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Determining the efficacy of additive manufacturing for the aerospace spare parts supply chain

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Determining the Efficacy of Additive Manufacturing for the Aerospace Spare Parts Supply Chain

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Abstract

This thesis investigates how additive manufacturing (AM) based on-demand part production can supplement or replace the traditional production and inventory in typical aerospace's spare parts supply chain systems. This study focuses on the operational characteristics of AM and its impacts on the overall logistics of plant-level operations. To capture the microscopic operational aspects of the AM production, a discrete-event simulation based approach was adopted, with key AM operation resources (e.g. AM system, operator) and attributes (e.g. AM manufacturing speed, individual part characteristics and demands) accounted for in the modeling process. In addition, a benchmark warehouse inventory model was also established separately based on classic theories, which was subsequently utilized to create a cost/benefit analysis for the AM based part supply strategies versus the traditional strategies. The results from virtual experiments with these models were analyzed in order to gain an understanding of the operational characteristics (e.g., production cost, system utilization, lead time) as a function of various production policies such as machine/operator configurations and part prioritization. Data analysis shows cost savings for AM as an alternative to warehousing under high penalty scenarios. Results also indicate higher cost savings with the addition of extra machines over extra operators to meet capacity. Finally, analysis shows that reprioritizing orders waiting in a queue has higher savings when assessing due date and penalty outcomes.

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I. Introduction

Traditional production uses an assembly-line of machines, personnel, and transportation equipment to produce vast quantities of products and stock them in inventory until ready to be shipped. The objective of such push-based production and inventory has been to exploit economies of scale and to reduce lead times and prevent back orders, minimizing ripple effects to downstream customers. However, in today's on-demand just-in-time economy, this production and inventory practice is viewed as obsolete due to low customer responsiveness and system inefficiency. The emergence of additive manufacturing (AM) with the underlying ability of manufacturing on demand, is being regarded as a promising solution to address this challenge. Up until now, the development of AM technologies has primarily focused on the perspectives of structural design and material property. Scientific investigation of the enterprise realization surrounding AM has been limited to manufacturing cost analysis, while largely ignoring the fact that this method of production is only an element of a larger supply chain.

A. Additive Manufacturing (AM)

A growing trend towards innovation and customization, with an expectation for high quality at a reasonable price is seen in almost every industry today. Product lifecycles have been shortened as technology rapidly evolves in an increasingly digital world [1]. With a movement towards globalization, companies are having to compete more often with foreign products. AM may prove to be a viable solution to produce innovative products at a reduced time to market, due to its geometric freedoms and on-demand production capabilities. Tie in the high technical and digital nature of this production method, and AM boasts the potential to become a cost-effective way to reshore manufacturing in countries like the US [2].

With current market size of over $7 billion and projected annual growth of over 20% [3], AM is anticipated to become a mainstream manufacturing technology with the potential to disrupt large industries (e.g., aerospace, automotive, consumer goods, healthcare). Therefore, economic aspects of AM in large scale production, as well as its optimization for both productivity and quality, will become critical. With an adequate understanding of the next-generation AM supply chain characteristics, customers, and suppliers at all levels of production will be capable of more intelligent decision making for their supply chain operations. The emergence of this on-demand production will transform existing supply chain design and operation paradigms and benefit a great range of industries and businesses. Adoption of AM in a broad range of production applications, accelerates advancement of this technology and its value benefiting society directly.

In comparison with conventional manufacturing, AM enables designers to concentrate more on product properties as opposed to a design that complies with traditional manufacturing limitations [1]. The aerospace, automotive, and electronics industries have become the primary users of AM with the highest promise for profit via innovative designs. Still the critical factor associated with the increased usage of AM is the cost to implement.

While cost models have been developed for additive, most have only incorporated direct costs of production, missing much of the impacts this technology exhibits on the supply chain. This absence in the literature is expected due to the novel characteristic of this technology's on-demand production. Traditional manufacturing benefits from large scale production and utilizes inventory to ensure high service levels. As the AM costs models are still being developed this paper investigates the incorporation of other supply chain considerations, particularly AM's impact on inventory, lead times, and customer responsiveness. In addition, AM-based production offers unique requirements for increasing operation efficiencies. In later sections this thesis investigates how various strategies of machine/operator configurations, part prioritization, postponement, and other policies can improve production costs and customer responsiveness.

B. Aerospace Spare Parts

Spare parts used to support the aerospace industry's maintenance, repair, and operations (MRO) services are critical, where the cost of grounded aircraft justifies innovative solutions to increase fleet availability [4]. For commercial airlines, the aftermarket parts sales are currently estimated to be $45 billion and a predicted CAGR (compound annual growth rate) of 7.63% over the next 3 years [5]. However, there are large costs associated with providing these parts. In 2009 the U.S. military spent $104 billion on supplies, $70 billion on maintenance, and $20 billion on transportation to manage their spare parts supply chain, and ultimately ended the year with millions of units still in stock valued at over $94 billion [6].

These after-sale parts often exhibit low demand yet are stored by OEMs in high quantities across distributed warehousing networks to ensure short lead times for customers [6]. As a result, this industry may benefit greatly from the inventory savings, shortened lead times, and high customer responsiveness promoted by AM's on-demand production. Therefore, it is of significant practical values to investigate the potential implementation of AM production in the aerospace MRO spare parts industry as a demonstrative example of the potential AM offers on a low-demand, high penalty supply chain.

In addition to covering the intended physical properties of Aerospace spare parts, AM-based production is ideal for these highly variable demands, essential to preventing prolonged aircraft grounding because of its ability to print on-demand with short production runs. The on-demand characteristic of AM would also provide a benefit on the entire supply chain by reducing inventory and distribution costs. For industries like aerospace that could create large cost savings for their MRO services.

II. Literature Review

A. AM-based Production: Direct Costs

In traditional manufacturing, the initial investment costs are often quite higher than AM. Injection molding or casting can be as high as millions of dollars for large parts. However, once fabricated this production exhibits an economy of scales relationship [7]. After the initial investment, production will only incur the cost of materials, which can be as low as fractions of a cent. In addition, a distinct characteristic of many mass-production processes is that the part production rate is high. Therefore, once production is initiated, large production volumes will significantly dilute the initial investment costs, driving the overall cost per part down. For AM, there is a similar initial investment for the purchase of a machine. Likewise, the cost of this purchase is shared among the production of parts. However, unlike these traditional production methods, AM machines are not unique to one pattern of part but can be used for many different designs that the machine building volume and technology can accommodate. This means that not only does AM avoid the need of art-specific dedicated tooling, but that the machine's investment cost is shared across the many different products a manufacturer may produce, and for the many years of usage [1, 8]. In terms, of individual parts, this initial investment becomes less significant, turning the biggest cost factor into process specific costs. These costs include the cost of time, labor, and materials, but stay relatively constant independent to the production volume Figure 1 is a graphical representation of the relationship between traditional forms of production and AM production [9]. As Figure 1 shows, AM-based production is at an advantage when production volumes stay relatively low. In fact, studies show that low to medium volume production is the current market where AM has the potential to be cost effective over traditional methods [7, 10].

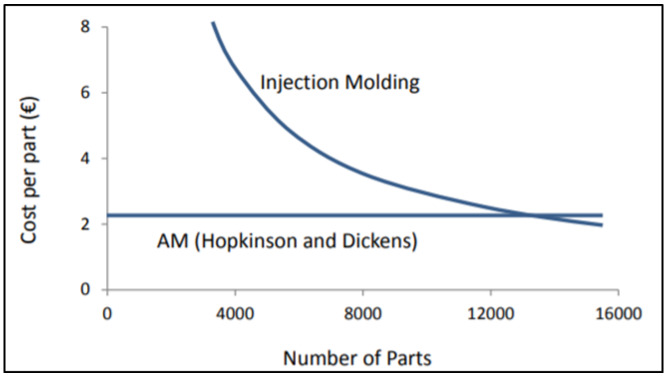

Figure 1. Low volume AM cost analysis.

Part complexity can also be accommodated in the AM process that fabricates parts layer by layer, where intricate designs and internal features can be introduced with ease [9]. For example, lattice structures, a matrix of unit cells, can be printed in series to form massive structures with the purpose of improving the per-mass-performance efficiency of a part. Producing lattice structures via traditional methods of injection molds, casting or machining would only be possible with some additional assembly, which would introduce large costs to a part. Part consolidation is also an example of how AM-based production can accommodate part complexity and decrease the overall cost per part [11]. Part consolidation is the process of taking existing part assemblies and consolidating them into a reduced number of sub-assemblies or even into single, fully assembled parts. This consolidation eliminates the cost of excess tooling designs, as well as the labor or machine costs for assembly. Figure 2, illustrates the cost associated with creating complex geometry using traditional methods versus AM-based production. As complexity increases there is a point where AM becomes cost justified over conventional manufacturing. This is because AM costs stay relatively constant regardless of the parts geometry, and as complexity continues to rise, the savings of switching to AM increase exponentially.

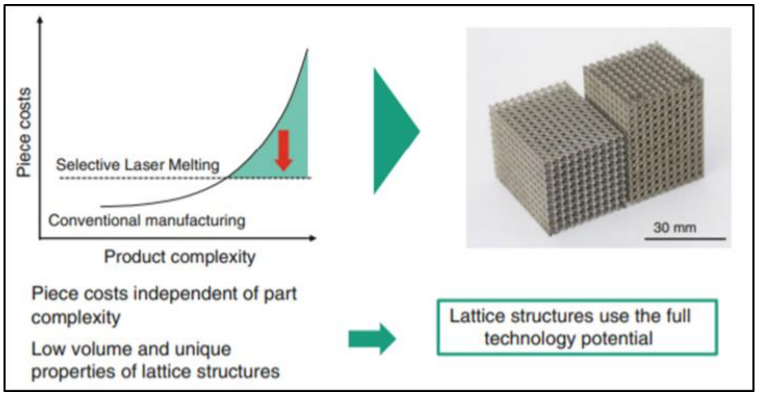

Figure 2. Complex geometry advantage of AM over traditional means of manufacturing.

Cost reduction can also be achieved with software tools performing topology optimization. Part optimization is a major benefit associated with AM and the reason it is heavily employed in the aerospace industry in the production of lightweight and material efficient parts [2]. Aspects that the designer could be looking to minimize include material use, support requirements, and process-technology feature limitations once target performance objectives such as safety, rigidity, or thermal residual stress have been met. Topology optimization employs various optimization search strategies achieve an optimal solution that maximizes the performance of a design under the functionality constraints specified by the user, typically resulting in the optimizing of material usage and layout (Figure 3). This leads to cost reductions of materials and build time, and in some cases even improved performance compared to the baseline product designs.

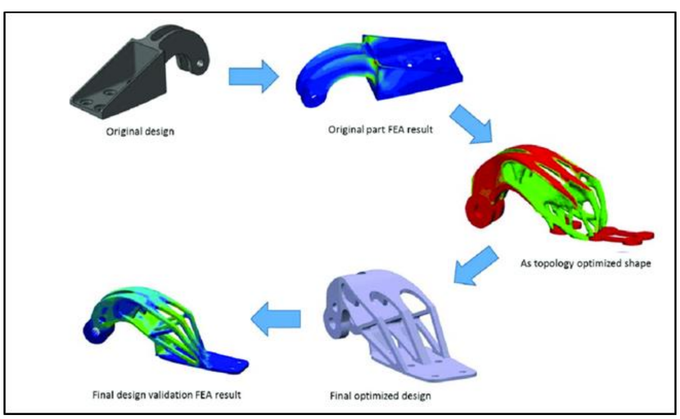

Figure 3. The stages of topology optimization.

Many direct cost models have been proposed for evaluating the trade-offs between AM and traditional manufacturing that investigate direct costs (i.e. machine hours, material use, and labor). Among them machine costs are most often the main driver of part cost (~60-80%). This includes machine purchase, storage, energy usage, and labor hours to maintain and use. This was supported in data provided by a Lindemann et al study analyzing the cost of AM metal parts [12]. Even at higher building rates 3 times the current average for many material extrusion printers the labor savings of AM provided minimal decrease in the high costs of purchasing and maintaining a machine.

