ABSTRACT

MOORE, TIMOTHY ANDREW. Evaluating the Augmentation of Army Resupply with Additive Manufacturing in a Deployed Environment. (Under the direction of Dr. Thom Hodgson.)

This thesis models the problem of keeping a M109A6 operational while in a deployed environment, comparing traditional resupply methods to additive manufactured spare parts. The additive technology is co-located with the howitzer unit, establishing a decentralized supply chain. Specifically, what conditions make it advantageous to deploy additive manufacturing technology to produce spare parts printed on demand? This model can assist decision makers determining when to augment a unit's typical safety stock with a 3D printing facility that can satisfy a howitzer unit's demand rate while deployed comparing cost and lead-time to make the best decision possible.

The model utilizes MATLAB to perform a simulation on the parts request process. In particular, the model was constructed so that different parameters could be manipulated based off of preference from the decision maker. For instance, the demand rate can easily be increased or decreased to simulate different phases of an operation or different environments altogether. For the purposes of this paper only parts comprised of metal were considered in the demand rate because those parts directly impact the validity of utilizing a Direct Metal Laser Sintering (DMLS) printer. Secondly, the model incorporates fixed and variable costs to demonstrate the fiscal requirements to implement such a program. Again, the parameters within the cost model can easily be adjusted to accurately reflect competitive pricing for the additive equipment and it can also be adjusted based on the unit size that the additive equipment is required to support.

Once the tools were built, it painted a realistic scenario for what conditions needed to be satisfied for additive capability to be useful in a deployed environment. This analysis enhances decisions that directly impact the capabilities of Soldiers in the most dire of situations: combat. The goal of this thesis is to highlight the areas that need to be focused on within additive manufacturing to become a realistic option for the military to adopt its technology. Ultimately, additive manufacturing will have an impact on spare parts fulfillment. As has been demonstrated in the civilian sector, companies that begin to invest early in the technology have begun to reap the largest benefits and the military should follow suit to remain on the cutting edge.

Evaluating the Augmentation of Army Resupply with Additive Manufacturing in a Deployed Environment

by
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DEDICATION

This work is dedicated to my wife, Kathleen. She is an amazing mother to my two children, Steven and Caroline, and easily the best example of a selfless person. Thanks for allowing me to pursue my goals while helping to raise a family.

BIOGRAPHY

Tim Moore was born and raised in Roanoke, VA before attending college at the United States Military Academy at West Point, where he received a B.S. in Economics in 2008. Upon commissioning as a Field Artillery Second Lieutenant in the United States Army he served as a Platoon Leader and Company Fire Support Officer while deploying in support of Operation Iraqi Freedom. He would go on to serve as a Battalion Fire Direction and Battalion Fire Support Officer while deploying in support of Operation Enduring Freedom in Afghanistan. He commanded in the 1st Brigade 41st Field Artillery Regiment at Fort Stewart, GA and completed two training rotations to Europe in conjunction with our NATO partners. In the summer of 2016 he began to study Operations Research at North Carolina State University and upon completion he will be assigned to the Mathematics Department at West Point.

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Chapter 1. INTRODUCTION

1.1 Additive Manufacturing

Additive manufacturing (AM) came to light in the 1980's but has recently garnered the attention of industry and hobbyists alike as a potentially time and cost effective way to make products. The accessibility of 3D printing continues to broaden and the technology itself continues to become more proficient and less expensive. The *Economist* recently went so far as to tout AM as a "third industrial revolution" that has the potential to change manufacturing on a global scale (Whadcock, 2012). People looking to experiment in their homes have certainly bought in, eager to exploit the new technology. In Wohler's Report 2016, desktop 3D printer unit sales (less than $5,000) grew at an astounding 69.7% in 2015, selling 278,385 machines (Wohlers, 2016). As Malcolm Gladwell put it, "there is a simple way to package information that, under the right circumstances, can make it irresistible" and 3D printing has certainly intrigued many (Gladwell, 2000). A tipping point is fast approaching where AM becomes widely used to augment product manufacturing.

AM application in a military context could be widely beneficial, allowing for a faster and potentially cheaper resupply of requested spare parts by simplifying the supply chain and reducing inventory costs. The military lends itself to the adoption of AM because it frequently operates in hazardous locations that naturally isolates its Soldiers from logistical resupply. In this scenario, the military stands to gain the most from AM technology and it therefore deserves to be analyzed as a practical option to augment traditional resupply methods.

1.2 Define the Problem

Like all companies, the military wants to save money when possible without cutting corners. However, this goal is coupled with the more serious desire to equip its employees, Soldiers, with the necessary equipment to deploy and win our nation's wars. Considering these two tenets, AM technology becomes a very attractive option to augment the military's current resupply chain. The problem, plainly put, is how can the military get necessary spare parts to the Soldier faster? Lead time on ordered replacement parts needs to be reduced so that Soldiers are able to accomplish their mission. If AM can bridge this gap, then what conditions need to be present and/or change altogether to be implemented as an impactful program?

1.3 Objectives

This thesis provides a synopsis of all current AM studies in the literature review, highlighting many of the advantages this technology can provide. The thesis goes on to describe a process, simulation, for evaluating the feasibility of augmenting an Army supply chain with AM technology. The demand data for parts requested was taken from actual units in Iraq during the US's initial invasion. Specifically, a M109A6 Paladin's parts are analyzed to reflect a realistic demand rate for just one end item. In this case, the Paladin is a self-propelled howitzer and is the main weapon system for a mechanized artillery unit. This data is manipulated through a series of assumptions and fed into a computer simulation in order to analyze the results. Lastly, these results are incorporated in realistic recommendations for how the Army can potentially improve its supply chain practices.

The buzz surrounding 3D printing is undeniable; the potential to disrupt current supply chains and even the entire manufacturing industry is plastered on every headline in the news. This thesis looks to serve as a framework for military decision makers, politicians, contractors and generals, to utilize in determining an appropriate application of AM for military resupply. Directly, what conditions need to be satisfied for AM to be viable in a deployed environment? Although much of the current literature is based on civilian companies, adoption and implementation by the military would consider many of the same guidelines.

Chapter 2. LITERATURE REVIEW

The current consensus is that there are enormous advantages to harnessing the capabilities of AM and many scholars have written extensively on this topic. The literature review aims to provide a cogent synopsis of all relevant work that has been done on the implications of additive manufacturing in order to highlight the research gap between well-structured costs analysis and those of the ill-structured variety. Well-structured costs consist of material, labor, and manufacturing system costs (Young, 1991). Ill-structured costs stand as the areas which can benefit the military the most: transportation and inventory costs.

2.1 Current State of Additive Manufacturing

AM at its simplest is the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies. The oldest technology, Stereolithography (SLA), uses a photosensitive resin and exposes it to a UV laser beam to create the product. The most common form of 3D printing is Fused Deposition Modeling (FDM) where a thermoplastic filament is heated and melted layer by layer in the X/Y direction and lowered in the Z direction. An emerging technology is Electron Beam Melting (EBM) that allows highly durable metals to be formed under an electron beam in a high vacuum that melts the metal powder. For this thesis, Direct Metal Laser Sintering (DMLS) is considered as the main AM technology. DMLS uses lasers to fuse powdered metals into functional prototypes and end-use parts. The key understanding is that AM technology is constantly improving and evolving so it is reasonable to expect that higher quality products will be created more quickly and less expensively in the future.

The above-mentioned techniques and others have been adopted by companies in many different civilian sectors including medical fields, aerospace, clothing, jewelry, prototyping, and even food products. The raw materials used to create these products are constantly evolving and include different types of steel, titanium, cobalt, plastic, Kevlar, nylon, glass, and aluminum to name a few. Given the excitement and potential practicality behind AM technology, many notable companies have begun to invest in AM to maintain their edge on current trends. Among these are GE (jet engines, medical devices, and home appliance parts), Lockheed Martin and Boeing (aerospace and defense), Aurora Flight Sciences (unmanned aerial vehicles), Invisalign (dental devices), Google (consumer electronics), and the Dutch company LUXeXcel (lenses for light-emitting diodes, or LEDs) (D'Aveni, 2015).

The fascination is warranted because AM allows for the creation of completely redesigned products: lighter weight with new strength properties, combination of multiple parts into one, or rapidly decreasing the time required to make a prototype into a reality. In a recent example, Amaero and Monash University were able to make multiple prototypes of a rocket engine, tweaking complex geometrical details, and save months of design time (Haria, 2017). However, in most circumstances the technology is not low-cost enough and cannot produce products quickly enough to immediately replace traditional manufacturing (TM). Nearly all academic studies up to date agree that AM technology will serve best as a complement to machining rather than an outright replacement for the foreseeable future (Bogers, Hadar, & Billberg, 2015). Despite that, the desire for AM to become the primary production method is heavily present in many sectors and the companies that begin to explore the uses of AM now will benefit the most later, once AM technology catches up to the demand levels that TM currently satisfies.

One important factor to note about the AM industry is that a lot of companies that produce the technology also own the raw materials to be able to print with AM. This creates a partially skewed market because the suppliers do not face as much competition as they would if it were a well-established technology. In the future, it is expected that more companies will enter the AM production field, thus driving prices down to a more a competitive rate.

There are still many obstacles that prevent companies from adopting and implementing AM in their own production processes. The largest problem is that AM simply cannot keep pace with large volumes of demand. Regardless of how inexpensive the technology becomes, build times will have to decrease drastically in order to produce at a rate sufficient for products in high demand. Another hindrance that often gets overlooked is having the correct personnel in place to ensure that AM is run properly. Not just anyone can hit “print” and be done with the production process. Highly specialized engineers are required to create Computer Assisted Drawings (CAD) that serve as blueprints for products being created through AM. Another large obstacle is maintaining the physical printers as well as the quality of the products that are being printed. Again, existing personnel would have to be trained on the AM technology or replaced altogether.

2.2 Background

The rise of 3D printing and additive manufacturing will replace the competitive dynamics of traditional economies-of-scale production with an economies-of-one production model, at least for

some industries and products (Petrick & Simpson, 2013). Areas that stand to gain the most from AM include: 1) Mass customization, 2) Resource efficiency, 3) Decentralization of manufacturing, 4) Complexity reduction, 5) Rationalization of inventory and logistics, 6) Product design and prototyping, and 7) Legal and security concerns (Mohr & Khan, 2015). Each of these areas are explained in depth with relevant literature that supports the advantages of implementing AM and relevant case studies that highlight some of these areas are further explained.

2.2.1 Ill-Structured Costs

Much of the relevant AM research that has been conducted does not accurately explain the potential benefit that AM can provide to ill-structured costs. Ill-structured costs are generally comprised of supply chain aspects. Inventory is a primary example of an ill-structured cost that provides tremendous upside for AM technology. The resources spent producing and storing these products could have been used elsewhere if the need for inventory were reduced. Suppliers often suffer from high inventory and distribution costs. Additive manufacturing provides the ability to manufacture parts on demand. Traditional production technologies make it too costly and require too much time to produce parts on demand. The result is a significant amount of inventory of infrequently ordered parts. This inventory is tied up capital for products that are unused. They occupy physical space, buildings, and land while requiring rent, utility costs, insurance, and taxes. Meanwhile the products are deteriorating and becoming obsolete. Being able to produce these parts on demand using additive manufacturing reduces the need for maintaining large inventory and eliminates the associated costs (Gilbert & Thomas, 2014).
In an (s-1, s) inventory model for spare parts, Sirichakwal & Conner demonstrated that the concept of virtual inventory, made possible by AM, has many appeals for spare parts inventory management especially in systems where inventory obsolescence and stock-out risk are of high importance. They also showed that a reduction in holding cost has more impact on reducing the stock-out probability when the average demand rate for spare parts is low. Additionally, lead time reduction can actually have a negative impact on the stock-out probability (Sirichakwal & Conner, 2016).

Transportation is another huge aspect of the supply chain that AM technology looks to alter drastically in the future. Additive manufacturing allows for the production of multiple parts simultaneously in the same build, making it possible to produce an entire product in one step. Traditional manufacturing often includes production of parts at multiple locations, where an inventory of each part might be stored. The parts are shipped to a facility where they are assembled

into a product. Additive manufacturing has the potential to replace some of these steps for some products, as this process might allow for the production of the entire assembly in one build. This would reduce the need to maintain large inventories for each part of one product, reduce the transportation of parts produced at varying locations, and reduce the need for Just-In-Time (JIT) delivery (Thomas, 2016). Another substantial transportation impact is the location of the production facility which can be nearer to the user and is described in detail in its own section due to its importance.

2.2.2 Supply Chain

The supply chain includes purchasing, operations, distribution, and integration. Purchasing involves sourcing product suppliers. Operations involve demand planning, forecasting, and inventory. Distribution involves the movement of products and integration involves creating an efficient supply chain (Robinson, 2015). AM provides the potential for many advantages in the manufacturing supply chain. A noticeable benefit is dematerializing the supply chain itself. If there are fewer steps along the chain, then efficiency increases and the chance for delays and disruptions decreases. Other advantages include true Just-In-Time manufacturing, reduced set up, changeover time, number of assemblies, and the elimination of waste (material, time, costs, distribution) (Tuck, Hague, & Burns, 2007). AM also enables JIT manufacture at the shop floor instead of JIT delivery of supplies to the shop floor. As a result, non-value added activities such as material movement and inventory holding can be reduced to a minimum. The result is a lean supply chain with low cost. Additionally, AM can improve the responsiveness of an agile supply chain. A build-to-order strategy can be implemented to ensure that no stockout would occur. The overriding cost for AM production is not labor but the machines and raw materials, which makes it economical to locate production facilities near the end customers. Lastly, it is possible to customize products to meet individual customer needs. This will facilitate the implementation of a build-to-order strategy and increase responsiveness to customer's demands (Huang, Liu, & Mokasdar, 2013).

All businesses aim to be efficient at every level and collectively the industry has adopted the 6 Sigma approach towards a lean and agile supply chain. Thomas et al (2014) described seven categories for a company to focus on in order to become lean:

1) Overproduction: occurs when more is produced than is currently required by customers

2) Transportation: transportation does not make any change to the product and is a source of risk to the product

3) Rework/Defects: discarded defects result in wasted resources or extra costs correcting the defect

4) Over-processing: occurs when more work is done than is necessary

5) Motion: unnecessary motion results in unnecessary expenditure of time and resources

6) Inventory: is similar to that of overproduction and results in the need for additional handling, space, people, and paperwork to manage extra product

7) Waiting: when workers and equipment are waiting for material and parts, these resources are being wasted

AM has the potential to improve efficiency for each of these tenets.

Manufacturing and delivering products to customers require the efforts of various companies that form the manufacturing supply chain. These companies may include raw material suppliers, component suppliers, original equipment manufacturers, wholesalers/distributors, logistics service providers, and retailers. In a supply chain, materials flow forward from suppliers through various stages toward customers, whereas information and funds flow backward. As described, AM has the potential to reduce the number of stages in the traditional supply chain. Specifically, AM technology offers two opportunities: (1) to redesign products with fewer components and (2) to manufacture products near the customers (i.e., distributed manufacture). The net effect is reduction in the need for warehousing, transportation, and packaging (Huang, Liu, & Mokasdar, 2013). These elements combined illustrate the enormous impact AM technology can bring to the manufacturing supply chain.

Hasan and Rennie (2009) noted that a fully functional AM supply chain was not yet available in 2009 in the spare parts industry. The authors proposed a business model to enable such a supply chain. The model is based on an e-business platform that provides the following services (Hasan & Rennie, 2009):

1) Sourcing: give buyers easy access to a pool of suppliers.

2) Demand identification: assist suppliers to identify customers and their demand.

3) Content display: provide an e-catalogue to display the products and services provided by the suppliers.

4) Transaction: enable the exchange of procurement information between the buyers and suppliers.

5) Promotion: help suppliers advertise their products and services.

2.3 Advantages/Disadvantages

2.3.1 Pros

This section consolidates the benefits of AM for particular industries to utilize. AM technology is constantly evolving and the upside is seemingly limitless (Steenhuis & Pretorius, 2017). AM opens opportunities for manufacturing companies in three regards: 1) AM offers the option of generating objects that would have been impossible to make with any other technology, 2) AM can be used as an automation technology which substitutes for human labor, and 3) AM allows for cost-efficient switching from traditional mass production to new areas of mass customization (Thiesse, Wirth, & Kemper, 2015).

As a result of Niaki & Nonino (2017), we can affirm that AM brought not only a process innovation but also product innovation. This revolutionary technology allows for the fabricating of creative products and construction of highly complex parts; sharing design and collaboration with consumers with a low cost of modifications; enabling the full customization of parts with more functionality and aesthetic appeal, which is impossible for general production to fabricate with traditional techniques. In addition to introducing new products, AM leads to new markets. Therefore, it is reasonable to expect a growing demand for AM as some firms in the study have found, as well as an increasing willingness of consumers to pay more for the higher value offered. This higher value is influenced by customer service through time-to-market reduction and full customization, and provides the possibility to charge higher prices, especially for parts made in metal. Consequently, it influences revenue in a positive way and is an attractive investment (Niaki & Nonino, 2017).

Another advantage is a simplified supply chain to increase efficiency and responsiveness in demand fulfillment. AM is conducive to innovative design and enables on-demand manufacturing. As a result, the need for warehousing, transportation, and packaging can be reduced significantly. With proper supply chain configuration, it is possible to improve cost efficiency while maintaining customer responsiveness using AM. With the advent of personal AM machine, the dream may come

true where customers can obtain desirable products economically whenever they want and without leaving their homes (Huang, Liu, & Mokasdar, 2013).

Many specific case studies conducted include multiple different types of industry and reflect the effect of AM's benefits in their results. Hearing aid companies in particular have been one of the most prevalent adopters of AM. In a specific case study, a hearing aid company bought AM technology and produced parts in house instead of by a third party. Although the company needed highly paid engineers to build the designs, new benefits far outweighed this downside. In fact, the company accomplished this by emailing scanned ear canals to a company in Germany that already had CAD model engineers. Since the CAD designs were now being sent electronically the process allowed for distributed manufacturing. This scenario reduced lead time by eliminating physical deliveries (email request of scanned ears). Overall, both companies in this case study were able to increase material utilization and improve efficiency (Oettmeier & Hofmann, 2016). In another empirical case study on a lamp company, the results showed the supplementary capacity of the AM process and how it improved the supply chain (SC) performance in terms of lead time and total cost. That work identified the research gap between AM and SC and gave a comprehensive investigation of different performance indicators such as order fulfill rate and waste rate (Chiu & Lin, 2015).

Another case study described many of the themes highlighted in this section. Specifically, General Motors offers a program called Retail Inventory Management (RIM) that allows dealers to return parts that do not sell in 15 months without any penalty. While the dealership avoids paying for the part, they still have money tied up in labor costs to stock the part, rent utilities, taxes, insurance, and the opportunity cost associated with carrying the part. It is easy to see that a dealership which implemented AM of parts on demand could significantly reduce

1) the type and quantity of spare parts needing to be stocked
2) procurement costs for parts the dealer would typically order from the manufacturer or another location
3) shipping costs for parts ordered as well as obsolete parts returned
4) costs involved in recall programs for malfunctioning parts

In addition, the dealer would always be assured of having parts that utilized the most current part design (Beyer, 2014). Another auto maker has been using 3D printers since 2014 to produce tooling components for use on the assembly line. Not only have direct manufacturing costs decreased

drastically for selected parts but lead time has been significantly reduced as well. One example of a component transformed by AM was a “liftgate badge tool” which is used to precisely place the car’s logo. Lead time dropped 89%, with outsourcing taking an average of 35 days and 3D printing just 4 (Jackson, 2017).

Lastly, in England two different types of companies were analyzed: wallpaper and chemical filter suppliers. The decoupling point was moved upstream to allow for high levels of customization which greatly enhanced the perceived value by customers. Through the adoption of AM, additional processes resulted in value stream (VS) creation, which co-existed with existing VSs to enhance and strengthen manufacturing (without replacing traditional methods or VSs). This provided both companies with the ability to grow their business and capabilities further to compete, positively impacting on their region with spillover of skill, knowledge and economic benefit (Rylands, Bohme, Gorkin, Fan, & Birtchnell, 2016). The case study resulted in the following hypotheses:

1) Incorporating AM into the manufacturing system results in growth across VSs due to close client engagement during the co-creation process.

2) AM is not replacing existing manufacturing/VS, rather it is complementing a company’s offerings.

3) Unless the VS changes, the business impact is limited (engineering solutions rather business solutions).

4) AM knowledge centers are critical supply chain nodes for a company pull driven implementation process.

2.3.2 Cons

Many barriers still exist to the adoption of AM and it is important not to discount these aspects and get swept up in the potential benefits. The results suggest the AM machine acquisition price and personnel intensiveness are major obstacles to a distributed deployment of this technology in spare parts supply chains (Khajavi, Partanen, & Holmstrom, 2014).

Another study reveals a number of disadvantages and challenges ahead of this emerging technology. In terms of operational costs, any additional sources of expenses, such as depreciation of machines, maintenance cost and, more significantly, higher prices of the material and machines, need further development to be efficient. In the perspective of processing, potential health hazards caused by some raw materials, small production platforms and the need for post-processing are the most challenging aspects. In addition, a limited range of available raw material and a shortage of

suppliers lead to a high negotiating power for AM material suppliers, in spite of efforts to develop new viable materials (Hao, Zhang, & Mellor, 2014) (Niaki & Nonino, 2017).

