Expedite," or an expensive extra shipment outside the set, regular routes. Inventory analysts monitor "run-out-time" on the mainframe system, which is the time when the plant will run out of a part, and then ask the transportation analysts to set up an expedite by truck or air.

A key goal of this project and the Nissan Supply Chain Group is to reduce the number of expedited shipments. An expedite can be the fault of the supplier (not ready to ship), Nissan (lost parts, did not order enough), or the trucking carrier (was late, got into an accident). Expedited shipments blamed on Nissan account for around $18MM in added costs annually. While only reductions in those expedites
labeled "Nissan fault" go directly to the bottom line, indirectly, carrier and supplier expedites affect Nissan's costs because these costs are reflected in vendor pricing. Nissan analysts are also responsible for setting up all expedites regardless of fault, at significant cost in terms of frustration and time usage. Some expedites are tied to inventory levels, like the need to hold extra inventory as a buffer against late deliveries or material rejected for quality reasons. Others, significant in the grey trailer study, are slightly different: for those expedites, it does not matter what happens once material is inside the plant, but the lack of an empty trailer or the fact that a trailer is damaged must certainly be taken into account. Factors like weather and traffic are relevant to both: Nissan must carry inventory as a buffer against weather delays and a trailer pool must be large enough to accommodate some routes taking longer than planned. In Figure 2 below, we map a few of the common expedite reasons to the two studies in this thesis.

**Figure 2 Common Expedite Reasons**

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<th>Expedite Reason</th>
<th>Fault</th>
<th>Relevant to</th>
<th>Float tool?</th>
<th>Grey Trailer?</th>
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<td>Carrier Service Failure</td>
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Nissan uses off-site warehouses operated by 3PLs at both the Canton and Smyrna plants to store some parts before they go to the assembly line, and, to sort empty packaging that must be returned to the suppliers. Because these warehouses are located at some distance from the plants (up to forty miles), Nissan plans to build larger consolidated on-site warehouses. Parts orders are released to the suppliers for a specific delivery time to the warehouse, and then separately, the assembly plant issues "pick orders" to the warehouses to bring parts to the plant. At each plant, there is a designated trucking carrier running shuttles between the warehouses and the plant. In Canton, about 300 separate "Pick" loads run each day. For parts delivered directly to the plant, there are small warehousing areas from which parts are picked as needed. The warehouses, plant storage spaces, and trailer yards were all filled to capacity during the period studied.
In the schematic diagram below, you can see the flow of parts and packaging from suppliers to off-site warehouses to plant to off-site warehouse back to suppliers. It is important to note the “yard” time between each step: this is when a trailer full of parts is sitting in the parking lot awaiting movement to the next location or unloading.

**Figure 3  Canton Supply Chain Schematic Diagram**

Figure 4 below illustrates the geographic spread of the four off-site warehouses at the Canton, Mississippi plant and the planned condition once a new on-site warehouse is complete. In combination with

**Figure 4 Canton Warehouse Current State and Want-to-Be-Condition**

Finally, the images below from publicly-available Google satellite views show the trailers on the yard at the plant (left) and at two of the off-site warehouses (right).
In addition to the physical and process structure of Nissan’s Supply Chain, several key points related to the people and organizational structure are important to understand both opportunities and challenges. At Nissan, inventory control, material handling, and transportation/logistics are all managed by different groups. There are separate inventory and material handling groups in each plant, while all transportation is managed out of the Smyrna plant, where a 3PL sits. The Renault-Nissan Purchasing Organization (RNPO), responsible for supplier and carrier agreements, operates out of Nissan’s Franklin, Tennessee, headquarters office building, rather than out of any of the three plants. Nissan uses contractors rather than Nissan employees in many direct operational roles, including transportation analysts (the people who day-to-day manage expedited shipments and truck status). Additionally, there are project-specific teams that include members from the Japanese headquarters as well as cross-functional teams analyzing problems across areas. There are communication gaps between the various teams, exacerbated by distance, infrequent contact, and different alignments of incentives. Talking and listening to each of these stakeholders and understanding their perspectives on inventory and truck transportation was essential for success.
The figure below maps the different groups to their geographies so the reader can better understand the complexity. The red circles denote Nissan internal teams, while the blue circles are logistics suppliers. Project success depended on buy-in from all of these parties.

**Figure 6 Stakeholders Map**

3. **Literature Review**

Understanding both long-established theories and cutting-edge academic research was essential in framing hypotheses and analysis methods for this project. We also hope to demonstrate in this section where our research sheds light on new aspects of previously analyzed issues. In general, the relevant literature fell into one of two categories: (1) highly academic optimization approaches; or (2) specific applications to industry. The first group provides the intellectual framework for the second, but often glosses over the realities of implementation in a business setting. Applications to industry, on the other hand, detail both engineering and management challenges, but often become so specific to the company or type of setting that the lessons are less transferrable.

This literature review has three sections, each of which corresponds to one of the three following chapters of research: lead time; inventory and safety stock; and pooling theory. In each section, we review the academic theory followed by a summary of industry applications that are relevant to Nissan.
3.1 Lead Time

"Lead Time" can refer to the lag time between any two steps of a supply chain process. There is significant research on the effects of shortening finished goods lead time to consumers, but we concern ourselves here solely with lead time between suppliers and manufacturing. Chen and Yu (2005) quantify the value of this sort of upstream lead time information, validating our argument on the value of this data to inform even simple calculations.

Lead time can be categorized as known, controllable, or stochastically distributed. The premise of this study is that Nissan’s lead times are highly variable, so work on stochastic lead times is particularly relevant. However, we found it was essential to segment the total time and carefully consider which portions were controllable versus which were stochastically distributed, as will be discussed further in the next chapter.

Pan and Yang (2002) discuss which parts of lead time are variable versus fixed: what is the so-called “crashing cost” of reducing lead time with expedited shipments? They point out that it is important to consider what segments of lead time are within the control of the company. In Nissan’s case, this is particularly important because a major conclusion of our research in both inventory optimization and safety stock, and with the grey trailer fleet, is the large and somewhat taken-for-granted cost of leaving trailers on the lot for a long time. Kouvelis and Tang (2012) also write about the decision to expedite shipments with uncertain lead time, as well as the importance of understanding the product’s journey from source to generation and tabulating which parts of lead time are truly stochastic versus in the control of the company. This is an area for potential future research for Nissan because expediting is such a high cost for the supply chain.

Other literature focuses on determining the distribution of lead time. Although a normal distribution can be an easy tool for consolidating masses of lead time data into a few numbers, Silver, Pyke, and Peterson (1998) note that normal may not be the most appropriate choice, especially when combining lead time with demand. Burgin (1972) and Hadley, Whitin (1963) both suggest that the gamma distribution could be a good representation of lead time, while Das (1976) and Cobb, Rumi, and Salmerón (2013) suggest exponential distribution. In the next section of the literature review, we will discuss demand distribution and the even more complex case of lead time – demand (LTD) distribution and how lead time and demand interact.

In the automotive industry, analysis of supplier lead times is usually discussed in conjunction with lean production and Just-in-Time (JIT) manufacturing, and the assumption that lead time is (partially) controllable. Womack, Jones, & Roos (1990) describe how more than 80% of Japanese suppliers
delivered daily or hourly as far back as 1982, while even in 1988, in the US, only 10% of suppliers delivered this frequently in 1988. They discuss how Japanese manufacturers in the US lead almost every other US industry in this respect, mentioning the Nissan plant in Smyrna by name. Nearly three decades of subsequent literature has focused on how to copy the advantages of Japanese automakers gained from short lead times and the techniques they used to get there, like close relationships with suppliers (Kraiselburd, Pibernik, & Raman, 2011). JIT applications, like Axsäter (2011) and, moving beyond Lean to Quick-Response-Manufacturing (QRM) research papers (de Treville, Suzanne, Bozarth, Cecil, Gallmann, Francesco, & Reiner, Gerald, 2014; Iyer, Ananth V. & Bergen, Mark E., 1997) often discuss lead time reductions or how to handle changes in lead time rather than analyzing and gaining benefit from information on existing lead times.

Although Womack et al. (1990) claim in their 2007 afterward that Toyota is more aggressive in terms of supplier logistics oversight than Nissan, and that this can explain their differences in financial results, Nissan North America's recent success moving suppliers on-site proves the company understands and is implementing a strategy to get shorter lead times from their suppliers. That said, Nissan calculates the cost savings of moving suppliers in house in terms of reduced transportation costs (shorter distance) rather than looking at reducing variability of lead times (which could be applied to holding less inventory).

### 3.2 Inventory and Safety Stock Policies

Brown (1959) first developed the theory of a “base” safety stock and inventory optimization based on uncertainty in demand. He explained that the most straightforward way of dynamically updating safety stock, rather than setting a level at number of parts, is to use a number-of-days-supply, which is similar to Nissan’s automated hours of supply approach. Since then, his approach has been expanded to include variation in lead time (Silver, Pyke, Peterson, 1998 and others). The equations below can be derived from the expectation of a random sum of random variables. They illustrate an approach to safety stock in the case where lead time and demand both vary:

\[
\text{Safety Stock} = k\sigma_x
\]

\[
\sigma_x = \sqrt{E(L)\text{var}(D) + [E(D)]^2\text{var}(L)}
\]

**Where:**

- **k**: service level factor
- **\(\sigma_x\)**: Leadtime – Demand joint standard deviation
- **E(L)**: Expected Leadtime
$E(D)$: Expected Demand
$\text{var}(D)$: Variation in Demand
$\text{var}(L)$: Variation in Leadtime

Bagchi, Hayya, & Chu (1986) demonstrate the significant increase in accuracy of understanding stockout risk when lead time and demand are both considered variable. Recent research on inventory policy looks to improve this basic optimization formula and apply it in the real world (Ross, 1996; Ruiz-Torres & Mahmoodi, 2010; Silver et al., 1998).

One key question in both practice and academia is the lead time – demand (LTD) distribution: What is the distribution of demand? What is the distribution of lead time? How do demand and lead time vary together and interact?

Cobb (2013), Rossetti and Ünlü (2011), and Mekhtiev, 2013) each provide good summaries of the different distribution options for lead time and demand. As discussed above in the lead time section, lead time can be considered constant, normal, gamma or exponential. Demand can be constant, normal, poisson, gamma, exponential, or lognormal. Lead time demand (LTD) can be constant, normal, lognormal, gamma, poisson, compound poisson, erlang, hermite, or negative binomial.

Moon and Choi (1998) and Eppen and Martin (1988) look at specific examples of means and variances to show that a normal distribution is not the best representation of demand. However, techniques vary in terms of how to determine correct distribution or work around determining the distribution at all: and Choi as well as Pan (2004) have tried using mini-max distributions, while Lordahl and Bookbinder (1994) used a bootstrapping approach. Ruiz-Torres & Mahmoodi (2010) revisit a reorder point model initially proposed by Estes (1973) that looks at all possible historical outcomes of demand and assigns a probability to each outcome. This approach is not only computationally complex, but unfeasible from a computing time perspective for 13,000 SKUs. In their paper, they only analyze three items.

For demand alone, it is generally accepted that fast moving items have normal demand distribution and slower moving items have poisson (Altay & Litteral, 2011; Emmett, 2005; Kocer & Tamer, 2011; Silver et al., 1998).

Ruiz-Torres & Mahmoodi (2010) argue that the traditional equation overestimates the joint variability of demand and lead time. Therefore, using that calculation could lead to holding a larger amount of inventory than is actually required to maintain service levels. Mekhtiev (2013) discusses the idea of
determining LTD in the case where lead time and demand distributions have been determined independently.

Standard approaches in the literature often include backorders or lost sales (Feeney & Sherbrooke, 1966; Zipkin, 1986). These are not relevant in the Nissan case, as these are not finished goods, but rather pre-production parts. Nissan would always expedite a part rather than have a back order.

In terms of equations to optimize, the literature suggests a few approaches (Silver, et al., 1998):

- \( P_1 \), or cycle service level: select a probability of no-stock out per replenishment cycle.
  \[ p_u(k) = 1 - P_1 \]
- \( B_1 \), minimize cost per stock-out event: If \( \frac{DB_1}{\sqrt{2\pi Q\sigma_d T}} < 1 \), \( k = \frac{2\ln\left(\frac{DB_1}{\sqrt{2\pi Q\sigma_d T}}\right)}{L} \)
- ETSOPY: minimize total stock-outs per year: select \( k_i \) to minimize \( \sum_{i=1}^{n} \frac{P_{u_i}(k_i)}{Q_i} \) subject to \( \sum_{i=1}^{n} k_i \sigma_d \sigma_l = Y \) where \( Y \) is the total safety stock expressed in dollars
- TBS: specified average time between stock-out occasions. If \( \frac{Q}{D(TBS)} > 1 \), \( p_u(k) = \frac{Q}{D(TBS)} \)

Where,

- \( D \): Demand per time unit (day)
- \( k \): safety factor
- \( L \): replenishment leadtime (days)
- \( p_u(k) \): probability that a unit normal variable takes on a value of \( k \) or larger
- \( Q \): prespecified order quantity (in Nissan terms, minRAN quantity)
- \( r \): inventory carrying charge, in $ per $ per unit time
- \( TBS \): time between stockout occasions
- \( \sigma_d \): joint standard deviation of leadtime and demand

In the chapter on our safety stock heuristic, we discuss further how each of these would be useful or not at Nissan.

Within the automotive industry, Womack (1990) points out the inventory implications of Japanese suppliers' lead time advantages discussed above, showing that in 1986, GM Framingham held two weeks of inventory while Toyota in Takaoka held two hours of inventory. Guerrero (2001) and Tranum (1995) both discuss the complexities of automotive safety stock and its differences from other industries including the enormously high cost of shutting down the line (stockout), SKU proliferation, new model
launches, and size of items / storage space. At the time of Guerrero’s writing about a Ford plant in Europe, they held about 0.9 days of inventory per part.

As early as 1963, Hadley and Whitin (1963) detailed the problems of practical application of inventory theory, listing the key challenges as relevance of the model, data problems, multi-item problems, personnel problems, procedural problems, and problems of evaluation, all of which will be discussed below. Nahmias (1979) writes “there currently exists a considerable gap between the theory and practice of inventory modeling. To a large extent the reason for this state of affairs is that the research has tended to focus on providing rigorous analyses of optimal policies for relatively simple problems rather than developing workable solutions to realistic problems.” His paper then goes on to a series of complex equations. Bagechi (1986) addresses a similar scale system to Nissan’s, the 500,000 SKUs of the Air Force Logistics Command and points out that recommended solution techniques become "computationally and economically infeasible for a larger number of items."