Second to machine costs, materials are another large cost factor. AM feedstock is often significantly more expensive and often highly variable in price, as in the case of powder metals or ceramics. These powders must meet stringent standards of density, flowability, and particle size, among others, to ensure build quality, but that requires costly quality control from suppliers, and without industry regulation it can be difficult to determine actual product quality. A case study conducted by Atzeni et al showed a single scenario indicating a 10-fold increase in material cost when switching from traditional to additive production [13].

Another study conducted by Ruffo et al. investigating a Selective Lase Melting (SLM) process for low part volumes confirmed machine and material costs to be the main contributors to part cost, with some scenarios showing material costs to be the higher of the two [14]. While machine and material costs both contribute the most to overall cost of AM, Atzeni et al's study also found that in comparison to low demand injection molded parts where the cost to procure a mold was high, AM was more economic.

Post-processing, or the process of manipulating a builds' physical properties to produce finished parts is another time consuming and expensive step of the AM process. Costs are typically large in comparison to other cost factors due to the intrinsic property of AM that, unlike conventional production, does not produce “industrial grade” parts without additional post-processing (removal of support structures, surface finishing, heat treatments, etc.) [1, 2].

Another production related cost not yet modeled in literature is quality control, which in some applications like aerospace can be significant since parts must be FAA certified, and certification is made difficult with the high process variability associated with AM-based production [2].

Current direct cost models tend to only address the investments of producing the traditionally manufactured equivalent of AM parts, and not on the potential cost savings of reduced material use and the prolonged life cycle during the after-sale of parts. In terms of sustainability, AM’s resource efficiency has been promoted from its first invention [15]. Compared to subtractive, AM is often less wasteful, even when support structures are required to ensure part quality. An example of how AM sustainability equates to real savings can be observed from the redesign of GE’s Leap engine fuel nozzles. Utilizing AM, the company was able to combine 20 separate parts into a single unit and print nozzles that were 25% lighter than the original parts [16]. In addition, AM often improves the mechanical properties of a part and has the added benefit of being able to repair, remanufacture, or refurbish worn out or broken parts. For AM this may correlate with fewer dollars spent on end of life care, or on replacement parts [17].

Overall, research has shown the costs of AM depend mostly on build volume and height, whereas traditional manufacturing costs are often associated with part complexity and production length [4]. Additionally, since AM does not have the requirement of producing large quantities of a single part in order to redistribute the high investment costs of traditional tooling, it is better suited for low-medium volume demand. The technology also accommodates the production of non-identical parts in a single build giving AM an advantage when aggregating small part production like the demands of the aerospace MRO spare parts industry. However, most of the available AM cost models have their limitations because they only incorporate direct costs of production.

B. AM-based Production: Logistic Costs

While it is important to be able to quantify the direct costs of AM-based production, these values are only the micro-level factors. To understand the full cost of AM, macro-level considerations of the entire supply chain need to be explored. These are logistical considerations of storage and distribution, which because of the on-demand nature AM promise the greatest potential for cost reduction. Reduced inventory, shortened lead times, and higher customer responsiveness are aspects of AM-based production being investigated. Combining these values with direct cost models will provide manufacturers a full picture of the supply chain's overall production costs [2, 18].

Inventory levels are driven by the concern of customer stockouts in traditional manufacturing. Therefore production costs also include the storage of finished goods and additional purchasing of spare parts [19]. In warehousing, this inventory is commonly associated with 10-20% of total cost. AM provides on-demand production, eliminating in many cases the need for inventory.

The on-demand nature of AM also provides for rapid fabrication of parts leading to shorter lead times. Juahar et al investigated the lead time savings by comparing AM material extrusion with wax pattern investment casting for two automotive parts (inlet manifold and rotor), showing a 54% and 58% (respectively) reduction in lead times [20]. In a well-distributed supply chain, where AM-based production occurs in more remote or regional areas, shortened transportation times may provide a further reduction in lead times. A study on the biomedical implant supply chain for the state of Mississippi conducted by Emelogu et al, found a single AM facility located within the state offered greater cost savings for parts than traditional manufacturing, and attributed the savings to the reduction in transportation and lead times [21].

Reduced lead times help to improve customer responsiveness. Traditionally, mass customization required a combination of product batching and shorter production runs. These steps included extra setup time for accommodating a tooling or die change. An example is the die changes used by the automotive industry to provide vehicle customization. These additional setups often translate into lost labor hours and lower productivity, and subsequently imposes a higher average costs on customized products [22]. AM, on the other hand, does not require tooling and offers a platform to produce highly variable parts within a single build, eliminating changeover costs. This makes customization feasible in medium-scale production because the results are a lower average cost and shortened delivery times for parts. The effects these customizable production runs have on lead times and customer responsiveness are explored in later sections.

Previous research performed by Westerwheel et al, suggested the logistical savings of AM-based production in terms of shorter lead times and improved customer responsiveness was in fact nominal in comparison to investment costs (i.e. machine purchasing) at low-demand rates, as result of low machine utilization [17]. Atzeni and Salmishow further demonstrated the effects of machine utilization on the cost for laser powder bed fusion, noting a significant decrease when introducing accumulating parts within a single build [7]. Increasing from a line of individual parts to an array and eventually filling the entire build envelope indicated an exponential step-wise decaying effect on cost per part (Figure 4) [23].

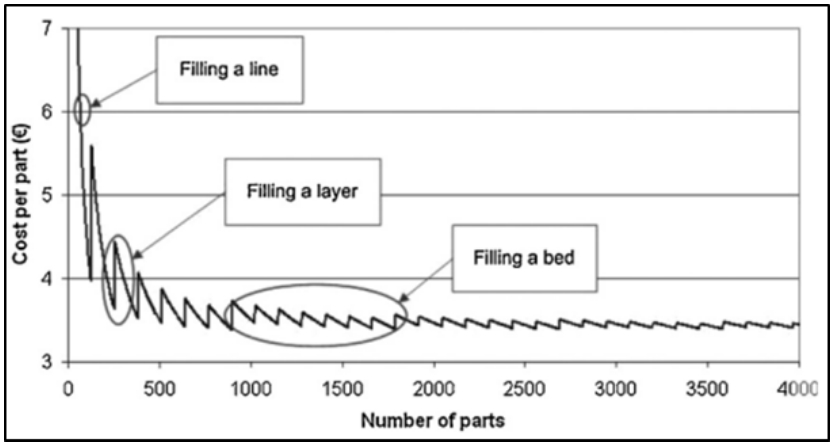

Figure 4. The realistic AM cost model.

Baumers et al, discovered through experimentation on machine utilization there was an overstatement of 157% for the average cost per part when not adequately filling the printer's capacity, resulting in the loss of a total potential production savings of 36-46% [24]. Machine utilization is AM's form of economies of scale [25]. Therefore, the factors leading to machine utilization are imperative to the cost effectiveness of AM.

A production allocation model proposed by Fera et al, provided a build time and total cost estimation, ultimately showing improvements in machine utilization through better part prioritization [26]. This was done by prioritizing small volume parts to fill the print bed to capacity. Other process parameters such as part orientation may also have significant effects on utilization. Alexander et al published an original model for increasing machine utilization through better orientation of parts built via layered manufacturing [27]. This study was expanded upon in the work of Rickenbacher et al, which considered simultaneous builds of SLM parts in their model indicating an even great effect on machine utilization [28].

The matter of increasing process efficiency and striking a balance between high utilization and quick production cycles is important in reducing AM-based production costs. Weller et al concluded from their industry study that AM's flexibility and decentralized production was best suited for markets with high demand uncertainty and product variety [29]. The aggregation of low-demand aerospace spare parts is therefore a strong illustrative example of the potential for AM, as these parts exhibit the above characteristics and are simultaneously expensive to store and incur high stockout costs.

C. Aerospace Spare Parts Supply Chain

“Nothing is more expensive than an airliner on the ground.”[4]. Maintaining high reliability of a company’s air fleet requires speedy repair and maintenance cycles. Therefore these MRO activities require a high availability of spare parts to reduce a plane’s downtime [6]. There are sizeable costs associated with providing these aftermarket parts too.

Aerospace MRO services are often completed following the manufacturer’s recommended scheduled maintenance. With proper planning companies can ensure minimal grounding time for aircraft, but a large portion of these services are also the result of an emergency part failure. In these cases, spare parts are required in a timely manner to complete repairs. The costs associated with a grounded aircraft permit higher spending on inventory and decentralized storage if it equates to faster maintenance and repair cycles. The penalty cost for a late part is more often significantly higher than the original part value because in this industry the impact of this portion of the supply chain transfers to all other parts (upstream and downstream).

Upstream, spare part suppliers must deal with large safety stocks and higher costs for distribution to obtain these high service levels. The goal for suppliers has been to decrease production and delivery lead times, and increase inventory turnover [4]. The aerospace industry requires complex logistical solutions, involving manufacturing as well as distribution supply chains, where the focus has begun to shift towards high value service, meaning aircraft that are in operating condition and demonstrate a higher availability [6].

The timely requirement for spare parts results in high inventory costs. For large commercial companies like Boeing that employ airplanes made up of 4 million parts or more, most of their inventory is comprised of parts that are infrequently needed [4]. Due to the unpredictable nature of these spare parts it can be costly to provide a high service level without also increasing safety stock. This problem is exacerbated for parts used in new products, where there is no historic data on the failure rates of each part. It is estimated that airlines hold up to 20% of excess inventory [4].

Longer life cycles for these fleets also play a role in expensive storage costs with an added risk of unsold inventory. Engine manufacturers estimate a 5% increase year over year to cover the costs of after-sales components necessary for MRO activities throughout an engine model's lifecycle (up to 25 years) [4], and in many cases this inventory may remain unsold as these planes are decommissioned. A common solution to cut costs is to utilize modular designs for planes, where a reduced number of common parts are used in several models. This can be beneficial in aggregating data for part forecasting but limits the freedoms of airlines manufacturers to optimize their planes and does not improve part lead times. Another solution employed by OEMs is to reduce the costs of storing parts by aggregating these products at more centralized warehouses, however this actually increases part lead times for customers served in remote regions [4].

Downstream these issues have been treated with some airline companies choosing to support their own warehouses to increase the availability of their parts. These warehouses incur high inventory holding costs and require part forecasting to reduce in-house stockouts when emergency parts are needed [30]. When inventory levels at the customer warehouse hit a reorder point, a purchase order will need to be made to the OEM. Additionally, in the case of accidental stock outs customers will need to order replacement parts through an OEM and incur the loss of time associated with the picking, packing, and shipping operations from their supplier. The same costs associated with the OEMs slow-movers or unsold inventory also plague the airlines choosing to stock their own warehouses.

Another solution may be to produce parts on-demand. However, low volumes for these parts have made the costs of traditionally manufacturing these parts significantly higher due to the lack of economies of scale. In addition, these traditional methods rely require large manufacturing facilities and are not suitable for distributed production, meaning parts will still be delayed due to shipping [31].

D. AM and the Spare Parts Supply Chain

AM-based production can support the physical properties of aerospace parts, which have high design complexity and require high mechanical strength. Often AM produced parts can even compete with the price of these traditionally manufactured parts, employing added cost reduction with better space usage and reductions in part weight, saving on material and fuel costs [29].

AM is expected to provide these savings by way of demand aggregation, reduced inventory holding, reduced downtimes, and the ability to provide decentralized (distributed) production.

There are other indirect benefits worth mentioning, including part individualization and part consolidation. Monolithic structures are prevalent in many AM designs, reducing the number of parts and assembly requirements in product manufacturing. This part consolidation results in cost reduction, as well as a simplified supply chain [2]. Fewer parts mean fewer suppliers for sourcing, tracking, assessing quality, storing in inventory, and transporting to customers.