2.4 Centralized vs. Distributed

As mentioned above, the largest potential for a disruptive change in supply chain management is the location of production. Holmstrom et al. (2010) proposed two different approaches to integrate AM technology in the spare parts supply chain. The first approach is to use centralized AM capacity to replace inventory holding. AM machines are deployed in centralized distribution centers to produce slow-moving spare parts on demand. Producing parts in a centralized location has the advantage of aggregating demand from various regional service locations to ensure that the investment in AM capacity is well utilized. The disadvantage is that the produced parts need to be shipped to the service locations, which results in an increase of response time. A method to mitigate this issue by locating production at third party logistics (3PL) sites. Hence, once a part is printed it can be immediately shipped to its final destination (D'Aveni, 2015). However, for certain parts that are needed in the first line maintenance, inventory still needs to be carried in the service locations. The centralized approach is desirable when parts produced using AM are limited and the required response time is not critical. The second approach, distributed AM at each service location, is suitable when the demand of AM producible parts is sufficiently high to justify the capacity investment. The advantage of the distribution of AM is the elimination of inventory holding and transportation costs and a fast response time. In addition to these two approaches, Holmstrom et al. (2010) also contemplates the feasibility of mobile AM but concedes that there are many challenges. The authors further discusses the trade-off between batch production and on-demand production, and the trade-off between specialized and general purpose AM. The key variables considered are materials and production costs, distribution and inventory obsolescence costs, and life-cycle costs for the user. They concluded that on-demand and centralized production of spare parts is most likely to succeed (Holmstrom, Partanen, Tuomi, & Manfred, 2010).

In a case study conducted on aircraft spare parts, it is shown that the advantages of AM technology can be introduced into different stages of the aircraft spare parts supply chain. Again, the centralized AM supply chain is more suitable for parts with low average demand, relatively high demand fluctuation, and longer manufacturing lead time. The distributed AM supply chain is suitable for parts with high average demand. It is also suitable for parts with very stable demand,

because in this case the benefit of demand aggregation in a centralized distribution center is greatly diminished. It can also be used for parts with very short manufacturing lead time, especially if their demand is low and unpredictable; because such parts can be produced on-demand. It is clearly demonstrated that AM has the potential to change the conventional supply chain configuration. In this industry it is possible to achieve inventory reduction, thus cutting inventory holding costs across the entire supply chain (Liu, Huang, Mokasdar, Zhou, & Hou, 2014).

The potential advantages of using AM machines for the distributed production of aircraft spare parts can be summarized as follows: lower overall operation costs, lower down time, higher potential for customer satisfaction, lower capacity utilization, higher flexibility, fewer supply chain disruptions, reduced need for inventory management and logistics information systems, and potential for sustainability improvements as AM machines become smaller and more energy efficient (Khajavi, Partanen, & Holmstrom, 2014). However, the same study identifies notable gaps that prevented a distributed approach. To combat this, it was suggested that higher automation, lower acquisition price, and shorter production time of AM machines are the factors that the producers of these machines should aim to develop to enable radical change in spare parts supply chain operations (Khajavi, Partanen, & Holmstrom, 2014).

Decentralized distribution can remain challenging to fully realize. In another study a company is unable to do decentralized production because they do not have a consistent customer base, therefore cannot predict where they are going to sell their product. As a result, post-production processes and costs are high so decentralization would only increase costs (Hao, Zhang, & Mellor, 2014).

2.5 Direct Manufacturing

Although the intent behind this paper is to utilize AM technology to satisfy realistic demand rates, a brief description of direct manufacturing cost research is deserved. In one of the first cost studies, Hopkinson and Dickens (2001) calculated the average cost per part based on three assumptions: 1) the system produces a single type of part for one year, 2) it utilizes maximum volumes, and 3) the machine operates for 90% of the time. The analysis included labor, material, and machine costs. Other factors such as power consumption and space rental were considered but contributed less than one percent of the costs; therefore, they were not included in the results (Hopkinson & Dickens, 2001). The cost of additive manufactured was later refined by Ruffo et al. (2006) using an activity based cost model, where each activity is associated with a particular cost. They produced

the same product that Hopkinson and Dickens produced using selective laser sintering (Ruffo, Tuck, & Hague, 2006). The cost model constructed in a more recent paper for EBM and DMLS demonstrates that machine productivity forms a main driver of per-unit manufacturing cost. It also suggests that this contributes to a general cost barrier to technology diffusion of AM into mainstream manufacturing (Baumers, Dickens, Tuck, & Hague, 2016). All these studies and others have to led to the conclusion that there is a value to be placed on the speed, versatility, and adaptability of AM as it allows for just-in-time manufacturing. Further, AM is favored in small production lots in which the higher cost of AM specific raw materials is offset by a reduction in fixed costs associated with conventional manufacturing (Frazier, 2014).

2.6 Ideal Candidate to Adopt

AM appeals to many different industries and in particular, ones that suffer from a natural divide from their customers and suppliers. For instance, space is a readily cited example for obvious reasons: distance to a supply depot! Other forms of isolation are encountered when the machine or blueprints required to produce an old part do not exist anymore. Additionally, a customer may be isolated due to a hazardous location, i.e. a war zone (Peres & Noyes, 2006).

Although AM technology has yet to be truly incorporated into the spare parts supply chain, it has been successfully used to supply certain consumer goods. Reeves (2010) described four such businesses that have adopted AM: (1) Fabjectory that enables players of Second Life to purchase models of individualized avatar characters, (2) FigurePrints that allows players of World-of-Warcraft to order 1/16th scale models of their online gaming characters, (3) Landprint that offers personalized 3D model of any place on earth, and (4) Jujups that offers a range of personalized gifts such as photo frames, badges, mugs, and even chocolate. All of these companies looked to capitalize on aforementioned benefits. In particular, with this type of business model, retailers do not carry any inventory. Goods are produced on-demand either in-house or through subcontract to a third-party manufacturer and then shipped directly to the customers. There is no need for warehousing and distribution, although the final products still need to be shipped to customers. Customers can design their own personalized products or obtain files of standard products online through a technology service provider. The products can then be built by the customers using their personal 3D printer. This disruptive technology has the potential to drastically change the landscape of the conventional manufacturing supply chain (Reeves, Tuck, & Hague, 2010).

Ultimately, the ideal AM market looks like: small production output, high product complexity, high demand for product customization to individuals, and spatially remote demand for products. In the long run, the largest payoff is for a company that can produce small batches to a customer that desires customization (Weller, Kleer, & Piller, 2015). All of these cited articles provide key concepts to consider within the AM industry but given the short amount of time AM has been prevalent, generally lack data to quantify these concepts. The military could capitalize on many of these touted benefits by producing spare parts with AM in a deployed environment; none more important than reducing lead time. Adopting a distributed manufacturing technique could alter how Soldiers get spare parts while deployed.

Chapter 3. DESCRIPTION OF DATA

3.1 Data Used

3.1.1 Data Sources

All of the demand data used in this paper was provided by RAND Corporation (Peltz, Halliday, Robbins, & Girardini, 2005). The provided data displayed all part requisitions for Operation Iraqi Freedom (OIF) during a 162 day period that spanned the initial invasion in 2003. Each requisition within the data set had specific information pertinent to the entire supply process and a sample of the data is provided in Appendix A.1. The most important pieces of information for this thesis included quantity, weight, volume, price, request date, and delivery date. An important distinction is the requisition data does not reflect true demand because it is supply side data, not consumption data. Considering this data comes from OIF, it is plausible that units ordered parts based off not only actual needs but projected needs as well. Ultimately, the requisition data used in this thesis is more conservative comprising of supply side data.

Another data source was build time data. This was collected from MakerBot™ Thingiverse, an online design community for discovering, making and sharing 3D printable things. Specifically, 53 different products were selected that directly reflected build time and volume, Appendix A.2. The metal parts were all built using Direct Metal Laser Sintering (DMLS) and ranged from simple to complex designs. The parts varied enough to accurately reflect eventual Paladin part CAD models given that current blueprints do not exist for Paladin spare parts. However, the data range was limited to smaller parts, not fully reflecting all sizes of Paladin parts.

3.1.2 Data Organization

The requisition data was organized by only focusing on specific Unit Identification Codes (UIC) to determine what parts were ordered by heavy artillery battalions (BNs). To manage the scope of data points, 4th Infantry Division (4ID) was selected so only artillery BNs in 4ID are reflected in the data. It is important to note that there were 3 artillery battalions requesting parts in the data set. The goal was to have a list of Paladin spare parts requested during this 162 day period but the given data set did not provide what end item (piece of Army equipment) each National Item Identification Number (NIIN) corresponded to. In order to solve this problem, a heavy artillery battalion's monthly Document Control Register (DCR) was utilized to generate NIIN's of spare part requisitions

specifically for a Paladin. The 4ID OIF data was scrubbed based off of the DCR which resulted in a list of Paladin parts that were requested during the first 162 days of OIF. Lastly, this list was filtered once more to only reflect spare parts made primarily of metal so that the demand rate used in the simulation model was solely for M109A6 Paladin spare parts made of metal during the first 162 days of OIF, Figure 3-1.

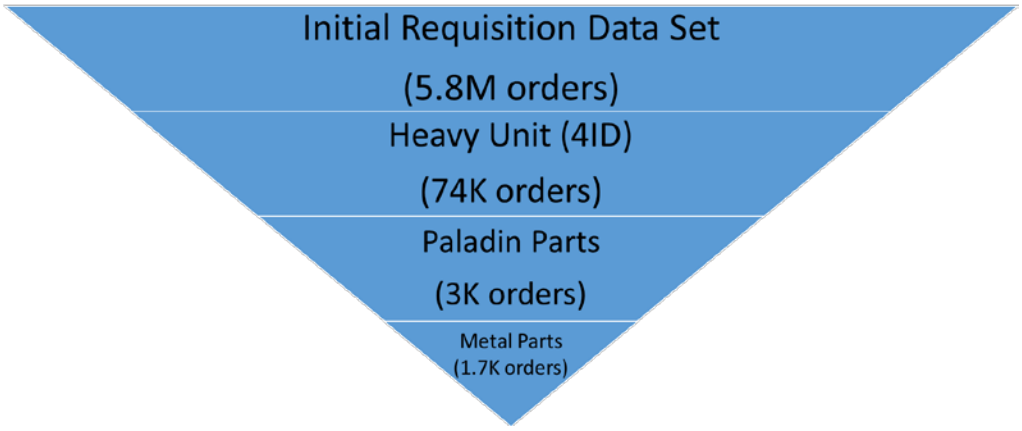

Figure 3-1 Organization of Requisition Data

3.1.3 Data Cleansing

Preparing the data was fairly straightforward for this data set. The first step was to eliminate erroneous orders. This was accomplished by filtering the orders and changing any order for a quantity of 0 to a quantity of 1. The assumption was made that if a supply clerk submitted the order then at least 1 part was required. This means part quantity is always greater than equal to 1, not to be confused with orders by day. There were multiple days during the 162 day period that no orders were submitted. The next step was to augment the request and delivery dates to reflect a more intuitive time. The supplied dates were provided with a Julian prefix for 2003, ex. 3053 represented February 22nd, 2003. So 3000 was subtracted from all dates for easier interpretation.

3.2 Converting to Model Input

3.2.1 Arrival Rate (λ(t))

The first step was to generate a random number of orders for each day. The assumption was made that although orders may realistically arrive at any point during the day, they would be compiled in a queue and processed at the start of the next day for simplicity. The number of orders were

analyzed using StatFit2 and the descriptive statistics are displayed in Figure 3-2. Again, 162 (data points) days were used and the data reflects that a maximum of 98 orders in one day were made and mode of 7 orders a day occurred most frequently.

descriptive statistics

data points	162
minimum	0.
maximum	98.
mean	10.716
median	7.
mode	7.
standard deviation	12.0663
variance	145.596
coefficient of variation	112.6
skewness	3.47802
kurtosis	18.7125

Figure 3-2 Number of Orders Per Day

Next, it was determined that a Weibull distribution, with shape parameter α = 1.10484 and scale parameter β = 11.9755, was the best fit for the continuous arrival rate of orders, Figure 3-3. The null hypothesis in this case is that the Weibull distribution is the proper distribution for the Number of Orders Per Day data. The large p-values indicate weak evidence against the null hypothesis, so we fail to reject the null hypothesis.

Weibull		
minimum	=	0. [fixed]
alpha	=	1.10484
beta	=	11.9755
Kolmogorov-Smirnov		
data points		162
ks stat		9.4e-002
alpha		5.e-002
ks stat(162,5.e-002)		0.106
p-value		0.108
result		DO NOT REJECT
Anderson-Darling		
data points		151
ad stat		0.896
alpha		5.e-002
ad stat(5.e-002)		2.49
p-value		0.417
result		DO NOT REJECT

Figure 3-3 Goodness of Fit

Furthermore, the fitted density and distribution reflect that Weibull is an acceptable distribution to generate random variables, Figure 3-4 & Figure 3-5.

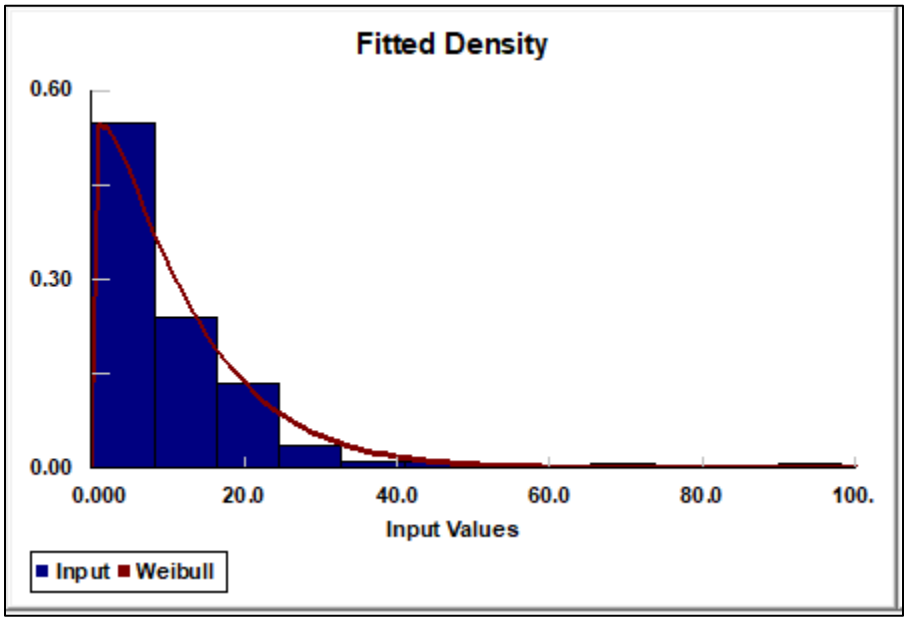

Figure 3-4 Fitted Density

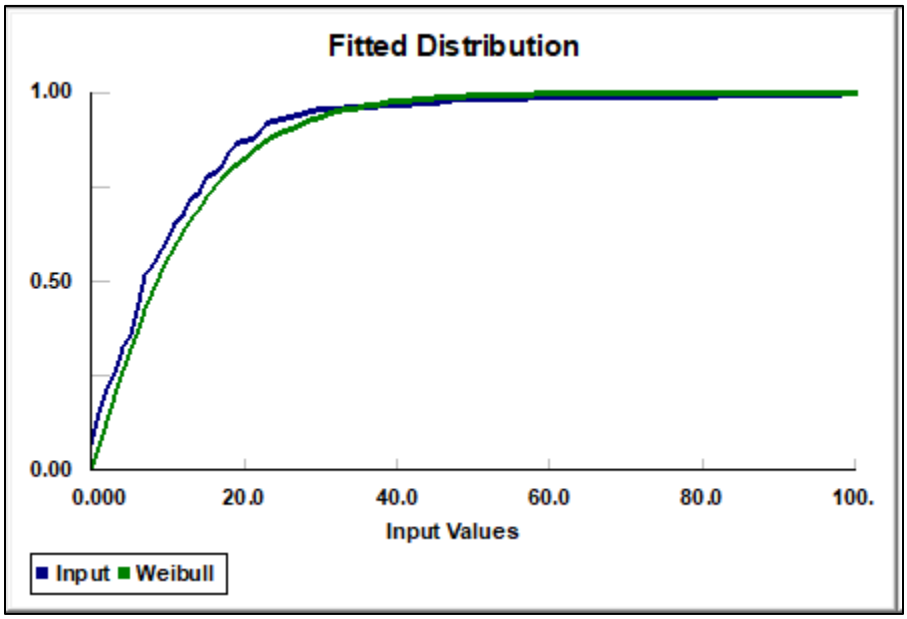

Figure 3-5 Fitted Distribution

Each day is assumed to be independent of one another. This is important because the simulation treats each day as independent of the past. Furthermore, Figure 3-6 defends this assumption with

the auto-correlation data because none of the data is highly correlated, meaning the previous day does not have a significant impact on the amount of orders made the next day.

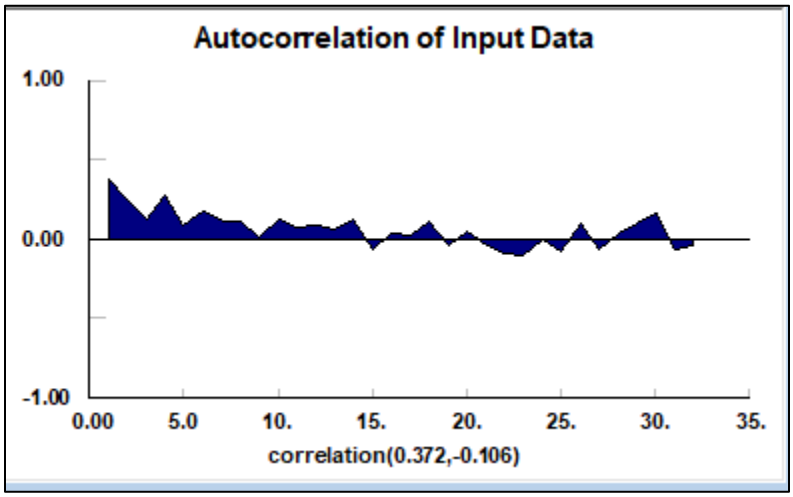

Figure 3-6 Autocorrelation of Orders Per Day

The arrival rate (λ(t)), number of orders per day, in this thesis varied based off the scenario the simulation was performing. For instance, the demand rate changed when different unit sizes were considered. Since the original data was reflective of 3 battalions making order requests, the demand rate decreased as the unit sizes decreased. All of the subsequent distribution fittings can be seen in Appendix D for reference. Additionally, all of the different scenarios are described and displayed in Chapter 5.

3.2.2 Service Rate (μ)

The first factor that needs to be satisfied to determine viability of AM implementation is for the production rate to meet the demand rate. This was accomplished by creating a simulation in MATLAB that kept track of the total sojourn time for requisitioned parts and discussed in further detail in Chapter 4. Figure 3-7 provides a depiction of all factors that were considered in the build time model. It is important to understand the entire process to accurately reflect the amount of time it takes to print a part.

3.3.2.1 Setup Procedures

Holistically, every product to be printed needs to begin with a CAD model, file preparation. From there, an engineer would be responsible for setting up the chamber and otherwise preparing the machine for operation. Lastly, the engineer would release the build and the printing would begin. All

of the steps occurring during the setup phase were accounted for with a Beta distribution which is described later in this section. This was selected because realistic bounds on setup times exist for every 3D build.

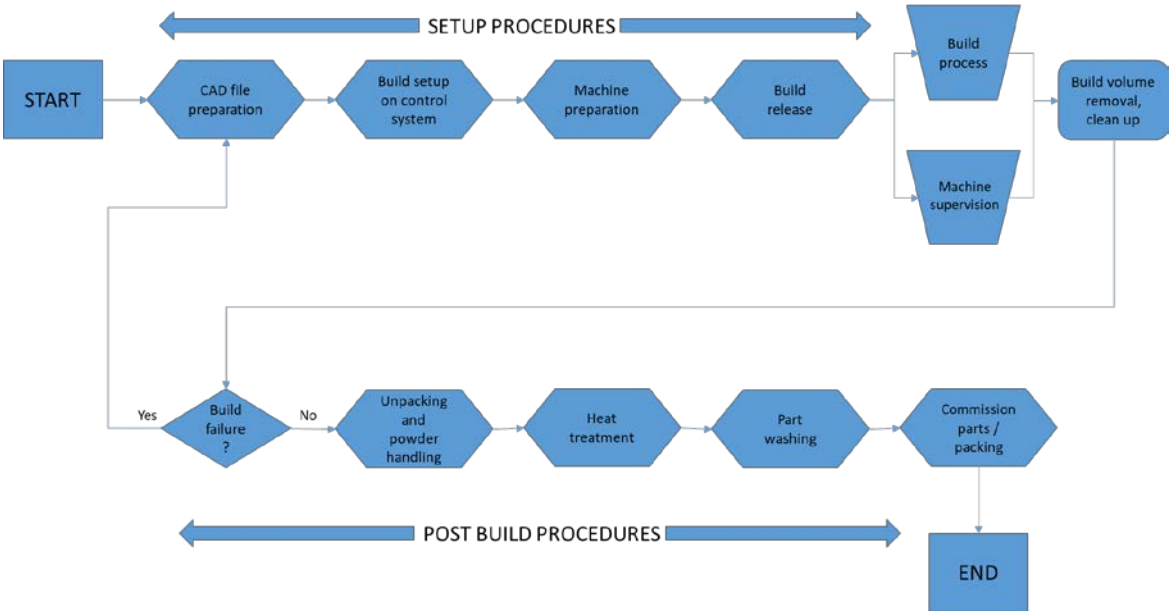

Figure 3-7 AM Build Process

3.3.2.2 Build Procedures

The actual build time estimation, given all necessary information about the CAD model, can be calculated precisely. In fact, there are many published papers that fully and accurately provide formulas to estimate build time for additive manufacturing. Equation 1 describes a globally accepted algorithm for estimating build times (Baumers, et al., 2012)

1) Fixed time consumption per build operation, T_{Job}
2) Total layer dependent time consumption, obtained by multiplying the fixed time consumption per layer, T_{Layer}, by the total number of build layers l
3) The total build time needed for the deposition of part geometry approximated by the voxels. The triple Σ operator in Figure 3 expresses the summation of the time needed to process each voxel, $T_{Voxel\ xyz}$, in a three-dimensional array representing the discretized build configuration

$$T_{Build} = T_{Job} + \left(T_{Layer} \times l\right) + \sum_{z=1}^{z}\sum_{y=1}^{y}\sum_{x=1}^{x} T_{Voxel\,xyz}$$

Equation 1. Baumers Build Time Estimation Formula

Baumers (2012) is referenced to acknowledge that there is a sophisticated approach to estimating build times. It is understood on a more simplistic level that build time is a function of the deposition speed and the length of the deposition in each layer. Additionally, the speed is certainly affected by the quality of the printer and the complexity of the part. However, all of these variables could not be captured for Paladin parts that do not currently have CAD models so the assumption was made that build time could be calculated given part volume. The statistical significance of this assumption is reinforced by the linear regression in Figure 3-9. The previously mentioned Thingiverse data reflected actual build times with their corresponding volumes, Appendix A.1.