Although supply chain software and general computing power has improved significantly over the last few decades, these “most optimal” solutions are still not as common as the capability of computing power might indicate. Blankley, Khouja, and Wiggins (2008) demonstrate the capability of modern inventory optimization software for cost savings and Soroor, Tarokh, and Keshtgary (2009) discuss the failure modes of such software. Hayden (2014) writes on the process and challenges of implementing such software (SmartOps), including data quality in decentralized supply chains and developing the specialized skillset for multiechelon optimization internally within a manufacturing company.

Enslow (2006) points out the contemporary mismatch between the literature and practice, noting that only 13% of companies actually do multi-echelon optimization, while most do a combination of rules of thumb, like weeks of supply, or ABCD rules. Anderson (2002) colorfully illustrates this point, by describing inventory policies in practice at Qualcomm: “inventory levels were chosen based on intuition and historic levels rather than scientific analysis. One buyer often joked that he chose his inventory levels using a Magic 8 Ball.” Mauro (2008) discusses the challenges of skipping from the “Magic 8 Ball” level to best-practices in the context of Honeywell Aerospace. He writes that historically, they “had tried to implement the cutting edge in inventory practice, multiechelon inventory optimization. These efforts were met with limited success. In reviewing past implementation attempts, we decided that the organization needed to develop a foundation in inventory knowledge rather than “jumping” into what is considered best practice.”
3.3 Pooling and Queuing Theory

Literature relevant to this problem includes both traditional queuing theory and pooling models and vehicle fleet sizing / routing problems that are more transportation focused.

Bielli, Bielli, & Rossi (2011) provide a good overview of trends in fleet management, and include whole sections on vehicle routing and scheduling, dynamic fleet management, city logistics, public urban transport, dial-a-ride transport, maritime transport, air transport, and rail transport, but do not mention freight trucking. As discussed below in the overview of modeling fleet sizing, much of the literature discusses how to both select the fleet and route the vehicles. In which order do different industries do these? Can they be optimized together?

In airlines, for example, the airlines plan their fleet with a much longer horizon (20+ years) than they plan their routes or frequencies (annually and monthly). Therefore, the network is determined by the fleet, at least in the short term (Belobaba, Odoni, & Barnhart, 2009). Conversely, in this case, if Nissan is able to flex a “grey” fleet up and down with a trailer lessor, but supplier locations and the plant build schedule are relatively fixed, Nissan explicitly has already determined the basic network and routing before the fleet. The 3PL has already used optimization software, some of which is described in Katcoff (2011) to route the shipments to minimize Nissan’s costs.

As a result, fleet routing considerations did not have as much of an impact on our fleet sizing and were out of scope of the project. This thesis also diverges from much of the research because the solution to the fleet sizing problem was to be used as an input into contract negotiations, rather than an output once contract terms were set: we did not have complete information around leasing costs to input into an optimization model including costs of underage or overage. We also used a pre-determined, set schedule (demand) and network design with highly variable lead time rather than stochastic demand. Although Nissan’s trailers’ lead time is actually stochastic, we did sensitivity analyses around a deterministic model. Finally, unlike much of the research, we were analyzing the problem from a customer perspective rather than a carrier perspective. Therefore, our model conforms more similarly to inventory management analogies around service level.

There is significant academic work on modeling the Fleet Sizing Problem, or “FSP.” Bartlett (1957) looked at a fixed schedule and assumed all transportation times were exact to develop an algorithm to determine fleet size based on schedule. Koenigsberg & Lam (1976) apply queuing theory to a cyclical shuttling of natural gas tankers between two terminals to determine fleet size. Turnquist & Jordan (1986) developed a model using fully independent travel times and no schedule to determine the size of a fleet of packaging containers for GM. Beaujon & Turnquist (1991) generalize this model into a non-linear...
network optimization using vehicle arrival into a “queue” to approximate travel times. Relevant to our study and our data, they write that “decisions on fleet size involve balancing expenditures to provide capacity against the potential costs of not meeting uncertain demands on the system. This is analogous to the basic problem faced in inventory management, in which the optimal stocking policy represents a balance between the costs of carrying inventory and the costs of stockouts or lost sales.” However, they also discuss how the inventory decision interacts with the vehicle routing decision, which is less relevant because Nissan’s vehicle routing was out of scope and fixed by the 3PL.

Żak, Redmer, & Sawicki (2011) provide an overview of recent research, much of which focuses on transforming stochastic transit times and demand into deterministic linear or non-linear optimization models, and how to work in multiple stages to optimize both the network design and the fleet sizing. The more complex optimization models take into account all portions of the costs of underage and overage. Most of these papers derive mathematical formulas rather than apply the FSP to industry applications. Additionally, they are solving a one-carrier problem, rather than a situation with pooling.

The most relevant vehicle routing paper to our study is Ball, Golden, Assad, & Bodin (1983), in which the authors use network optimization to determine the size of a leased trucking fleet for a chemical company. In their work, the routing optimization was solving to minimize the size of the fleet, rather than determining the size of a fleet based on routing.

Moving towards pooling, Andersen, Crainic, & Christiansen (2009) provide a model for how fleet management, specifically sharing of assets, like locomotives, across borders can be tied to network design to maximize utilization. However, once again they use vehicle routing as a part of the solution.

Operations management research has proven repeatedly the benefits of pooling in contexts as varied as telephone call centers, bank teller waiting lines, and location pooling for inventory distribution. Combining resources lessens the impact of negative variability (a too-long call or transaction, or a jump in demand) on any one resource and provides a higher service level to the system as a whole without adding new resources. The economies of scale allow an operation to reduce customer waiting time without having to staff extra workers or reduce the number of workers while maintaining the same responsiveness (Cachon & Terwiesch, 2013). Queuing models like M/M/N/N, M/M/n/k, and G/G1/n/K are often used to model the expected benefits of pooling depending on the distribution (Gans, Koole, & Mandelbaum, 2003). These models depend on stochastic arrivals, and because we treat the Nissan network as deterministic, the model is less important than fact that queuing theory forms the basis for mathematical proof of the benefits of pooling.
There is limited research on pooling as it relates directly to freight transportation. Sherali, Hanif D (2000) writes about a project similar to ours at Nissan, in his case analyzing the correct size for a pooled fleet of railcars, managed by the railroads themselves and their automotive customers. They used historical information on transit times and daily O-D flow patterns to develop both a static model and a more complex dynamic network flow problem, and estimate that this approach saved 12-18% of the size of the fleet. Their model is not fully transferable because of the variability in "demand" for rail cars, where both the network and transit times are variable. In our case, the network is taken as a set given.

Dao (2011) writes about a 30% reduction in the State of Michigan’s Department of Environmental Quality car fleet when it was pooled between different offices. In a more similar application to trailers and at a more similar scale, the E.P.A. reports that the Port of Virginia experienced a 20% reduction in the number of container chassis required when it moved to a pooled fleet of chassis (“A Glance at Clean Freight Strategies: Common Chassis Pools for Drayage,” n.d.).

4. Nissan’s Lead Time Data

In this section, we provide an overview of the data set that drives our research. We discuss what lead time from suppliers means in this context by examining the distribution and variance of lead times on average, by supplier, and by part, and look in greater depth at a specific SKU case studies.

We had several important questions to answer, all of which were key to how the data would fit into inventory and transportation fleet analyses:

(1) What portions of lead time should be considered?

(2) How do the different segments of the lead time differ in terms of distribution?

(3) Which of these segments are dependent on Nissan’s actions and which are out of its control?

(4) How are lead times different by supplier and by part?

As discussed below, we conclude that the two most important segments of lead time are the transit time from suppliers and the time that parts spend in trailers on the Nissan yard. In general, transit time is normally distributed within a narrow band that can be predicted based on distance from supplier. Time on yard, however, varies widely. Although Nissan can chose when to unload which trailers, it generally does not practice this in any systematic way. Therefore, it must be included in calculations for inventory. Finally, we examine how, for a specific supplier, lead time can differ between parts, an essential point to understand when planning for inventory.
4.1 Description of the Data

To track shipments in progress, Nissan's mainframe computer stores each separate order for a part with a unique "RAN" number. For each RAN, we can see the quantity ordered, the date Nissan released the order to the supplier, and the due date and time Nissan has told the supplier that the part must arrive ("RAN Due"). In addition, Nissan tracks when the RAN actually leaves the supplier, when the trailer containing the RAN enters the gate of the Nissan plant, and when the RAN is fully unloaded and stored in Nissan's warehouse or plant. Inventory and transportation analysts use this data on a day-to-day basis to answer questions like "has the next shipment of Part X left the supplier yet? Should we order a special expedited shipment because it looks like the plant is going to run out?"

Once the part is in the warehouse and accounted for, they do not look back at historical RANs. We discovered that the system stores this valuable shipment information on all RANs for six months, providing a treasure trove of data on lead times by supplier, by part, and by trucking carrier, that is rarely used. Six months of RANs equates to about 1.5 million individual orders for the three plants.

In contrast to the valuable unused data on certain portions of the lead time, there is a lack of data in other segments. The data trail ends when a RAN is received in the warehouse or at the plant. Parts that must move from an off-site warehouse to the plant are not tracked by RAN. Instead, any RAN of a particular part number, no matter when it was received, can satisfy a "pick order", meaning that some RANs sit in the warehouse for weeks, while other RANs of the same part could leave that same day because there is no tracking of FIFO. Once the part is picked, there is also no tracking of when it is actually used or received at the assembly line.

Finally, transit times are tracked by RAN rather than by trailer, so, for the grey trailer fleet study, significant data scrubbing and combining is required to gain an accurate understanding of on-road and yard times, especially for suppliers served by "milk runs." Even so, the relative distributions of RANs shown below are meaningfully similar to a distribution of trailers because so many of the parts arrive in similarly sized unit load containers that would fill up a trailer.

4.2 What is Lead Time in this Context?

Traditionally, lead time is the amount of time between ordering something from a supplier and receipt of the order. However, because of the high-volume nature of automotive production combined with Nissan's contracts with suppliers, in which they are obligated to deliver by the RAN time set by Nissan, and Nissan's mainframe system of releasing RANs as soon as it has visibility into the build schedule, the time
between order receipt and supplier shipment is both not as relevant and more difficult to understand in this context.

Another key question is which time counts as receipt by Nissan. Is it the time the trailer arrives in the yard at the Nissan warehouse, or the time it is fully unloaded and documented? The transit time by truck is not in Nissan's control, but the order in which trucks are unloaded should be within Nissan's control. See Figure 7 for a diagram of the different components of lead time, including where we lose visibility into the path of a specific package.

Figure 7 Lead Time Stages

Nissan currently only considers a user inputted transit time (7 hours, for example), in planning inventory and the transportation network, while our data goes comprehensively from release order to warehouse receipt and shows all of the variability in each step of the process. Although we have visibility into some portion of time in the warehouse by looking at the difference between RAN due time and receipt, it is possible that the part is used before its RAN due time because it was delivered early or, conversely, sits in the warehouse long after its RAN due time.

A third question we asked when analyzing the data was whether we should be looking at lead time by part or by supplier. We wanted to be as granular as possible to understand suppliers that treat different SKUs differently, but at the same time, statistically, the data is more meaningful when you can include everything shipped from a specific supplier, especially for low volume parts that only might include one or two RANs.

4.3 Lead Time Averages

Our first step was to look at the data set as a whole, to get a snapshot of lead time in Nissan's supply chain. The diagram below shows the averages of six months of US and Canadian RANs at each stage of the inbound process:

Figure 8 Canton Plant Average RANs
Looking at these averages, we see that parts spend significant amounts of their journey on the yard and are received a short time before the RAN is due. It would appear that the full 24 hours parts spend getting processed at Nissan before they are due would be an area of opportunity—although it could be risky to ship that RAN on the next day’s scheduled run, perhaps a 3PL could schedule delivery for only 4-8 hours before the RAN was due, rather than allowing such a large buffer, and Nissan could manage the yard unloading accordingly. The averages, however, gloss over the full story.

The figure below shows the distribution of transit times (the time between “supplier ship” and “yard receipt”) over a three day period. The left axis is the number of RANs that were in a specific time bucket (blue bars), while the right axis shows the cumulative percentage of RANs that had arrived a certain number of hours after they had shipped. This distribution is almost entirely based on the geographic spread of Nissan’s suppliers shown in Figure 1. The longest transit times (more than 72 hours) make up about 5% of the total and generally include parts shipping from places like California.

The next figure shows the number of hours each part spends on the yard (the time between “yard receipt” and “warehouse receipt”). Although the average is under 24 hours, there is a very long tail and about 6% of part orders actually spend more than 72 hours, or three days, sitting on the yard. 81% of RANs are received within four hours on the yard and 30% within two hours.
By adding together these two segments, we can look at the full period between when a part leaves the supplier and when it is put away in the warehouse.

Finally, we move to examining at when parts are received in the warehouse compared to when they are due ("the RAN due"). As initially conceived, this should have represented the time the parts spend in the warehouse. Although the average from above shows a time of 1.4 hours, which seems reasonable, Figure 12 shows the massive variation. The negative numbers denote the number of hours after a part is due that it actually arrives. On the other side, the high positive numbers show parts that are delivered early. About 4% are more than three days late and about 3% arrive more than three days early.
It would seem troubling that almost half of all parts are received in the warehouse after they are due. However, in thinking about why parts would be late, we must consider two potential reasons:

1. Supplier is not reliable (therefore should add more safety stock)
2. Nissan had the parts on a trailer in the yard and did not unload them in a timely fashion.

To investigate which of these was more typical, we looked at the time between receipt on the yard and RAN due. In Figure 13, we see clearly that more than 80% of parts arrive to the yard before they are due. This means that the receipt-to-RAN-due metric is more about yard efficiency than time spent in the warehouse, a place where the gap in information continues.

Parts that arrive late, by this metric, fall into two categories: either they were not actually needed yet and therefore it is to Nissan’s benefit to not have to take ownership and store them, or, they were required and an expedited shipment was arranged to send more. The second group, the late ones, would then be stored...
in the warehouse. This would not actually add to warehouse space requirements in the long term because the computer would know the inventory levels and not order more.

Figure 13 shows that a large majority of parts arrive early, before they are due. More than 30% arrive a full 24 hours before they are due. These parts both affect warehouse space because Nissan must allocate space to store them and simultaneously affect trailer requirements because the parts not unloaded (early parts in Figure 12) require storage on trailers. If Nissan were to adopt a policy of not unloading trailers until the part was due, that would significantly increase the number of trailers required. However, if Nissan were to unload every trailer when it comes in, that step would significantly increase the warehouse space required. A key tension in this thesis is the trade-off between trailers required and warehouse space required.

4.4 Individual Lead Time Case Studies

Our next step to more fully understand Nissan's processes and the data collected on lead time was to do time studies on specific parts, selected at random. Going to the warehouses and talking to the trucking carriers not only gave us insight into the process; it provided valuable contacts for the rest of our research.