The fundamental problem for supply chains is balancing supply with demand, which means relying on accurate forecasts. Problems of forecasting unpredictable spare part demands to be stocked at warehouses can be solved by aggregating production into sheer volume of parts to be printed on-demand through AM technology [4]. This will transform the supply chain into a simple capacity problem with a network of distributed AM production sites used to balance regional customer demands.

A stochastic dynamic programming model proposed by Knofius et al, found cost savings for AM use in spare parts supply despite a typically higher price per part, as a result of reduced stock and stock-out penalties [32]. The dilemma of stocking to meet demand and prevent stock outs, while also reducing purchasing and inventory holding costs means that OEMs must find optimal levels for their safety stock. With the on-demand nature of AM, this becomes obsolete, and although each individual part is slightly higher in costs, the savings benefit of reduced inventory outweighs this cost.

A case study conducted by Westerwheel et al on the Royal Netherlands Army's spare part supply found through a Markov decision process that AM on-demand production saw a 26% reduction in downtime for mission critical equipment [31]. AM not only improved customer responsiveness for these remote areas, but simultaneously reduced overall costs of receiving parts.

For the private sector utilizing AM for slow moving parts in centralized distribution centers would eliminate a large portion of costs dedicated to inventory holding [6]. However, the remaining logistics costs of shipping these small quantity parts would still need to be subsidized by fast movers, unless this production is performed through distributed sites.

Attempting to decentralize AM production to better accommodate customer locations and reduce shipping costs, might however reduce the utilization of machines and limit the offset of high fixed costs for purchased machines and the necessary personnel employed to operate them. Therefore, if more parts can be identified as candidates for AM there will be an increase in the utilization of machines, which would result in situations such as one technician operating multiple machines, thus reducing the cost of labor for each part. Understanding the characteristics of distributed AM-based production on the entire supply chain is imperative for realizing the cost benefit this solution may provide to the aerospace spare parts supply chain.

1. Distributed Production

Distributed on-demand production improves overall costs by utilizing more accurate information on regional demand, increasing production efficiency, and improving the supply chain network's reliability. It may also provide lower capital investment for facilities, lower shipping costs, and lower inventory costs. Work conducted by researchers Pérès and Noyes, showed the feasibility of this concept noting. In addition, it was noted that the substantial decreases in penalty costs arise from the routing and supply times of spare parts [33]. While a single-part demand may still warrant the use of traditional manufacturing methods for cost effective and fast production, AM provides an attractive alternative for aggregated demands of many unique parts using distributed production sites.

However, despite numerous advantages there is still a trade-for AM-based production in a supply chain, when factors such as all costs of personnel, transportation, inventory, material, downtime of aircraft, AM capital investment and depreciation are considered. To understand when this shift to distributed production became more cost effective than centralized production sites, a case study was conducted for the U.S. Navy's F-18E/F/ Super Hornet fighter jet air cooling ducts spare part supply [6]. Distributed and centralized scenarios were established and optimized using a Monte Carlo simulation to find the cheapest operating settings for each scenario. A non-linear relationship was associated with cost and the autonomy of AM (number of machines per worker). The resulting two main factors determining the trade-off were machine acquisition price and personnel cost. Distributed production performed better only when the machine acquisition price and personnel salaries were relatively low (<\$65,000/unit and <\$70,000/year, respectively). However, this disparity is a direct result of machine utilization between centralized and distributed production (95% and 25%, respectively). The study did not evaluate stochastic demand levels or the impact of downtime costs, as service levels were held constant. The variation in demand is crucial when evaluating the aerospace spare part supply chain.

Other work related to this distributed supply chain by Durão et al, found autonomous capabilities will be a key driver of cost, especially the automation of in-process quality control [34] where a considerable amount of man-hours are spent to check for failures. These limitations of cost and autonomy for AM technologies have slowly improved as the technology has matured [6].

2. Part Feasibility

A review process like the one proposed by Walter et al, includes seven key steps for reviewing part eligibility for the AM spare part supply chain: technical analysis, business benefit, production cost analysis, capacity cost analysis, cost-tradeoff, AM use, and reevaluation of AM [4]. Technical feasibility relates to the limitations of the AM technology including building volume, intrinsic material properties and other considerations. The business benefit is clear, shorter lead times that lead to higher aircraft availability. Production costs need to be confirmed along with costs of providing the capacity of this production along the supply chain before analyzing the cost trade-off. The assumption being that large and fast-moving parts will almost always be better suited for mass production of traditional warehousing solutions. By contrast, small infrequent movers might benefit from the use of AM. In either case, the final step is to reevaluate the other steps as the costs and applications of the technology change.

A business model needs to be established for investigating the investments associated with the purchase of machines, as well as the staffing and material requirements to maintain production. Finally, it will need to consider the costs of meeting customer demands including lead time variation and penalty of downtimes.

As AM becomes more autonomous and exhibits shortened production cycles it will begin to provide a better alternative to warehousing, as it reduces both the production and logistics costs [6]. Further studies need to be made to understand how various AM configurations and settings impact overall cost and service to the customer.

E. Simulation Models for Spare Parts Supply Chain

Simulations have been widely used to model manufacturing systems in part due to their capability of analyzing complex systems and capturing the effect of local changes on the performance of the overall system. It is an effective analytical tool for solving problems that arise in manufacturing design and operation.

Few business decisions are straightforward. Changes in one area of business impact other areas—often in ways not anticipated. Business process simulation provides a method of evaluating the full implications of business decisions before they are put into practice. Discrete event simulation (DES) describes a process with a set of unique, specific events in time. The flexible, activity-based models are well suited for simulating a production process.

For the aerospace spare parts supply chain, inventory control is essential since excess inventory leads to high holding costs and stock outs can have a great impact on overall cost. Different from work-in-process (WIP) and finished product inventories, which are driven by production processes and customer demands, spare parts are kept in stock to support maintenance operations and to protect against equipment failures.

Although this function is well understood by maintenance managers, many companies face the challenge of keeping stock of large inventories of these spares due to their excessive holding and obsolescence costs. Thus, effective cost analysis can be an important tool to evaluate the effects of stock control decisions related to spare parts. However, the difficulty in assessing good strategies for the management of spare parts lies in their specific nature, normally very slow-moving parts with highly stochastic and erratic demands [74]. Therefore, simulations with their ability to model stochastic and probabilistic scenarios, offer a method for investigating a solution by evaluating the impacts on key performance measures and determining the best operational procedures and allocation of resources to minimize overall cost.

1. AM On-demand Production Simulations

Several publications have investigated AM-based production and point out the potential cost benefits compared to other common manufacturing techniques, within small lot sizes. Brody and Pureswaran published a report which describes the combined impact of 3D manufacturing, intelligent robotics and open source electronics [35]. They analyzed the bills of materials down to the part, modeled the manufacturing and distribution of parts and applied a software defined supply chain. The model allowed changes to the requirements, scale, location, cost, etc. They found an average cost savings of 23%, due to improved economies of scale and the "supply chain" footprint (in terms of transportation fuel). This report was the most complete model found. However, it does not directly look at the spare part problem, focusing only on the overall supply chain impact of this new technology.

In 2014, Simkin and Wang [36] presented a cost-benefit analysis of finished parts. They applied this analysis through simulating the effects of changes to the AM parameter setup like what is presented in this work. However, their focus was again only on regular production. Specific logistical topics related to spare parts are not taken into consideration.

Holmström et al [37] work does look at the spare parts industry and the concept of including AM into this supply chain. They compared distributed and centralized AM supply chains as a replacement of traditional warehousing and distribution solutions. They presented an example of deploying a distributed AM system in the aircraft spare parts supply chain, where significant reductions in holding cost with an improved service level were achieved as a result. They conclude that centralized AM, by specialized service providers, shows the biggest benefits at current state. However, they predict this will ultimately change to favor decentralized AM as this technology matures and costs continue to decrease. This means a shift of deploying AM technology closer to end users. Their article also recommends further research to find possible applications of AM and the setup in the supply chain, which this paper will cover.

Other work by Hasan and Rennie [38] or Peng et al [30] strongly refer to the work of Holmström and extend the issue to the effects of AM on the supply chain for specific cases. Peng et al applies the Supply Chain Operations Reference Model (SCOR) for the aircraft spare part supply chain, and they conclude that AM is contributing to improvements in the industry, proving a strong interest in research related to this topic as it relates to aerospace.

To sum up, general research for common industrial situations is missing. Researchers have yet to show the results of altering an AM-based setup at the facility level on a decentralized network, and what impacts it would have along the rest of the supply chain. Furthermore, no simulation has been created to look directly at how this production setting can be optimized for meeting the needs of spare parts customers, like the aerospace industry.

III. Research Objectives

In a preliminary work, a framework of an AM production model was generated and using discrete event-based simulation various experiments evaluating unscheduled spare part production were performed [39]. The simulation results from the preliminary model revealed some unique behaviors of the AM supply chain system, such as the nonlinearity between arrival rates and time in system for parts, inspiring further investigation into other production characteristics, such as the utilizations and efficiencies of different resources and the applicability of existing supply chain operation strategies. On the other hand, various knowledge gaps were identified with the preliminary models, such as the lack of an identified system bottleneck, an inaccurate representation of emergency part demand generation, and the impacts of parameter settings on the downstream supply chain. Additional developments to the model were needed to determine the efficacy of AM for supply spare parts to the aerospace industry. The objective of this thesis is to enhance the robustness and representativeness of the preliminary model and utilize this new model to provide further insights into the impact of integrating AM in production. Of particular interests to this study were some of the fundamental understandings of the AM production operation characteristics such as lead time, capacity, resource bottlenecks, as well as the performance of this operation under various operational strategies employed in supply chain systems. This knowledge will not only help in establishing fundamental understandings of the AM supply chain but will also enable well informed decision making in real world practice. More specifically, the research consists of three main objectives.

Objective 1: Understanding the performance of AM on-demand production of spare parts for high-impact supply chain

The objective aims to gain fundamental understanding of the cost and performance characteristics of AM for spare part production under high penalty levels that correspond to the significant downstream impacts the aerospace industry experiences for late order deliveries. This will include an in-depth analysis of machine utilization as it relates to AM service level and the direct and indirect costs associated with this method of production. Data analysis will be conducted for increased penalty rates to determine the optimal service level setting that reduces overall cost. Using the traditional warehousing solution as a baseline, the results will establish the relationships between the supply chain downstream impact (penalty), the demand rate, and the efficiency of AM's on-demand production.

Objective 2: Understanding AM-based on-demand production system characteristics

A comprehensive simulation model will be established for the AM on-demand production system and utilized to capture system performance and the flow of the production orders. Comprehensive system operation characteristics of waiting time in queues, worker and machine utilization, and throughput rates will be analyzed through experimentation with part demand and various production configurations. The designed experiment will be able to evaluate both the efficiency and robustness of the AM on-demand operation for dealing with aerospace spare part demand.

Objective 3: Understanding the optimality of AM-based on-demand production via operational strategies

This objective is to understand how AM on-demand production could be potentially optimized for the aerospace spare parts supply chain through use of some generic operational strategies. Optimal order prioritization strategies will be assessed based on their resulting effect on cost per part. Part characteristics will be altered to determine the trade-offs between different strategies. The results of the experiments will be collected and analyzed, and recommendations on optimal production strategies will be made.

IV. Model Methodology

A. AM Production Discrete Event Simulation

To analyze the AM production scenarios a discrete event simulation (DES) is created in ARENA. DES models define discrete events occurring at instances in time and indicates changes in the state of entities or variables in that system. The ARENA software tool allows for complex logic that would not be possible in spreadsheet modeling. The ARENA AM Production Model illustrates a common AM-based production flow consisting of reception, queueing, batching, setup, calibration, preheating, printing, cool down, and post-processing steps.

In addition, in order to generate stochastic parts demand, a separate order generation model is created in Simio, another DES tool. The Simio Order Generation Model allows for quick of the order list via random number generators in the software. The complex routing logic in Simio also allows for correlations between order attributes. The output of this model is then fed into the AM Production Model in Arena to replicate stochastic orders.