Table 3-1 below shows a sample of the parts selected for the regression.

Table 3-1 Build Time Data based on Volume

part	v (in^3)	Total Print Time (hrs)
calibration_angle	0.17	0.33
clip_mk1	0.01	0.07
DCU224C-M4-adapter	0.37	0.37
Desk_Knob	0.22	0.28
drawer_bracket	1.07	1.1
egranaje_carro	3.83	2.02
embudo_con	3.17	4.53

The regression was based on the following model in Equation 2.

$$y = \alpha + \beta x + \varepsilon$$

$$y = PartBuildTime$$

$$\alpha = intercept$$

$$\beta = scalar$$

$$x = PartVolume$$

$$\varepsilon = error\ term$$

Equation 2. Simple Linear Regression Model

The expected response, $PartBuildTime$, is found by adding the intercept term (α) which is an unknown and non-random parameter, to another unknown and non-random parameter (β),

multiplied by the known covariate, $PartVolume$, plus an error term (ε). The error term is assumed to be independently and identically distributed $N(0,\sigma^2)$. The regression fitted an α parameter of 0.93994 and β parameter of 0.29150 with an R^2 value of 0.8334, seen in Figure 3-8. Figure 3-9 displays the 53 points of build time data regressed using R software. Time is displayed in hours and volume is in cubic inches. The regression's intercept was not forced to 0 so that the model could more accurately predict small volume build times.

```
> summary(m1)

Call:
lm(formula = time ~ volume, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.1222 -0.7002 -0.2231  0.2054  4.0845 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.93394    0.19677   4.746 1.66e-05 ***
volume       0.29150    0.01807  16.128  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.179 on 52 degrees of freedom
Multiple R-squared:  0.8334,	Adjusted R-squared:  0.8302 
F-statistic: 260.1 on 1 and 52 DF,  p-value: < 2.2e-16

> cor(volume,time)
[1] 0.9129016
```

Figure 3-8 Regression Data Using R Software

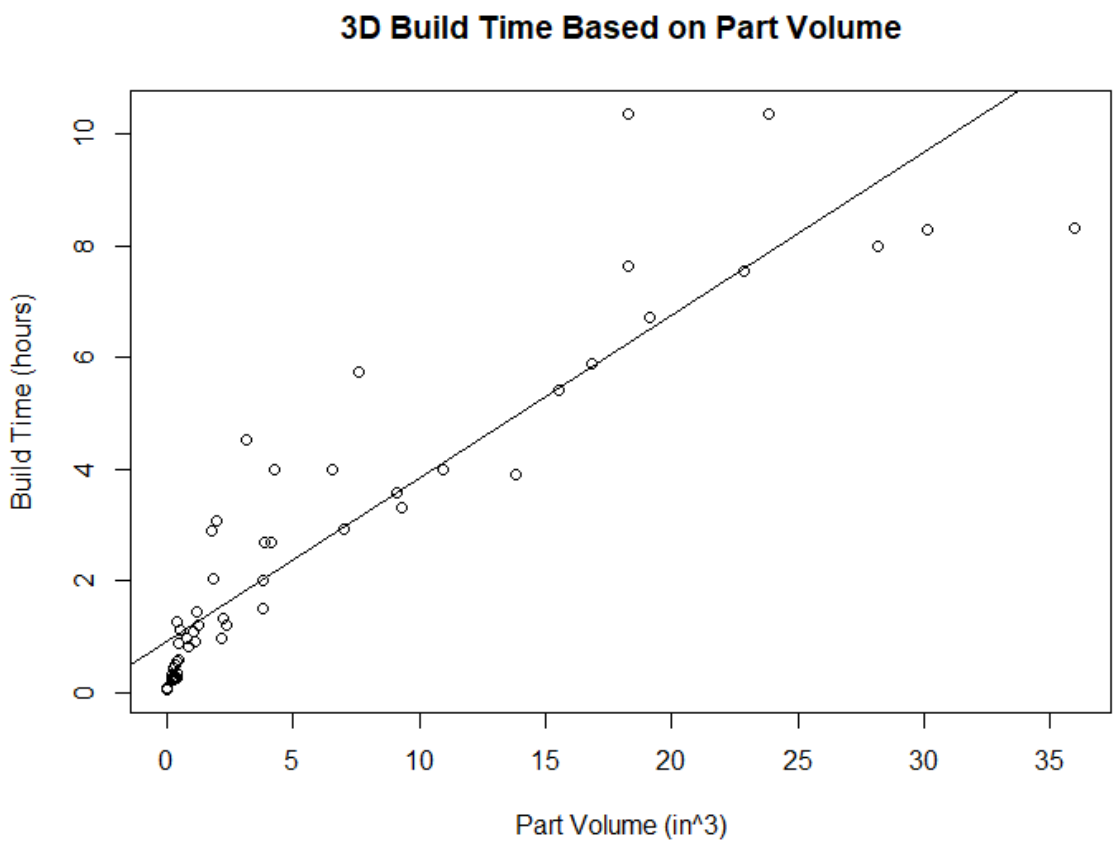

Figure 3-9 Linear Regression of Build Times Based on Volume

The volume for each Paladin part was plugged into the regression described above to get the build time for each part. Of note, print speed can be optimized in a chamber if small batches are created and products are printed simultaneously in the horizontal direction. This of course requires available space in the chamber and identical raw material between parts. This level of fidelity was not possible for the build time model in this thesis so it was assumed that only one part would be built at a time.

3.3.2.3 Post Build Procedures

Now that the build process is complete, the printed part needs to be removed from the chamber. Routine cleaning inside of the chamber would be conducted by the engineer once the product has been removed.

The next and most obvious question that needs to be answered is quality of the product. If the quality and control engineer fails that part for any reason, then the entire build process will need to be repeated. For the build time model, this increases the amount of time and subsequently will

increase the cost in the following cost model because additional material is used. In discussions with the Center for Additive Manufacturing and Logistics (CAMAL) at NC State, the assumption was build failure occurs at a 10% rate.

However, if the part passes inspection then post build procedures would commence. Although technology is improving rapidly, nearly all metal parts would have to undergo some kind of post-treatment to finalize the production process. An emerging technology to augment finishing of metal parts is Additive systems Integrated with subtractive Methods (AIMS). This is exciting technology because the subtractive techniques replicate traditional finishing techniques. This method would require custom tooling and fixtures but could be operated by one engineer (Manogharan, Wysk, Harrysson, & Aman, 2015). For this model, heat treatment and part washing were directly considered.

Once the product was completely finished the typical Army resupply system would initiate with parts tracking and shipping through logistical convoys. Similar to setup times, a Beta distribution was used to account for post processing times, with a realistic upper and lower bound.

The assumption was made to not incorporate utilization rate, hence the AM technology is available to operate 24 hours a day. Routine maintenance would need to take place during natural lags in part requests.

In summary, the model design is an $M_t/GI/1$ queue. The arrival process is a Non-homogeneous Poisson process that utilizes a time varying rate, $\lambda(t)$, to assign arrivals based off the predetermined Weibull distribution (within each replication). The service rate is a general distribution accounted for with the previously mentioned regression. Lastly, 1 server (3D printer) processes 1 part at a time for the baseline scenario. Figure 3-10 provides an overview of the simulation, illustrating arrivals and how each part request was serviced.

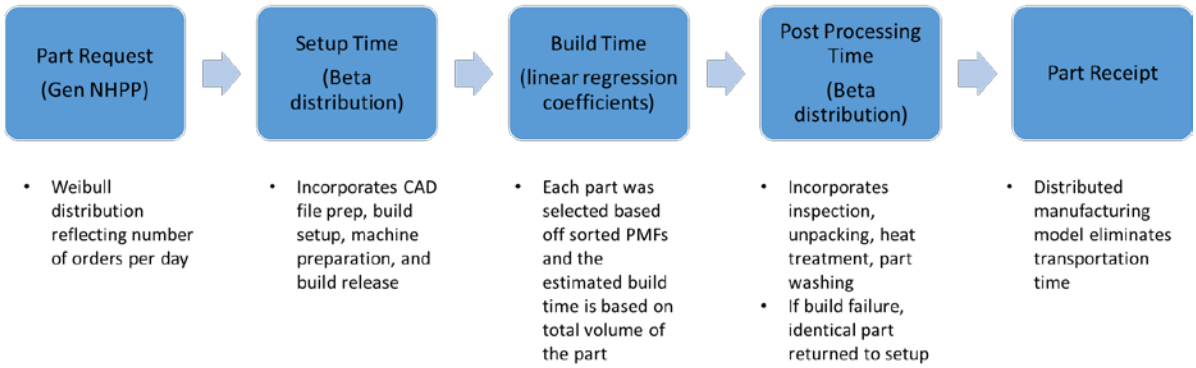

Figure 3-10. Simulation Process

3.3 Additional Model Inputs / Cost

Another factor that is of particular interest to decision makers in the military is cost. The cost model was developed based off of knowledge gained through extensive research and actual implementation of 3D printing facilities in the civilian sector. Design, setup, material, production, and post processing costs were considered in the cost model described below.

The first consideration is the actual design for AM produced parts, Equation 3. This model accounts for the incurred cost and effort that is required to produce a CAD model for existing Paladin parts. In order to run the simulation, it is assumed that every existing part has the potential to be produced with AM. Realistically the CAD models would be outsourced through a third party contractor, not created by internal Army assets. With that being said, the time and money the third party invested in creating the CAD models would be reflected in the purchase price of the CAD model rights. In an effort to account for the design cost, this model made the following assumptions: 10 hours of design time by a design engineer that earns $120,000 per year would be required for each unique part. This works out to approximately $75,000 for all parts. This cost would then be spread across the total amount of parts to be produced. The total number of parts was taken from the initial demand data and the design costs were divided by the number of parts. Intuitively, this cost decreases as the number of unique parts decreases.

$$DesignTotalCost = EngineerHourlyRate * DesignTime$$

Equation 3. Design Costs

Once a CAD model has been created there are incurred setup costs prior to the actual build process, Equation 4. Certain parts require specific orientation in the chamber and it is the responsibility of the experienced engineer to setup the build area/platform. A deterministic setup time of 7.2 minutes was used for the cost analysis (not the build simulation) and it was estimated that a fully burdened engineer would average 2,000 hours per year.

$$SetupCosts = (SetupTime * NumberOfBuilds) * EngineerHourlyRate$$

Equation 4. Setup Costs

The next cost area to consider is the actual production of the product, Equation 5. Raw material costs vary greatly and most certainly the prices will continue to fluctuate as more suppliers enter such a competitive market. This model assumed a fixed price of $240 per pound of raw material based off current research (Wohlers, 2016). The total volume processed was pulled from the simulation, converted from cubic inches to pounds, and multiplied to determine the total material cost. One of the previously described benefits of AM was the ability to reuse scrap parts from the build because the raw material was pure. The assumption was made that a 10% salvage value would be applied to each build.

$$MaterialCosts = RawMaterialCost * partsWeight * ScrapRate$$

Equation 5. Material Costs

Another area of the build that cannot be overlooked is probability of a build failure. Ideally, if an engineer is observing the production process then they might be able to identify a defect before the build is complete. Hence, saving time and money. However, for this model all build failures were identified after the build was complete at a certain probability, (*1 – p)*. This build failure was accounted for during the simulation, hence reflected in the total volume processed.

The next set of costs dealt with production, Equation 6. The machine run time is partly determined by a fixed investment in the purchase of AM equipment and then associated maintenance costs for the life of the printer. The purchase price for a high-end DMLS printer was $750,000 and annual maintenance was 10% of the purchase price. It was assumed that the Army would be responsible for maintenance costs. The asset utilization was 100% so the assumption was made that maintenance would be completed during natural lulls in production. The actual print time was determined based off the average aforementioned service rate. Lastly, a generic assumption of a 2 year life span for each printer was made based on current literature reviews.

$$ProductionCosts = (AverageBuildTime * NumberOfBuilds) * \left(\frac{PurchasePrice + MxCosts}{AvailableTimeToPrint}\right)$$

Equation 6. Production Costs

Once the build is complete the engineer must inspect the part to ensure it passes necessary quality and control checks. For metal parts in particular, post-processing is essential. Similar to the setup and machine run time costs, post-processing would involve some of the engineer's time. It is assumed that there is no failure rate during the post-processing steps and the spare part has passed all inspections for quality once complete.

$$PostCosts = (PostTime * NumberOfBuilds) * EngineerHourlyRate$$

Equation 7. Post-Production Costs

Although one of the recognizable benefits of AM is the ability to print on-demand or JIT, there are still overhead costs associated with setting up an AM facility. While the inventory cost of spare parts on warehouse shelves decrease, there are still incurred fixed costs such as operating (energy costs) and consumable items. Although acknowledged, these costs were not directly incorporated into the cost model because of minimal impact on total cost.

Equation 8 reflects the total cost formula used in each trial and provides a point of reference for the decision maker when implementing AM technology.

$$TotalCost = DesignTotalCosts + SetupCosts + MaterialCosts + ProductionCosts + PostCosts$$

Equation 8. Total Cost Formula

Figure 3-11 illustrates the cost breakdown in detail. It is evident that material costs dominate the total cost function, implying that if raw material prices decreased then the total cost would decrease significantly.

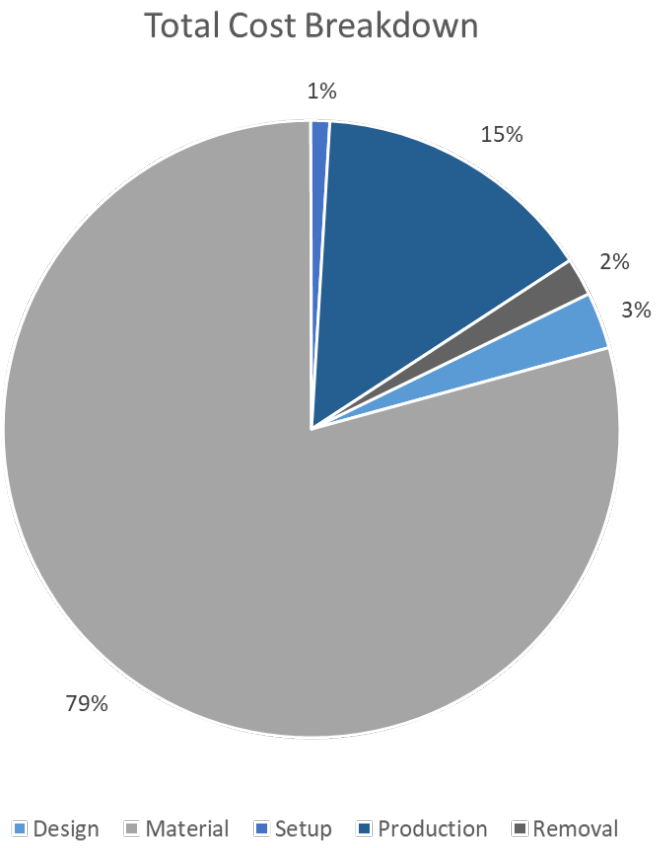

Figure 3-11. Total Cost Breakdown

Chapter 4. METHODOLOGY

4.1 Development of Simulation

This section describes in detail each step and subsequent inputs for the simulation model used in this thesis.

The simulation was designed in MATLAB and provides 2 key outputs: total sojourn time and total cost. All code is provided in Appendix B and an overview is depicted in Figure 4-1 and described in detail below.

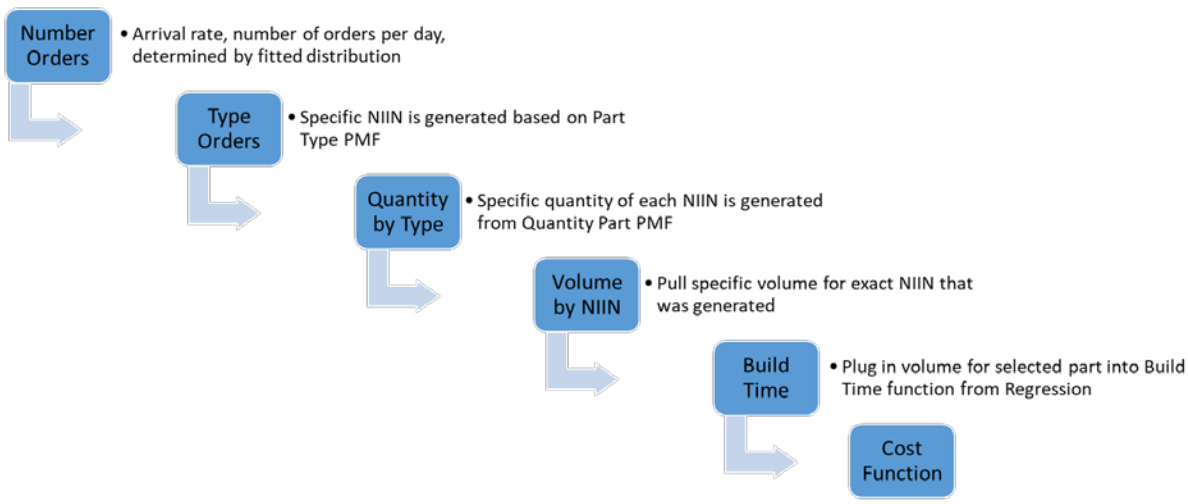

Figure 4-1 Requisition Simulation Process

4.1.1 Simulation Setup

The orders arrival rate was described in detail in 3.2.1 and a sample Weibull distribution is displayed below. The histogram reflects the distribution that was calculated in StatFit2. For this histogram 5,000 samples were generated with the maximum number of orders in one day being 74 and the mode being 1 which is acceptable given the initial data.

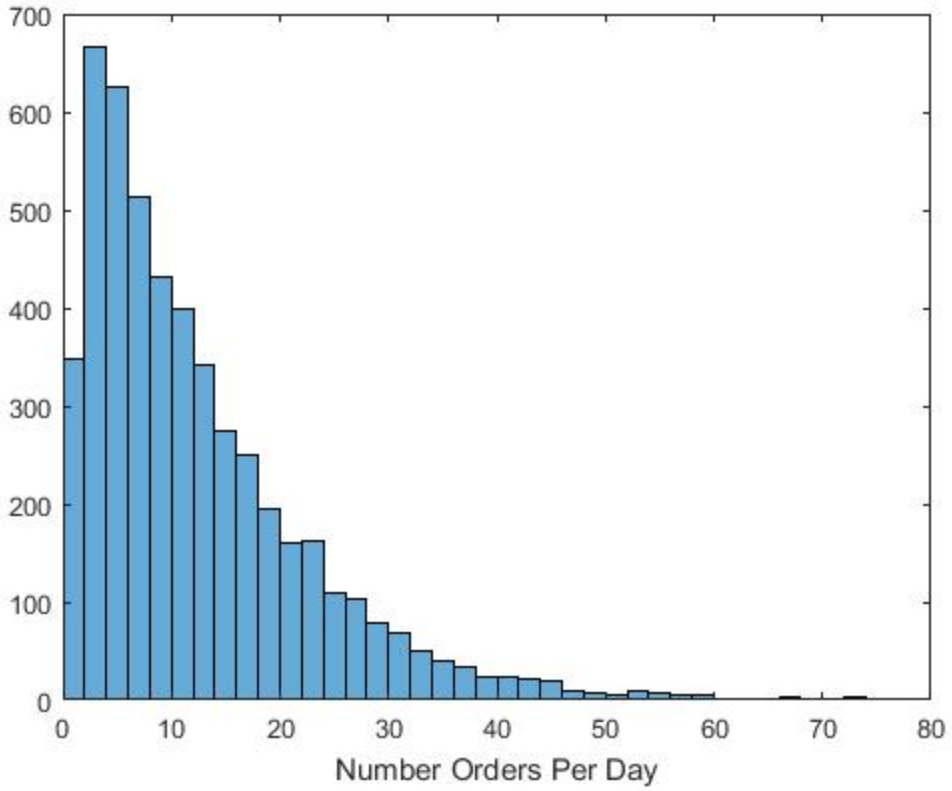

Figure 4-2 Number of Orders By Day

The simulation uses multiple sorted probability mass functions (PMFs) to ensure that the number of orders per day are comprised of a realistic type and quantity of each spare part.

The first PMF created reflected a sorted list of all unique parts based on the likelihood of being selected. The RAND data set provided 1,736 different orders during the 162 day period. These 1,736 orders totaled 7,904 parts. Of those 7,904 parts there were only 120 unique types. Utilizing a for loop, the simulation setup scans the entire list of orders, categorizes like parts, and outputs the probability that each part will be randomly selected. For instance, the most frequently ordered part was a SWITCH ASSEMBLY with 0.136 probability of being selected.

Now that the type of part could accurately be selected at random, the quantity would need to be known for that part. Again, a for loop scanned the sorted part list described above and recorded every time that part was ordered and the subsequent quantity of that part. The result was a matrix of probabilities for quantity for each unique part type. For instance, there was a 0.6907 probability of ordering 1 SWITCH ASSEMBLY when a SWITCH ASSEMBLY was randomly selected.

Now that the type and quantity of parts for each order were determined it is easy to match the volume from the original RAND data set with the unique type of part. The total volume was critical in calculating the build time and subsequent cost of production.

Every time the simulation needed to generate a build time, it would simply call the sorted and stored PMFs that were separate from the actual simulation. This setup made the simulation run faster because less data needed to be computed for every iteration. Specifically, function handles that can be seen in Appendix B were created that pulled from the stored PMFs when a build time was needed.

Another major consideration for setup was configuring all time, *t*, in hours. The previously mentioned Weibull distribution would then provide a random number of orders each day at subsequent 24 hour intervals. Hours were chosen because most build times could take less than a day to complete. The number of trials, *x*, was determined during the setup, resulting in pre-generated arrival times of orders for *x* trials.