In Figure 14 below, we follow Part A shipping from City X in Michigan to the Canton, Mississippi plant. It is a sealing assembly used on the Armada at a rate of about 3 per hour, or 1/3 of a container per day, and the supplier is served by a milk run once per day. The circled times are the ones we can see for all RANs from our data set, while the additional detail comes from our calling people at the cross dock that day (i.e. "around lunch") and sitting in the warehouse watching the team unload the trailer. While trailers are on the yard, they are tracked using GPS based RFID tags, but historic data on trailer locations is not stored.

Figure 14 Part A RAN Time Study

To summarize the figure, the actual transit time was 22 hours and 28 minutes and the RAN spent 13 hours and 8 minutes on the yard and being unloaded, for a total time of 35 hours and 36 minutes.
According to the data in the mainframe system that the Nissan team uses for decision making, the "Transit Time" is set to 35 hours. At first glance, it seems as if this is close to our total, and therefore the system "Transit Time" is calibrated to include both time the truck is on the road and yard/unloading time. However, when we asked more questions, we discovered that the 35 hours was meant to be just our "Actual Transit" of 22.5 hours, calculated based on miles, speed limits, and mandatory driver rests. The reason it was so much shorter in reality was that the trucking carrier had added a "Relay" point, or a place where the drivers would switch to continue driving on through the night.

This RAN was due on Day 3 at 8:20am, meaning it was fully received 9 hours and 37 minutes before it was due. It was on the yard almost 24 hours before it was due, but not a full 24 hours, meaning that it could not have gone on a shipment one day later without being late.

Based on the inventory of Part A in the warehouse, we determined that, if the system were fully FIFO, the RAN we tracked would not have been picked for another 12 days. The time between supplier shipment and use on the line could be as long as 14-15 days, hardly a leading "just-in-time" automotive supply chain. We return to this same Part A in our discussion of safety stock and how it came about that there was so much inventory.

The next thing to look at using a time study was a specific "pick," or movement from off-site warehouse to the plant. Because we were standing there in the warehouse watching, we could use the RAN number on the packaging to track specific parts back to their original shipment. However, this is not tracked in the IT system, and the RAN due date of a specific container bears no relationship to when it will be picked. In Figure 15 below, we follow parts B and C, both part of the same pick order, due at the plant at 3:15pm on Day 3. They both shipped from their suppliers near the same time, although Part B is coming from Michigan, much further away than Part C from Tennessee.
There are two key things to note in this chart: first of all, Part B is picked long before its RAN due time. Looking at the inventory of Part B in the warehouse on Day 3, we see this as a clear example of failure of FIFO, as there were several Part B RANs that had arrived days before that were left in the warehouse. Second, we see that the warehouse has begun staging the pick almost eight hours before it is due at the plant. After sitting in the yard on the way in for over seven hours and over three hours respectively, Parts B and C return to the yard for another almost three hours on Day 3. While FIFO may not seem as obviously essential in car parts as more perishable goods, it is considered a priority for several reasons. First, the longer a part sits in a warehouse, the more at risk it is for damage, from a forklift, for example. Second, FIFO allows for tracking of supplier defects or small engineering change management. Third, a small percentage of products do decay over time or in heat, like sealants for doors. The decision for Nissan and other automakers to make regarding FIFO is how close to perfect FIFO is worth the additional costs in terms of touches, space, and management software.

The final leg of the process, from the Pick to use on the line, was very difficult to study because of the enormous variety of line-side storage techniques and lack of data. Nonetheless, we walked along various parts of the assembly process and looked at both the RAN labels and Pick tickets to get a general sense of how things worked. For the most part, we saw containers picked that day or the day before. However, there were several instances of Picks and RANs from months before.

Going to the floor and studying specific case studies was a very important input to our process because it illustrated in clear terms the enormous variability in Picks and RANs, something we could not see from
our data in the computer because there was no connection between Picks and RANs. Additionally, showing management specific examples of processes helped illustrate the broader points.

### 4.5 Distribution Case Studies

While we did not attempt to analyze the distributions individually for all of the more than 13,000 parts or more than 400 suppliers, we saw generally that for a specific supplier or part, the actual transit time followed a fairly normal distribution, in a narrow band with relatively low standard deviation. Conversely, the amount of time on the yard varied quite widely and had little relation to the supplier. Although we hypothesized that suppliers with a higher frequency of shipments per day (for example 10 shipments) were more likely to be unloaded quickly because the network was designed so that they had to be, this did not prove to be the case. There is a long right tail in almost every instance of the data.

In this section, we analyze three separate part-supplier pairs, each with different characteristics. The first is a supplier that ships once per day and a part with medium usage that makes up a low percentage of its shipments. Next, we look at a supplier that similarly ships once per day, but a high volume part that comprises the majority of the shipments from its supplier. Finally, we look at a fairly high volume part from an extremely high volume, local supplier.

These three suppliers and three part numbers are meant to serve as an illustration of the categories of parts and suppliers that make up a majority of Nissan’s network. The conclusions we describe below and the opportunities identified are generalizable to hundreds of other parts.

For each histogram, we select buckets of identical size for Ship-to-Yard and Yard-to-Receipt. The buckets are selected with the goal of best illustrating the data and are identical for each Part and Supplier. The buckets for total Ship-to-Receipt are the sum of the two earlier buckets. The cumulative distribution function allows for comparability across all of the examples.

The first part is the same Part A from the time study. There were only ten RANs of this part in the month studied and their distribution is shown below. We see, as expected, that the coefficient of variation is significantly higher for yard-to-receipt than for ship-to-yard. This difference affects the distribution of the total ship-to-receipt.
Most of the ship-to-yard times are in the band we observed during the time study, as is the yard-to-receipt. It is interesting to observe how many RANs had significantly higher times in the yard than we saw in our specific case. Therefore, although ship-to-yard is skewed to the left, total ship-to-receipt seems more evenly distributed. One potential explanation for this is that ship-to-yard and yard-to-receipt are not independent: a trailer that arrives early to the yard could end up waiting for a longer time to be unloaded because there are no urgent RANs. Because there are only ten RANs, we looked more closely to see if this hypothesis is true in this case: of the three longest ship-to-yard times, only one of these had a yard-to-receipt on the shorter end, illustrating independence of ship-to-yard and yard-to-receipt.
Looking at Supplier A as a whole over this time period, we see it had 176 RANs of fifteen different products. It is important to note that there were some journeys that took a quite a long and statistically significant time in the yard-to-receipt process, causing the RAN to be late. Looking deeper in the data, we see trailers that were left on the yard as long as ten days with 22 RANs on the yard for more than 180 hours.

Figure 17 Supplier A Lead Time Distributions (In Hours)

<table>
<thead>
<tr>
<th></th>
<th>Ship to Yard</th>
<th>Yard to Receipt</th>
<th>Total Ship to Receipt</th>
<th>Receipt to RAN Due</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>30.1</td>
<td>52.7</td>
<td>82.8</td>
<td>(17.3)</td>
</tr>
<tr>
<td>Median</td>
<td>25.5</td>
<td>19.5</td>
<td>52.4</td>
<td>1.0</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>12.3</td>
<td>63.9</td>
<td>63.9</td>
<td>69.6</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>0.4</td>
<td>1.2</td>
<td>0.8</td>
<td>na</td>
</tr>
<tr>
<td>Min</td>
<td>23.5</td>
<td>13.8</td>
<td>43.4</td>
<td>(13.9)</td>
</tr>
<tr>
<td>25%</td>
<td>25.5</td>
<td>19.5</td>
<td>52.4</td>
<td>1.0</td>
</tr>
<tr>
<td>75%</td>
<td>30.8</td>
<td>68.1</td>
<td>100.5</td>
<td>21.1</td>
</tr>
<tr>
<td>Max</td>
<td>85.4</td>
<td>258.8</td>
<td>281.6</td>
<td>49.4</td>
</tr>
</tbody>
</table>

Comparing to Part A, the distribution is quite similar and the coefficients of variation are about the same at a supplier level and at a part level. Because they are so similar and there are so few data points for Part A, we would conclude that for parts in this category (low delivery volume, low percentage of supplier volume), it would make sense to use lead time information collected by supplier.
The next example, Part D, is a higher volume, more frequently used part, an air duct assembly shipped from Ohio. There is one shipment per day between this supplier and Nissan and the daily average usage at the plant is 23 containers. In this time frame, there were 67 RANs ordered to the Canton plant, of which 13 were received at the plant after the RAN due time.

Figure 18  Part D Example Lead Time Distribution (Hours)

<table>
<thead>
<tr>
<th></th>
<th>Ship to Yard</th>
<th>Yard to Receipt</th>
<th>Total Ship to Receipt</th>
<th>Receipt to RAN Due</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>34.2</td>
<td>18.3</td>
<td>52.5</td>
<td>15.2</td>
</tr>
<tr>
<td>Median</td>
<td>27.7</td>
<td>12.0</td>
<td>44.5</td>
<td>10.2</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>16.2</td>
<td>18.9</td>
<td>21.3</td>
<td>17.5</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>0.5</td>
<td>1.0</td>
<td>0.4</td>
<td>1.2</td>
</tr>
<tr>
<td>Min</td>
<td>26.6</td>
<td>7.4</td>
<td>36.7</td>
<td>3.7</td>
</tr>
<tr>
<td>25%</td>
<td>27.7</td>
<td>12.0</td>
<td>44.5</td>
<td>10.2</td>
</tr>
<tr>
<td>75%</td>
<td>30.4</td>
<td>24.2</td>
<td>58.7</td>
<td>19.7</td>
</tr>
<tr>
<td>Max</td>
<td>79.6</td>
<td>92.3</td>
<td>118.9</td>
<td>63.1</td>
</tr>
</tbody>
</table>

Compared to Part A, Part D displays a more clustered both ship-to-yard and yard-to-receipt. None of its shipments experienced as extreme times on the yard as Part A.

From this same supplier, there were 120 RANs of 5 different part types, including the part above. Part D is a bigger percentage of Supplier D's total shipments than Part A was of Supplier A.
Here we see that the yard-to-receipt data is quite different on a by-part versus by-supplier level. The coefficient of variation by supplier is almost twice as large. Which, then, would be a better way to think about lead time for Part D? There are more data points looking at the supplier data, but it also could include abnormalities that Part D did not experience itself. Because Part D has a statistically significant number of data points, we conclude that lead time for parts like Part D should be considered independent of lead time aggregated by supplier.

Finally, we look at Part E, which is an example of a part quite different from Part A or Part D. Supplier E is an extremely high volume supplier located just a few miles down the road from the plant. Parts are delivered 18 times per day, or about once every hour and a half. Of Supplier E’s 12,512 RANs during this month, there are 349 RANs of Part E.
The coefficients of variation in this case are quite large, and time on the yard is the majority of the time between supplier and plant. For parts like this, it becomes obvious that even if time on yard is within Nissan’s control, not including this time in calculations of lead time for inventory optimization would be to severely underestimate and under calculate lead time.

For Supplier E below, the results are quite similar to Part E, except there are more RANs on the extreme end (weeks on the yard). At first we would assume that these are entry errors or bad data, but looking more closely, it becomes clear that these RANs were on trailers that “got lost” on the yard or were partially unloaded and then, without any documentation, put back on the yard until they were found months later. Situations like this one are discussed in greater depth in the grey trailer fleet chapter as a potential “bad path.”
To summarize our conclusions from these examples and in-depth looks at a much larger number of similar parts with these sorts of characteristics, we decided that if there are a large number of RANs in the time period for a part, it is worthwhile to use lead time data by part rather than by supplier to account for different behaviors related to different parts. However, if there are only a small number of RANs, it is more statistically significant to look at all shipments from a supplier.

We also conclude that yard time was fairly independent of transit time and makes up a large proportion of the lead time for many parts. Therefore, not including it in our analyses would underestimate both parts and trailers required. Moreover, it is essential to understand the impact it has on other processes and worthwhile to break it out to illustrate the savings opportunities from reducing yard time.
4.6 Key Opportunities Identified

Simply by parsing the lead time data set and examining it under several lenses, we could identify several opportunities, some of which will be quantified further in the next two chapters.

- Inventory spends significant **time on the yard**. While there, Nissan is incurring holding costs because the suppliers have already delivered the inventory, Nissan is paying the trucking companies for the trailers, and the yard crowding decreases efficiency of other operations. Inventory time on the yard does not add any value to Nissan's supply chain process.

- Suppliers often **deliver early** before they are due, meaning that we can identify one of the reasons Nissan's warehouses are fuller than expected simply by looking at lead time data. If suppliers were not allowed to deliver materials before they were due, a practice currently enforced by Nissan in the UK, Nissan would also be able to lower holding costs and reduce warehouse crowding.

- The warehouses **pick** eight to ten hours **ahead** of the time a part is required at the plant, regardless of how close the warehouse is to the plant, thus making parts spend time on the yard again. Reducing this “pick ahead” time is a way of reducing overall lead time for the assembly line and lowering inventory.

- The process is **not traceable** end to end from RAN to Pick. Not only does this mean **FIFO is not enforced**, but Nissan also **cannot measure** dwell time in the warehouse, throughput, or other important KPIs for improving inventory flow. Because this is not measurable, we cannot quantify the savings, although we assume they are significant. This is certainly an area for future study for Nissan.

At the outset of the study, the supply chain team had heard anecdotally about many of these opportunities, but didn't really understand the magnitude of the problem until I showed them the data. For example, they knew the yard was crowded with trailers, but didn't realize that for some parts, the majority of their time en route to the line was actually on the yard waiting to be loaded or unloaded. They also knew that they were incentivizing suppliers and a 3PL to fully utilize the cube capacity of the trailer, but had not considered that this could lead to RANs being delivered earlier than they should and clogging the warehouse. Examining the mix of RANs on each trailer and comparing this mix to trailer cube ratio is an area for further study.
5. **Application 1: Safety Stock**

Because Nissan was in the process of constructing new consolidated warehouses, as discussed in the Project Motivation, understanding and optimizing inventory levels was a key goal of this project. We created a tool to set safety stock and collected original research data on the performance of this tool via two pilot tests. In this section, we will demonstrate that a systematic approach to inventory, even one using fairly simple calculations, outperforms rule-of-thumb approaches, and we will also demonstrate and quantify the value of using lead time data within this approach. Using such a tool helps eliminate non-strategic variability in safety stock due to not having a set process, while retaining the flexibility to include many types of considerations by part. Our heuristic tool includes several elements related to quality, delivery times per day, storage space requirements and inventory loss that are essential to include in the automotive context, but are difficult to quantify into more academic formulas.

Our research identifies more than $2.5MM in immediate cost saving opportunity, including reductions in inventory and expedited shipments. The tool also helped us to quantify potential process improvements that would create additional savings of almost another $5MM in inventory, including reducing trailer time on the yard and lowering pick-ahead time in the off-site warehouses.