1. Order Generation Model

As mentioned previously, a set of spare part orders are pre-generated for the AM Production model. This is done in Simio, see Appendix II. Simio Order Generation Model for a detailed description of the Simio DES model. The Order Generation Model classifies each entity into two order types, regular or emergency. It is common in inventory control to separate spare parts into classes based on priority [40]. Regular part orders represent a set of parts being ordered for scheduled maintenance, they follow a normal distribution and are assigned relatively low priorities, whereas emergency part orders represent part failures and follow a Poisson distribution and receive the highest priority. The parts in each order are also assigned four other attributes: allocated manufacturing time, volume, value, and demand (number of parts in the order). For the generation of regular spare part orders, the model follows Algorithm 1 (Appendix I. Algorithms for Creating Stochastic Part Orders). A similar algorithm (Algorithm 2) is used for creating emergency spare part orders, where the only difference is emergency part orders will always receive a priority level of 0 (the highest priority level).

To generate orders, the model creates entities as either emergency or regular parts then assigns attributes to each order according to routing logic, then the values assigned to each order entity is recorded in an output table.

Entity Arrivals

Since, part order (emergency or regular) types follow a different arrival rate, they are separated. A random number generator is used for arriving entities. The interarrival time of regular orders follow a Normal distribution with a mean (μ) and a standard deviation (σ) defined in the model. Interarrival times for emergency orders follow an Exponential distribution with a defined mean (λ).

Assigning Attributes

Once a part is created, the order entity, will be routed to assign steps using routing logic, based on the proportions and correlations specified in Table 1-Table 5, below. When an entity is being processed by a server it is assigned an attribute value using random number generators following distributions also shown in Table 1-Table 5.

When assigning the allocated manufacturing time, volume, and demand attributes to regular spare part orders, the order is first routed into one of three levels: low, medium, and high (except priority 0 for emergency orders), based on a proportion of total. Then, a value is assigned to the order that follows a Uniform distribution with a pre-defined range associated with each attribute and level. Table 1-Table 3, below, shows the proportion and ranges for each level of these three attributes.

Table 1. The proportion of each level and their ranges for allocated manufacturing time.

1. Allocated Manufacturing Time (hrs)		
Low	[24,48] or 1-2 days	5%
Medium	[72,120] or 3-5 days	20%
High	[168,336] or 7-14 days	75%

Table 2. The proportion of each level and their ranges for volume.

2. Volume (mm^3)		
Low	[1000, 10000]	75%
Medium	[10001, 500000]	20%
High	[500001, 1000000]	5%

Table 3. The proportion of each level and their ranges for demand.

3. Demand (# of parts in one order)		
Low	[1, 10]	5%
Medium	[11, 30]	20%
High	[31, 50]	75%

For emergency spare part orders, the only difference is these orders always receive the lowest range of allocated manufacturing time (24-48 hours) and are also assigned the lowest range of demand (1-10 parts).

In order to create more realistic order sets, correlations between manufacturing time values and priority, as well as volume and part value, are considered. When assigning priority, the model algorithm first determines which of the three levels the allowed manufacturing time falls into (low, medium, or high). This of course, is neglected for emergency orders that are already assigned a priority level 0.

- If the random value of allowed manufacturing time falls into its high value range [73,192], then the probability that the random value of priority obtains its low value 3 is 80%.
- If the random value of allowed manufacturing time falls into its medium value range [49,72], then the probability that the random value of priority obtains its medium value 2 is 80%.
- If the random value of allowed manufacturing time falls into its low value range [5,48], then the probability that the random value of priority obtains its high value 1 is 80%.

Similarly, when assigning part value, the model algorithm first determines which of the three levels the order falls into.

- If the random value of volume falls into its low volume range [1000,10000], then the probability that the random value of part value falls into its low value range [10,50] is 80%.

- If the random value of volume falls into its medium value range [10001,500000], then the probability that the random value of part value falls into its medium value range [51,200] is 80%.
- If the random value of volume falls into its high value range [500001,1000000], then the probability that the random value of part value falls into its high value range [201,1000] is 80%.

Then, a quantity is assigned to these orders that follow a Uniform distribution with a pre-defined range associated for part value and order priority, as shown in Table 4-Table 5, below.

Table 4. The ranges for each level of part value.

4. Part Value ($)	
Low	[10, 50]
Medium	[51, 200]
High	[201, 1000]

Table 5. The ranges for each level of priority.

5. Priority	
Low	3
Medium	2
High	1
Highest (emergency)	0

Output

Once the order entity has passed through the network, the attributes are recorded as rows in an output table (See Table 6. Outputs and their descriptions. below). For each simulation 1000-part orders are created of both regular and emergency parts and exported from the output table to a .csv file to be used in the AM-based Production model.

Table 6. Outputs and their descriptions.

6. Output	Description
Index	Part order index (used to keep track of partial part orders during post-analysis)
Arrival Timestamp	Time order arrives (hr) based on algorithm.
Part Type	Type of part (Emergency or Regular) in each order based on algorithm.
Priority Level	Priority level (0, 1, 2, or 3) of order based on algorithm.
Allocated Mfg Time	Allocated manufacturing time (hr) of the part order based on algorithm.
Volume	Volume (m3) of each part in order based on algorithm.
Part Value	Value ($) of each part in order based on algorithm.
Demand	Demand of parts (#) in order based on algorithm.

2. AM Production Model

The AM Production DES model is created in ARENA, see

Appendix III. ARENA AM Production Model for a detailed description of the ARENA model. This model illustrates a typical laser powder bed fusion production process (see Figure 5). Though many parameter settings are manipulated in the subsequent case studies the structure and flow of the AM production process remains mostly the same. Part orders arrive in the system, they are received by an operator, and enter a queue. When a printer is available, orders may become batched or postponed before being sent to an AM machine. A worker will then setup and preheat the machine, then orders will be printed and allowed to cool down before finally going through post-processing and exiting the system.

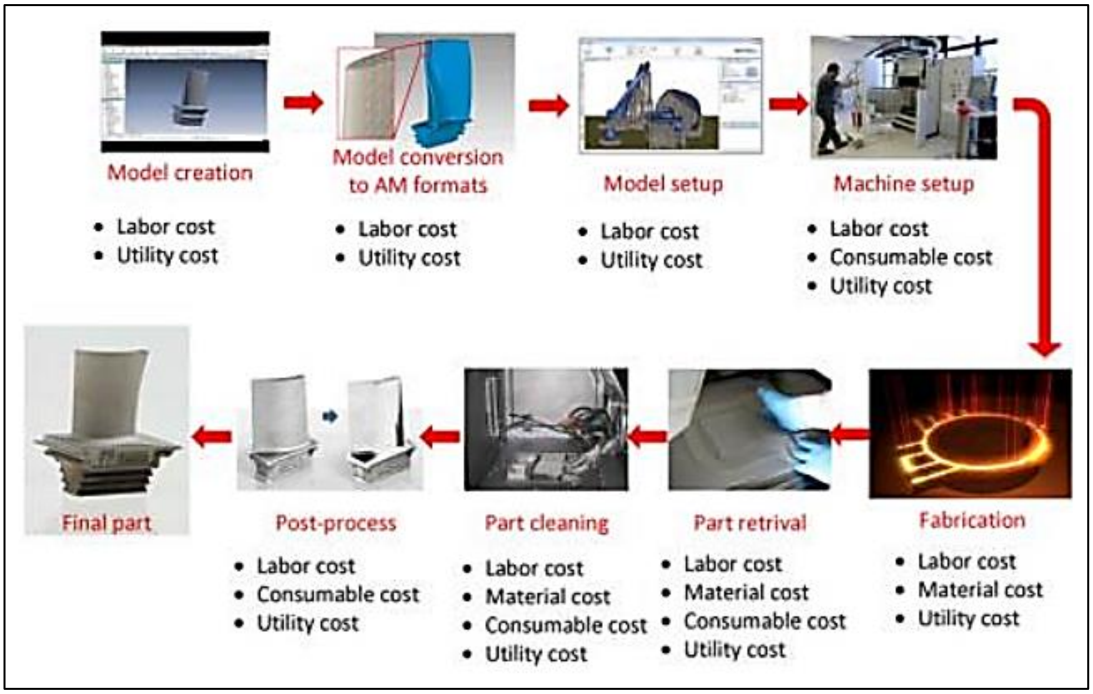

Figure 5. Laser Powder Bed Fusion Process.

The only significant variations to this process occur when investigating a two-machine scenario, where orders flow through an additional set of logic steps to be sent to one of two AM machines for batching, postponement, printing, cooling, and post-processing.

Order Arrivals

ARENA uses the output file from the Order Generation Model created in Simio, or a deterministic part order file generated manually, to create entities and read in their attributes following the flow diagram below (Figure 6). Regular and emergency parts arrive and are assigned attributes, then received by an operator before being sent to the preparation station.

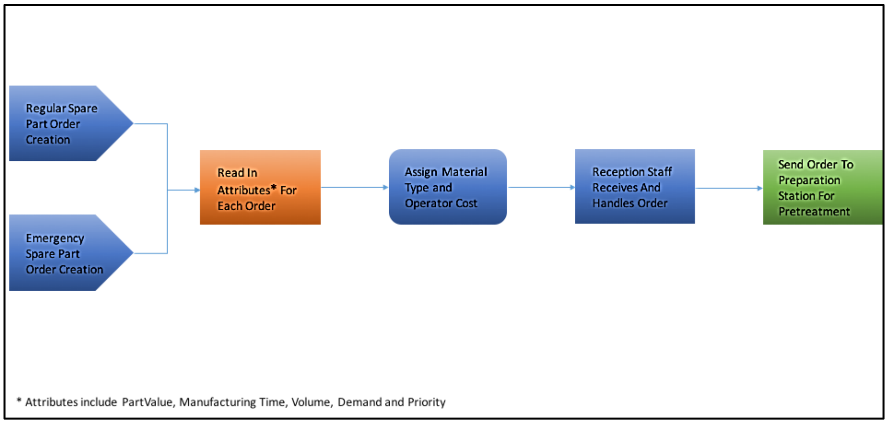

Figure 6. Order Arrival and Reception Steps.

Reception

After a part order (entity) arrives it is processed at reception. The processing time for receiving part orders and manipulating the CAD file for AM production is modeled with a triangular distribution using a range of 0.05 to 0.15 hours and a mode of 0.1 hours. Before reception starts a worker is requested. If no operator is available at the time of the request, then the order must wait to be processed. Each part order is assigned the current time before entering this step and a calculated total reception time immediately after exiting. This value is used in determining the operator's utilization and cost.

Queueing

Next the entity is routed to the preparation station. This model exhibits the characteristics of a queueing system, where each machine can be viewed as a server and operators as a resource, seized for various steps in the process. Due to the variation in order arrivals and service times, a queue is inevitable. At the preparation station, entities will go through logic steps to decide if they must be queued. Figure 7 below, shows the decision steps (in diamonds).