Lastly, the pre and post processing requirements described in 3.2.2 were incorporated using a Beta distribution. A Beta distribution was selected because an engineer's pre and post processing times could easily vary based on experience or repetition but would not vary outside of likely minimums and maximums. This model assumed that the most likely setup time is 0.12 hours, with a min of 0.1 hours and max of 0.2 hours. Whereas the most likely post processing time is 0.3 hours, with a min of 0.2 hours and max of 1 hour. Equation 9 describes the Beta distributions used in the simulation.

$$f(x) = \frac{1}{B(p,q)} \frac{(x - min)^{p-1}(max - x)^{q-1}}{(max - min)^{p+q-1}}$$

$$min \leqslant x \leqslant max$$

$$min = minimum\ value\ of\ x$$

$$max = maximum\ value\ of\ x$$

$$p = lower\ shape\ parameter > 0$$

$$q = upper\ shape\ parameter > 0$$

$$B(p,q)\ Beta\ Function$$

Equation 9. Beta Distribution (min, max, p, q)

4.1.2 Simulation Assumptions

The assumptions that had the largest effects on total sojourn time centered around build time estimates. The first assumption did not consider batch service rates. The second assumed that the Paladin parts would behave linearly based off the Thingiverse build time data. This is easily justifiable for small Paladin parts, consisting of 40 cubic inches and less, but became more significant when considering large part volumes. These volumes forced extrapolation, far beyond what the provided Thingiverse data included. Additionally, the Paladin part volumes were "packaged" volume, rather than actual part volume. Ideally, the dimensions of the parts and surface area would be known so that a multiple linear regression could fully and more accurately calculate the build times. All of these assumptions were conservative, serving as a worst case scenario for implementation.

The probability of failure was selected to be 10% for the simulations. This is in line with current technology but could potentially worsen given an unstable environment that a military 3D printing facility might find itself in.

All of the distributions have been defended in previous sections. In general, Beta distributions were used for the pre and post processing times while a Weibull distribution with varying parameters was used for the arrival rate of orders per day.

4.2 Actual Simulation

The simulation that was built for this thesis was a single-server queuing system with discrete events. All of the stochastic nature in the ordering process was captured prior to the actual simulation so that the simulation itself could run faster and more efficiently.

Given the pre-generated set of arrival times for each replication, the simulation would cycle through all arrival times until reaching a predetermined stop time. Again, the arrival times reflect the number of orders per day. For every iteration, the time the order arrived in the system and departed the system were recorded. The service rate (μ) was generated from the same function handle described above that provided a random pre-processing, build, and post-processing times.

4.3 Simulation Outputs

As previously mentioned, the information most pertinent to military decision makers would be lead time and cost. This simulation provided both total sojourn time and an estimated total cost. The

sojourn time reflects the amount of time the order spent in the system, i.e. how long it would take an engineer to setup the build chamber, print the entities of the order, and inspect the parts for future use. The cost is the summation of everything required to produce the parts. Total volume processed was determined to be an important stat, indicating the general capability of the 3D printing system. With this being said, total volume was also recorded as an output for comparisons between scenarios.

Chapter 5. ANALYSIS

5.1 Case Study Scenario

The original RAND data was scrubbed, as previously mentioned, to reflect metal Paladin parts for 3 BN's during a 162 day period. The requisition data was adjusted based off allowable part size, replicating smaller sized 3D printer build chambers. Table 5-1 reflects a decreasing size (in^3) threshold for allowable part requests based on the actual OIF data. For example, Baseline All considered every part request, regardless of size. Whereas, Base less than 250 only considered parts less than 250 cubic inches. Regardless of the size, it reflects that the mean lead time was approximately 39 days. When considering the entire 162 day invasion period, it appears that due to exterior conditions (security, changing unit locations, etc.) only about 4 resupplies were afforded because all of the part sizes were fulfilled in approximately 39 days. The total cost is the wholesale cost of the part and excludes transportation and overhead costs. The total volume processed is displayed because it provides a consistent and logical way to visualize the total orders processed. It follows that the total volume processed would decrease in line with the allowable part sizes because fewer parts that had smaller volumes were considered. All subsequent scenarios are compared to this baseline data. Lastly, each scenario was replicated 100 times to achieve acceptable confidence intervals.

Table 5-1. Baseline Data drawn from original RAND demand data.

	Lead Time (days)		**Total Volume Processed (in^3)**
	Mean	**Total Cost ($)**	
Baseline All	39.94	$691,096	3,566,792
Base < 250	38.94	$349,508	355,078
Base < 100	38.57	$186,284	304,389
Base < 57	39.00	$184,327	129,237
Base < 40	39.50	$22,343	33,323

5.1.1 Scenario 1 – Decrease Allowable Part Size

In Scenario 1, the allowable part size was incrementally decreased starting with all parts considered, then less than 250 cubic inches and so on. The results overwhelmingly indicate that 1 AM printer cannot satisfy the full demand rate for 3 BN's requesting Paladin parts. However, when the allowable part size is limited to less than 40 cubic inches, then 1 AM printer can actually decrease

the average lead time from 39.50 days to 10 days. The obvious tradeoff deduced from Table 5-2 is the cost. The cost balloons by nearly 72 times the original cost. Again, the major advantage of AM technology is distributed manufacturing, so incorporating transportation costs into the baseline could narrow these margins.

In general, the simulation reflects a higher total volume processed than TM because of the build failure rate. However, less than 100 actually showed a decrease from the base which is most likely explained by the high probabilities of selecting smaller parts in this threshold, i.e. it was very rare to select parts close to 100 cubic inches.

Table 5-2. Simulation results decreasing the allowable part size.

	Lead Time (days)					Total Volume	
(in^3)	**Mean**	**Halfwidth**	**Difference From Base**	**Total Cost ($)**	**Difference From Base**	**Processed (in^3)**	**Difference From Base**
All Parts	6,939	177.83	17272.83%	$122,056,634	17561.31%	4,428,379	24.16%
< 250	662	19.46	1600.48%	$12,524,344	3483.42%	454,289	27.94%
< 100	374	11.87	869.67%	$7,028,465	3672.98%	254,886	-16.26%
< 57	219	7.93	461.54%	$5,093,894	2663.51%	184,695	42.91%
< 40	10	0.66	-74.79%	$1,630,834	7199.08%	59,047	77.20%

5.1.2 Scenario 2 – Increase Build Speed

This scenario attempts to illustrate how advances in AM technology could impact satisfying the demand rate. In the base simulation only 1 AM printer is utilized. Alternatively, this scenario mimics utilizing 10, 20, and 30 AM printers. In order to test other options that might provide a more realistic solution, 10 DMLS printers were considered. They were incorporated by adjusting the build time coefficient, decreasing it by a factor of 10. Equation 10 displays the build speed function used with the adjustable build time factor, τ.

$$y = \frac{(\alpha + \beta x)}{\tau} + \varepsilon$$

Equation 10. Regression Model with Adjustable Build Rate

This build speed adjustment assumes that orders would be evenly and simultaneously spread among all 10 printers. While this may not be true in practice, the assumption was made to provide context on how much faster AM build speeds need to be to satisfy a realistic demand rate. However, 10 printers only reduced mean sojourn time to 608 days. The results indicate that even if AM technology were able to increase build speed, reducing build time, by 30 times that still would not be enough to meaningfully impact the service rate. As displayed in Table 5-3 the lead time remains at 186 days with an increase of 30. For clarification, demand rate and part size were kept constant.

Table 5-3. Simulation results holding demand and allowable part size constant.

	Lead Time (days)					Total Volume	
(in/s)	Mean	Halfwidth	Difference From Base	Total Cost ($)	Difference From Base	Processed (in^3)	Difference From Base
All Parts	6,939	177.83		$122,056,634		4,428,379	
10x	608	15.68	-91.24%	$117,920,705	-3.39%	4,278,318	-3.39%
20x	241	7.06	-96.53%	$121,783,924	-0.22%	4,418,485	-0.22%
30x	186	4.44	-97.32%	$121,845,092	-0.17%	4,420,704	-0.17%

5.1.3 Scenario 3 – Adjusting Military Unit Size

This scenario adjusts the size of the artillery unit from 3 BN's all the way down to 1 Paladin. It is important to note that during the period the demand data was generated (2003), a mechanized artillery battalion was composed of 2 batteries, each with 8 Paladins. When considering this, the original demand data reflects part requests for 48 Paladins. In order to reflect new demand rates, the Number of Orders Per Day (arrivals, λ(t)) were divided by the respective decrease in unit size. Maintaining build speed and allowable part size constant, even the smallest unit size of 1 Paladin's demand rate could not be satisfied. Table 5-4 shows that 1 AM printer increases average lead time to 497 days. A cost estimate is not provided because the original data could not be manipulated to accurately reflect individual Paladin orders.

Table 5-4. Simulation results decreasing the demand rate.

	Lead Time (days)		Difference From Base	Total Volume Processed (in^3)
(orders/day)	**Mean**	**Halfwidth**		
All Parts	6,939	177.83	17272.83%	4,428,379
1x BN	1,997	88.59	4900.22%	1,633,224
1x BTRY	1,467	81.50	3573.01%	880,594
1x GUN	497	43.82	1144.37%	387,348

5.2 Factorial Design Simulation Results

The simulation's main purpose was to assess the feasibility of utilizing 3D printing to augment the spare parts supply chain. In an effort to illustrate AM's capability the following scenarios were run and condensed into the following simulations. A factorial design approach ensured a systematic process to account for all interactions of the parameters (volume (f), echelon (g), and speed (h)). Table 5-5 describes the 3 different factors and the 4 different levels within each factor.

Table 5-5 Factors for Simulations

Volume (f)	Echelon (g)	Print Speed (h)
(1) Less than 250 cubic inches	(1) 3 Battalions	(1) 1
(2) Less than 100 cubic inches	(2) 1 Battalion	(2) 2
(3) Less than 57 cubic inches	(3) 1 Battery	(3) 5
(4) Less than 40 cubic inches	(4) 1 Gun	(4) 10

All of the factors are accounted for in the following design points in Table 5-6.

Table 5-6 Factorial Design Points for Simulations

Design Points

			Print Speed			
		Echelon	1	2	5	10
Volume (cubic inches)	250	3 BN	f(1), g(1), h(1)	f(1), g(1), h(2)	f(1), g(1), h(3)	f(1), g(1), h(4)
		BN	f(1), g(2), h(1)	f(1), g(2), h(2)	f(1), g(2), h(3)	f(1), g(2), h(4)
		BTRY	f(1), g(3), h(1)	f(1), g(3), h(2)	f(1), g(3), h(3)	f(1), g(3), h(4)
		GUN	f(1), g(4), h(1)	f(1), g(4), h(2)	f(1), g(4), h(3)	f(1), g(4), h(4)
	100	3 BN	f(2), g(1), h(1)	f(2), g(1), h(2)	f(2), g(1), h(3)	f(2), g(1), h(4)
		BN	f(2), g(2), h(1)	f(2), g(2), h(2)	f(2), g(2), h(3)	f(2), g(2), h(4)
		BTRY	f(2), g(3), h(1)	f(2), g(3), h(2)	f(2), g(3), h(3)	f(2), g(3), h(4)
		GUN	f(2), g(4), h(1)	f(2), g(4), h(2)	f(2), g(4), h(3)	f(2), g(4), h(4)
	57	3 BN	f(3), g(1), h(1)	f(3), g(1), h(2)	f(3), g(1), h(3)	f(3), g(1), h(4)
		BN	f(3), g(2), h(1)	f(3), g(2), h(2)	f(3), g(2), h(3)	f(3), g(2), h(4)
		BTRY	f(3), g(3), h(1)	f(3), g(3), h(2)	f(3), g(3), h(3)	f(3), g(3), h(4)
		GUN	f(3), g(4), h(1)	f(3), g(4), h(2)	f(3), g(4), h(3)	f(3), g(4), h(4)
	40	3 BN	f(4), g(1), h(1)	f(4), g(1), h(2)	f(4), g(1), h(3)	f(4), g(1), h(4)
		BN	f(4), g(2), h(1)	f(4), g(2), h(2)	f(4), g(2), h(3)	f(4), g(2), h(4)
		BTRY	f(4), g(3), h(1)	f(4), g(3), h(2)	f(4), g(3), h(3)	f(4), g(3), h(4)
		GUN	f(4), g(4), h(1)	f(4), g(4), h(2)	f(4), g(4), h(3)	f(4), g(4), h(4)

Now that the experimental design is created, a simulation was run for each of the 64 design points. In previous simulations it was discovered that less than 250 cubic inches was a realistic threshold for the maximum allowable part size. Additionally, there was not much differentiation between 10, 20 and 30 times print speed so those parameters were adjusted to 2, 5, and 10. Also, a random number generator seed was set so that the number of orders per day followed the same rate as the print speed increased within each row. Lastly, 100 replications were achieved for each design point.

Table 5-7 Factorial Design Simulation Results (Lead Time in days)

Lead Time (days)

			Print Speed			
		Echelon	1	2	5	10
Volume (cubic inches)	250	3 BN	782.84	362.08	109.85	25.83
		BN	247.15	89.65	4.57	0.8
		BTRY	109.79	17.68	1.13	0.56
		GUN	9.81	2.26	0.96	0.42
	100	3 BN	389.8	164.21	28.86	1.42
		BN	105.19	16.61	0.84	0.4
		BTRY	22.69	0.83	0.29	0.17
		GUN	5.48	2.24	0.68	0.27
	57	3 BN	278.39	107.55	5.94	0.9
		BN	44.82	2.26	0.81	0.37
		BTRY	4.54	3.21	0.67	0.33
		GUN	2.82	1.61	0.52	0.29
	40	3 BN	26.05	1.3	0.43	0.3
		BN	1.65	2.32	0.74	0.35
		BTRY	8.08	0.72	0.52	0.14
		GUN	1.44	2.09	0.26	0.14

Using the results from Table 5-7, decision makers could implement AM technology at different echelons (BN, BTRY, GUN) with a realistic understanding of the demand rate the 3D printer could satisfy. For instance, all of the green shaded boxes indicate a lead time that was less than the baseline of 39 days lead time determined from the OIF data. Table 5-7 displays a lot of scenarios where AM produced parts could prove to be beneficial. Additional details are provided in Appendix E which include half-width, cost, and total volume processed for each design point.

There are a few design points that do not appear to be monotonic. For instance, a battery's demand rate for parts less than 40 cubic inches at print speed 1 (f4, g3, h1) resulted in an increased lead time when compared to a battalion's. This was only true in the simulation because of the high probability of selecting parts that were close to 40 cubic inches. A separate simulation was run that removed the seed and increased the replications to 50,000. A more intuitive lead time of 1.94 days was calculated. The takeaway is that less than 40 cubic inches was more sensitive to what parts were selected from its PMF.

5.3 Requirements for Implementation

The likely scenario that AM will be most useful to the military is in an isolated deployed environment where resupply is incredibly dangerous, expensive, or virtually impossible. In this scenario, the ability to produce essential spare parts is invaluable.

There are many necessary requirements before 3D printing can even enter the conversation of becoming a viable option for implementation. The simplest: can the spare part be printed with AM technology? For this thesis to be at all relevant, it is assumed that all the spare parts can be printed with on-hand technology at the established AM facility. Inherent in the ability to print is the existence of CAD blueprints for the part. Naturally, all of these would theoretically exist in some database that could be electronically transferred to the engineers that would be producing the parts at a distributed location. In this model, the design cost is considered but it never terminates the possibility of being able to physically print the spare part.

The AM equipment would need to be capable of global transport, most likely being outfitted in a shipping container. Given the highly sensitive nature of metal 3D printers, studies would need to ensure that the printing equipment would not be damaged in transit and could be setup, fully functional, upon arrival to its destination.

From a strategic military standpoint, the capability needs to exist to build a facility. Security would be the first and most paramount concern. Building an AM facility, whether it is a hardstand building, a clamshell tent structure, or a CONEX container, implies that it can safely exist long enough to effectively produce parts. Understanding if this facility could be secured with the unit's internal assets or would require additional attachments would be determined through practice on a mission by mission basis.

Once security is established, more robust security element for a static location, consistent power with enough wattage to run the AM systems would have to be setup. This would require a redundant network of generators in most situations, perhaps tapping into a power grid in less austere locations. For reference, DMLS printers can require up to 200 megajoule (MJ) per part or 55 kilowatt hour (kWh) (Baumers, Tuck, Wildman, Ashcroft, & Hague, 2011). The Army could furnish enough power to run the printer but this obviously means that more equipment would have to be deployed with that unit (i.e. generators). Furthermore, considering Scenario 2 where the build speed is increased, the power requirements might be even greater. Unequivocally, if the AM facility had

more than just 1 printer then there would need to be additional power beyond just the standard generators.

Another requirement is for the actual air in the facility to be regulated to avoid material contamination during the build process. Most likely, an exhaust system would be necessary to achieve a minimal standard for printing metal products. This would include maintaining a certain humidity level, temperature, and dust free environment. Additionally, to meet the high tolerance standards required in 3D printing, gases would need to be furnished. In most cases, Argon and Nitrogen at a minimum are necessary to provide inert atmospheres for the printing process.

Mentioned throughout this thesis is the requirement for knowledgeable personnel to run the AM equipment. Given the assumption that the 3D printer is most beneficial in an isolated environment implies that the people utilizing the printer need to be highly competent on its capabilities, limitations, maintenance: everything involved. Perhaps in the future when 3D printers are highly reliable the Army could train Soldiers to use the printers but for now, contracted engineers are required. Just as with power requirements, the more printers the more engineers are needed.

Chapter 6. CONCLUSION

There is no denying the potential disruptiveness that AM can have on industries by replacing or at least complementing existing manufacturing techniques, specifically enhancing process and product innovation (Niaki & Nonino, 2017). The military is currently looking at options to exploit this technology and with an increased budget, decisions seem to be moving in the right direction. The Navy has implemented FabLabs that consist of a suite of digital fabrication and rapid prototyping machines. These mobile labs educate Soldiers on the capabilities of 3D printing and are an integral step in making 3D printed parts a reality. As for now, the Marines cite examples of printing HUMVEE handles and drone rotors to serve as temporary replacements while waiting for actual parts that have been ordered to be received (Jackson, 2017).

In this thesis, a Paladin was used to demonstrate that a demand rate for a large piece of equipment could be satisfied under certain constraints with current AM technology. However, there are millions of parts in the military, many of which do not need to be as heavily scrutinized in a quality control setting. Table 5-2 demonstrated that roughly 60,000 cubic inches is the threshold for total output during a 162 day period. Along this line of thinking, any other end item could be selected and roughly 60,000 cubic inches worth of spare parts could be printed for that item. One example of other applications is with communications equipment. There are hundreds of small metal parts for radios and antennas that constantly break through routine use by Soldiers. A 3D printer could make communications spare parts while deployed and if the part failed during use, the only liability would be a down radio. Whereas, if 3D printed parts were being used to fire a Paladin or a fly a helicopter, the risk of injury from defective parts would be much higher.

6.1 Recommendations

The notion of 3D printed parts needs to start with CAD files. AM technology will never be fully realized in a military setting if Soldiers are expected to create the part designs. Pressure needs to be placed on contracted suppliers to either create CADs for existing parts or at a minimum, start providing them with newly purchased equipment. This pressure would be applied many echelons above the Soldier level. A steadily improving technology consists of sophisticated scanners that can instantly produce a CAD blueprint. Perhaps this could stand as a viable option to bridge the gap between TM and AM produced parts.

Similar to the Navy, the Army needs to continue experimenting with AM facilities in the field which replicate realistic demand rates and environment scenarios. The most obvious choice is to utilize existing environments at Combined Training Centers (CTC) and see how an AM facility performs. A pilot program could consist of a 3D printing facility in a hardstand building at a CTC that receives part requests from actual units training and then determines how many and what type of parts it can print. This would start to give a feel for utilization rates, maintenance issues, troubleshooting techniques, as well as provide an architecture to route the part requests from Soldier to 3D printing engineer.

Real world applications would most likely start with smaller, more specialized units that deploy to every corner of the globe and are not afforded consistent resupply. These types of units, suffering from extreme isolation, could benefit the most from the implementation of a 3D printer.

Another application for AM technology would be in the sale of equipment to other countries. 3D printed parts could substantially assist in providing spare parts to countries that have purchased antiquated US military equipment. This is a large fiscal requirement because under most circumstances, when the buyer requires additional spare parts they request them through the US. The resupply then is even more costly because of additional overheard and transportation costs. Imagine if, along with the initial purchase of the end item, CAD files were provided for all components. Then the third party could furnish all future parts internally, eliminating time and money spent by the US.

6.2 Future Work

Future work would need to focus on the direct comparison between traditional Army resupply and a proposed pilot program utilizing additive manufacturing. Although it is easy to assume that transportation and inventory costs would be dramatically decreased using AM, quantitative data would help bolster this claim.

The demand rate changes drastically based off the phase of the operation. The demand rate in this thesis is for an invasion but testing out different demand rates would give a better sense of how AM could impact the supply chain over the course of a conflict. Additionally, only one end item, a Paladin, was considered in this thesis. Testing the simulation on other end items would solidify if the notion that “Total Volume Processed” is a good indicator of service capability.

Lastly, one of the largest ways to decrease build time is by batching part builds. This thesis lacked enough fidelity on part descriptions to implement batching criteria. However, this could hold the ability to dramatically decrease build times, thus increasing supply chain efficiency. Another improvement when considering batching is to provide prioritization in the queue. This model used first come first served (FCFS) basis but under the context of printing mission critical parts, reordering the queue would be paramount. Perhaps the greatest use of AM technology would be to print parts when TM lead time exceeds a certain threshold, subsequently providing the part to the Soldier faster and getting their equipment back in the fight.