5.1 **Methodology and Approach**

In order to answer the question of how much inventory belongs in the new warehouse, we started with the lead time data and worked with the team at Nissan to create a heuristic tool. From a business perspective, it was essential to understand and work within the current situations and existing processes and use data from our tests to prove the efficacy of our tool. From a supply chain and operations management best practices perspective, we were able to analyze the results and tweak the tool based on clear understanding of inventory policies.

Understanding Nissan's current situation included both documenting the existing process (who was involved? what did they do?) and the actual levels of safety stock on both an aggregate and by-part level that resulted from that processes. Next, we met with managers across departments to understand the goals for a safety stock tool, and created a prototype based on the input we received. We tested this first heuristic in a 25-part pilot test, analyzed the results, and tweaked the algorithm to improve the metrics for a second 100-part pilot test. Finally, we worked to make our concepts and know-how transferable, so that our safety-stock tool could go on to be implemented more widely within Nissan North America.
5.2 Current Condition

5.2.1 Safety Stock Setting Process

Nissan does not use a set process or methodology for determining safety stock. Instead, it sets safety stock manually, relying on a few individuals' years of acquired knowledge to determine the number of hours of inventory on-hand ("float") for each SKU that the system will use for ordering. Senior managers dubbed this process the "WJK" or "We Just Know," approach because the inventory experts would look at a part number and say something like, "oh, that should have 100 hours of float." From a personnel perspective, these trusted experts operate independently from their managers with little systemic or institutionalized transparency into their reasoning.

Some of the literature (Enslow, 2006; Kanet, Gorman, & Stosslein, 2010) provides a progression from simplistic safety stock policy to the most optimal, cutting-edge multi-echelon inventory optimization programming. In Figure 22 below, I created a diagram to map out these policies, versus the processes used to calculate inventory levels for each one. The star denotes Nissan's current condition: float levels are integrated into the MRP, calculated dynamically by hours of supply rather than number of parts, and segmented by part. These are nonetheless far from optimal, not calculated whatsoever within the MRP, Excel, or optimization software. The arrow shows the direction companies move as their inventory policies grow more sophisticated. Moving along this axis should correlate positively with higher service levels and reduced costs. Mauro (2008) and Anderson (2002) both describe the difficulties of jumping steps and managing process change.

Figure 22 Safety Stock Policy and Process Sophistication

At Nissan, it was generally acknowledged that the people who set float in Smyrna were more experienced than those in Canton. Therefore, we started by interviewing the Smyrna team. They provided a long list of factors they consider in their head before coming up with that “100 hour” number, including average
daily production usage, transit time from supplier, criticality of part, daily deliveries from supplier, 
scrappage and loss, quality issues, price of the part, space required per package, and warehousing 
location. The first two factors are the most obvious, average demand and lead time. The number of daily 
deliveries from the supplier and the warehouse location also play into lead time, while scrappage, loss, 
and quality issues could be considered part of demand (i.e. the plant actually needs more than the 
production usage because some will be thrown away or lost). Finally, the criticality, price, and space 
required all relate to weighing the cost of a stock-out (shutting down the assembly line or ordering an 
expedite) with the cost of holding additional inventory, in terms of dollars or space.

When we talked to the people in the same role in Canton, they referred us to two documents: 
"Establishing Safety Stock Levels (=Float=Operational Reserve)," and "Determining and Setting Float 
Levels," both created by Nissan's supply chain team, the first in 2004 and the second in 2013. Although 
the Smyrna team had never heard of either of these documents, they provide deep insight into the mindset 
and training methodology for teaching people the "WJK" methodology. These are valuable examples of 
the sophistication of safety stock thinking in industry, however removed it seems from academic 
formulations. In addition to observations below, I've included excerpts from both in the appendix.

The 2004 document is written in a conversational tone and starts with the following introduction: "The 
primary mission of Supply Chain Management is to provide a steady flow of materials to the assembly 
lines to support production schedules... Material Handling and Inventory Control activities are aimed at 
not running out of parts on the assembly lines" (emphasis in original). It goes on to say that "safety stock 
strategies will come with experience, and be different for each plant," and that "this paper will try to give 
advice and strategies learned over the years at the NNA facilities, but each plant and analyst will have 
different situations to contend with." It explains the concept of safety stock in easy-to-understand terms. 
In addition to the factors listed above, it says analysts should also think about rack capacity (how many 
packages can actually sit line-side), the number of line-feed locations (if a part is used on multiple lines, 
for example, and you need to have one container of it at each location), and the delivery method to the 
line ("Establishing Safety Stock Levels (=Float=Operational Reserve)," 2004).

The 2013 document is shorter and more direct, claiming its purpose is "to provide a procedure to 
determine and set floats to accurately and efficiently maintain inventory levels." It goes on to list factors 
to take into account when determining safety stock, although it provides no procedure to take these 
factors into account. In addition to what we heard verbally from the Smyrna experts and those from the 
2004 document, it adds for the first time the concept of variation in demand and lead time. It asks "is the 
usage consistent or does it fluctuate?" and "is it a consistent or varying supplier?" (Hoey & Weller, 2013).
Figure 23 buckets the factors Nissan's inventory analysts consider qualitatively against the related quantitative academic inventory policy calculations. Although they provide no calculations, they not only explain in simple terms all of the relevant factors but also include additional considerations that are not typically discussed in the literature. These serve as examples for explaining inventory policies and trade-offs to operators without an academic background.

Figure 23 Comparison Between Academic Inventory Policy and Nissan's Current Condition

<table>
<thead>
<tr>
<th>Academic Inventory Policy</th>
<th>Nissan Current Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand</td>
<td>Daily scheduled production (on date of float decision)</td>
</tr>
<tr>
<td>Lead Time</td>
<td>Transit Time (system entered)</td>
</tr>
<tr>
<td>Demand Variation</td>
<td>Scrappage / Loss</td>
</tr>
<tr>
<td>Lead Time Variation</td>
<td>[Variation in a general sense]</td>
</tr>
<tr>
<td>Service Level (k-value)</td>
<td>Part criticality</td>
</tr>
<tr>
<td>Other</td>
<td>Rack capacity</td>
</tr>
</tbody>
</table>

The comment in the 2004 document that the aim is to "not run out of parts" echoes the sentiment we heard repeatedly: the inventory analysts are incentivized to make sure there are always enough parts because they get blamed if there is a stock-out. Although the documents explain why holding too much inventory can add costs and take up space, there is no feedback loop for these costs to be traced back to the inventory analysts.

Additionally, although these analysts are the only people who theoretically should be changing float, the mainframe system allows many others to manually enter a number of hours. In practice, a material handler on the dock who has been chastised for not being able to find a part can ensure in the future that he will have more than enough by going into the mainframe and increasing the hours of float. This creates a vicious cycle, shown in Figure 24 below, because the higher floats are set, the more crowded warehouse space gets, and the more difficult it is to find inventory, leading to more losses, and again incentivizing
the worker who cannot find the part to increase the float. As more parts come in than the warehouse can handle, the team creates work-arounds, putting material wherever there is room, rather than in its designated spot, where they could find it, or leaving it on the yard in an unknown trailer.

Finally, the inventory analysts do not systematically go through each SKU or each supplier once a month or once a quarter. Instead, they react to issues as they arise, so float levels could remain far above what is necessary for years before someone notices.

Figure 24 Inventory Loss Vicious Cycle

Because so many parts go to an off-site warehouse before they are brought to the line in the plant, there are actually two steps: the “float” as described above, and the “order point,” which is essentially the same as float except that it represents the safety stock held in the plant. If the number of parts is projected to go below the order point, a “pick” is generated to the warehouse. Because the float has to be higher than the order point (otherwise there would be no parts to pick), inventory analysts can raise the order point like the vicious cycle above, and this also drives the float up.

Based on our analysis of the process, we identify several key opportunities for improvement:

- Develop a systematic process for setting float and order point
• Add real quantitative data on variation in lead time and demand into float process
• Manage control over who can change float in the system
• Cultural emphasis on reducing inventory and its benefits

Below we describe how we tackled each of these, and the challenges in creating change.

5.2.2 Results of Current Condition Inventory Policy in Specific and Aggregate
Because the motivation for the project was to help the Canton plant move toward the "Want-to-Be-Condition," we next tried to assess what the current condition in Canton was.

A first pass was to compare Canton's average float levels to those in Smyrna. While there are differences between the two plants in terms of products and distance from suppliers (Canton is further south), this provided a benchmark as we worked both to create a policy and sell key stakeholders in Smyrna on its implementation. Taking a simple mean of float by SKU, average float in Canton was 13 more hours than average float in Smyrna. If you removed low-usage parts (in Smyrna set to 450 hours, in Canton set to anything between 3-450 hours), the average float in Canton was 22 hours higher, a metric that easily explained to senior management how a safety stock improvement could help storage and inventory loss issues in Canton without causing more stock outs.

Next, we looked to understand the service levels, as proposed by the current float levels, but first we had to make decisions regarding lead time and demand. Demand varies based on the mix of models and options Nissan will build as well as the number of shifts the plant will be running that week. Typically some lines run five days per week and others run six days, but occasionally a Sunday could be scheduled in order to make up for underbuild earlier in the week. Figure 25 below is an example of demand data by part number (numbers changed to preserve proprietary information). We see that for some parts, demand is quite steady, while others vary widely.

Figure 25 Illustrative Snapshot of Demand Data
In the next section of analysis, we make the simplifying assumptions that demand and lead time both vary normally. This assumption worked well from both a technical perspective, because this is the most common distribution used in inventory and safety stock calculations per academic literature and because it was easy to explain to the Nissan management team.

Figure 26 shows the k-value, or safety factor, calculated in three different ways. First, we ignore variation in lead time entirely and solely consider variation in demand. Next, we use the joint-variation formula below to look at implied safety factor using lead time as either solely “Ship to Yard” or the combined “Ship to Receipt,” which includes both time in transit and time on the yard.

\[
\text{Safety Stock} = k \sigma_x
\]

\[
\sigma_x = \sqrt{E(L)\text{var}(D) + [E(D)]^2\text{var}(L)}
\]

Where:

- \(k\): service level factor
- \(\sigma_x\): Leadtime - Demand joint standard deviation
- \(E(L)\): Expected Leadtime
- \(E(D)\): Expected Demand
- \(\text{var}(D)\): Variation in Demand
- \(\text{var}(L)\): Variation in Leadtime

**Figure 26 Canton Distribution of Safety Factor Levels by Part**

For reference, a \(k\) value of 0 implies a 50% probability of running out of a part during the lead time, 0.5 implies a 31% chance, 1.0 a 16% chance, 1.5 a 7% chance, 2.0 a 2% chance, and 3.0 a 0.1% chance.
Anything about 3.0 is a service level of over 99.9%. Since we know that Nissan does not come close to a 99.9% service level, we can see that lead time variation is important to consider. Now comparing the red and green bars, we see that both show a wide range of safety factors, with lower service levels implied for when considering the total joint variation from ship to receipt. The differences in safety factors can be explained by two metrics: (1) other part characteristics beyond lead time and demand distribution, like quality holds or part criticality, and (2) lack of a process to make sure float levels stay in a reasonable range if demand characteristics change. There are opportunities to improve service level (and decrease expedited shipments) by increasing the safety factor of parts on the low end, and opportunities to cut down on inventory holding costs and space requirements by reducing the safety factor of parts on the high end.

A final way both to understand the current condition for our own research and heuristic development and to illustrate the problem to management (and obtain their buy in) was to do case studies on specific parts. For example, the daily average usage for Part A (the one we followed in terms of its transit time above) was approximately 90 (about 5 per hour), the float was set at 150 hours (about six days), and the order point was set at 33 hours. Because one package contained 200 parts, it was picked from the warehouse about every two and a half days. The inventory at the time that RAN arrived was 800, or four packages. A float of 150 hours at 5 parts used per hour would predict 750 parts in stock which makes sense, but seems quite high given that it will take nine full days to use the 1,000 parts in stock after that RAN and the supplier ships every day. From a holding cost perspective, each part cost $3.88, so a package of 200 cost $776. The implied k-values for part A were 70.6 not taking into account lead time variation, 6.6 based on ship to yard, and 3.8 based on ship to receipt. All three of these were much higher than a rational tool based on service level would have recommended.

5.3 Development of Algorithm

Our goal was to create an algorithm that simultaneously reduced inventory holding costs in terms of both space and dollars, while decreasing expedited shipments for stock outs. The simplest approach based on safety stock theory is to set specify a safety factor K. However, we wanted to avoid making changes that were too drastic or that the experts would say created unreasonable float levels. Because the current condition implied k-values spanned such a wide range, when we calculated the recommended floats based on these metrics, many results were so far from what the experts were comfortable with that getting buy-in would be difficult. Additionally, although using the k-value included more accurate demand and lead time data than the WJK method, it excluded valuable inputs that differ by SKU around cost and criticality.
As discussed in the literature review, research recommends a few approaches that could incorporate more of these factors (Silver et al., 1998):

- **P₁**, or cycle service level: select a probability of no-stock out per replenishment cycle.
  \[ P_{u_2}(k) = 1 - P_1 \]

- **B₁**, minimize cost per stock-out event: If
  \[ \frac{DB_1}{\sqrt{2\pi Qv\sigma_x}r} < 1, k = \sqrt{2\ln\left(\frac{DB_1}{\sqrt{2\pi Qv\sigma_x}r}\right)} \]

- **ETSOPY**: minimize total stock-outs per year: select \( k_i \)s to minimize \( \sum_{i=1}^{n} \frac{D_i}{Q_i} p_{u_2}(k_i) \) subject to \( \sum_{i=1}^{n} k_i \sigma_x v_i = Y \) where \( Y \) is the total safety stock expressed in dollars

- **TBS**: specified average time between stock-out occasions. If \( \frac{Q}{D(TBS)} > 1, p_{u_2}(k) = \frac{Q}{D(TBS)} \)

Where,

- **D**: Demand per time unit (day)
- **k**: safety factor
- **L**: replenishment leadtime (days)
- **p_{u_2}(k)**: probability that a unit normal variable takes on a value of \( k \) or larger
- **Q**: prespecified order quantity (in Nissan terms, minRAN quantity)
- **r**: inventory carrying charge, in $ per $ per unit time
- **TBS**: time between stockout occasions
- **\sigma_x**: joint standard deviation of leadtime and demand

That list of equations allowed the management team to select a goal that made sense in the context of their business: in the automotive industry, stock-outs are disproportionately expensive because the line needs to shut down, so it makes sense for managers to say we need to minimize stock outs, either by setting a target time between stockout occasions or designating a cost to assign to a stockout that would be weighed against the cost of keeping the part in the warehouse (Guerrero, 2001; Tranum, 1995). Other options related to costs per unit short, demand satisfied directly from shelf, and expected total value of shortages per year were harder for managers to conceive of a target and not relevant in the automotive context, so we did not pursue them further (Silver et al., 1998). Costs per unit short (B2) uses a fractional charge per unit, decided on as an input, like cost equal to 25 percent of unit value, and is often used for finished goods inventory. On an assembly line, the cost of a unit short is totally unrelated to the specific part's value, and instead is tied to the cost of an expedite or shutting down the line. Similarly expected total value of shortages per year is time-based rather than part-value based in the automotive context. For percentage of demand satisfied by shelf, a manager would respond that “all demand must be met,” either by parts in the warehouse or via an expedite.
Although we considered optimizing by P1, B2, ETSOPY, and TBS, we chose not to do so for two reasons. First, the team struggled to define exactly what costs were in terms of cost of stock-out and holding costs. Was the cost of stockout ordering an expedite (about $2,000), or was it instead shutting down the assembly line (millions of dollars)? While everyone understood intuitively that cost of stockout was essential to determining safety stock, there was little agreement on what to use. In terms of holding costs, what was the cost of a square foot of warehouse space? How should this be weighted with traditional dollar holding costs? Second, it was important that the end-users, the inventory analysts, could understand and tweak how the float level was calculated, rather than it being a "black box." The formulas listed above are intimidating for someone with only a high school education, and using Lagrange multipliers and partial derivatives to figure out the ks for ETSOPY is not a process easily taught.