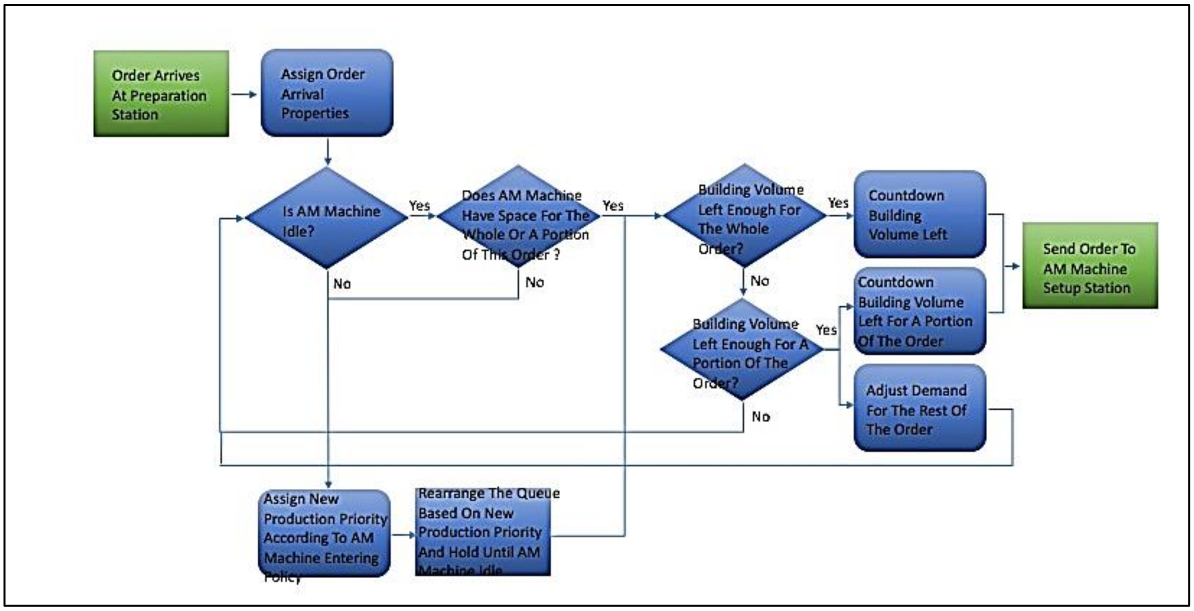

Figure 7. Order Queueing Steps.

Prioritization Strategy

Before part orders are routed to a printer, the model verifies that the AM machine is not in the process of setting up, printing, cooling down, or post-processing (Figure 8). If the machine is busy, entities are given new priority levels and placed in a queue. This is a crucial step in the model, allowing the system to make decisions on how to prioritize parts that will reduce late order penalties.

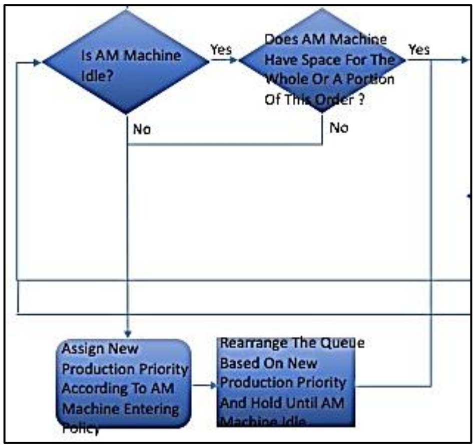

Figure 8. Order Prioritization.

Batching / Order Separation

Once the machine is idle again, part orders will go through another series of decisions before they can fill the printer. These steps ensure the machine is not overfilled. If a new order would exceed the printer's capacity the model will first attempt to split the order to accommodate a portion of the job (Figure 9). If this occurs, the split portion order will be routed to the printer, while the remaining parts reenter the queue and wait to be prioritized for the next batch.

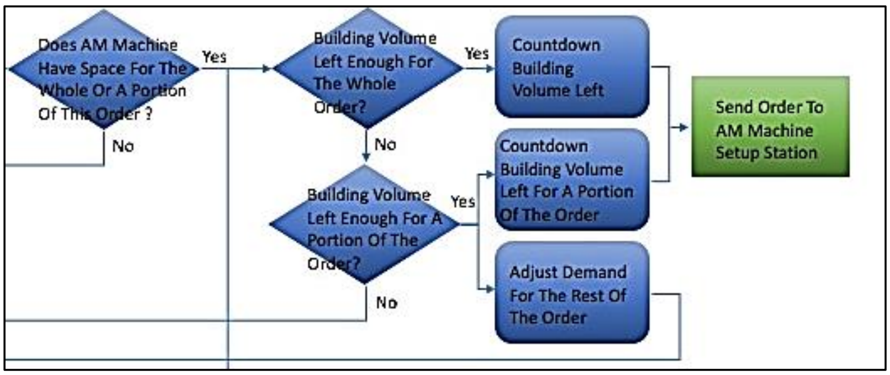

Figure 9. Order Separation Steps.

AM Station

Once orders arrive at an AM station, they will begin a postponement period before a machine is setup, calibrated, and preheated. After these steps, parts are printed, allowed to cool, and then go through post-processing to become finished goods. These steps are illustrated in Figure 10, below.

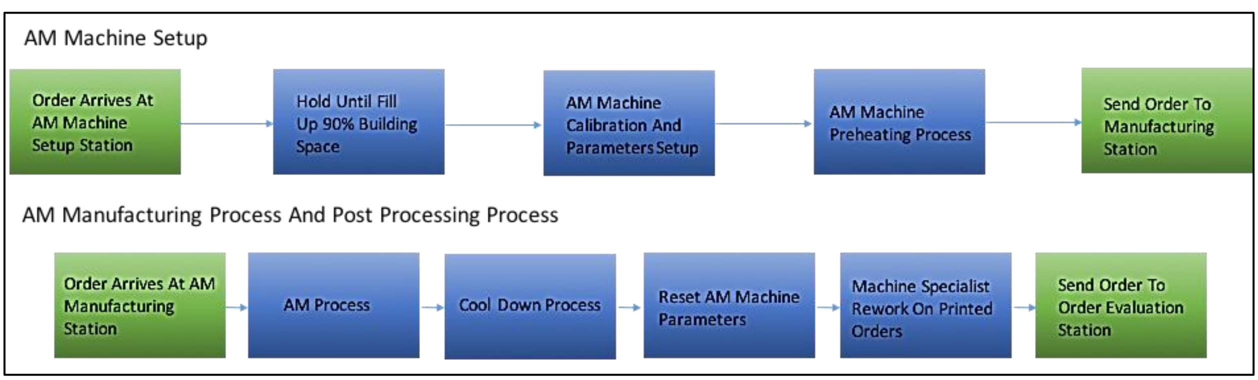

Figure 10. AM Station Steps.

Postponement Strategy

The general purpose of postponement is to delay the actual processing of the orders to avoid running the AM machine when the order batches do not meet a certain scale, thus creating an inefficient use of the AM machine. Figure 10 shows the postponement strategy. For example, it may be desirable to wait until a batch can fill 90% of the machine's capacity. This may delay the initial batch until more orders are received into the system. Other postponement strategies explored in this paper, include imposing a waiting period from the arrival of the first order, or a combination of ensuring both machine capacity and wait times meet their respective threshold values. These strategies are common in production and the model's logic will help improve decision making to ensure parts are printed on time at the lowest cost.

AM Setup, Calibration, and Preheating

Once a batch has gone through postponement, the model will wait for the next available operator to begin the setup, calibration, and preheating of an AM machine. These steps are shown in Figure 11.

To replicate the time required to setup files for the machine, each order is individually assigned a random value following a triangular distribution with a minimum of 0.008 hours, a mode of 0.016 and a maximum of 0.024 hours. This value is multiplied by the part demand of that order and then added to a rolling value for the entire print setup time. An additional calibration time is added to the total setup and follows another triangular distribution with a minimum of 0.05833, a mode of 0.06667, and a maximum of 0.075 hours.

It is known that for an 8,000,000 mm^3 machine printing at full capacity, the powder feedstock would take roughly 1 hour to preheat. To maintain that ratio with respect to print volume a preheating time of 125 (1/0.008m^3) hours is multiplied by the total print volume of the batch (in m^3) and added to the setup and calibration delay.

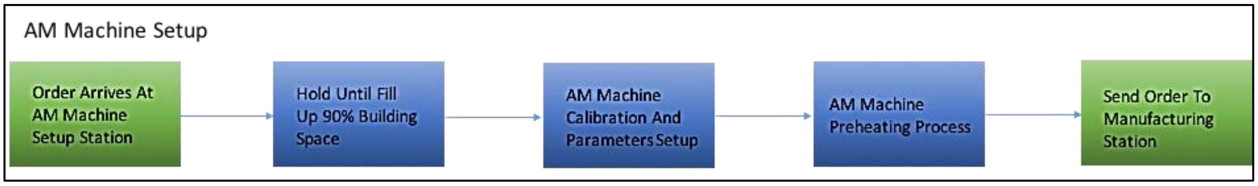

Figure 11. AM Setup and Preheating Steps.

Printing and Cool Down

Finally, orders are ready to be printed. Printing speed associated with the powder material is multiplied by the entire print volume to determine the total print time. Once the build is complete, a cool down step is imposed to allow the build to settle into its final geometry, a crucial step in AM production. This cool down follows a normal distribution with a mean of 5 and a standard deviation of 1 hour. Finally, the orders are ready for post-processing (see Figure 12).

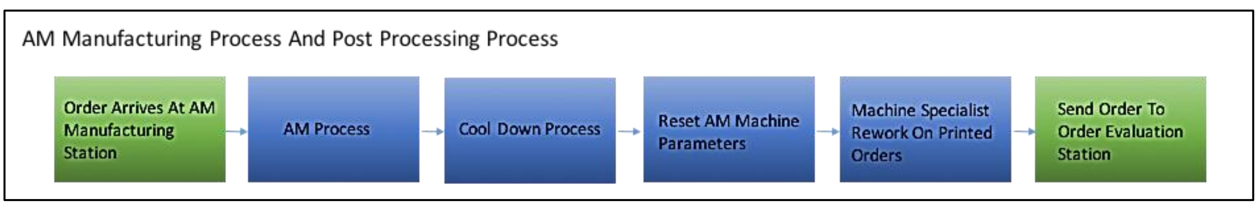

Figure 12. AM Printing, Cool Down, and Post-Processing Steps.

Post-Processing

Post-processing is an important step in most AM processes to achieve desired physical properties of strength, surface finish, etc. It is a labor-intensive task and requires many worker hours. This process will begin after the model seizes the next available operator. To model the time to complete post-processing a random value is assigned to each order following a triangular distribution with a minimum time of 0.08, a mode of 0.5, and a maximum of 1.2 hours, and then multiplied by the order’s part demand. Parts leaving this step are now finished.

Output

Once orders are complete, the model will calculate if the output time has exceeded the allocated manufacturing time, if this occurs the order will be penalized for the number of hours late (Figure 13. Calculations and Output Steps.. Additional calculations are made based on the order attributes and recorded as rows in an output table (See Table 6. Outputs and their descriptions. below).

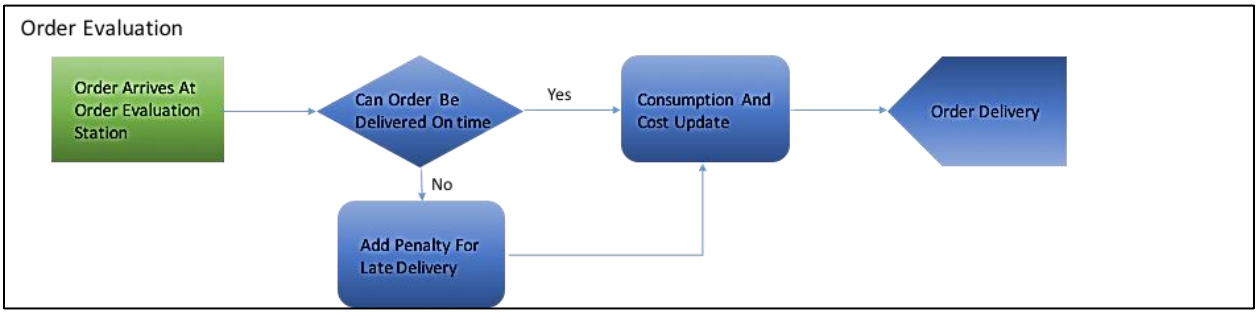

Figure 13. Calculations and Output Steps.