6.3 Summary

The simulation in this thesis provides a cogent process to evaluate the effectiveness when integrating additive manufacturing technology in order to complement existing traditional manufacturing techniques. It was determined, under current technology, that 1 DMLS printer could satisfy the demand rate for a battalion's M109A6 Paladin parts in a combat environment up to 57 cubic inches in total part volume. In order for AM to have a more drastic and ubiquitous impact, faster build speeds for larger parts is the single point of improvement. Build rate failure is an additional point of focus that will not only enhance lead time reduction but more importantly, guarantee printed parts satisfy structural requirements creating minimal risk when used. Cost reductions of raw materials and purchase price of printers will naturally occur as more competitors enter the space and more efficient techniques are discovered for building printers.

AM will have an impact on the resupply of spare parts in the military, it is just a matter of when. The Army Chief of Staff Gen. Milley understands this urgency and was recently quoted that "static bases will be sitting ducks, and supply convoys will be so dangerous that they might be entirely automated, so units will be largely on their own, purifying their own water and 3-D printing spare parts for broken gear" (Freedberg, 2016).

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APPENDICES

Appendix A. Data Sets

Model Input

This appendix contains the model input data for the simulation model.

A.1 RAND Data

This appendix contains the requisition data for spare parts during combat operations in Iraq 2003 for a heavy division. The data below represents a sample and has been cleansed of all SECRET data.

niin	sqty	nomen	UWEIGHT	UCUBE	UPRICE	div	unit	poe	pod	depo	docdt	estdt	mrodt	shipdt	ccpr	ccps	poer	poes	podr	pods	d6s
290388	2	FILTER ELEME	2.62	0.159	4.53	4ID	4 FSB	CHS	SDA	DDSP	3151	3154	3154	3154	3154	3156	3173	3174	3179	3179	3201
290388	4	FILTER ELEME	2.62	0.159	4.53	4ID	4 FSB	CHS	SDA	DDSP	3155	3157	3164	3165	3165	3167	3168	3170	3170	3171	3211
290388	4	FILTER ELEME	2.62	0.159	4.53	4ID	404 GRD	CHS	SDA	DDSP	3182	3183	3184	3190	3190	3191	3195	3196	3196	3196	3250
290388	4	FILTER ELEME	2.62	0.159	4.53	4ID	404 GRD	CHS	SDA	DDSP	3190	3190	3191	3209	3209	3221	3224	3224	3226	3226	3237
290388	12	FILTER ELEME	2.62	0.159	4.53	4ID	4 FSB	CHS	SDA	DDSP	3193	3194	3198	3223	3223	3226	3227	3229	3231	3231	3237
290388	1	FILTER ELEME	2.62	0.159	4.53	4ID	4 FSB	CHS	SDA	DDSP	3193	3194	3198	3203	3203	3205	3206	3211	3213	3214	3250
290388	1	FILTER ELEME	2.62	0.159	4.53	4ID	4 FSB	CHS	SDA	DDSP	3194	3194	3198	3203	3203	3205	3206	3211	3213	3214	3250
290388	1	FILTER ELEME	2.62	0.159	4.53	4ID	4 FSB	CHS	SDA	DDSP	3195	3196	3198	3203	3203	3205	3206	3211	3213	3214	3250

A.2 Build Time Data

This appendix contains actual build time data for a DMLS printer in 2013.

		length	width	height	surface area	volume (in3)	projected area	volume (ft3)	height*SA	X*Y*Z	
part		x	y	z	SA	v	xy	v	ZSA	EV	Total Print Time (hrs)
calibration_angle		1.97	1.97	0.2	5.05	0.17	3.88	0.000098379	0.99	0.76	0.33
clip_mk1		0.39	0.26	0.3	0.73	0.01	0.1	0.000005787	0.22	0.03	0.07
DCU224C-M4-adapter		1.26	2.05	0.16	6.07	0.37	2.58	0.000214119	0.96	0.41	0.37
Desk_Knob		1.08	1.08	0.66	3.31	0.22	1.17	0.000127314	2.18	0.77	0.28
drawer_bracket		2.36	1.68	1.63	16.12	1.07	3.98	0.000619209	26.21	6.47	1.1
egranaje_carro		3.19	3.16	0.85	28.03	3.83	10.06	0.002216421	23.85	8.56	2.02
embudo_con		5.12	4.72	5.12	76.55	3.17	24.18	0.001834479	391.81	123.76	4.53
eninge		2.49	2.49	4.14	50.77	10.96	6.18	0.006342552	210.23	25.59	3.98
gear		4.17	4.17	1.13	44.39	13.8	17.38	0.00798606	50.16	19.64	3.9
gopro_adapter		7.51	3.77	3.3	92.51	22.89	28.34	0.013246443	305.6	93.63	7.55
HotTub		2.79	2.47	1.65	35.62	7	6.89	0.0040509	58.87	11.39	2.92
InnerCircle		5.63	5.63	0.89	52.61	1.98	31.7	0.001145826	46.87	28.24	3.07
knob2		0.77	0.77	0.65	3.3	0.22	0.6	0.000127314	2.14	0.39	0.23
M8_nut_knob		5.67	5.67	0.71	42.51	9.33	32.14	0.005399271	30.13	22.78	3.3
motor_mount(1)		1.1	1.43	1.18	8.86	0.44	1.58	0.000254628	10.47	1.86	0.58
patita_qav500		8.84	4.26	1.06	81.68	19.1	37.69	0.01105317	86.82	40.06	6.73
pinza_izquierda		9.21	3.68	0.55	47.41	9.1	33.91	0.00526617	26.19	18.73	3.57
rod_holder		6.11	2.01	3.38	69.39	16.83	12.28	0.009739521	234.58	41.51	5.9
saw_elbow		2.68	2.68	4.33	62.05	4.26	7.17	0.002465262	268.71	31.04	4
SpoolHolder1		2.56	2.56	0.98	15.12	2.35	6.55	0.001359945	14.88	6.45	1.2
Teil1_Light		4.72	4.72	1.1	45.77	1.77	22.32	0.001024299	50.46	24.6	2.9
thumb_screw		1.15	1.15	0.39	3.48	0.23	1.32	0.000133101	1.37	0.52	0.23
K8200_webcam_mount1		2.56	2.56	0.53	12.61	0.85	6.55	0.000491895	6.71	3.49	0.83
Spool_sleeve1		1.78	1.78	3.27	31.55	1.8	3.15	0.00104166	103.11	10.3	2.03
1inch_filter_adapter		2	2	0.35	10.05	0.38	4	0.000219906	3.56	1.42	0.55
FPV250		2.02	2.02	0.07	7.96	0.24	4.1	0.000138888	0.53	0.285628	0.45
PRN3D		1.18	0.79	0.79	7.31	0.33	0.93	0.000190971	5.76	0.736438	0.5
Manifold		4.08	4.08	4.2	131.3	23.84	16.63	0.013796208	551.48	69.91488	10.35
Ring		1.34	1.55	0.4	4.49	0.26	2.07	0.000150462	1.78	0.8308	0.3
RocketPlug		5.13	5.12	4.78	81.55	35.98	26.27	0.020821626	389.92	125.5496	8.3
WheelHub-3		5.63	5.63	2.36	92.78	28.15	31.7	0.016290405	219.15	74.80468	8
Print_Bed		6.3	5.63	1.34	92.51	30.16	35.46	0.017453592	123.97	47.52846	8.28
i3support		7.87	4.85	1.92	72.92	15.53	38.18	0.008987211	140.24	73.28544	5.4
i3_LCD		8.67	3.47	1.03	54.41	6.53	30.12	0.003778911	56.29	30.98745	3.98
AC_Adapter		0.49	0.49	0.48	0.87	0.03	0.24	0.000017361	0.42	0.115248	0.08
shiny_juttuli-fulffy		2.87	3.99	0.59	38.2	3.87	11.48	0.002239569	22.538	6.756267	2.68
flag_piece_1_red		6.39	3.73	1.58	160.1	18.29	23.86	0.010584423	252.958	37.65883	10.35
Filamento_Filtro_UP		1.01	1.33	0.59	4.18	0.23	1.35	0.000133101	2.4662	0.792547	0.27
calibrator_50mm		2.68	3.03	0.79	19.59	2.21	8.12	0.001278927	15.4761	6.415116	1.32
reinbezcarbon		1.84	5.63	0.28	22.4	1.18	10.36	0.000682866	6.272	2.900576	1.45
rodToPvcElbow3		1.13	1.94	1.56	14.79	1.11	2.19	0.000642357	23.0724	3.419832	0.93
Multirotor_Motor		2.65	1.3	3	13.84	0.51	3.45	0.000295137	41.52	10.335	1.13
i3carriage_fuse		5.34	5.45	2.52	89.79	7.63	29.1	0.004415481	226.2708	73.33956	5.75
DriveBlockLeverLeft		1.64	1.28	0.37	4.48	0.25	2.1	0.000144675	1.6576	0.776704	0.28
Prusa_I3_Rework		1.58	1.57	2.01	14.28	0.46	2.48	0.000266202	28.7028	4.986006	0.88
simple shiny		2.87	3.99	0.59	37.57	4.15	11.45	0.002401605	22.1663	6.756267	2.68
simple flag		6.39	3.73	1.58	105.13	18.26	23.83	0.010567062	166.1054	37.65883	7.63
simple filamento		1.01	1.33	0.59	4.07	0.36	1.34	0.000208332	2.4013	0.792547	0.28
simple calibrator		2.68	3.03	0.79	19.67	3.82	8.12	0.002210634	15.5393	6.415116	1.52
simple reinbezcarbon		1.84	5.63	0.28	18.14	1.23	10.36	0.000711801	5.0792	2.900576	1.2
simple rodtopvc		1.13	1.94	1.56	14.99	2.13	2.19	0.001232631	23.3844	3.419832	0.98
simple multirotor		2.65	1.3	3	13.94	0.41	3.45	0.000237267	41.82	10.335	1.27
simple driveblock		1.64	1.28	0.37	4.04	0.35	2.1	0.000202545	1.4948	0.776704	0.27
simple prusa		1.58	1.57	2.01	16.92	0.77	2.48	0.000445599	34.0092	4.986006	0.98

Appendix B. MATLAB R2016b Simulation Script

Simulation to test feasibility of additive manufactured spare parts for a M109A6 Paladin while deployed.

The data set in this simulation uses all metal spare parts, regardless of size. The largest metal 3D printer, DMLM X line 2000R, 160 liters (9763.8 in^3) & 800 x 400 x 500mm (31.4961 x 15.748 x 19.685in) can facilitate all jobs.

Find Num Orders Released by Day

```
dir = 'C:\Users\tamoore5\Documents\Thesis\Excel\Final Data Used\';
fn = 'Paladin_Data_Cleansed_Metal_Only.xlsx';

Docdt = xlsread([dir fn],1,'M2:M1737');
Docdt = Docdt - 3000; Docdt = Docdt - min(Docdt) + 1;   % cleanse dates

NumOrdersByDay = nrel(Docdt,[1,max(Docdt)]);
vec2txt('NumOrdersByDay.txt',NumOrdersByDay)            % create txt file to fit dist
```

Type of Part PMF

```
NIIN = xlsread([dir fn],1,'A2:A1737');
PartList = unique(NIIN);
PartCount = zeros(length(PartList),1);
for p = 1:length(unique(NIIN))
    PartCount(p) = sum( NIIN == PartList(p) );
end
PartPMF = PartCount ./ sum(PartCount);                  % result: prob that each NIIN is ordered

[SortedPartPMF, indSort] = sort(PartPMF,'descend');
SortedPartList = PartList(indSort);
NumUniqueParts = length(SortedPartList);
```

PMF for Qty by Part

```
QTY = xlsread([dir fn],1,'B2:B1737');
QTY(QTY == 0) = 1;
PMF_MAT = cell(length(PartList),1);
for p = 1:length(SortedPartList)
    Qp = QTY(NIIN == SortedPartList(p));
    Countsp = histcounts(Qp,max(Qp));                   % Note: should only use histcounts if max order size is not too large
    PMF_MAT{p} = Countsp./sum(Countsp);
end
```

Finding the AM Build Time

```
coefBuildTime = .29150;                                  % Linear regression ind var 'time'
and dep var 'volume'
PrintSpeed = 1;                                          % Adjustable parameter for
technological advances
```

Volume for Specific Part Selected IOT calculate Build Time

```
partVolume = xlsread([dir fn],1,'E2:E1737');             % volume is in cubic inches
SortedPartVolume = zeros(size(SortedPartList));
for i = 1:length(SortedPartList)
    NIINi = SortedPartList(i);
    Volumesi = partVolume(NIIN == NIINi);
    SortedPartVolume(i) = Volumesi(1);
end

VolumeList = unique(partVolume);                         % not necessary for SIM but provides
context
VolumeCount = zeros(length(VolumeList),1);
for p = 1:length(unique(partVolume))
    VolumeCount(p) = sum( partVolume == VolumeList(p) );
end
VolumePMF = VolumeCount ./ sum(VolumeCount);
[SortedVolumePMF, indSort_V] = sort(VolumePMF,'descend');
SortedVolumeList = VolumeList(indSort_V);
NumUniqueVolumes = length(SortedVolumeList);
```

At time t there is an arrival, gen build time

```
getNIINh = @() gendiscreterv(1:NumUniqueParts,SortedPartPMF,1);
get1QTYh = @(niin) gendiscreterv(1:length(PMF_MAT{niin}),PMF_MAT{niin},1);
get1VOLh = @(niin) SortedPartVolume(niin);

get1BuildTimeh = @(niin) (0.93394 + SortedPartVolume(niin)*coefBuildTime)/PrintSpeed; %
intercept added from regression
getNIINh();
get1QTYh(getNIINh());
get1VOLh(getNIINh());
get1BuildTimeh(getNIINh());                              % returns a random build time based
on all the sorted PMFs previously built
```

Finding Pre & Post Processing Times for each Build

AM Pre-Processing

```
minSetupTimeAM = .1; maxSetupTimeAM = .2;                % hours
mostlikelySetupTimeAM = .12;
r = (maxSetupTimeAM-mostlikelySetupTimeAM)/(mostlikelySetupTimeAM-minSetupTimeAM);
alpha1 = (4 + 3*r + r^2)/(1 + r^2);
alpha2 = (1 + 3*r + 4*(r^2))/(1 + r^2);
SetupTimeAM = makedist('Beta',alpha1,alpha2);
getSetupTimeAM =@(n) minSetupTimeAM + (maxSetupTimeAM-
minSetupTimeAM)*random(SetupTimeAM,n,1);
% AM Post-Processing
minPostTimeAM = .2; maxPostTimeAM = 1;                   % hours
mostlikelyPostTimeAM = .3;
r = (maxPostTimeAM-mostlikelyPostTimeAM)/(mostlikelyPostTimeAM-minPostTimeAM);
beta1 = (4 + 3*r + r^2)/(1 + r^2);
beta2 = (1 + 3*r + 4*(r^2))/(1 + r^2);
PostTimeAM = makedist('Beta',beta1,beta2);
getPostTimeAM =@(n) minPostTimeAM + (maxPostTimeAM-minPostTimeAM)*random(PostTimeAM,n,1);
% AM Build Failure Probability
PassPercentage = .9;                                     % quality control
```

Simulation Setup

```
s = rng(2017);
iterations = 100;
SeedValues = [1:iterations]';
totVolume = zeros(iterations,1);
for trial= 1:iterations
```

```
    s = rng(SeedValues(trial));
NumDays = 162;                              % 162 is requisition period from OIF
T = NumDays*24;                             % hourly stepsize to capture small build times
SigLevel = 0.05;
NumInvasions = 1;
StopTime = T*NumInvasions;
% Arrival Rate
pd = makedist('Weibull',11.9755,1.10484);   % predetermined parameters for distribution
OrdersByDay = ceil(random(pd,1,NumDays));

ArrivalTimes = [];
for i = 1:length(OrdersByDay)
    RTi = ones(OrdersByDay(i),1)*i;
    ArrivalTimes = [ArrivalTimes; RTi];
end
ArrivalTimes = ArrivalTimes*24;
```

AM Simulation

Initialize

```
tic
t = 0;
NA_AM = 0; A_AM = zeros(length(ArrivalTimes),1);    % NA - number of arrivals (Orders Per
Day)
ND_AM = 0; D_AM = zeros(length(ArrivalTimes),1);    % ND - number of departures
done = false;
tA = ArrivalTimes(1);                               % time of 1st arrival is 24 hours
tD = Inf;
NumOrders = 0;
OrderHitTimes = []; OrderSojournTimesAM = zeros(length(ArrivalTimes),1);
    while ~done
        if tA <= StopTime & tA < tD                     % Arrival
            t = tA;
            NumOrders = NumOrders + 1;
            OrderHitTimes(end+1) = t;
            NA_AM = NA_AM + 1;
            A_AM(NA_AM) = t;

            if NumOrders == 1
                CurrentOrderNIIN = getNIINh();
                CurrentOrderQTY = get1QTYh(CurrentOrderNIIN);
                CurrentOrderVOL = get1VOLh(CurrentOrderNIIN)*CurrentOrderQTY;
                CurrentOrderBuildTime = get1BuildTimeh(CurrentOrderNIIN)*CurrentOrderQTY;
                tD = t + CurrentOrderBuildTime + getSetupTimeAM(1);
                EstSojournTime = CurrentOrderBuildTime + getSetupTimeAM(1);   % not including
PostTimeAM
            end

            if NA_AM < length(ArrivalTimes)
                tA = ArrivalTimes(NA_AM+1);
                else tA = Inf;
            end
        end

        if tD < tA                                      % Departure
            t = tD;
            if rand() > PassPercentage;                 % Build Failure
                tD = EstSojournTime + CurrentOrderBuildTime + getSetupTimeAM(1);
                totVolume(trial) = totVolume(trial) + CurrentOrderVOL;
                else
                    ND_AM = ND_AM + 1;
                    D_AM(ND_AM) = t;
                    NumOrders = NumOrders - 1;
                    OrderSojournTimesAM(ND_AM)= t+getPostTimeAM(1)-min(OrderHitTimes);
                    OrderHitTimes(argmin(OrderHitTimes)) = [];
                    totVolume(trial) = totVolume(trial) + CurrentOrderVOL;
            end
                if NumOrders == 0
                    tD = Inf;
                    else
                        CurrentOrderNIIN = getNIINh();
                        CurrentOrderQTY = get1QTYh(CurrentOrderNIIN);
                        CurrentOrderVOL = get1VOLh(CurrentOrderNIIN)*CurrentOrderQTY;
```

```
                        CurrentOrderBuildTime =
get1BuildTimeh(CurrentOrderNIIN)*CurrentOrderQTY;
                        tD = t + get1BuildTimeh(getNIINh()) + getSetupTimeAM(1) +
getPostTimeAM(1);
                end
        end

        if StopTime < tA & StopTime < tD & NumOrders == 0 % Stop Simulation
            t = StopTime;
            % Collect Stats
            done = true;
        end
    end

end
toc
```

Output Analysis - Sojourn Time

```
hw_AM = tinv(1-.5*SigLevel,length(OrderSojournTimesAM-
1))*(std(OrderSojournTimesAM)/sqrt(length(OrderSojournTimesAM)))/24 % days
meanOrderSojournTimeAM = mean(OrderSojournTimesAM)/24   % days
CI_OrderSojournTimeAM = [meanOrderSojournTimeAM-hw_AM meanOrderSojournTimeAM+hw_AM];
% Total Volume
totVolumeProcessed = sum(totVolume)/iterations          % cubic inches
mean(totVolume);
% Histogram
figure
plot(1,1)
histogram(OrderSojournTimesAM)
```

Finding the AM Est. Cost

```
% Cost Formula with Inputs/Setup

% Design Costs
DesignTime = NumUniqueParts*10;             % hours, time for an engineer to create the part
design
EngineerSalary = 120000;                    % $/year
EngineerHourlyRate = EngineerSalary/(240*8);% assume 240 days/year and 8 hours/day

DesignTC = EngineerHourlyRate*DesignTime;
PerPartDesignTC = DesignTC/NumUniqueParts;

% Material Costs
mostlikelyCostMatAM = 240;                  % $/lb, metal material typically $200-$300
partsWeight = totVolumeProcessed * .087;    % convert to pounds, taken from simulation
ScrapRate = 1.1;                            % 10% standard assumption

MaterialTC = mostlikelyCostMatAM*partsWeight*ScrapRate;
```

```
% Setup Costs
SetupTC = (mostlikelySetupTimeAM * numel(A_AM))* EngineerHourlyRate; % $

% Production Costs

% Fixed Costs
NumPrinters = PrintSpeed;
PurchasePrice = 750000*NumPrinters;         % $, est cost for DMLS
MxCost = (.10*PurchasePrice)/(365/NumDays); % $/time horizon, est. 10% of purchase price
Utilization = 1;                            % 100% assumption

% Variable Costs
% Find Average Build Time
loops = 10000;
listBT = zeros(loops,1);
for i = 1:loops;
    BT = get1BuildTimeh(getNIINh());
    listBT(i) = BT;
end

mostlikelyBuildTimeAM = mean(listBT);       % hours

MachineCost = (PurchasePrice+MxCost)/(365/NumDays); % $/time horizon
AvailableTimeToPrint = (NumDays*24)*Utilization;
HourlyMachineCost = MachineCost/AvailableTimeToPrint; % dollars/hour

ProdPartsTC = mostlikelyBuildTimeAM*HourlyMachineCost*(numel(A_AM));
% Post Production Costs
RemovalTC = (mostlikelyPostTimeAM * numel(D_AM))*EngineerHourlyRate;
% Total Parts Costs
PartsTC = DesignTC + MaterialTC + SetupTC + ProdPartsTC + RemovalTC;
FailureRate = 1;                            % already accounted for in totVolume
OverallTC = PartsTC*FailureRate
```

Publish to Word

```
publish('Paladin Parts Simulation_Sojourn_Cost.m','doc');
winopen('Paladin Parts Simulation_Sojourn_Cost.doc')
```

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Custom Function – vec2txt creates text file compatible with StatFit2

```
function [ ] = vec2txt(filename,vec)

%VEC2TXT Writes column vector to text file
%   Takes a column vector vec and writes it to a text file

% INPUTS:
% filename:  string with filename   example:  'data.txt'
% vec:  column vector of data
```