Next, we examined a template of rules-of-thumb that had been created, but never applied for Smyrna. We modified it slightly after consultation with the Canton team, used real lead time from data rather than the user-inputted lead time, and added in service level collars. It works by choosing the maximum number of hours from the three buckets identified in Figure 27, then applying a maximum and minimum service collar based on calculated k-values. Therefore, it does not needlessly go to a 99.9999% service level, nor does it fall below a reasonable level. We set the k-value collars for the first test as 0.5 and 3.0. The algorithm is hardly elegant, but met the requirements of looking at space and holding cost as well as "making sense for the user." Because this algorithm had already been developed, it sufficed as a starting point. Applying the heuristic to all of Canton's parts, it recommended reducing float for 92% of them and brought the average float to only 1.5 hours higher than float in Smyrna.
5.4 Pilot Test 1

5.4.1 Design of Experiment
To validate the algorithm, we selected a group of 50 parts, all going to one dock in Canton. We split the parts into two 25-part groups, one a control group where float would remain constant, and the second a test group where we would apply the newly recommended float. The parts for each group were selected to include a similar mix of volume, size, locations, shipment frequencies, and expedite history. Where we could, we selected essentially the same part for both the control and the test group by putting the part for the left side of the car in one group and the part for right side in the other group. These two parts should have the exact same usage and same transit times from the same supplier and we could measure the effect of float on inventory.

We designed the experiment to include a test group and a control group rather than comparing the test group against its own historical performance because the Canton Plant had experienced severe underbuild and operational issues unrelated to inventory levels in the month before the test which would have made the data difficult to compare.

Before the test began, we estimated that test group inventory cost would go down by 14%, space required would be reduced by 11%, and service level overall would increase by 5%, hopefully reducing expedites. Of the 25 parts, the algorithm actually recommended float increases on 15 of them, and on these 15 parts,
the service level increased by an average of 14%. We calculated increases in service level by looking at the implied k-value of the recommended float. To ensure that our data was as accurate as possible, we counted all of these parts before the start of the test period.

Figure 28 below shows the distribution of the control group and the test group by number of hours. For most of the test group, the number of hours of float moves just a small bit away from the diagonal line. However, for two parts, the hours go up dramatically. Both of these were parts with a large order/container size (out of scope to adjust for this project) that were used very infrequently, less than one part per day.

**Figure 28  Pilot Test 1 Float Hours Distribution**

Using a similar format, Figure 29 below shows the cost of inventory in float for the test group and the control group. For many of the cheaper, low dollar value parts, we see that the new float increases the cost, adding safety stock against expedites without significantly increasing costs. Conversely, as the price per part goes up, the safety stock in float goes down below the diagonal line of the control group.
The next figure looks at implied k-values based on the float level and our calculations of lead time and demand. As discussed above, we had put a collar on safety factors so that they could not go above 3.0 or below 0.5. For most of the parts, the k-value increases. The only part for which it decreases significantly (3.03 to 1.12) is a part where the supplier delivers seven times per day and there had not been inventory losses or quality problems.

Finally, Figure 31 shows our calculations of space requirements to store the inventory in float. To calculate space, we not only had to take into account unit load container size, but also estimate how high the containers could be stacked on a shelf or on the floor. Therefore, this chart looks like it has fewer dots.
than the others because so many of the container sizes are standardized and we assumed that each of these standard containers could be stacked to the same height.

**Figure 31**  Pilot Test 1 Storage Space Distribution

![Figure 31](image)

Figure 32 below summarizes the frequency of each of the selection criteria used to select the appropriate float level. As you can see, the “Dynamic Space” calculation was never actually used, we eliminated it for Pilot Test 2. About half of the parts would use a safety-factor based float while the other half was using the heuristic and rules of thumb.

**Figure 32**  Pilot Test 1 Selection Criteria Frequency

![Figure 32](image)
5.4.2 Business Execution Challenges

The hardest part of the test to get buy-in on was actually increasing the float on those 15 parts. Many of them had a history of expedites, were very low value piece-price wise, or very small, but nonetheless, people asked, "if the purpose of this safety stock tool is to reduce inventory, then why would we actually increase it?"

A second major challenge from a business perspective occurred during the monitoring of the test. One day, several of the players who were skeptical from the start looked at the inventory levels for various parts. At that moment, at that snapshot in time, the inventory was higher for those parts than at the exact moment the test began, so they again worried that we were actually increasing inventory. To combat this, we put together some educational diagrams showing both the dangers of only looking at a point in time rather than averages, and the fact that it would take longer for results to show up for some of the lower volume parts.

Figure 33 is an example of the first diagram, explaining that we are looking at average inventory not just a snapshot in time. It shows the quantity of a part in stock on the vertical axis over time (horizontal axis). The dots along the line are the quantity as reported by the computer each day. These are evenly spaced along the time axis. The light blue horizontal lines are the minimum float level, lowered per the test about midway through this time period. You can see that each time the quantity reaches that float level, an order (green vertical line) comes in. Because Nissan uses fixed order quantities, each of these green lines is the same height. The diagonal lines are usage of the part, and their slope varies as the build schedule on the line varies. The challenge for a few stakeholders was that looking at the two circled dots, eight days apart, it seems as though the inventory has gone up although the float is lowered. We worked to explain that we needed to consider the average inventory, not just the inventory at a snapshot in time.

Figure 33 Pilot Test Monitoring Educational Chart: Snapshot in Time
Next, we had to explain that changes from lowering float would not show as quickly for slow-moving, low volume parts. The charts below use the same axes (quantity and time) and depict a slower moving part on the top and a faster moving part on the bottom. Although the float is changed at the same time, the average does not change as quickly for the lower volume part. This was key in persuading them to allow us to run our test for a few weeks so that we would get accurate data on all the parts involved.

Figure 34 Pilot Test Monitoring Educational Charts: High Volume vs. Low Volume

We also assuaged their fears mid-way through the test by presenting a side-by-side comparison of two parts, one in the test group, one in the control group. Both had the same usage and transit time and the float was reduced on the test part from 50 hours to 33 hours. We showed that although they started in week zero with similar inventory (566 test, 567 control), by week two, we saw that reducing float does reduce comparative inventory (331 test, 537 control). The next question was whether this inventory reduction correlated to more expedites and the answer turned out to be that there were no expedites for the test part, but there actually was one for the control part!

5.4.3 Results
Analyzing the final data at the end of the four weeks for all 50 parts, we were able to show the same points on a larger scale by averaging inventory levels on a weekly basis before the change and after the change. Although we could have completed more complex analysis, normalizing for slower moving parts that had fewer RANs during the study, we felt these averages proved the point that the heuristic worked to management in a way they could understand.
Expedites were comparatively lower, with 14 in the control group and only 5 in the test group, and we saw a 19% reduction in square footage / 13% reduction in the number of unit loads (packages of parts). Inventory costs were slightly up, which helped us revise the algorithm for the second pilot test. Our original estimates of inventory did not take into account the fact that there would be underbuild, meaning that demand was not as high as we had planned for. In the previous system, the inventory analysts would have just figured this out intuitively in their heads, but by applying a safety-factor k collar calculated in Excel, we found that we were setting some too high.

In considering expedites, we were careful to only include those that were ordered as a result of something that related to safety stock levels. Referring back to Figure 2 Common Expedite Reasons, we were looking at things like inventory loss, scrap material, and late RANs.

5.5 Pilot Test 2

5.5.1 Design of Experiment
In order to improve the algorithm, we examined parts in Pilot Test 1 that had performed poorly. For example, parts that had expedites even though we had raised service levels, or parts that had inventory increases beyond what we had estimated, both in terms of holding cost and space.

For our second pilot test, we tweaked the algorithm to increase the service level collars, but simultaneously made cost and space more important, by not adding as many hours depending on piece price and subtracting more hours for larger items. Because we believed one reason for the higher inventory costs in Pilot Test 1 was significant underbuild, we also added underbuild % as an input for the user. Putting in a 5% underbuild condition would reduce the daily demand used by the algorithm by 5%. We also removed the legacy “dynamic space calculation” which had not been used for any parts in Pilot Test 1. Finally, we got the qualitative feedback that it was easier to think about 1 Unit Load than 0.75 Unit Loads so we made that bucket be 1 unit load for ease of use.

Figure 35 details the heuristics used in the second test. In red are the criteria that changed between Pilot Test 1 and 2. The k-factor service level collars this time were 0.75 and 4.0, but we made an important addition to the way we calculated the minimum collar, based on seeing what the algorithm recommended for the group of 400 parts and sanity checking these recommendations against what seemed logical. We found that some parts from very nearby suppliers, like Part E, were subjected to an enormously large number of hours of float because of minimum service level collar. The minimum service level was basing this calculation on variation in lead time, which as we saw in Figure 20 was enormous. The algorithm spit out this illogical recommendation when the minimum service level was far above the “sum of adders”
calculation. We determined that for these types of parts, that would very rarely be above eight hours. Therefore, the minimum service level was capped at eight hours of float for this test.

Figure 35 Safety Stock Tool Iteration 2

<table>
<thead>
<tr>
<th>1 Unit Load (450 Hours Max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Number of hours to use 1 unit load unless this is greater than 450 hours, then 450 hours</td>
</tr>
<tr>
<td>• If transit time &gt; 8 hours, add 6 hours, otherwise 3 hours</td>
</tr>
<tr>
<td>• If part is critical, add 8 hours</td>
</tr>
<tr>
<td>• If part is on quality hold, add 2 hours</td>
</tr>
<tr>
<td>• If it uses less than two unit loads per day, add 8 hours</td>
</tr>
<tr>
<td>• If part goes through a crossdock, add 8 hours</td>
</tr>
<tr>
<td>• If one unit load is &lt;$1,000, add $200 of product</td>
</tr>
<tr>
<td>• If &gt;8 deliveries per day, add 0 hours, if 2-8 deliveries, add 2 house, if 2 deliveries, add 4 hours, if 1 delivery per day, add 8 hours</td>
</tr>
<tr>
<td>• If YTD scrap + losses + gains divided by daily usage is greater than zero, add zero, if less than zero, and absolute value is less than daily usage, add 3, if greater than daily usage add 6</td>
</tr>
<tr>
<td>• If the sum of all of the above leads to cubic feet of &gt;10,000, subtract 15 hours. If it is greater than 1,000 cubic feet, subtract 10 hours, and if it is greater than 200 cubic feet, subtract two hours</td>
</tr>
</tbody>
</table>

The second pilot test involved 400 parts that all passed through one warehouse, with different end destinations in terms of docks at the plant. Similarly, 200 of these were put into a control group and 200 into a test group. As you can see in Figure 36, most floats were lowered (64%) although some were raised to improve the service level.

Figure 36 Pilot Test 2 Float Hours Distribution
Figure 37 shows the cost by part of the safety stock level from the control group and the test group. While it is still exactly the same percentage of parts that show a decline, the scatter plot shows that especially the inventory in stock becomes more valuable, the tool almost always recommends decreasing the float, aligned with the goals of the project.

**Figure 37 Pilot Test 2 Inventory Cost Distribution**

Figure 38 shows the distribution of k-values before and after. With 200 parts in the test group, compared to only 25 in Pilot Test 1, it becomes clear the effect that the collars at 0.75 and 4.0 have on the overall distribution, creating the horizontal lines of blue dots.

**Figure 38 Pilot Test 2 Safety Factor Distribution**
The final graph showing the experimental distribution for Pilot Test 2 shows the storage space requirements. Similar to the case with Figure 31 and Pilot Test 1, there appear to be fewer dots on this graph than the other Pilot Test 2 graphs because there are a limited number of standard packaging sizes, so many of the dots are actually showing the placement of several parts. It is important to note here that as the space requirements grow larger, there are no parts for which the tool recommends an increase. Since space was one of the key adjustments to the algorithm from Pilot Test 1, this proves that the change produced the desired affect, at least in theory.

Figure 39 Pilot Test 2 Storage Space Distribution

Figure 40 should be compared to Figure 32, which also shows selection criteria frequency. Although the ratio of safety factor based choices vs. heuristic based choices is similar, for this set of parts, the modified algorithm uses max service level and unit load rules much more frequently. The unit load compared to "sum of adders" can be explained by the fact we increased from 0.75 to 1 unit load. The max service level change we believe stems from the different mix of parts included in this test. Because they all go through a crossdock, rather than some going straight to the dock, as in Pilot Test 1, all have additional hours which could put them above a high calculated max service level.
5.5.2 Business Execution Challenges

We flagged both groups on the computer with a "DO NOT CHANGE FLOAT" marker, but because this was a much larger set of parts, we were constantly getting emails saying things like "I need to change Part G float to 200 hours, please confirm," when we had it set at 40 hours. Not once did the team get an email about lowering existing float levels. This reconfirmed our earlier findings on the knee-jerk reaction to raise float as well as the importance of carefully controlling the float-setting process to eliminate the vicious cycle and countering people's incentives to increase float for their localized goals and incentives.

5.5.3 Results

Results from this study showed expedites similar between the two groups, but in the test group space was reduced by 17% in terms of square footage / 11% in terms of number of containers, and inventory costs were reduced by 25%. We calculated these numbers similar to the results of Pilot Test 1, using averages over weeks of float to take into account several RAN cycles after the change was made in the system.

As expected from the changes to the algorithm, the square footage and inventory costs reduced significantly. However, we were disappointed in the lack of reduction in expedites and believe this is an area that requires further study.