Table 7. Outputs and their descriptions

7. Output	Description
Index	Part order index (used to keep track of partial part orders during post-analysis)
Arrival Timestamp	Time order arrives (hr) based on Algorithms 1 and 2.
Part Type	Type of part (Emergency or Regular) in each order based on algorithm.
Priority Level	Priority level (0, 1, 2, or 3) of order based on algorithm.
Allocated Mfg Time	Allocated manufacturing time (hr) of the part order based on algorithm.
Volume	Volume (m^3) of each part in order based on algorithm.
Part Value	Value ($) of each part in order based on algorithm.
Demand	Demand of parts (#) in order based on algorithm.
Finish Time	Time (hr) a whole or portion of a part order is completed.
Consumed Material Cost	The total volume of the part order (m^3) multiplied by the density of the material (Ti6Al4: 4,430,000 g/m^3) and by the cost of the material ($0.2/g)
Consumed Energy Cost	The total print time of a part order (hr) plus the total pre-heat time (hr), multiplied by the energy cost ($0.02/kWh) and the energy usage of the machine (400W). Print time is determined by taking the total volume of a part order (m^3) and dividing it by the printer's speed (0.000012m^3/hr) Pre-heat time is determined by taking the total volume of the part order (m^3) and multiplying it by a constant (1hr/0.008m^3), as explained in AM Setup, Calibration, and Preheating.
Operator Cost	The total operator work time (hr) multiplied by the hourly rate of an operator ($70/hr). The total operator work time is the time spent receiving the original part order (hr, this is pro-rated if order is separated), plus the part order's setup time (hr), and the post-process time (hr, proportion of parts in the batch multiplied by the total post-processing time for the batch).
Penalty Cost	This value will either be zero for any part orders completed on time, or the total time to manufacture (hr) minus the allocated time (hr), multiplied by the part's value ($) and a constant penalty cost ($0.00001/hr).
Total Maintenance Cost	Annual Maintenance Cost ($50,000). *This is NOT included in the output table and must be added in post-analysis.
Total AM Cost	Consumed Material Cost + Consumed Energy Cost + Operator Cost + Total Maintenance Cost + Penalty Cost
AM Parts In	The total number of parts that have entered the system at the current output time.
AM Parts Out	The total number of parts that have been completed at the current output time.

B. Warehouse Monte Carlo Simulation

Unlike AM-based production, warehousing is a well-studied topic, and common rules of thumb and equations have been established to model the cost of implementing warehouse solutions. In order to provide a better analysis of the trade-off between warehousing and AM a Monte Carlo simulation is created in Excel. Monte Carlo simulations provide repeated random sampling to identify probability distributions for specified variables. A spreadsheet model can handle the warehouse scenarios given the simple logic of this option. A common warehouse setup is used to capture events such as purchasing, inventory holding, stockouts, and penalties for late deliveries.

1. Warehouse Model

The Excel Warehouse Model defines 100 SKUs (parts), where 80% are classified as regular parts representing those being ordered for scheduled maintenance, and 20% are categorized as emergency parts, or those being ordered as a result of part failures. The part value ($50) and 10% inventory holding costs are kept the same.

Inventory

A common inventory approach of stocking parts to fulfill predicted demand and achieve a desired service level is used to calculate the purchasing and inventory holding of parts. It is assumed for the warehouse scenarios that the predicted demand of each SKU is 100 parts per year. However, the demand distribution for regular part SKUs follows a normal distribution with a mean (μ) of 100 parts/yr and a standard deviation (σ) of 20 parts, whereas emergency part SKUs follow a Poisson distribution with a rate (λ) of 100 parts/yr.

To achieve a desired service level, the model performs a safety stock (SS) calculation (see **Error! Reference source not found.** below). In this calculation a z-score defined by the service level (α) is multiplied by the standard deviation (σ) of demand.

$$SS = z_{\propto} * \sigma \tag{1}$$

Stockouts

In order to provide actual demands the model uses random number generation following the same distributions described for regular and emergency SKUs. Now the model can calculate stockouts, or the difference between the actual demand and SS if the demand is greater than inventory (See **Error! Reference source not found.**).

$$Stockouts = Actual\ Demand - SS \tag{2}$$

Cost Calculations

There are only three costs calculated in the Warehouse Model: purchasing, inventory holding, and penalty. For purchasing costs the calculated SS (inventory) for each SKU is multiplied by part value (**Error! Reference source not found.**). Inventory holding is calculated by taking SS and multiplying by the inventory holding (**Error! Reference source not found.**). Using the previously calculated stockouts, a penalty cost is assessed based off days late for each part (**Error! Reference source not found.**). In the event of stockouts the days late of each part follows a uniform distribution with a range of 2 to 5 days. Finally, a total cost for the scenario is calculated (**Error! Reference source not found.**).

$$Purchasing\ Cost\ (\$) = SS\ (parts) * Part\ Value\ (\$50/part) \tag{3}$$

$$Inventory\ Holding\ Cost\ (\$) = SS\ (parts) * Inventory\ Holding\ (10\%\ of\ Part\ Value) \tag{4}$$

$$Penalty\ Cost\ (\$) = Stockouts\ (parts) * Penalty\ (\$/day) \tag{5}$$

$$Total\ Warehousing\ Cost\ (\$) = Purchasing\ Cost\ (\$) + Inventory\ Holding\ Cost\ (\$) + Penalty\ Cost\ (\$) \tag{6}$$

C. Experiment 1:

This experiment looks to model a typical aerospace spare part supply chain to determine the cost trade-offs when selecting between a traditional warehousing solution or an AM-based production solution for satisfying demand for spare parts. 100 simulation trials are run with the Excel Monte Carlo model to calculate the warehousing operations costs, and the AM costs are averaged with five replications simulated in ARENA. In both models, a part list of 100 SKUs is given as demand. Of these, 80% are identified as scheduled maintenance parts, following a normal distribution for interarrival time. The remaining 20% are marked as emergency parts, meant to represent a part failure, and follow an Exponential distribution interarrival time.

A total of 6 scenarios are produced, 3 for the warehouse and 3 for the AM spare part supply chain models. Each scenario represents a varying level of penalty related to the late delivery of a spare part. In the warehouse scenario if a stockout occurs, then a penalty of either 1x, 2x, or 10x is multiplied by the part's value ($1,000) for each day late. In the AM scenarios, parts that do not meet the allocated manufacturing time are given a similar prorated penalty of the part's value ($1,000) based on hours late (1x, 2x, or 10x per 24 hours). See **Error! Reference source not found.**, for details on how penalty is calculated.

$$Penalty\ (\$) = (Completion\ Time - Allowed\ Time) * Part\ Value\ (\$) * Penalty\ Factor \tag{7}$$

Under each penalty scenario the level of service is compared to see what the total operating cost would be for each solution seeking a given service level. In the warehouse scenarios the service level is calculated based on the percentage of stockouts, or whenever demand exceeds the inventory. In order to set the service levels in this warehouse model, a safety stock calculation is made following the normal and Poisson distributions (as described in the Warehouse Model section).

The AM model calculates service level based on the percentage of late deliveries, or whenever a part exceeds its allocated manufacturing time. In order to achieve these service levels, the demand interarrival rates (not the distributions) are changed until the system performed at the desired level of service.

Finally, cost per part is used to compare these two models, this ensures that no matter the actual demand of these stochastic models the variable and fixed costs are applied to all parts that enter the system. The costs given to the parts in the warehouse solution represent the part purchasing, inventory holding, and penalty for stockouts. In the AM solution each part incurs costs from machine purchasing ($1,000,000), machine maintenance ($25,000), material cost ($0.2/g), energy usage ($0.02/kWh), operator salaries ($300,000), and penalty (**Error! Reference source not found.**) for late delivery. See **Error! Reference source not found.**, for details on the total cost of AM production.

$$Total\ AM\ Cost\ (\$) = Machine\ Purchasing\ (\$) + Material\ Cost\ (\$/g) + Energy\ Usage\ (\$/kWh) + \ Operator\ Salary\ (\$) + Penalty\ (\$) \tag{8}$$

D. Experiment 2:

For this experiment, simulations are run to capture the system performance of the AM-based production model, under various configurations. The AM Production Model built in ARENA illustrates a conventional laser powder bed fusion process and exhibits the characteristics of a queueing system. In order to understand the effects of this queue on system outputs, such as utilization of the two resources (machine and worker) as well as the ultimate throughput and cost per part, the model is altered to accommodate four unique production configurations.

These four configurations are one operator: one machine, two operators: one machine, one operator: two machines, and two operators: two machines. Operators are easily added to the model as an additional resource to be seized during the applicable steps as described in the AM Production Model. Adding an AM machine, however, requires additional logic. Orders must be able to route to the second machine, and therefore a simple routing rule is applied: incoming orders will always route to the next available machine. This model, therefore, resembles a two identical-server queue.

Experiment 2 uses the same parameters for modeling aerospace spare part orders as Experiment 1. A part list of 100 SKUs, which contain 80% scheduled maintenance parts (normal distribution) and 20% emergency parts (Poisson), is read into the model at varying demand rates. Five replications are run and used in the average for the calculated utilizations, throughput, and costs described below.

E. Experiment 3:

Experiment 3 investigates scenarios with stochastic part demands settings by changing parameters described in Algorithms 1 and 2 for parts order generation. These baseline values were originally obtained from the previous work conducted by Zhang et al [39]. The order lists for regular and emergency parts were then created in the Simio Order Generation model. Part attribute values and distributions closely match actual production characteristics of a small aerospace manufacturer, making a good argument for the real-world application of the changes made in the model.

The objective of this experiment is to investigate how various prioritization strategies for part orders can affect the system performance and downstream impact on the aerospace supply chain. The AM Production Model allows for part prioritization, resulting in reordering (i.e. re-arranging sequence of orders) while in the queue. To understand the effects this reordering has on cost per part, the model simulates three different strategies: first come first serve (FCFS, baseline), earliest due date, and highest current penalty. FCFS is the default queueing discipline in any orderly queue and is straightforward, the first order to enter the queue is the first to exit. Earliest due date is achieved by assigning each order a new attribute. This due date attribute is created by subtracting the allowed manufacturing time attribute by the current time spent in the system, see **Error! Reference source not found.** These orders are then reordered in the queue based on the lowest (earliest) corresponding due date.

$$Due\ Date = Allowed\ Manufacturing\ Time + Arrival) \tag{9}$$

A similar attribute is given to orders to assess their current penalty for the highest penalty prioritization strategy. Current penalty is the same calculation as seen in **Error! Reference source not found.** with the "Penalty Factor" indicating 1 for each 24 hours passed and multiplied by the total demand of the order (number of parts), see **Error! Reference source not found.**.

$$Current\ Penalty(\$) = (TNOW - Allocated\ Time) * Part\ Value\ (\$) * \left(\frac{1}{24}\right) * Demand \tag{10}$$

Experiment 3 also increases the system capacity to 12 times the current output. This value was determined through experimentation on utilization and total cost using the new stochastic order lists. To achieve this capacity increase, part volumes were scaled down by a factor of 12. This decreases the processing time for the volume-dependent steps of setup, preheating, and printing.

The model in this experiment exhibits the rate of production similar to a 12-machine configuration.

Lastly, the model is run to completion of all part orders in the order list, a total of 1000 orders. Regular part orders make up 800 (80%) of that total and emergency 200 (20%). In addition, the baseline arrival rate of regular parts has an interarrival time following the normal distribution with a mean (μ) of 100 hours and a standard deviation (σ) of 5 hours, whereas the interarrival times emergency part orders follow an exponential distribution with a mean ($1/\lambda$) of 400 hours.

V. Experimental Results

A. Experiment 1:

For this and two subsequent experiments, five replications for both options, i.e., AM production and warehousing, are performed. The statistics reported in this section there are the average of various output variables of either model.

First, it is expected that under a low penalty (1x of part value) scenario, the major cost driver for the warehouse solution was inventory and part purchasing costs. On the other hand, for AM production, it was the initial machine purchasing cost that is the main driver for the system cost. Figure 14 shows that as service level increases the warehouse solution costs decrease until an inflection point is reached and then the penalty cost savings provide no additional benefit to the overall cost. In the latter scenario, inventory and purchasing costs continue to rise in order to achieve for higher service levels. For the AM option, Figure 15 shows that the AM operation characteristics are somewhat similar to the warehouse operation, that is, as the overall cost continues to improve at higher service levels until an inflection point is reached where increasing service level exhibits minimal cost savings. The difference with AM lays in the flattened slope in total costs as the service level increases, indicating AM is able to operate efficiently and achieve on time deliveries reducing penalty. It's also important to notice the substantial costs associated with fixed values of machine purchasing, machine maintenance, and operator salary costs. Furthermore, although demand rates increase saturating the system at lower service levels; values associated with these variable costs of material and energy are not substantial. The decreasing cost is therefore mostly attributed to the decreasing penalty cost of parts.