Function Code

```
fid = fopen(filename,'wt+');
for i = 1:length(vec)
    fprintf(fid,'%f\n',vec(i));
end
fclose(fid);

end
```

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Custom Function – gendiscreterv takes individual items and based off probability mass functions, generates an item

```
function [ X ] = gendiscreterv( XDomain,P,n )
%UNTITLED3 Summary of this function goes here
%   Detailed explanation goes here
% Domain = XDomain(:);
% P = P(:);
% Q = cumsum(P);
% trials = n;
%
% Yvec = zeros(trials,1);
% for t = 1:trials
%     U = rand(); i = 1; done = false;
%     while ~done
%         if U<=Q(i)
%             Y = Domain(i);
%             done = true;
%         end
%         i = i + 1;
%         if i ==length(Q)
%             Y = Domain(i);
%             done = true;
%         end
%     end
%     Yvec(t) = Y;
% end
%
% X = Yvec;


Domain = XDomain(:);  P = P(:); Q = cumsum(P);
trials = n;   Xvec = zeros(trials,1);
for t = 1:trials
    U = rand(); i = 1; done = false;
    while ~done
        if U<=Q(i)
            X = Domain(i);
            done = true;
        end
        i = i + 1;
    end
    Xvec(t) = X;
end
X = Xvec;
end
```

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Appendix C. R Regression Script

The following script was used in R software to produce the linear regression, relating build time to part volume.

```
data <- read.csv(file.choose(), header=TRUE)
data

volume = data$v
time = data$Total.Print.Time..hrs.

plot(volume,time,
xlab = "Part Volume (in^3)",
ylab = "Build Time (hours)",
main = "3D Build Time Based on Part Volume"
)

m1 = lm(time ~ volume, data = data)
summary(m1)
abline(lm(time ~ volume))

cor(volume,time)

coeffs = coefficients(m1); coeffs
volume = 20
time = coeffs[1] + coeffs[2]*volume
time
```

Appendix D. StatFit2 Distribution Fitting

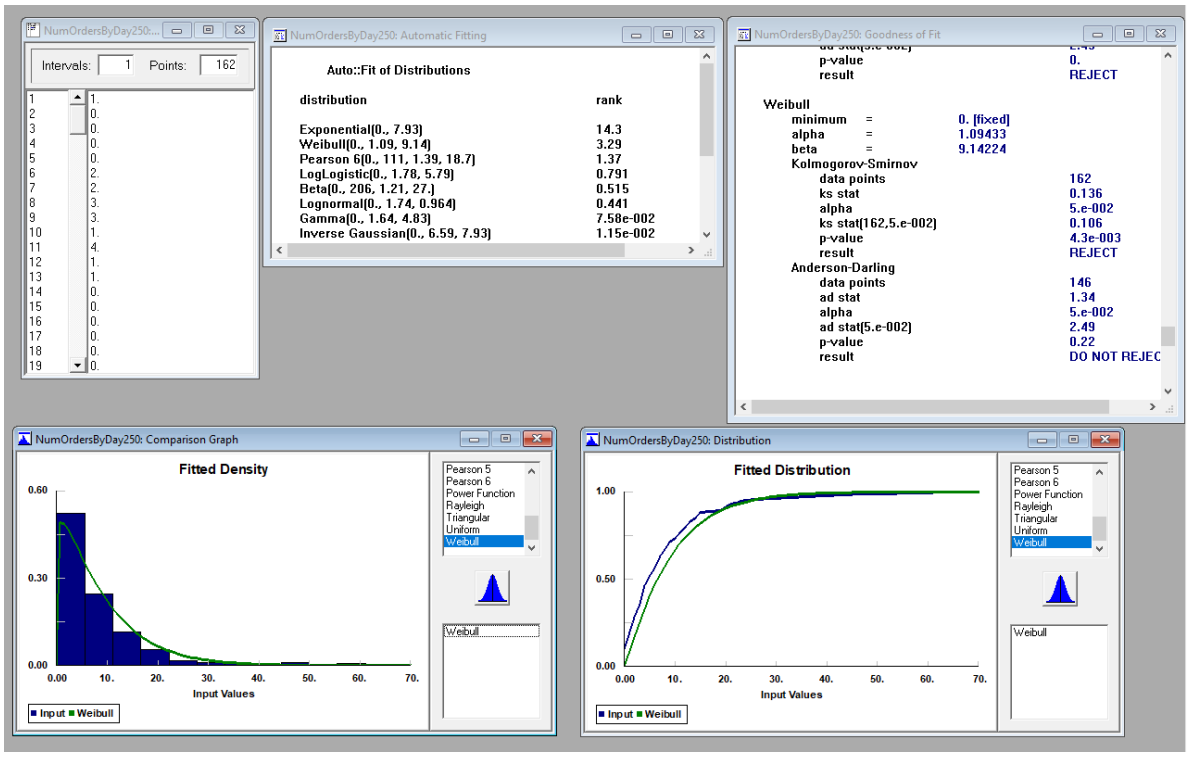
The following figures display the various distributions required for the different scenarios included in this thesis. The Weibull parameters are recorded below for all of the different scenarios. Again, these distributions reflect the number of orders per day.

Weibull Parameters

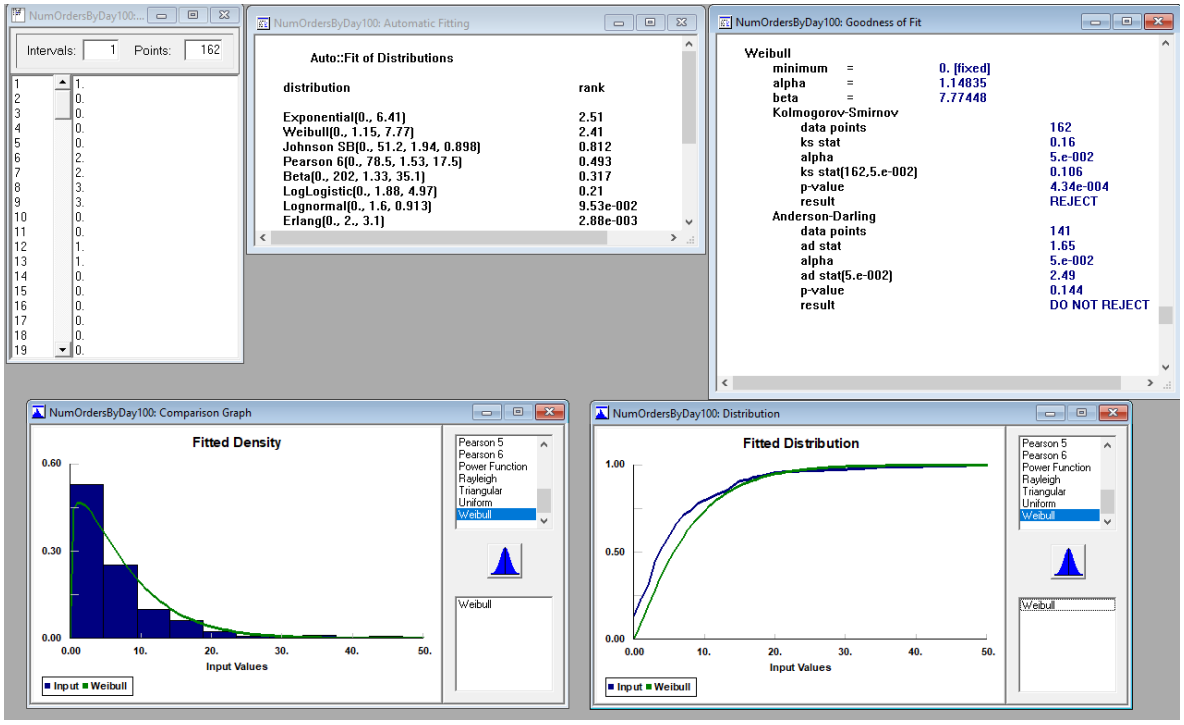
		alpha	beta
All Parts	3 BN	1.10484	11.9755
	BN	1.10484	3.99183
	BTRY	1.10484	1.99592
	GUN	1.10484	0.249489
250	3 BN	1.09433	9.14224
	BN	1.09433	3.04741
	BTRY	1.09433	1.52371
	GUN	1.09433	0.190463
100	3 BN	1.14835	7.77448
	BN	1.14835	2.59149
	BTRY	1.14835	1.29575
	GUN	1.14835	0.161968
57	3 BN	1.12349	6.77025
	BN	1.12349	2.25675
	BTRY	1.12349	1.12838
	GUN	1.12349	0.141047
40	3 BN	1.38774	3.53959
	BN	1.38774	1.17986
	BTRY	1.38774	0.589932
	GUN	1.38774	0.073741

D.1 3 Battalions Demand Rate (orders per day)

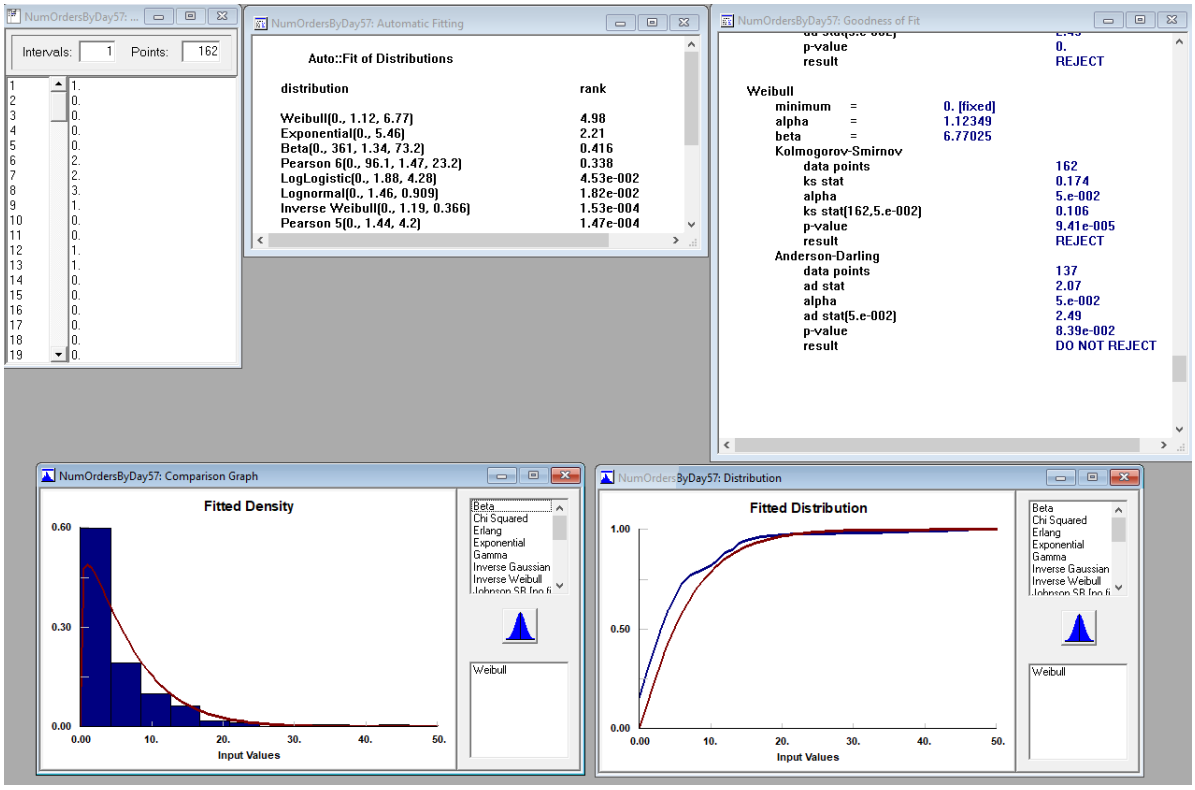
<u>250 cubic inches and less</u>



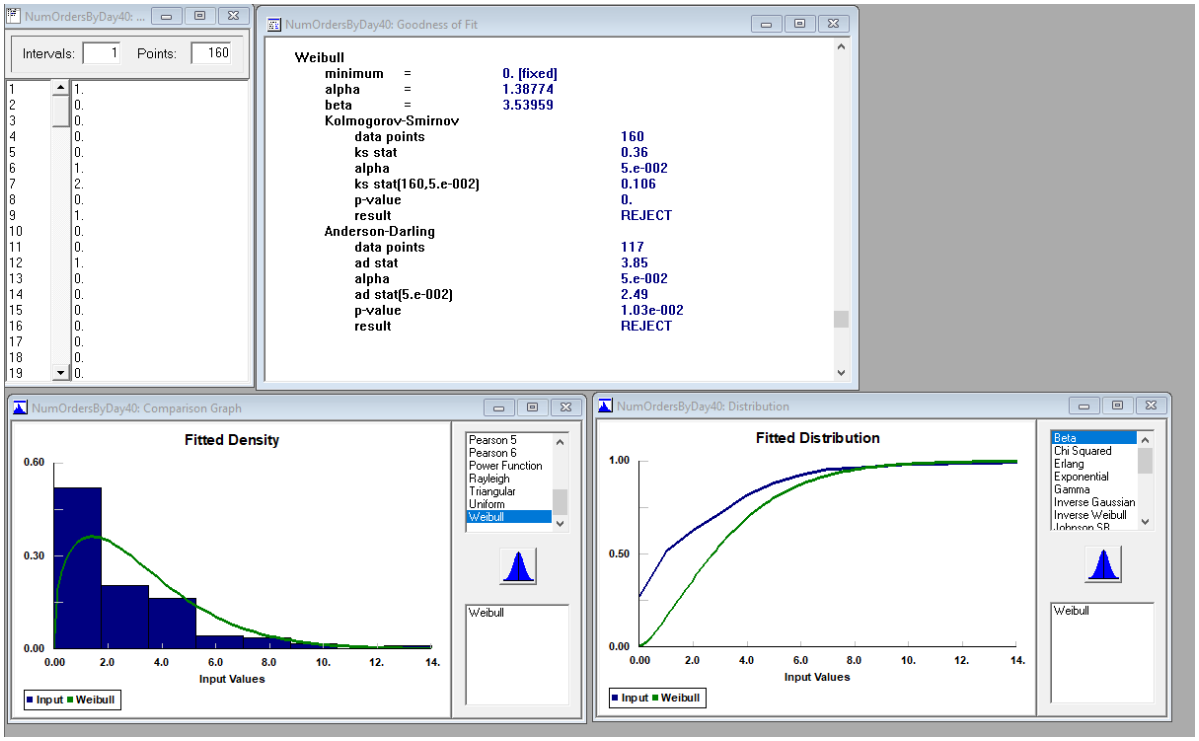
100 cubic inches and less



57 cubic inches and less

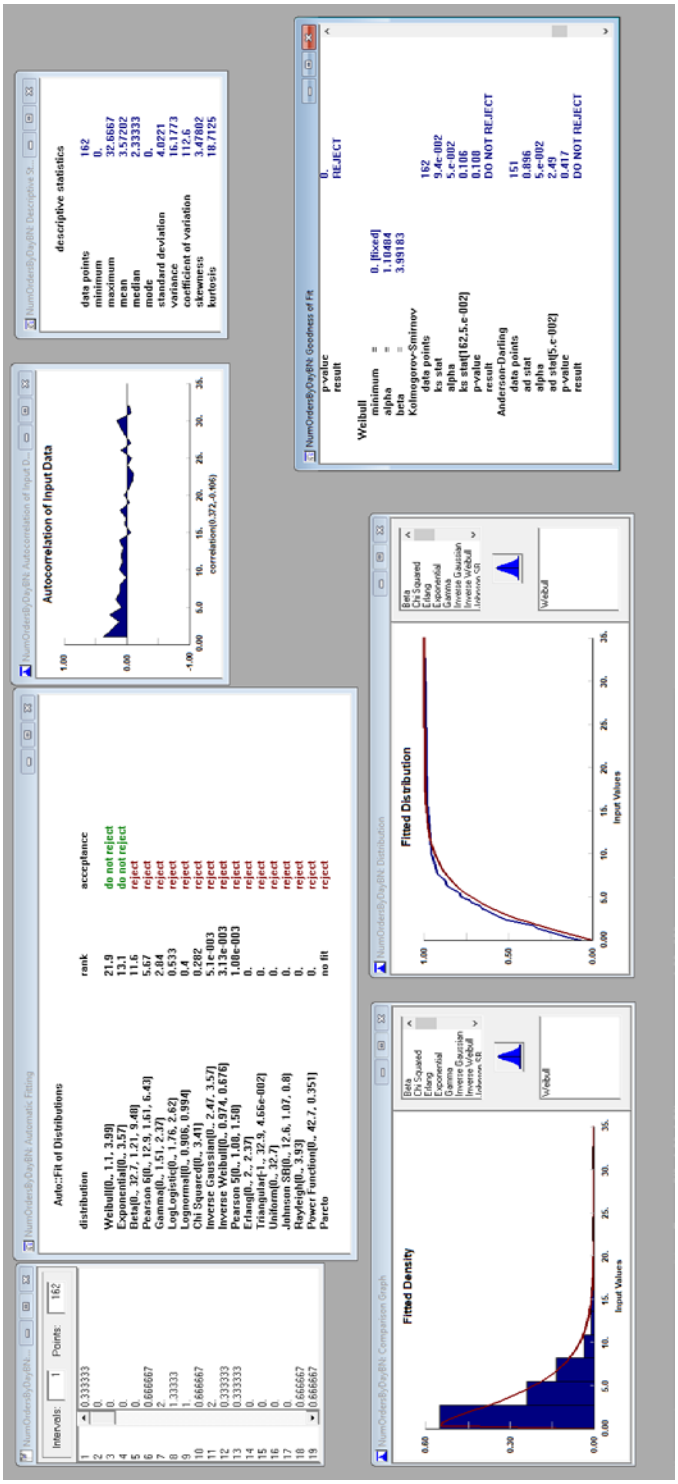


40 cubic inches and less

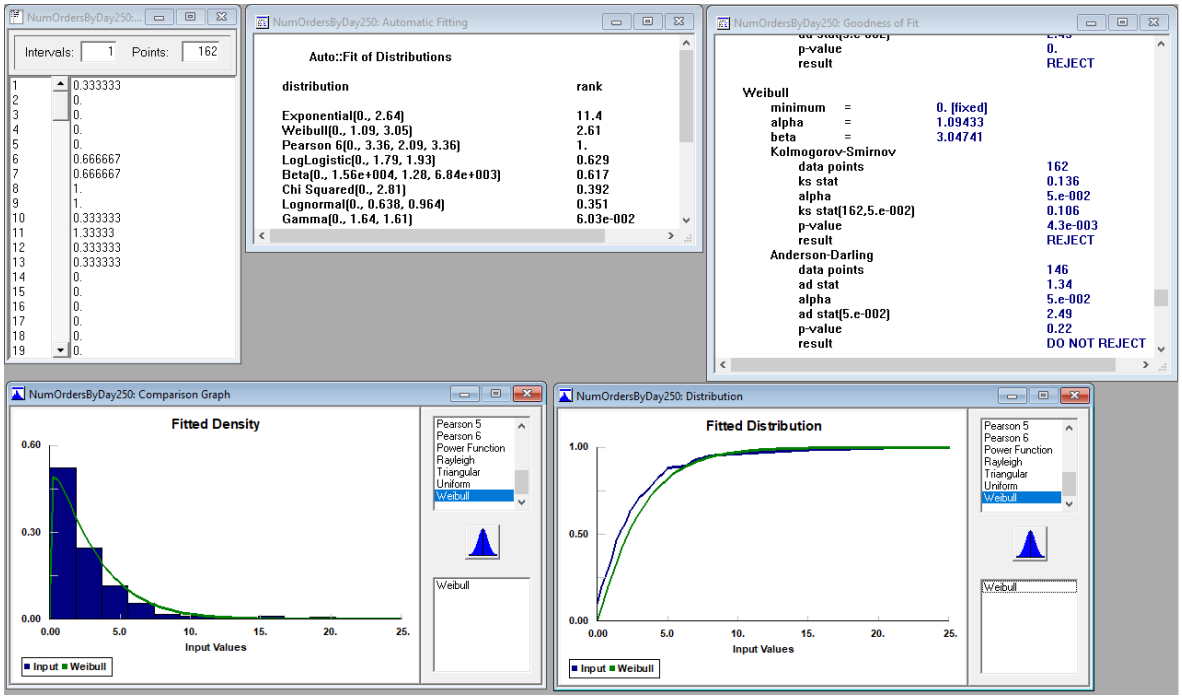


D.2 Battalion Demand Rate (orders per day)