5.6 Recommendations and Implementation Analysis

After validating the heuristic a second time, most of the team was sold on the idea of having a set methodology in place to determine float levels. Even if not perfectly optimized, our tests demonstrated clear improvements in the three metrics Nissan targeted: space required, holding costs, and expedites.
Using the algorithm allowed inventory analysts to focus their attention and time on special cases and exceptions while still being able to monitor the full set of SKUs. Because it could be run fairly easily, approximately once a month, by pulling refreshed data from the mainframe, no part would go unexamined for too long. While we were not removing all variation from the float selection process, we were replacing non-strategic variation in methodology with strategic variation as determined by the algorithm.

Before moving forward to recommending implementation in Canton, we tweaked the model one more time, based on the results of Pilot Test 2. We had noticed some odd outputs based on scrap levels and realized that the original heuristic that had worked in July made less sense in December and that the reason was that it was just using the mainframe generated “YTD Cycle Scrap.” We normalized cycle scrap by days elapsed since the beginning of the fiscal year.

We also joined with a team already looking at order points at one of the warehouses to add in order point to the heuristic. This once again ensured that order point would never be higher than float and increased the usefulness of our tool.

One of Carlos Ghosn's well-known methods for cutting costs is creating cross-functional teams that come together for a common goal. We had the opportunity to present our float tool to two "Total Delivered Cost" reduction "Intensive Activity" projects. It was well received in both. One participant said, "I've been wondering for years if you could do something like this, but it just seemed too complicated and I didn't ever have time." The inventory analyst in Decherd's reaction validated that we had made it easy for the user to understand. He said, "I like how this works because it is like how I think!" Although the exact Canton model had to be slightly tweaked for the specific circumstances, which required some time, it still predicted remarkable savings. In Decherd, for one engine line, the inventory code savings we estimated to be $1.12 per engine.

At this stage, we once again faced the same questions we had inoculated against by educating the Canton team. People wanted to only change the float on parts where the tool suggested a reduction: "If we are trying to save costs, why would we raise inventory?" they asked. The inventory people were not part of the same P&L as those affected by expedites because of the different departmental silos. Our constant refrain was that we were not aiming for the lowest float, we were aiming for the right float. Education is a very important part of implementing inventory optimization more sophisticated than WJK, especially when certain cost savings are directly incentivized while others are not. During the Smyrna intensive cost reduction, they only agreed to change the float for the parts that the tool recommended decreasing float.
We estimate full scale implementation the Canton plant to save $2.5 MM in one time inventory costs and $250,000 annually in holding costs (using a 10% assumption for holding cost). From a space perspective, this equates to about 5% of space required, very valuable given the space needed for planned new model introductions over the next few years. These numbers do not include the reductions in expedites, which are difficult to predict but still quite valuable. A 25% reduction in Nissan-fault expedites would equate to $4.5MM annually.

More analysis of the distributions of parts and characteristics of them are required to give an estimate of savings from an implementation across all three plants, including Smyrna and Decherd.

Beyond applying our float tool real-time to Nissan's current production and inventory, it allowed us to assess the impact of several changes to the network and processes, including some of the opportunities identified in this chapter and chapter 4, looking at the lead time data. For example, as discussed, the lead time we used included time on yard. If we reduced time on yard from what the actual averages are to a uniform two hours, we could reduce safety stock in Canton by an additional $4.4MM, bringing the total amount of one-time reduction to almost $7MM, and warehouse space by an additional 5%. Because 30% of parts are already unloaded within two hours, this is actually raising the lead time on these parts. As a second example, the offsite warehouses currently pick parts hours before they are required in the plant and our algorithm is calibrated accordingly to account for this reality. If process improvements could improve the reliability of shuttle loading and unloading, allowing pick-ahead time to be reduced to only four hours, safety stock could be reduced by an additional ~$200,000 in Canton.

6. Application 2: Grey Fleet Study

We used the same database of lead times from suppliers to build a model simulating Nissan’s trucking network. The model would help us understand how many trailers would be necessary if Nissan were to move from using trailers owned by its trucking carriers to a common fleet. We examined different scenarios around transit times and unloading times between actual data and what the planning team thought was reasonable. The study concludes that a pooled fleet offers significant opportunity to reduce Nissan’s pool size and therefore costs. Careful examination of the data also, once again, illustrates enormous savings potential from reducing loaded trailer time on yard.

Nissan bids out and assigns supplier lanes to each of its eight core trucking carriers. Each of these carriers can only pull its own trailers. Often there will be many empty trailers on the Nissan yard, but none of the correct carrier for a specific supplier. In this situation, Nissan creates an expedited shipment to get materials to or from the supplier. The annual cost of these expedited shipments was more than $10MM in
the last fiscal year. One proposed solution is a common trailer pool, or "grey" fleet, in which any carrier could pull any available trailer. At the time of the study, management had heard anecdotally that other companies, including Toyota, at some plants, and Dollar General, had successfully implemented a pooled grey trailer fleet. From the perspective of the trucking carriers, improving trailer availability would allow them to better allocate drivers, rather than having them show up and Nissan only to discover there was no trailer to pull, they would be able to maximize their driving time during legal hours of service. For Nissan, cost savings from a grey fleet would include both a significant reductions in expedites and lower carrier transportation rates because the carriers would not be taking on the risk of supplying trailers. However, Nissan would now incur the cost of leasing or buying trailers, so net cost savings depend on the size of the grey pool.

At the time of our analysis, the team had concluded that the project would be about break-even if the number of trailers remained constant with the current total sum of carrier trailers, “2,400” in this thesis. Therefore, all cost savings would result from the benefits of pooling and the reduction in the number of trailers below 2,400 Nissan could achieve while maintaining a high service level.

Through this study, we identified that, if Nissan can keep the trailer-on-yard process in control, it can save $1.4MM in annual trailer leasing costs through a grey trailer program.

6.1 Methodology and Approach

We formed a hypothesis about the expected reduction by taking just a simple percent reduction from the 2,400 number. Next, we examined Nissan’s fleet requirements by building a very detailed model of the trucking network using both planned transit and the actual lead time data. We ran sensitivities on this model, and compared these results to expected results from pooling theory as well as the “trailer ratio” metric familiar to Nissan.
6.2 Grey Trailer Fleet Sizing

6.2.1 Percent Reduction Hypothesis
Previous published literature on transportation fleet pooling shows a range of 12% to 30% reduction in fleets. Applying these numbers to the 2,400 trailer number used in this thesis, we would expect a total number of 1,680 to 2,112.

6.2.2 Model Approach
Before building a model, we had to understand clearly the different paths trailers move within Nissan’s system, and the stages at which the trailer is stopped or moving. These nuances proved absolutely essential for sizing the fleet because we found that more than 50% of trailers were not moving in the straight-forward, full-truckload way that would have been easy to model. We interviewed people internally at Nissan, including people who managed the yards in Canton and Smyrna; people who track transportation day-to-day; and external stakeholders like the trucking carriers and a 3PL.

As discussed above, Nissan outsources the design of the trucking network to a 3PL, who uses daily shipment volumes by supplier (in linear feet) to optimize each origin-destination lane into daily frequencies. There are both direct routes and milk runs. Nissan also consolidates shipments from multiple suppliers at cross-docks and breaks apart shipments from a single supplier destined for multiple plants at a "break-out" center in Smyrna. Engines move in direct shipments between the Decherd powertrain plant and the Smyrna and Canton assembly plants, and some stamping parts are shipped between Smyrna and Canton.

Because the current carrier trailer fleets do not have RFID or GPS tracking devices, we identified a large gap in understanding the path a typical trailer takes once it is unloaded at the plant. Are trailers that came from suppliers being re-loaded with different parts and acting as a shuttles from warehouses to the plant? How long do they get stuck in the shuttle loop before getting loaded with rack returns and getting sent back to a supplier? Not only could we not track what the path is, but there was also little consensus within Nissan about what it should be, although everyone agreed there were several "bad paths." For example, sometimes to clear excess material off of their docks, material handlers at the plant loaded random parts and racks onto a trailer and put it back on the yard, where it could stay for months before someone looked inside or put it back into the flow of the network. This was called the "black hole."

Therefore, we came up with an idea of a "correct path" and built our models around that. Of course to be valid, operational changes would need to be implemented to ensure compliance. In our model, we assume a trailer starts being occupied when rack returns are loaded. Next, it travels to the supplier, gets loaded
with parts at suppliers, travels back to the plant, and is unloaded at the plant. When it is finished being unloaded and empty on the plant yard, it is free to start the cycle again.

6.2.3 Model Mechanics

Our Excel model illustrated the “correct path” for every schedule trailer route every day of the week for all three plants. We assumed that a trailer would be in rotation at one plant, and when empty it would be free to fill in for the next route at that plant requiring a trailer. However, an empty trailer in Smyrna could not fill in for a trailer needed in Canton because it is not actually there.

The figure below illustrates a daily route over the course of three days. The numbers at the top of the row are hours, where 0 is midnight of the first day, 12 is noon of the first day, 24 is midnight of the second day, 36 is noon of the second day and so on. Each row is a daily pick-up and the colored boxes denote a trailer in use. “A” is a trailer being loaded with racks, “B” is on the way to the supplier, “C” is being loaded at the supplier, “D” is on the way back from the supplier, and “E” is being unloaded at the plant. In this example, the trailer has 20 hours of transit time to and from the supplier and it takes three hours each to load rack returns, load at the supplier, and unload parts at the plant. Every day it is scheduled to leave the supplier at exactly 8am (transition from “C” to “D”), a reasonable example of how Nissan schedules daily shipment routes with its suppliers. Because it must pick up every day at 8am, the third day trailer must begin being loaded with racks before the first day trailer is free. Similarly, the trailer for the 8am pick-up on the fourth day begins loading with rack returns before the trailer from the second day 8am pick-up is free. Therefore, the minimum number of trailers required to keep this route on schedule is three. While it would be easy to say two trailers because only two are ever in transit at the same time (“B” and “D”), we must allow enough time for loading and unloading, the overlap of steps “E”, “B”, “C”, and “A” in the chart. Although there are four total rows, the total used at one time is three.

Figure 42 Illustrative Example of Grey Trailer Model
The full model is quite similar, but both longer duration and more granular. It is built to include a full week of shipments and counts at 30 minute intervals. We modeled in all of the scheduled Truck Load and Milk Run routes from every supplier to every plant.

Additionally, we added in categories for other activities requiring trailers in the scope of the grey fleet. These include:

- **Pick**: trailers to shuttle parts from the off-site warehouses to the plant (at “pick” time)
- **Engine**: trailers to move engines from the Decherd power-train plant to the two assembly plants
- **Xdock**: trailers used by one carrier’s cross dock to consolidate loads, do not come to plants
- **Dropped**: trailers staged at suppliers for them to load so they are ready in advance of pick-up
- **Damaged**: trailers out of the regular rotation during repairs
- **Storage**: trailers on the yard with parts or other things being stored on them
- **Underbuild**: trailers on the yard with parts not required yet because the plant is behind schedule

The numbers in all of these categories were based on reasonable assumptions and knowledge of the team because it was challenging to get accurate data from the carriers or Nissan’s system. The storage and underbuild trailers are both “bad path,” while “dropped” and “damaged” trailers are a subject for further research. Is it better to reduce load time by having the supplier reload the trailer before the trailer with empty racks arrives? Or does instead dropping trailers lead to them getting marooned away from the Nissan network and take them down a “bad path”?

Our analysis below focuses almost entirely on the truck load / milk run trailers and the pick trailers, but to see fully the benefits of the grey fleet and the potential pitfalls of pooling, we need to include all the paths. Recalling the comparison to call center operators or bank tellers, storage trailers could be like an operator who gets stuck out of the general queue because they were called away from their desk for unscheduled but necessary training.

### 6.2.4 Model Sensitivities

The first run of the model used the scheduled transit times and assumed that trailers were unloaded at the time the first RAN was due, no sooner and no later. The figure below illustrates the results. Comparing the total number here, 2,001 to the 2,400 current number of carrier trailers, we see a 17% reduction which seems reasonable given our hypothesis based on queuing theory and the literature. Like the example in
Figure 42, the total number of rows (routes per week) is much larger than the largest number of trailers required at any one moment. In this case, the total number of rows was 7,623, while the total used at one time was only 2,001.

Using the good data on lead time, we further examine the scheduled portion, which makes up just under 50% of the total. We simulated the following scenarios:

<table>
<thead>
<tr>
<th>Transit Time</th>
<th>Yard Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Planned</td>
<td>• RAN Due</td>
</tr>
<tr>
<td></td>
<td>• 2-4 Hours Dwell</td>
</tr>
<tr>
<td>Six-Month Averages by Supplier – Route</td>
<td>• Average Yard</td>
</tr>
<tr>
<td></td>
<td>• 2-4 Hours Dwell</td>
</tr>
<tr>
<td>Weeks of Actual Historical Data (Canton Only)</td>
<td>• Actual Yard Time</td>
</tr>
<tr>
<td></td>
<td>• 2-4 Hours Dwell</td>
</tr>
</tbody>
</table>

Figure 44 shows the number of trailers required for planned vs. average transit time and unloading after time on the yard based on RAN Due, historical averages, and set dwell times for all scheduled routes for all three plants:
Comparing the two bars with the same yard dwell-times (2 hour and 4 hour), we see for Smyrna and Canton, average transit times require more trailers than planned transit times although for Decherd the total number decreases. For Smyrna, unloading everything at RAN due time actually requires fewer trailers than a two-hour or four-hour dwell, while for Canton and Decherd, unloading at RAN due time requires significantly more trailers. This reflects the key reality that RANs for Canton are scheduled further out than for Smyrna as a brute-force coping mechanism for variability. We see in the data, however, Smyrna experiences significant variation in terms of trailers on the yard, as using average on-yard times produces quite a large number. On a percentage basis, the increase for Canton from unloading at RAN Due time to after the average time on the yard is 14% while for Smyrna it is 65%.

Inserting actual historical data in the model required significant scrubbing because data is by RAN, not by shipment. As discussed earlier, further examination of the mix of RANs in each trailer would be interesting in terms of considering network schedule and inventory levels. For this study, though, we had to consolidate all of the RANs that were in the same shipment, a fairly manual process. We ran the model for Canton for two week-long periods using actual transit time, varying yard time to be actual, two hours, or four hours. We could not show unloading at RAN due time because many of the shipments were unloaded after the first RAN due time. However, comparing these numbers to the above, we see that the total trailers required using actual yard time is quite similar to using RAN Due time. The two weeks
studied are also quite similar, showing only 3 – 7% variation. Although it would have been interesting to run a more statistically significant number of weeks, these two weeks act to confirm our earlier modeling using planned transit times and averages. We validate the structure of the model although do not learn anything additional about variation.