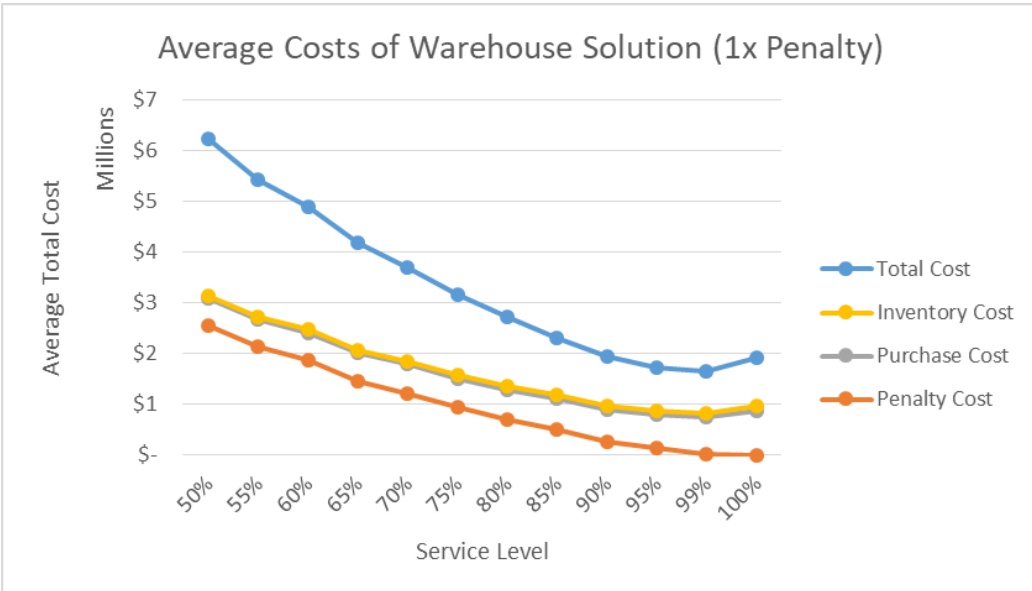

Figure 14. Average Costs of the Warehouse Solution Under 1x Penalty.

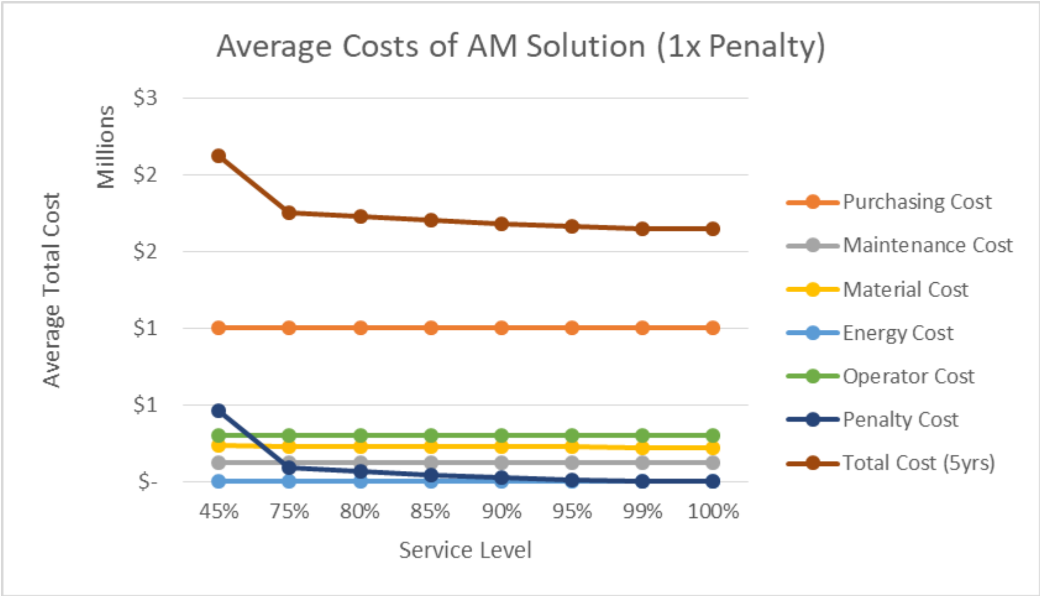

Figure 15. Average Costs of the AM Solution Under 1x Penalty.

Under both scenarios, as penalty level increases at low service levels it becomes the leading cost factor. As penalty costs increase the inventory holding and purchasing costs under the warehouse solution become insignificant, and the optimal service level to achieve the lowest cost per part shifts further to higher service levels. However, as the penalty savings gradually diminish at the extreme high end of service level, these inventory costs become important again and the cost per part increases once again (Figure 16). Likewise, for the AM solution, as penalty costs increase the fixed machine purchasing, machine maintenance, and operator salary costs also become less significant, and the point of efficiency shifts towards these higher service levels. However, the benefit of sharing these fixed costs among the number of parts outweighs the savings return of penalty at higher service levels, as the curve passes this point of efficiency (Figure 17).

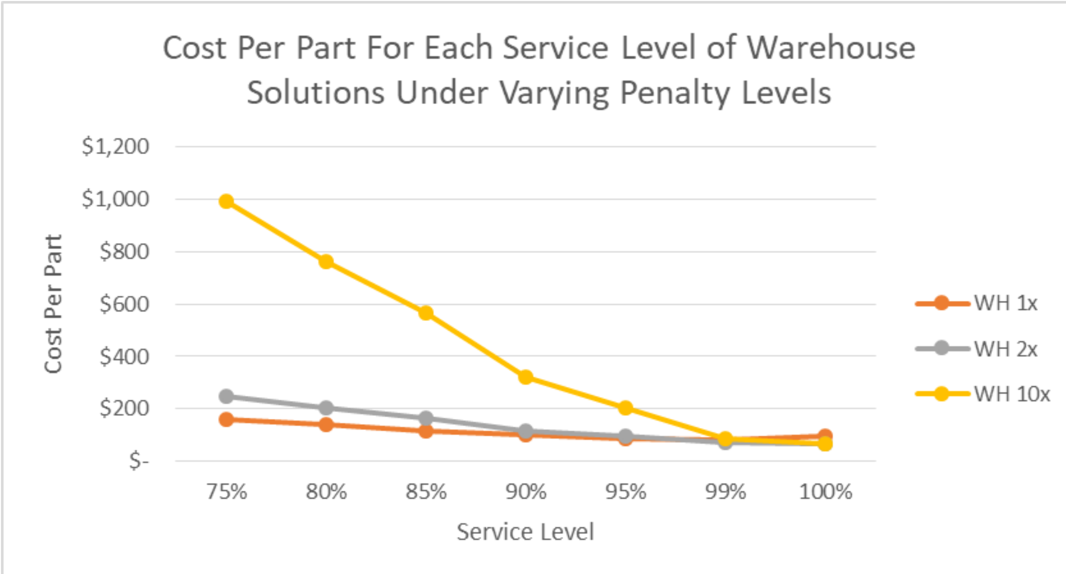

Figure 16. Cost Per Part of Warehouse Solution Under Various Penalty Levels.

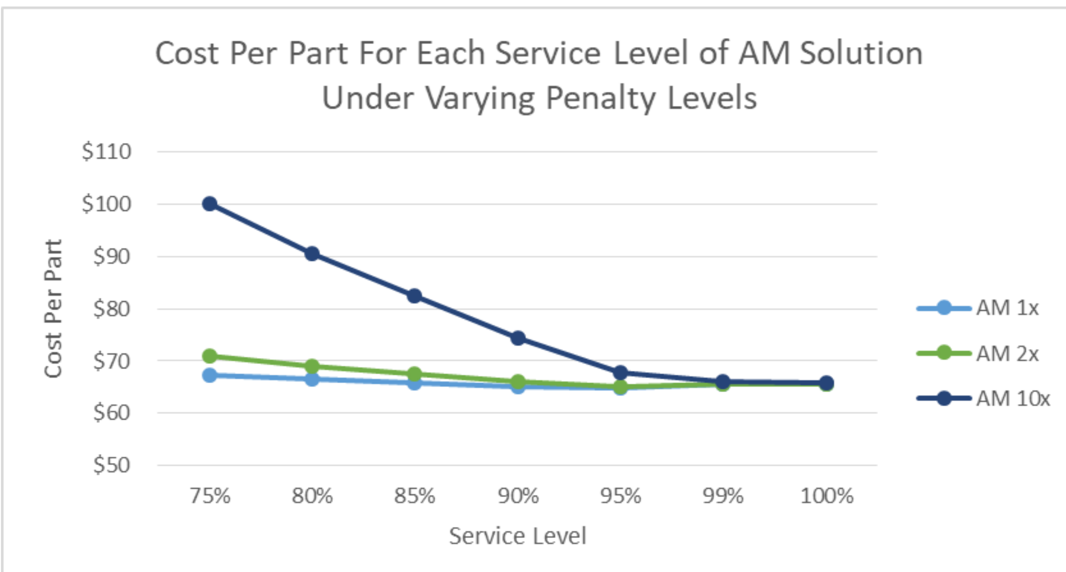

Figure 17. Cost per Part of AM Solution Under Various Penalty Levels.

Figure 18 demonstrates the comparison between the two options in terms of cost per part. For the warehousing option, it is estimated as the cost per part of procuring and storing the parts and for the AM option, as the cost per part of producing the parts. It is known that AM production is more expensive than other forms of production, except for low volume and complex parts like the ones analyzed in our case study. AM produced parts are typically more expensive compared to the procurement of parts made via traditional manufacturing methods, but Figure 18 shows that when including the cost of inventory holding, AM becomes slightly less expensive at higher service levels. AM is unique in that the necessary powder material used in production is most often stored directly within the machine itself, providing negligible costs of holding this inventory. This shows then that the real costs benefits seen in the AM scenarios are not only from reduced penalties as a result of the on-demand nature of this production, but also in the possibly less expensive cost per part as warehouse inventory is expensive at higher service levels. Furthermore, Figure 19 illustrates how AM cost per part is impacted by production speed. As the speed decreases and places a burden on the system, the cost per part for AM exponentially increases. It is noted that these results are independent on the spare part set used for the simulation and therefore should not be valued quantitatively. However, the trends established hold valid use in generalizable cases.

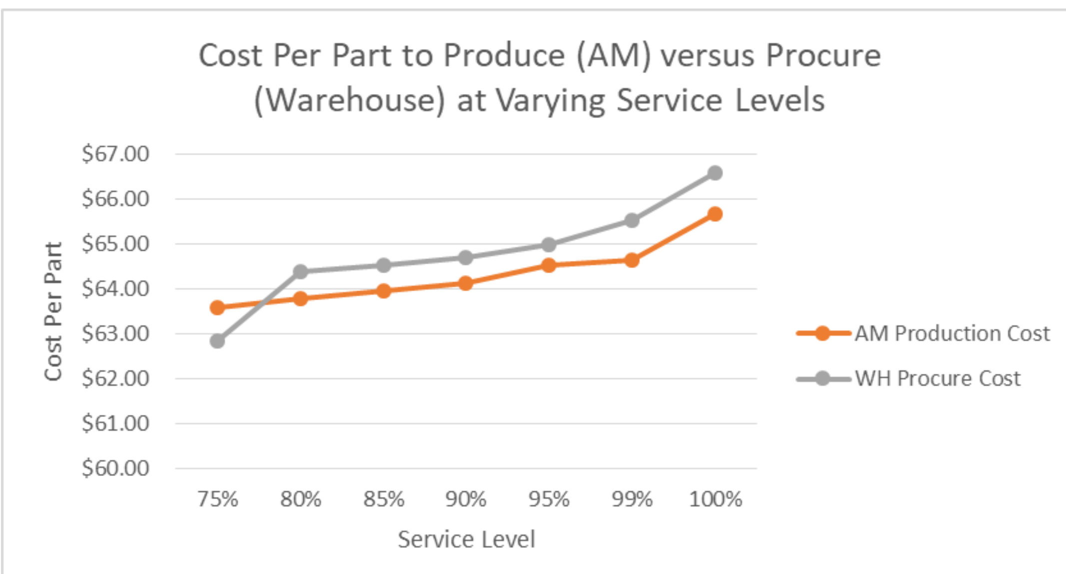

Figure 18. Cost Per Part to Produce or Procure Parts for Various Service Levels.