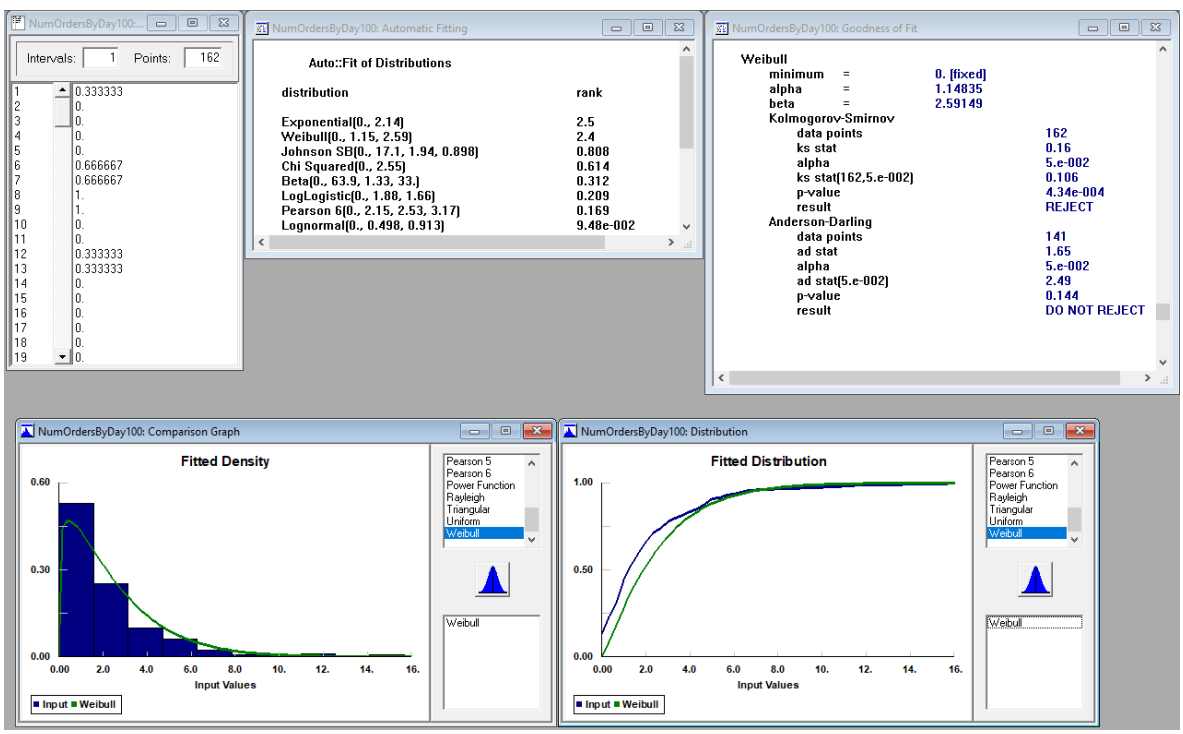
<u>All Parts</u>



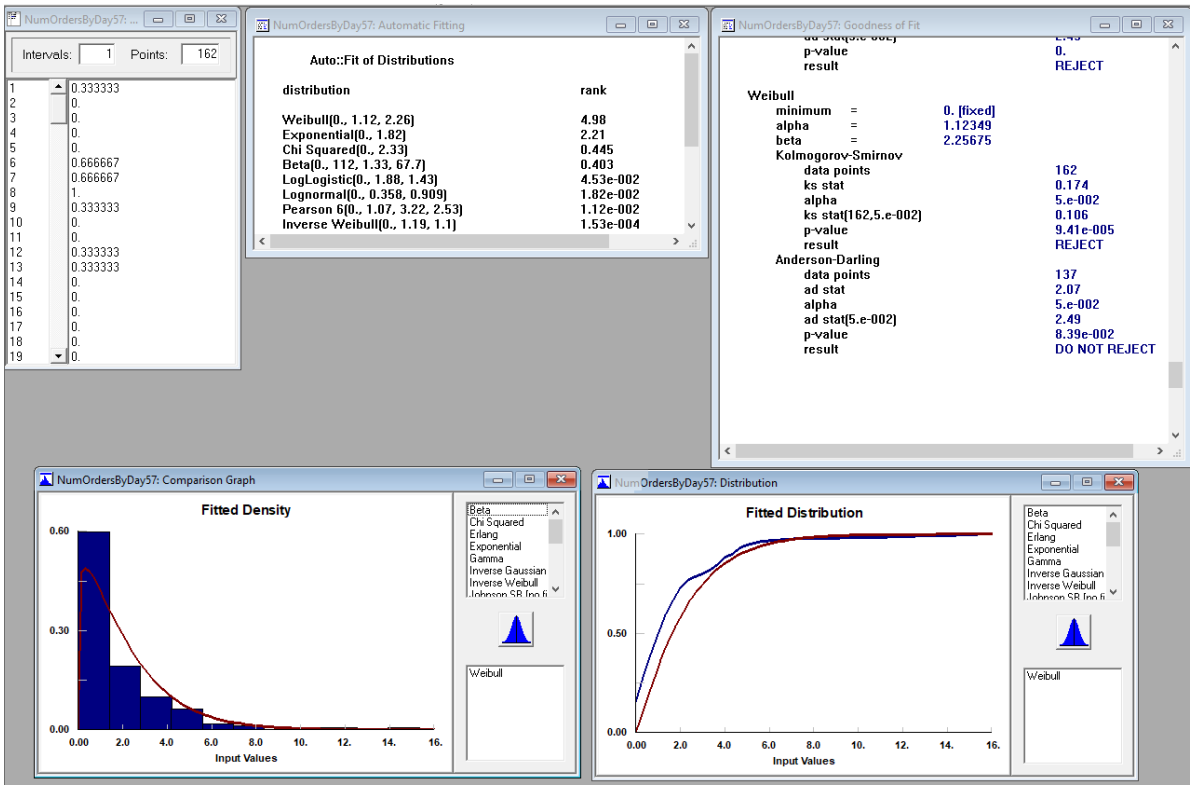
250 cubic inches and less



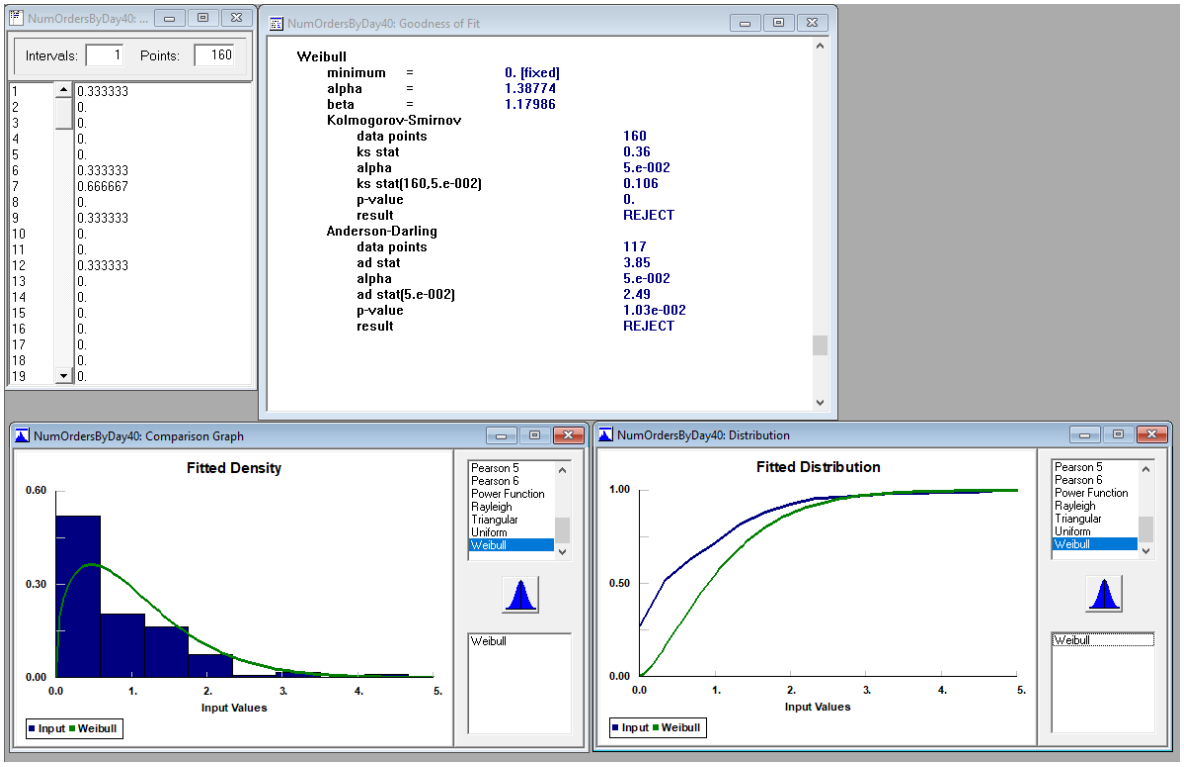
100 cubic inches and less



57 cubic inches and less

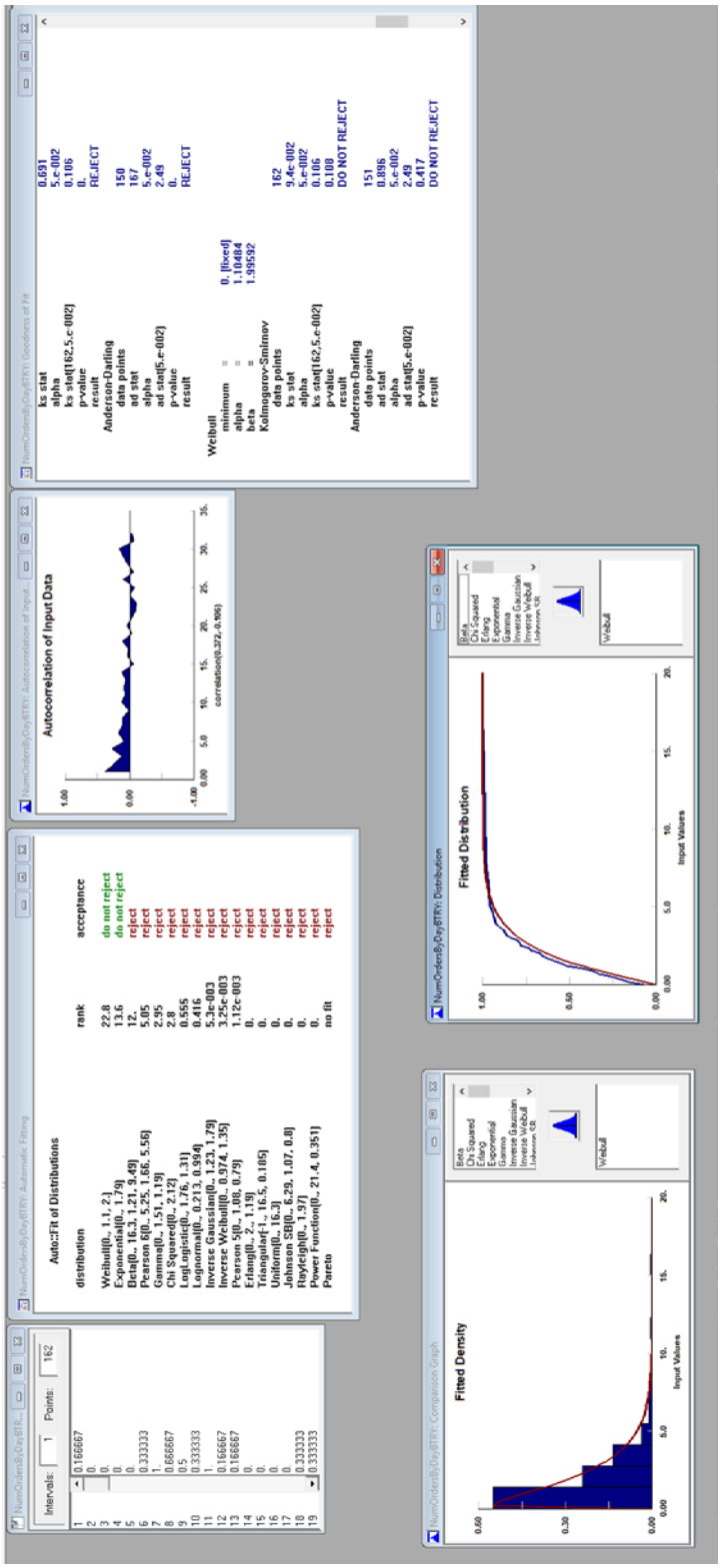


40 cubic inches and less

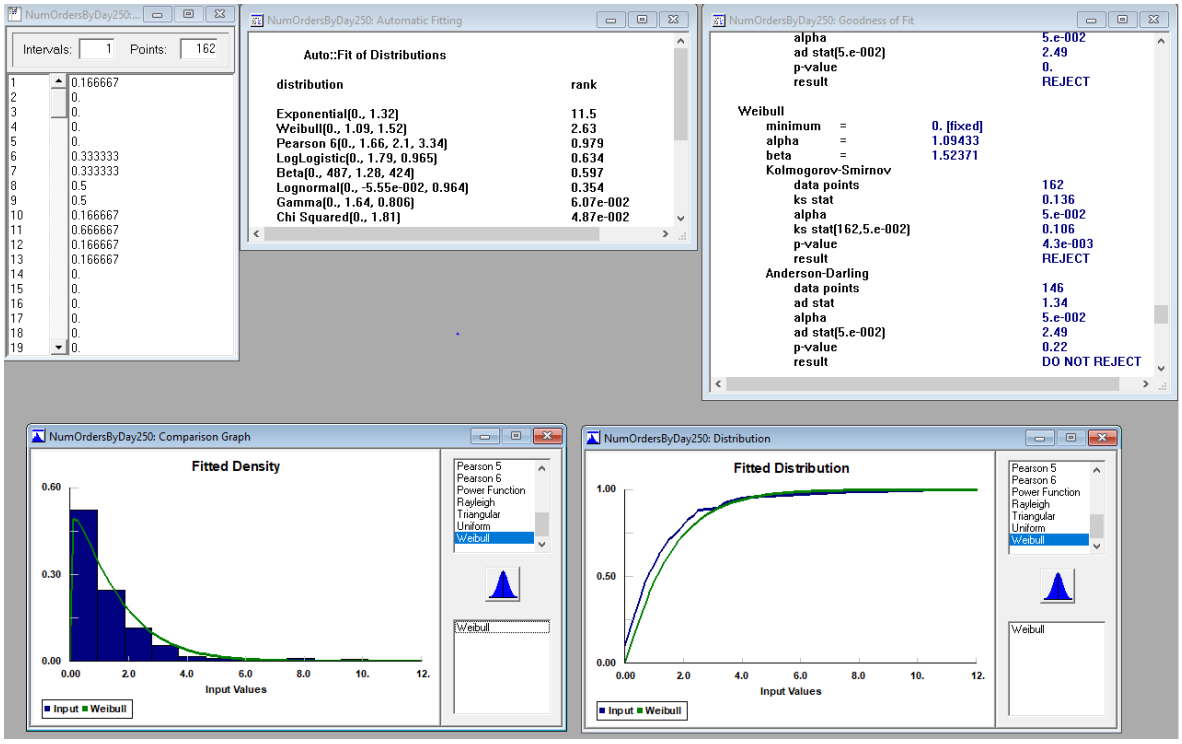


D.3 Battery Demand Rate (orders per day)