**Figure 45 Canton Grey Trailer Model Using Actual Data**

Trailers used to transport parts from the offsite-warehouses to the plant, or “pick” trailers, are calculated in the model using scheduled “pick times” and an assumption for how far ahead of the scheduled time the warehouse begins to load the trailer. As discussed in the inventory section, the loading typically begins significantly in advance of the scheduled time. For inventory, we considered eight hours because that is when the last item would need to be received to make it on the trailer. However, in this context, per Figure 15, we know that it takes more than two hours for the pick load to be loaded at the warehouse. Therefore, we used ten hours, plus an assumption that transit always equals one hour, we generate the 431 trailers required in Figure 44. However, running the model for six or eight hour pick ahead times reduces the number to 327 trailers or 378 trailers required respectively. Although when considering safety stock, we looked at going down to four hours pick ahead, once again here we added an additional two hours of trailer in use for staging and loading.
6.2.4 Pooling Theory with Variance

Similar to the inventory discussion above, the number of trailers required to provide a buffer for variance will be the minimum required if everything goes according to plan plus a safety factor times the standard deviation. With one carrier, this would be,

\[ \text{Total Trailers} = x + k\sigma \]

where \( x \) is the minimum required, \( k \) is the safety factor, and \( \sigma \) is the standard deviation.

For \( n \) fleets with different safety factors and different variances, the formula would be:

\[ \text{Total Trailers} = (x_1 + k_1\sigma_1) + (x_2 + k_2\sigma_2) + (x_3 + k_3\sigma_3) \ldots (x_n + k_n\sigma_n) \]

We make the simplifying assumption that the safety factor is constant, so the formula simplifies to:

\[ \text{Total Trailers} = \sum_{1}^{n} x_n + k \sum_{1}^{n} \sigma_n \]

If we were to simplify even further, and assume that all the pools were the same size and all the variations were the same, the formula would be:

\[ \text{Total Trailers: Separate Fleets} = nx + k \sum_{1}^{n} \sqrt{\text{var}} \sqrt{n} \]

Square-root of \( n \) as a way to determine the effects of variation of pooled resources is used in queuing theory as well as when considering, for example, consolidating operations into a centralized location. In our case, this formula implies that the ratio in the buffer number trailers required when moving from separate pools to a common pool is simply proportional to the square root of the number of carriers, or in this case, the square root of 8.

\[ \text{Total Trailers: Pooled} = nx + k \sum_{1}^{n} \sqrt{\text{var}} \]

The below figure illustrates a 2,400 fleet divided equally between eight carriers. We use an 88% service level, which is similar to what Nissan currently experiences, calculated by taking the number of trailer availability related expedites divided by the total number of scheduled shipments per week.
The 65% reduction in buffer is exactly:

\[
1 - \frac{1}{\sqrt{n}} = 1 - \frac{1}{\sqrt{B}} = 65\%
\]

Figure 46 Expected Pooling Reduction for Carriers of Equal Size

<table>
<thead>
<tr>
<th>Number in Current Fleet</th>
<th>Minimum Required</th>
<th>Buffer Stdev (88% Service Level)</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier A</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier B</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier C</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier D</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier E</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier F</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier G</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Carrier H</td>
<td>300</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>Total Required: 8 Fleets</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sum of Variances: 56,875
Pooled Std Dev (based on Sum of Variances): 238

The calculations become slightly more complicated for a situation like Nissan's, where the carrier fleets are of different sizes and carry different amounts of buffers. However, using the same methodology and assuming the same service level, we get a similar reduction in the buffer size. These numbers are rounded and illustrative, but the “minimum required” numbers below are similar to what could be extrapolated from the model using planned transit times and unload at RAN due. At the 88% service level, we see a total required of 1,878 or 28%.

Figure 47 Expected Pooling Reduction for Carriers of Different Sizes

<table>
<thead>
<tr>
<th>Number in Current Fleet</th>
<th>Minimum Required</th>
<th>Buffer Stdev (88% Service Level)</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier A</td>
<td>800</td>
<td>648</td>
<td>152</td>
</tr>
<tr>
<td>Carrier B</td>
<td>400</td>
<td>268</td>
<td>132</td>
</tr>
<tr>
<td>Carrier C</td>
<td>350</td>
<td>235</td>
<td>115</td>
</tr>
<tr>
<td>Carrier D</td>
<td>250</td>
<td>107</td>
<td>74</td>
</tr>
<tr>
<td>Carrier E</td>
<td>200</td>
<td>126</td>
<td>75</td>
</tr>
<tr>
<td>Carrier F</td>
<td>175</td>
<td>100</td>
<td>76</td>
</tr>
<tr>
<td>Carrier G</td>
<td>125</td>
<td>49</td>
<td>63</td>
</tr>
<tr>
<td>Carrier H</td>
<td>100</td>
<td>37</td>
<td>63</td>
</tr>
<tr>
<td>Total Required: 8 Fleets</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sum of Variances: 67,573
Pooled Std Dev (based on Sum of Variances): 260

One of the key proposed benefits of the grey fleet plan, however, is a reduction in trailer-related expedites, so this 88% service level is not enough. Performing the same reverse calculations for a 90%,
95%, and 99% service level return total trailer numbers of 1,903; 1,998; and 2,175 respectively. Even with a 99% service level, we still expect a 10% reduction in total number of trailers required.

6.2.5 Trailer Ratio

Nissan currently pays its trucking carriers to maintain a specific ratio of trailers to truck tractors. The so-called “trailer ratio” is a metric everyone in the company is familiar with and is standard to the industry. Therefore, it was important to show the results of the model and study in this format to management. In the model, per the above discussions, only some of the segments of each route require the truck to be attached to the trailer. Specifically, the driver is only required for segments “B” and “D”: on the way to the supplier and driving back to the plant. Therefore, we can run the model counting trailers only, which depends solely on transit time, not on yard time. The dropped, damaged, storage, and underbuild trailers do not require a tractor, which is how the trailer ratio takes into account these “bad paths”. The below chart shows tractors required for the other four categories, a total of 732.

Figure 48 Model of Tractors for Trailer Ratio

Applying a 3:1 trailer ratio (multiplying 732 by 3) implies a total number of trailers would be 2,196 while a 3.5:1 trailer ratio would be 2,562 trailers. Assuming Nissan strives to maintain a 3:1 trailer ratio, this would imply a reduction in trailers from 2,400 to 2,196.

6.3 Scheduling Opportunities Identified

In the process of coding each route our model, we did a detailed audit of a 3PL’s scheduling of Nissan’s transportation network. Through this process, we were able to identify secondary opportunities to improve Nissan’s transportation network, reinforcing our view throughout this thesis that significant cost savings can be found through careful analysis of existing data that people do not spend the time to examine.
We discovered that several of the routes, especially milk runs, were scheduled to arrive more than 24 hours before the first RAN due. Planning in an extra day of buffer both increases the inventory Nissan holds at all times as well as the number of trailers required. They called this the “Monday for Wednesday” convention, meaning that a supplier would put loads due Wednesday on their shipment going out Monday, even if the supplier was only a few hours away. As an extreme example, one milk run picks up from three suppliers, all within 30 minutes of the plant, between 7am and 9:30am on Monday morning and arrives at the warehouse at 10 am. RANs aren’t due until, at the earliest, Wednesday at 4:20 pm. Therefore, the inventory sits either in the warehouse or on the yard for 54 hours before it is due.

Previously, they had shipped everything Monday for Tuesday, but for some far-away suppliers this did not allow enough time to account for variability. The warehouses would then have to rush to get the picks sent out on time, so warehouse managers lobbied a 3PL to schedule in more time. Instead of considering on a case-by-case basis, a 3PL implemented Monday to Wednesday across the board and Nissan had not taken note of the change. Once this was brought to management attention, the route plan began to be shifted to Monday for Tuesday.

Finally we had an easy-to-fix explanation for some suppliers delivering early as well as at least a partial rationale for the vast variation in on-yard times. Suppliers were delivering early because 54 hours of early was built into the parts orders. If the general yard policy was to try to unload things at RAN due time, some trailers would sit for days while others would have to be unloaded immediately. The process had broken down because different stakeholders with different goals had not coordinated: Nissan management wanted the parts to come in just in time, while warehouse managers wanted plenty of buffer so that they could get parts out on-time for picks (metrics they were measured on), and there was no cost to a 3PL in terms of scheduling in additional time. Further analysis is required to fully quantify the savings from fixing a 3PL scheduling buffer problem.

6.4 Conclusions and Cost Saving Estimates

Below is a summary of all of the methodologies used and the number of trailers they estimate. This type of chart, commonly called a “football field” in investment banking where it compares different methods of valuation, shows the viewer the results of several different types of analysis on the same problem and sensitivities within these results. For example, the “12-30% Percent Reduction” bar shows that a 30% reduction, on the left side, would require 1,680 trailers, while only a 12% reduction would make the number 2,112. Because our model and each of our other analyses rely on many assumptions, rather than solve an optimization problem for a one-number answer, we believe it is more effective to show management a chart conveying more of the analysis. We can select a value by looking at the clustering of different methodologies and how much we trust in the assumptions that went into each one.
Based on our football field, it seems reasonable that Nissan could reduce its fleet from 2,400 to 2,000 trailers. Assuming a lease cost of ~$300 per trailer per month, reducing trailer requirements by 400 trailers is $1.4 million in annual savings from the trailers alone, without taking into account the reduction in trailer-availability-related expedited shipments and carrier rate reductions. The 400 trailer reduction requires the yard time process to be a process in control, centered around either unloading at RAN due or a set target time on yard of two to four hours. Therefore, the success of a grey trailer program depends on structures in place to manage and maintain yard. We see that reducing from four hours to two hours lowers the trailer requirement by about 70 trailers, equating to $252,000 of annual savings. Similarly, reducing pick ahead time equates to almost a 100 trailer reduction, or $360,000 of annual savings. Finally, assuming that 80 trailers will always be needed to deal with underbuild, we see the opportunity for Nissan to save $288,000 if it is able to meet plant schedule more often.

Moving from pure analysis to the actual implementation of a grey trailer model, Nissan and other similar companies will have to consider several additional operational and business challenges. The lease agreement should include clauses that allow Nissan to flex up and down the number of trailers required. Depending on the terms of this contract and the cost of adding or subtracting, that would determine how Nissan weighs the trade-offs between having too many trailers and having too few. An additional cost that Nissan must consider is how to track trailer movements: using RFID or geofencing or other technology will provide visibility into the network and show when trailers go down a bad path, staying in one place for too long or being used for storage. Additionally, from an organizational structure perspective, Nissan
must consider how to manage or outsource the management of the maintenance and yard switching system. Beyond keeping the trailer on-the-yard and unloading process under control, these contract details and the decisions about which costs get paid and managed by Nissan, the trucking carriers, and the trailer leasing company are critical drivers of the success of a grey trailer pool. Although these decisions were out of scope of this project, it was key for us to keep them in mind and in front of management during any discussion of cost savings.

7. Conclusions and Further Research

Both studies in this thesis applied lead time data to a similar formula for determining buffer stock, either of inventory, or of trailers. The idea that companies have significant amounts of data that they do not analyze is certainly not novel, but these two applications, one a validation of heuristic measures, and one a model for fleet sizing, prove that there is valuable cost savings opportunities within lead time data in specific. In both cases, we determine that the elimination of non-strategic variability of trailer time on the yard will save the company significantly.

In this chapter, we detail the logistics operations learnings from our research, some key business and management take-aways, summarize the cost savings, and propose areas for further research at Nissan or similar companies.

7.1 Operations Management

In academic settings, people analyze and program for the optimal solution for inventory and safety stock. However, in our research, we found that even without sophisticated programming, companies can significantly reduce their holding costs, warehouse space, and even stock-outs by applying a heuristic tool. Specifically, in the automotive context, with a high cost of stockout and stable demand over the lead time periods, these heuristics work if they take into account lead time variation as well as factors like part criticality, quality, and size. Standardizing the safety stock setting process is an important step on the way toward better inventory management and visibility into problems in the warehouse.

In solving a fleet-size problem in conjunction with an application of benefits of pooling, we found that our situation-specific origin and destination model aligned very closely with the expected results from looking at the square root of n pooling theory. Instead of using non-linear programming to solve our problem, and come up with a single number that would say “this is how many trailers should be in a grey fleet,” we used several different methodologies to hone in on a reasonable range of numbers. We believe this is more practical in a business setting and using a football field display allows management to have valuable conversations around the assumptions and methodologies.
7.2 Business and Organizational Behavior

Following directly from our commentary on how to display data so that it allows management to have conversations about methodology, a clear conclusion of our research is that quantitative decisions cannot appear to be a “black box.” Transparency about and understanding of the rationale behind calculations is essential for user buy-in, down to the level in the organization that the tool will be used. Sometimes changing systems require education, as we found with objections to our float tool trials, but a well-designed tool will both deliver cost savings and be easy to use. The best feedback we got was from the inventory analyst who told us “this is how I think.” Running experiments works to validate proposed changes to skeptics and additionally, lessons from these experiments allows for improvements on the proposed changes before they are widely implemented.

A key implementation challenge for our recommendations will be the division between groups within Nissan and the different incentives for performance different stakeholders see. For example, the 3PL was not worried about scheduling trailers to have more than 24 hours on the yard and the warehouse managers encouraged this costly buffer time because their success metrics depended on shipping things out on time. Similarly, the material handler who was penalized for inventory loss would try to increase float without regard for the cost of holding this inventory. Moving to the problem of trailers staying to long on the yard, not enough stakeholders are incentivized to keep the process in control: the carriers relinquish responsibility when they drop the trailer, the warehouse management 3PLs are focused on getting RANs required immediately, and Nissan only focuses on the yard when the total number of trailers creates so much congestion that it impedes other processes.

7.3 Summary of Cost Savings

Figure 50 below details the almost $10MM in savings we identified and the process changes required for each one. Only the Canton Float Tool savings are implementable immediately, while other saving opportunities were identified but require process changes to be realized.
Figure 50  Summary of Cost Savings Identified

<table>
<thead>
<tr>
<th></th>
<th>One-Time</th>
<th>Annual</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Immediate Cost Savings</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base-Line Implementation of Float Tool in Canton (Inventory Costs)</td>
<td>2,500</td>
<td>250</td>
<td>2,750</td>
</tr>
<tr>
<td>Space (calculated at $2.50 / sq ft / year)</td>
<td></td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td><strong>Requires Yard Process in Control (4 Hours)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safety Stock Reductions (Inventory)</td>
<td>4,300</td>
<td>430</td>
<td>4,730</td>
</tr>
<tr>
<td>Grey Trailer Fleet</td>
<td>1,400</td>
<td>1,400</td>
<td>1,400</td>
</tr>
<tr>
<td><strong>Further Reduction in Yard Time (2 Hours)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safety Stock Reductions (Inventory)</td>
<td>100</td>
<td>10</td>
<td>110</td>
</tr>
<tr>
<td>Grey Trailer Fleet</td>
<td>252</td>
<td></td>
<td>252</td>
</tr>
<tr>
<td><strong>Warehouse Pick-Ahead Time Reduction (8 Hours to 4 Hours)</strong></td>
<td>200</td>
<td>20</td>
<td>220</td>
</tr>
<tr>
<td>Safety Stock Reductions (Inventory)</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Grey Trailer Fleet</td>
<td>360</td>
<td>360</td>
<td>360</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>7,100</td>
<td>2,763</td>
<td>9,863</td>
</tr>
</tbody>
</table>

The most important conclusion here is that the majority of savings, both in terms of inventory and a grey trailer fleet, relies on bringing the trailer-on-yard process into control. Comparing a four-hour time with a two-hour time, we see that Nissan can realize significant savings ($6.4MM) without moving towards an almost live-unload procedure. Per the data in Figure 10, 81% of RANs are already unloaded within four hours, so these savings exist even when raising the yard time for a large majority of the parts. Although proposing steps for controlling yard unloading was out of scope for this research as was analyzing the costs of changing the yard process, we believe the cost would be significantly less than $6MM and would recommend careful examination of the 19% of RANs that so significantly cost Nissan in Canton.