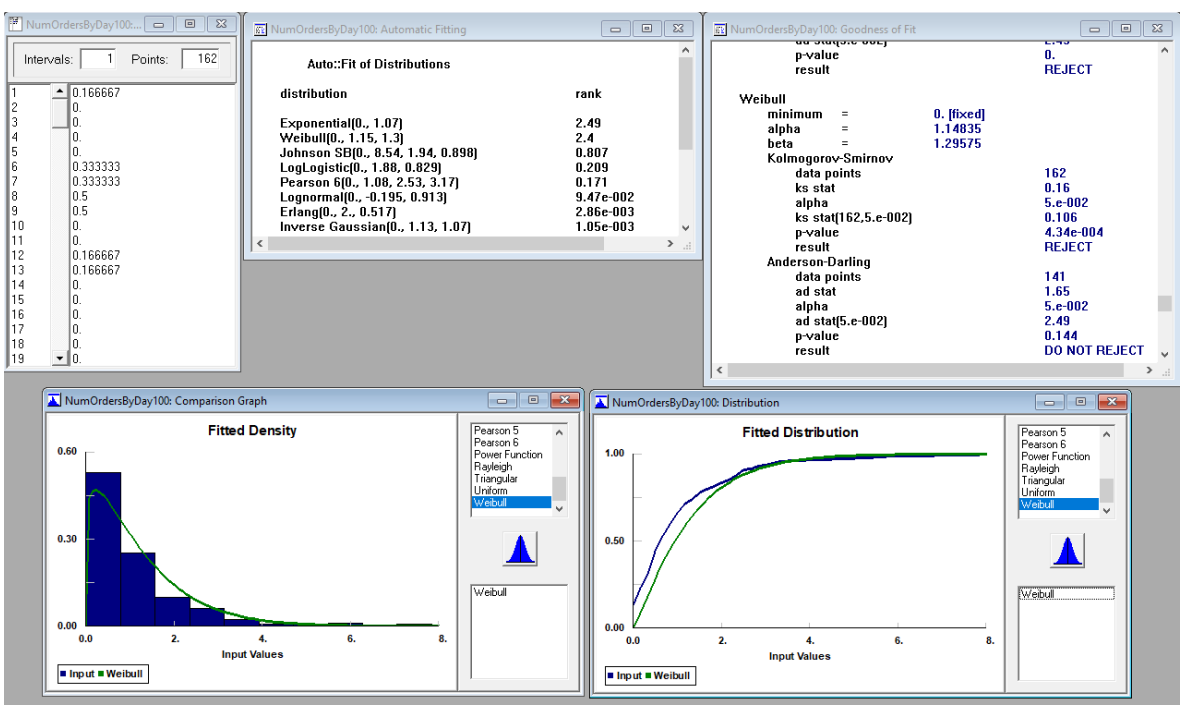
<u>All Parts</u>



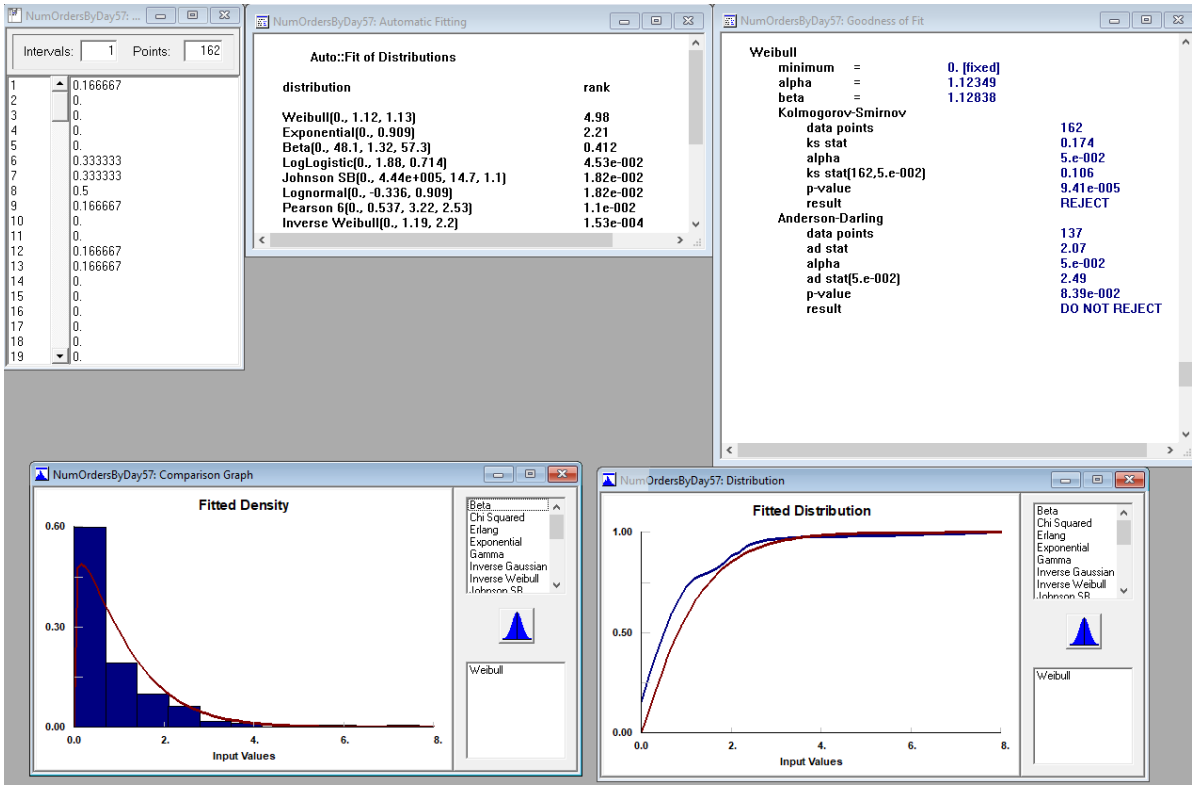
250 cubic inches and less



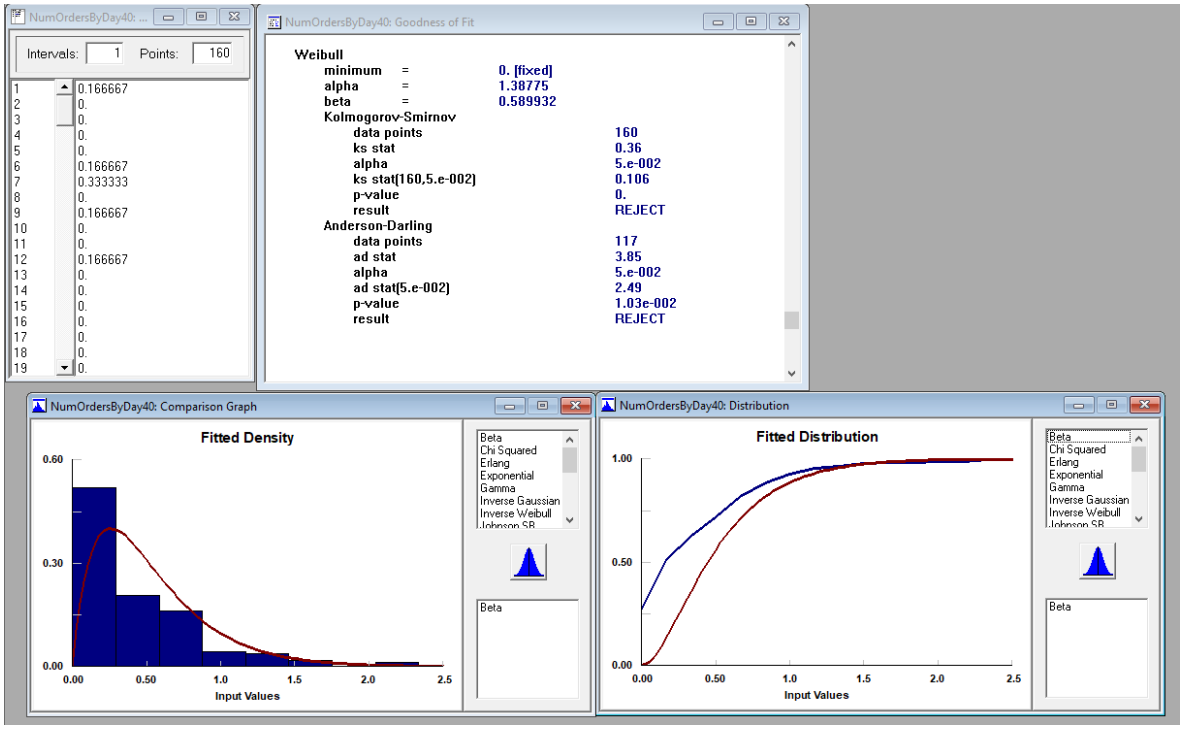
100 cubic inches and less



57 cubic inches and less

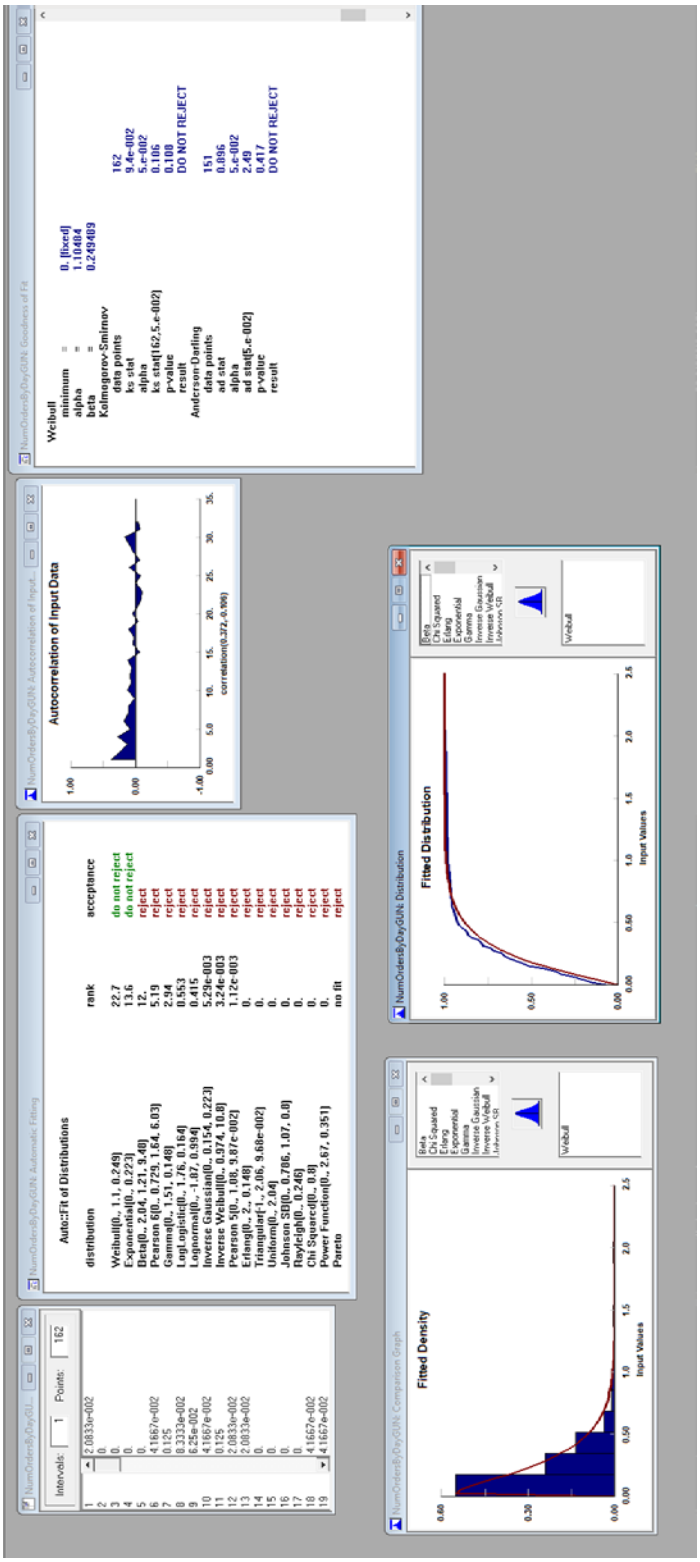


40 cubic inches and less

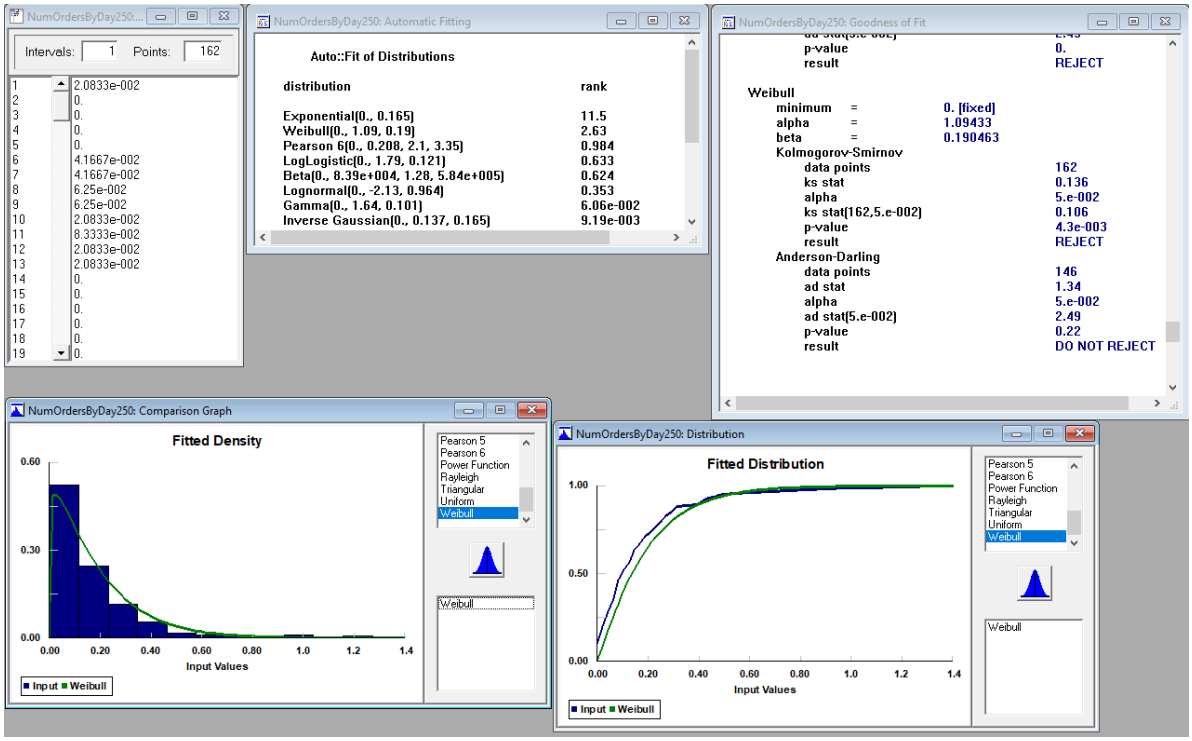


D.4 Gun Demand Rate (orders per day)

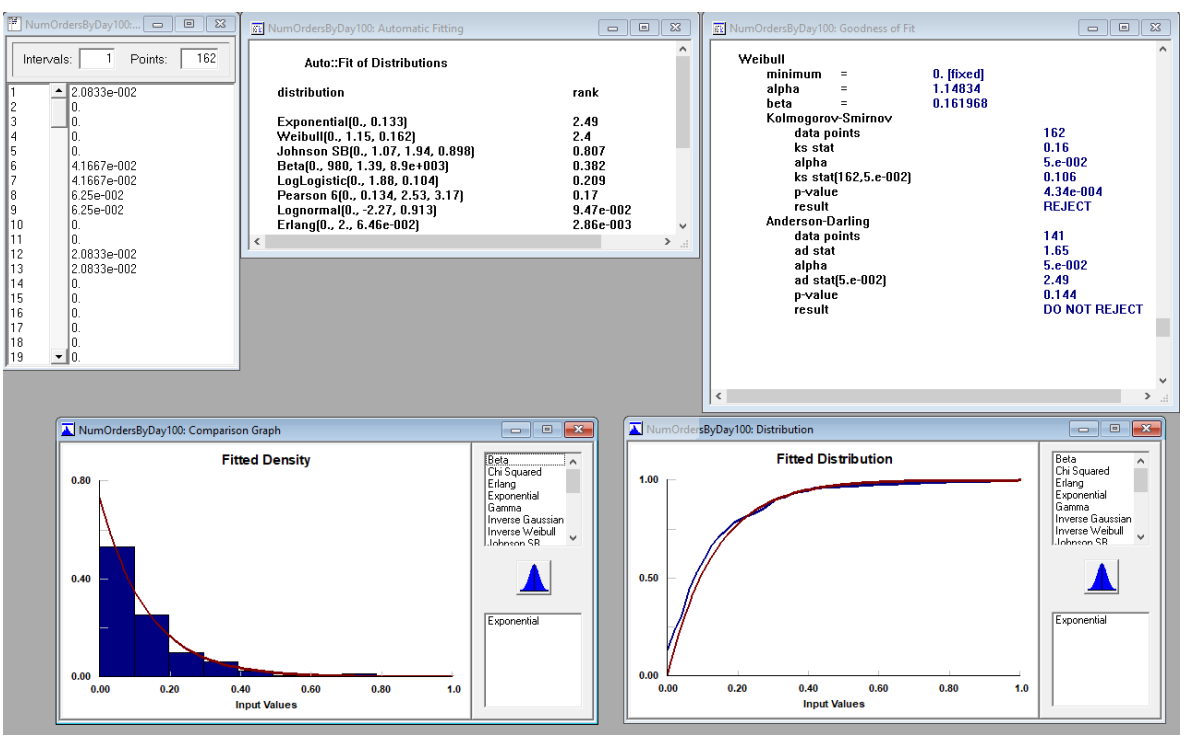
All Parts



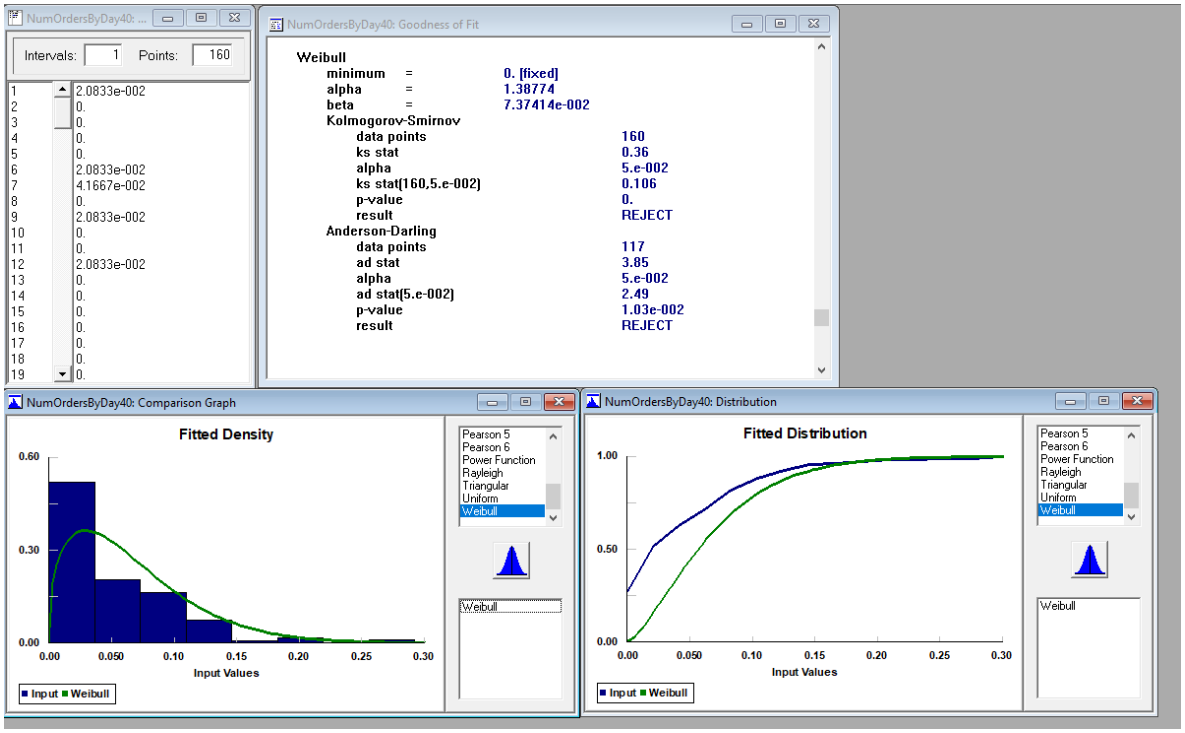
250 cubic inches and less



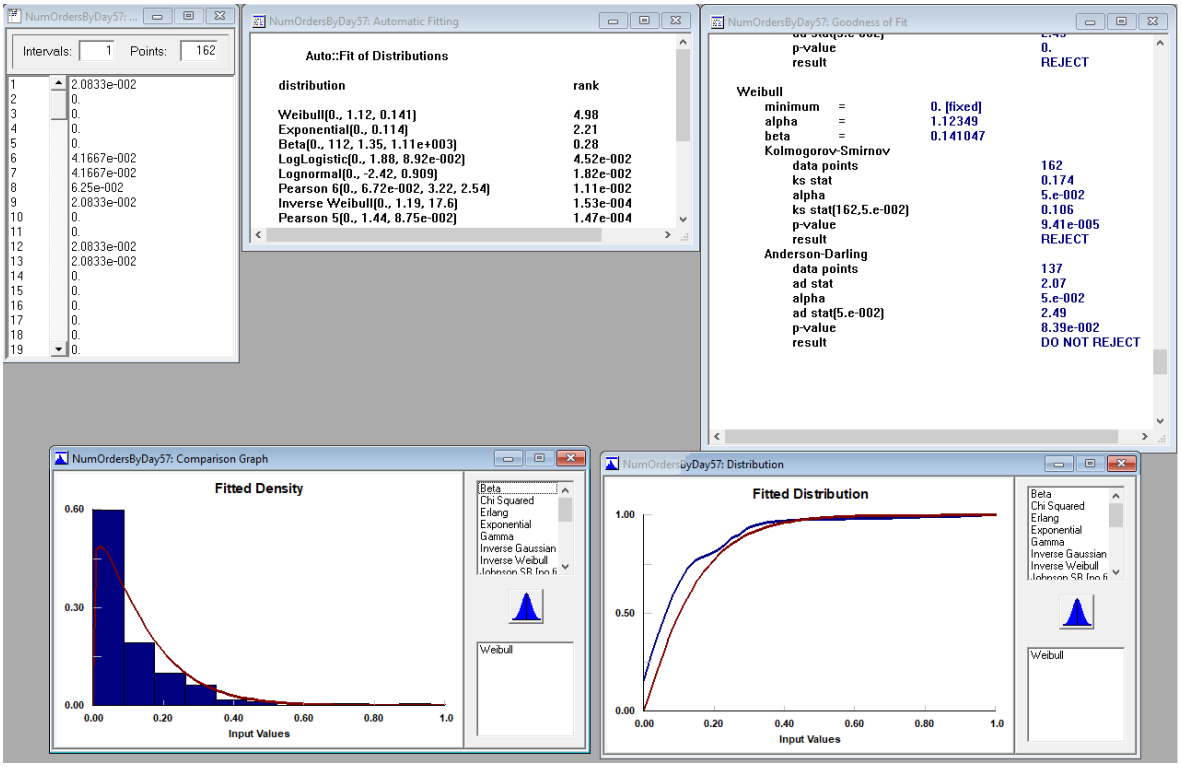
100 cubic inches and less



57 cubic inches and less



40 cubic inches and less



Appendix E. Factorial Design and Results

The following tables show the factors and levels considered in design point simulations with respective results for lead time, cost, and total volume processed. Additionally, one outlier is defended by the results from 50,000 replications.

Volume (f)	Echelon (g)	Print Speed (h)
(1) Less than 250 cubic inches	(1) 3 Battalions	(1) 1
(2) Less than 100 cubic inches	(2) 1 Battalion	(2) 10
(3) Less than 57 cubic inches	(3) 1 Battery	(3) 20
(4) Less than 40 cubic inches	(4) 1 Gun	(4) 30

Design Points

			Print Speed			
		Echelon	1	2	5	10
Volume (cubic inches)	250	3 BN	f1, g1, h1	f1, g1, h2	f1, g1, h3	f1, g1, h4
		BN	f1, g2, h1	f1, g2, h2	f1, g2, h3	f1, g2, h4
		BTRY	f1, g3, h1	f1, g3, h2	f1, g3, h3	f1, g3, h4
		GUN	f1, g4, h1	f1, g4, h2	f1, g4, h3	f1, g4, h4
	100	3 BN	f2, g1, h1	f2, g1, h2	f2, g1, h3	f2, g1, h4
		BN	f2, g2, h1	f2, g2, h2	f2, g2, h3	f2, g2, h4
		BTRY	f2, g3, h1	f2, g3, h2	f2, g3, h3	f2, g3, h4
		GUN	f2, g4, h1	f2, g4, h2	f2, g4, h3	f2, g4, h4
	57	3 BN	f3, g1, h1	f3, g1, h2	f3, g1, h3	f3, g1, h4
		BN	f3, g2, h1	f3, g2, h2	f3, g2, h3	f3, g2, h4
		BTRY	f3, g3, h1	f3, g3, h2	f3, g3, h3	f3, g3, h4
		GUN	f3, g4, h1	f3, g4, h2	f3, g4, h3	f3, g4, h4
	40	3 BN	f4, g1, h1	f4, g1, h2	f4, g1, h3	f4, g1, h4
		BN	f4, g2, h1	f4, g2, h2	f4, g2, h3	f4, g2, h4
		BTRY	f4, g3, h1	f4, g3, h2	f4, g3, h3	f4, g3, h4
		GUN	f4, g4, h1	f4, g4, h2	f4, g4, h3	f4, g4, h4

Lead Time (days)

Volume (cubic inches)	Echelon	Print Speed 1	2	5	10
250	3 BN	782.84	362.08	109.85	25.83
	BN	247.15	89.65	4.57	0.8
	BTRY	109.79	17.68	1.13	0.56
	GUN	9.81	2.26	0.96	0.42
100	3 BN	389.8	164.21	28.86	1.42
	BN	105.19	16.61	0.84	0.4
	BTRY	22.69	0.83	0.29	0.17
	GUN	5.48	2.24	0.68	0.27
57	3 BN	278.39	107.55	5.94	0.9
	BN	44.82	2.26	0.81	0.37
	BTRY	4.54	3.21	0.67	0.33
	GUN	2.82	1.61	0.52	0.29
40	3 BN	26.05	1.3	0.43	0.3
	BN	1.65	2.32	0.74	0.35
	BTRY	8.08	0.72	0.52	0.14
	GUN	1.44	2.09	0.26	0.14

Lead Time Half-Width (days)

Volume (cubic inches)	Echelon	Print Speed 1	2	5	10
250	3 BN	21.54	9.88	2.87	0.55
	BN	11.37	3.96	0.35	0.07
	BTRY	6.52	0.9	0.13	0.07
	GUN	0.55	0.45	0.19	0.1
100	3 BN	11.47	4.71	0.67	0.06
	BN	4.98	0.58	0.05	0.03
	BTRY	1.43	0.07	0.02	0.01
	GUN	0.73	0.4	0.16	0.06
57	3 BN	8.98	3.37	0.15	0.04
	BN	2.34	0.11	0.08	0.03
	BTRY	0.25	0.41	0.09	0.05
	GUN	0.31	0.28	0.14	0.08
40	3 BN	1.07	0.06	0.03	0.03
	BN	0.14	0.5	0.18	0.08
	BTRY	1.54	0.12	0.18	0.02
	GUN	0.26	0.62	0.05	0.02

Cost (dollars)

Volume (cubic inches)	Echelon	Print Speed 1	2	5	10
250	3 BN	$13,698,490	$14,447,519	$16,703,767	$20,455,455
	BN	$5,079,697	$5,854,470	$8,084,269	$11,840,208
	BTRY	$2,976,497	$3,734,263	$5,975,623	$9,730,710
	GUN	$1,502,490	$2,230,196	$4,480,826	$8,243,924
100	3 BN	$7,685,998	$8,437,869	$10,695,913	$14,466,029
	BN	$2,899,401	$3,653,838	$5,917,512	$9,651,572
	BTRY	$1,745,148	$2,495,148	$4,745,148	$8,495,149
	GUN	$1,001,696	$1,757,875	$4,003,977	$7,736,730
57	3 BN	$5,623,141	$6,373,440	$8,594,597	$12,350,803
	BN	$2,184,733	$2,931,723	$5,179,290	$8,946,173
	BTRY	$1,339,860	$2,076,996	$4,351,480	$8,098,659
	GUN	$811,993	$1,558,276	$3,805,149	$7,549,698
40	3 BN	$1,768,123	$2,515,459	$4,763,164	$8,504,683
	BN	$765,579	$1,529,532	$3,773,656	$7,519,598
	BTRY	$545,427	$1,282,997	$3,546,833	$7,287,841
	GUN	$483,523	$1,231,183	$3,488,325	$7,234,572

Volume Processed (cubic inches)

Volume (cubic inches)	Echelon	Print Speed 1	2	5	10
250	3 BN	455,721	455,679	455,951	456,024
	BN	168,251	168,945	168,076	168,409
	BTRY	97,427	97,765	97,243	97,595
	GUN	48,548	47,570	47,593	48,177
100	3 BN	257,172	257,254	257,604	258,462
	BN	95,738	95,930	96,526	95,808
	BTRY	57,082	57,082	57,082	57,082
	GUN	32,414	32,691	32,520	31,765
57	3 BN	185,709	185,722	184,465	184,744
	BN	71,078	70,919	70,794	71,545
	BTRY	43,178	42,611	43,688	43,561
	GUN	25,840	25,674	25,546	25,307
40	3 BN	59,355	59,267	59,149	58,825
	BN	25,098	25,707	25,458	25,273
	BTRY	17,766	17,229	17,829	17,435
	GUN	15,591	15,488	15,798	15,632

Outliers

40		50,000 iterations for 1 build speed resulted in:			
		Lead Time	HW	Cost	Volume
	BTRY	1.94	0.26	551117	17775