We did not include reductions in expedites into our cost savings, although we believe there will be a significant reduction in expedited shipments both from right-sizing the inventory and moving to a grey fleet. During the research period, there was not enough time to gather valid data on the expedite savings and calculating a percentage from current expedites would be difficult to do with the specificity of our other estimates.

The dollar value of the space savings seems low, but using a per square foot quantification of space blurs the reality that warehouse space is a step function: either you need to rent/build another warehouse or it is not necessary. Saving space in the warehouse, even if not a full square foot, also ties directly into some of the other opportunities we identified but did not quantify, like reductions in inventory losses, designing
a system robust for an underbuild situation, and making room in the warehouse to implement FIFO systems. A cleaner, less crowded warehouse will mean that material handlers will have an easier time finding parts and a warehouse with some buffer space will provide the logistics team some room for the times that manufacturing does not meet its schedule. FIFO with stacked containers can also require slightly more space.

7.4 Further Research Opportunities

As discussed above, at Nissan, some interesting areas for future projects and additional research include inventory loss, underbuild effects on the rest of the system, and warehouse FIFO. We would also recommend investigating supplier early deliveries and the ties to trailer cubing and utilization. The largest and most significant opportunity we see, as discussed throughout this thesis, is the trailer on yard process. A potential project could center around understanding “bad path” root causes, controlling a time on yard mean, and then controlling time on yard variance. The on-time to yard and on-time to receipt metrics shown in Figure 12 and Figure 13 would be a starting place for this sort of research or process improvement project.

At other companies with similar structures, further benchmarking of heuristic safety stock setting and fleet pooling would be interesting. Are there other factors related production parts or a trailer network that should be considered?
References


Excerpts from Nissan Safety Stock Documents

What is Safety Stock = float = operational reserve: Excerpt
The primary mission of Supply Chain Management is to provide a steady flow of material to the assembly lines to support production schedules. Whether it be individual parts, stampings, fascias, fuel tanks, engines, or transaxles, Material Handling and Inventory Control activities are aimed at not running out of parts in the assembly area, or on the assembly lines.

One of the elements used to prevent stock-out situations is the assignment of Safety Stock, or ‘float’.

To help explain, let’s use a part in the daily order system with a safety stock of 4 hours. What are some of the ways Safety Stock can be thought of?

Analyst 1 might say; “If a RAN is late, I should have 4 hours of stock at the line before I run out…”

Analyst 2 might say, “Safety stock is the amount of extra stock kept to protect me from an inaccurate record on-hand balance, a delivery being late, unreported scrap, a surprise receiving discrepancy, or a hidden cycle loss.”

Another analyst may look at Safety Stock as the amount of material they should always have on hand. Or, the amount available in case the plant wants to overbuild to the schedule.

Another view is that it is a ‘pull-ahead’ of material requirements. It is a way to bring in material early for upcoming production.

All of the above are true about ‘Float’, but I favor viewing float as “the level of material in the plant when the next RAN is due.” In our example, if the next RAN is due at 10 a.m., then the plant should have an on-hand balance equal to the next 4 hours requirements. The view that float is a pull ahead of requirements is true, because the 4 hours float should be the next 4 hours of part gross in the build schedule for the part. So, if the next hourly build schedule is 6-4-6-5, then when the truck backs into the dock at 10 a.m., the line should have 21 pieces on-hand.

Note also, that safety stock strategies will come with experience, and be different for each plant.

This paper will try to give advice and strategies learned over the years at the NNA facilities, but each plant and analyst will have different situations to contend with.

How the release uses safety stock assignments.

The secret to understanding float can be found in the parts ordering system. This system uses the Safety Stock assignment in its calculation of the ‘recommended on-hand’ at the end of each hour. The program will compare each hours recommended ending balance to the projected inventory at the end of each hour. If the projected inventory falls below the recommended inventory, a RAN will be issued. So:

\[
\text{Recommended on hand} = \text{the amount represented by the safety stock} + \text{the estimated installed system.}
\]
Projected on hand = the previous hours ending balance, + any RANs due, minus the usage requirement for the hour in DOS, and the day in WOS.

To simplify, we can reduce the ‘recommended on hand’ to the float, and the ‘projected’ to the available on-hand.

In the weekly order system the mechanics are the same. If a part has a 6 day float for example, the RAN will be issued for the day the projected ending inventory falls below the requirements for the next 6 days.

Why have safety stock?

If the world was perfect, the material delivered for the next RAN would magically appear at the lineside at the time the linefeeder has just used the last part he had. Of course, the world isn’t perfect. If the RAN is due at 10 am, and the supplier truck backs into the dock at 10 am, then at the very least, the safety stock must protect for the time it takes material handling to unload the material and take it to lineside. Other reasons for safety stock are:

1. To protect against late delivery, which also entails a review of supplier location. Currently the normal safety stock level for NML supplied material is 4.5 days, due to the distance involved in the material pipeline. If low hourly floats of 3 or 4 hours are desired, it is necessary to have disciplined, reliable suppliers and trucklines who can be counted on to deliver the material at the designated date and time.

2. Possible cycle loss. Anyone who has worked in Inventory control knows that no matter how often a part is cycled, the inventory always shows a gain or loss variance. To protect against the actual material available being less than the record on-hand, some safety stock is required (one factor is often unreported scrap).

3. Sub Assemblies. To cover the build up of sub-assemblies ahead of production, you must add safety stock since sub-assembly is not part of the part gross (based on offline vehicles).

4. Special request. One example of a special condition is ‘snow float’. It was a common practice at NNA-SP to add additional safety stock to protect against bad weather, where roads might be closed due to ice or snow. The floats would be increased for a few winter months, and the additive would be removed in Spring.

5. Surprises. These would include mislocated material, RDR’s discovered when the parts were to be used, quality issues, or possible misusage.

Reasons for low safety stock

Two factors have always played an important role in safety stock strategies: cost and space.

In the early days of NNA-SP, float levels for NML material was set at 10 or 12 days. This was acceptable because the plant had large storage areas, the plant was only on one shift, delivery performance was being established, and so on. As delivery performance became regulated, and a second shift was added, and as models were added, reasons for lower safety levels were recognized.

1. Carrying cost of excess material. For example, if we lowered safety stock from 10 days to 5 days on NML material, theoretically we would be able to keep some money in the bank for 5 days longer.
If the value of NML parts is $4,000,000 per day, then carrying costs for 5 days would be $4,000,000 \times 5 = \$20,000,000 \times \text{interest rate est. } 5\% = \$1,000,000 \text{ savings over the course of a year by not paying for 5 days worth of material ahead of time.}

2. Space. The biggest factor in safety stock reduction became plant space. NNA-SP now builds 5 models on two shifts. Warehouse space disappeared, modular assembly took up valuable floor space, production departments needed meeting areas, and so on. There simply is not enough storage space for excess material. Just-In-Time material supply methods dictate that parts are delivered multiple times during the day, in smaller lot sizes, and are delivered to the lineside multiple times per day. Material should not sit idle for days before use. With the daily order system, many parts have only 3 or 4 hours of safety stock, and get rotated quickly.

3. Other factors. Cycle counting is much easier when stock levels are low, and it is not necessary to look in overflow areas. Material that sits idle is susceptible to damage and dirt, and potentially turn into obsolescence at model end and if there is a sudden engineering change.

Why Float at the Part Level?

Each part has its own unique circumstances. Perhaps it is a part that uses 500 per day, and comes in a steel rack of 20. If delivered once a day, it will have 25 racks delivered. To have 2 days safety stock would mean 75 racks in storage after the part is delivered. Another part might also use 500 per day, but it is a small part that comes 2000 in a tote. Two days of safety stock isn’t even a full tote. Certainly the larger part calls for the lowest safety stock possible, and the smaller part calls for increasing the safety stock since the space impact is negligible.

Each plant should have a basic strategy for the parts that come from each supplier, based on each parts unique conditions.

Basic factors for establishing float

1. Weekly order or daily order?

If the part is in the Weekly order system, the float will be expressed in days (or tenths of days).

If the part is in the Daily order system, the float will be expressed in hours (or tenths of hours).

The maximum float in the Daily Order System (DOS) is 300 hours.

2. Is the part packaged and shipped in totes or as a unit load?

A basic factor in the handling, storage and linefeeding of a part is its packaging. Almost all parts can be divided into 2 main categories: totes or unit loads. Unit load here refers to pallets, skidboxes, steel racks... packaging that must be handled by a fork lift. Totes (or cartons) are boxes that can be picked up by a person. Safety stock strategies will be different for totes and unit load because of where they are stored, how they are linefed and how much space is available.


When unloaded from the supplier truck, does the part go directly to the line? Does it go to the ‘recon’ storage area until pick tickets are generated? Is it a tote that goes into a roller rack at lineside? If the part is a ‘picked’ part, the float must exceed the LCCN order point quantity so there will be stock to pick.

4. How many totes per day, or unit loads per day, does the plant require?
Remember that SPACE has become the prime consideration for setting safety stock...the number of totes or unit loads per day will give an indication of how much space the float will require...also, it will help visualize how many totes or unit loads will be in storage or at lineside when the next RAN is due.

A common ‘rule of thumb’ is that the lower the snp’s per day, the higher the float. The higher the snp’s per day, the lower the float.

5. **Rack Capacity.** On the LCCN screen Z575, material handling can assign a rack capacity for tote items which are put into gravity feed ‘roller’ racks at lineside. Rack capacity is the number of totes that the roller rack will hold, which is an important consideration when setting floats and order points. If the part is to be taken directly to the line without going to any storage for picking, then the float amount can not exceed the rack capacity. In fact, since the float amount can be thought of as the amount in the rack when the RAN is brought to the line, then the float plus the normal RAN quantity should be kept to less than the rack capacity. If not, material will have to be stacked on the floor around the roller rack. Since most tote items first go to storage for the pick system, this consideration will also be important when discussing how order points are set.

6. **Number of Linefeed locations** In most cases, the more linefeed locations for a part, the more safety stock is required. There is always present a condition referred to as ‘excess to lotting’ *, and the more locations there are, the more the excess adds up. Usually parts with numerous locations are linefeed by pick tickets, which are based on LCCN order points. There will usually be a bit more stock at the lines than the order point.

* Excess to lotting: This term usually refers to the excess of the amount in a package versus what the true requirement was. For example, if the system calculated the line location required 53 pieces at a certain pick hour, but the SNP is 100, it will issue a pick for 100. The excess to lotting is 47. This excess can add up over multiple locations.

7. Number of deliveries by a supplier.

With the daily order system it became possible to schedule deliveries from a supplier throughout the day. For example, some of the NNA-SP suppliers have over 20 trucks a day to the plant, all having RANs for the specific time needed. Since some high usage parts are on almost every truck, it is safe to lower float to 2 or 3 hours.

Even with parts from Japan, it is the parts with high usage and snp’s per day that will be on containers allocated for each day. This lessens the danger of an RDR or surprise in-plant loss from causing a stock-out situation. There should always be a container in the yard that can be unloaded to solve the problem.

Conversely, if the snp of a part is 1000, and its usage is 50 per day, then a RAN is only coming to us once every 20 days. We will raise the safety stock on a part like this to about 24 days to be safe. This high float is only 1 package and will not impact space or cost, but should protect us against misplaced material or a surprise cycle loss.

**Float versus Order Point**

When setting safety stock on parts picked from the crossdock or logistic centers, the float assignment must be higher than the total of the order points. If not, the warehouse area will not have material to fill the picks.

For example, if a part uses 300 per hour at two locations. Location A uses 200 per hour and has an order point of 800. location B uses 100 per hour and has an order point of 700, for a total of 1500 pieces or 5 hours. The problem is, we have assigned a float of 4 hours.
When the warehouse attempts to fill the pick to take material to the line, the RAN may not have arrived yet from the supplier. In fact with 2 locations whose combined order points equal 5 hours, it would be practical to have at least 8-10 hours float to make sure there is stock in the pick warehouse to meet the pick requirements. Remember that the order point controls how much material is expected at lineside when a pick is due from the warehouse, while the safety stock controls how much is expected in the plant when the RAN is due from the supplier.

Setting and Determining Float Levels: Excerpt
1. PURPOSE:

To provide a procedure to determine and set floats to accurately and efficiently maintain inventory levels.

2. SCOPE:

The scope of this procedure covers logistics processes relevant to Supply and Chain needs and includes processing both internal and external parties involved.

5. PROCEDURE

For determining float levels:

1. Float is the amount of inventory set in hours or days that should be in plant at all times, including the X-docks. When inventory levels get down to the float level, the plant should see its next shipment from the supplier.

2. The current float level can be reviewed in CICS screen X581 under Op Rsv for hours or days of float and Op Qty for float quantity. (See Attachment 1)

3. When determining a float level, the following things should be considered before setting:
   - **Type of part / Rack size:** How is the part packaged? What is the SNP qty? What is the ULD qty? What is the MIN/MAX RAN qty? Where is the part stored / warehoused? How much space will it use, in storage and/or line side? What is the rack capacity?
   - **Delivery Method:** How is the part delivered? PTB, Direct to Line, Local WH, Kanban or MH, picked from CLC or X-dock (parts set up on a pick system should always have a float higher than its order point)
   - **Usage:** Is the part a high or low runner? What is the weekly, daily and hourly usage? Is the usage consistent or does it fluctuate?
   - **Supplier:** Is it internal sourcing or an external supplier? Is it a consistent or varying supplier? What is the transit time and delivery schedule?
   - **Cycle History / Scrap:** Does the part have gains and/or losses? Is there a history of scrap?
   - **Quality Hold:** Is the part on Quality Hold? Does the part have any current issues or does it have a history of issues?
   - **Cost:** What does the part cost? Is it expensive or inexpensive?

4. Min / Max Guideline to setting Float in hours and days:
   - No less than 3 hours and No more than 300 hours (Mostly Domestic Parts)
   - No less than 4.5 days and No more than 40 days (Mostly NML Parts)