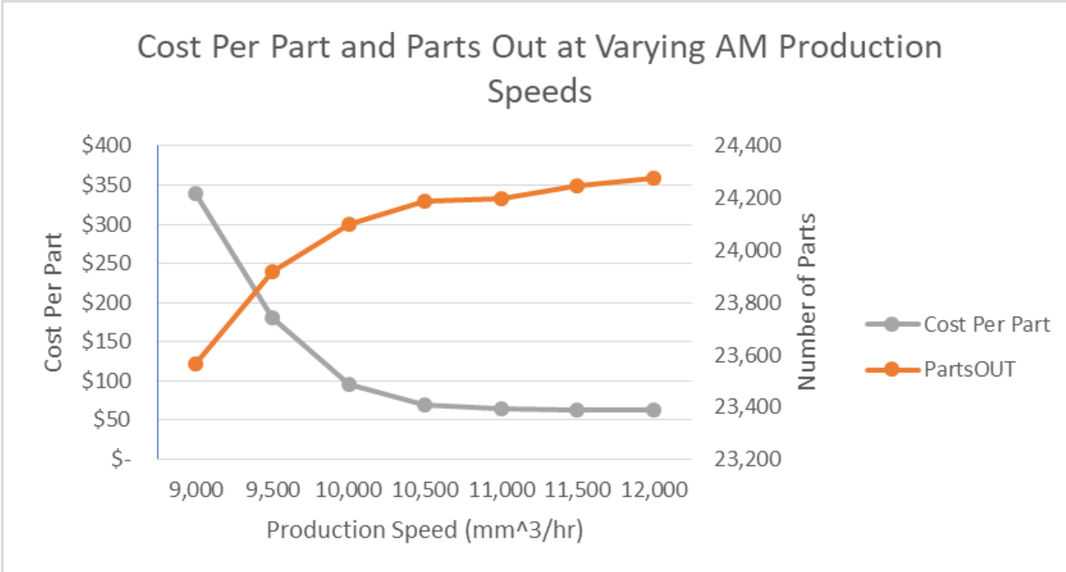

Figure 19. Cost Per Part and Parts Produced at Varying AM Production Speeds.

Finally, Figure 20 compare warehouse results with the AM solution under various penalty levels for late deliveries. It can be seen that the warehouse solution is significantly more expensive under high penalty levels with a slight increase in cost per part at higher service levels. AM is the least expensive option at all penalty levels and remains relatively flat regardless of penalty and service level. This cost trade-off shows for the two solutions AM is favorable in all scenarios, but especially with higher penalty scenarios. This is because the penalty costs are less severe at lower service levels where parts are still manufactured quicker than they can be delivered in the warehousing solution. This does not consider the extremes of an overburdened AM system. It's important to note again the sensitivity of production speed (Figure 19). To achieve lower costs AM users will need to ensure not to exceed the capacity of their production to achieve costs low enough to compete with warehousing.

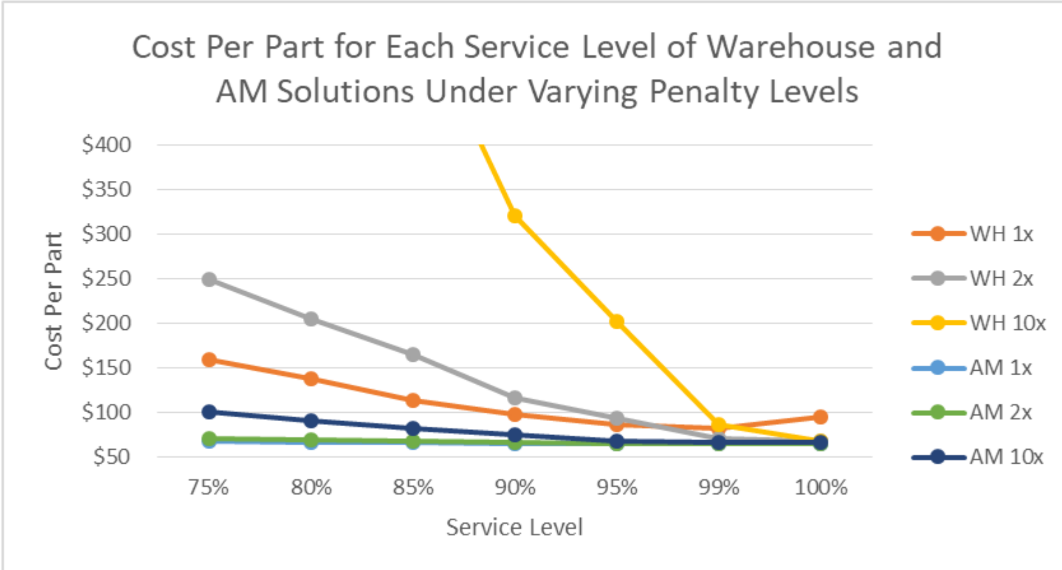

Figure 20. Cost Per Part of Warehouse and AM Solutions under Various Penalty Levels.

B. Experiment 2:

In this experiment, we study the effects of four configurations of the AM production with different levels of resource availability: 1 operator and 1 machine, 2 operators and 1 machine, 1 operator and 2 machines, and 2 operators and 2 machines. The average time waiting in queues matched the common exponential growth curve, which is commonly observed in classic queueing theory (Figure 21. Average Time in Queue for Various AM Production Configurations. For the baseline one operator and one machine configuration, the system appeared to reach capacity limit at 5,000 parts per year. Adding an additional worker improved the waiting times significantly, however a larger reduction in waiting time occurred with an additional machine.

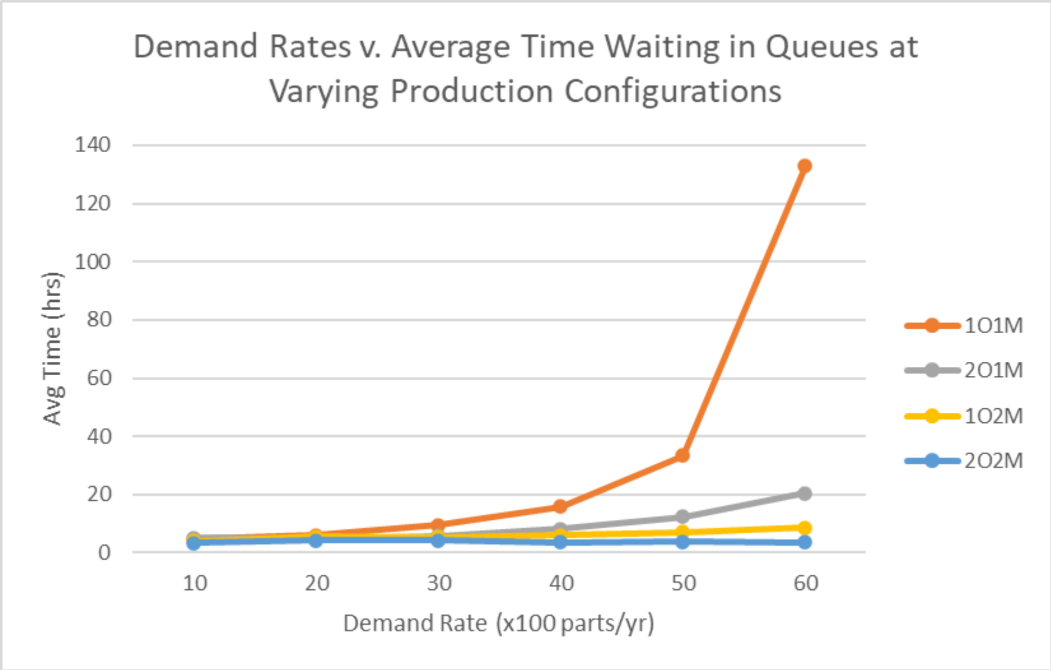

Figure 21. Average Time in Queue for Various AM Production Configurations

Since the 2 operator and 2 machine configurations did not exhibit any increases in waiting times, more simulations were run to identify its capacity limit (Figure 22. Average Time in Queue for a 2 Operator and 2 Machine Configuration. Only when demand rate increases past 12,000 parts/year did the queue start to grow exponentially for this configuration. For 1 operator and 1 machine this was around 5,000 parts/year. Therefore, doubling these two resources more than doubled the system's capacity. This indicates a synergetic effect between operators and machines.

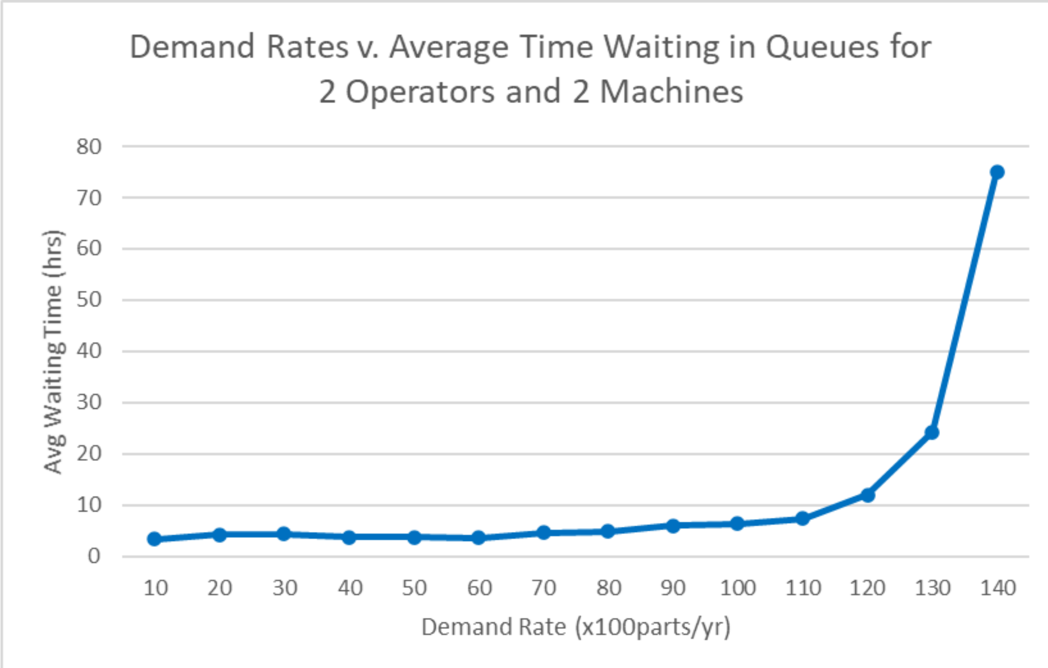

Figure 22. Average Time in Queue for a 2 Operator and 2 Machine Configuration

Adding an additional worker reduced waiting times, but to understand the burden placed on system resources, worker and machine utilizations are also calculated for all four configurations. Operator utilization is provided as an output in the ARENA model. It is calculated as a percent of time operators are busy at seized servers. However, the machine utilization is only given for the percent of time spent printing part orders. Average times spent in queue are also collected as outputs of the ARENA model. Figure 23, shows the average worker utilization was the highest under the two machine configurations in comparison with the one machine setups, which intuitively makes sense as workers are required more often for machine setup. In addition, all configurations followed a similar slope, indicating at higher demand rates more utilization of the worker is required. Figure 24, illustrates the average utilization of the machine while printing, and shows a difference between machine and worker utilization. There is only a slight increase in utilization for the given four scenarios as demand rates increase, implying that the manufacturing system adapted well to the increase of demand rate due to the order batching in place in the production process.

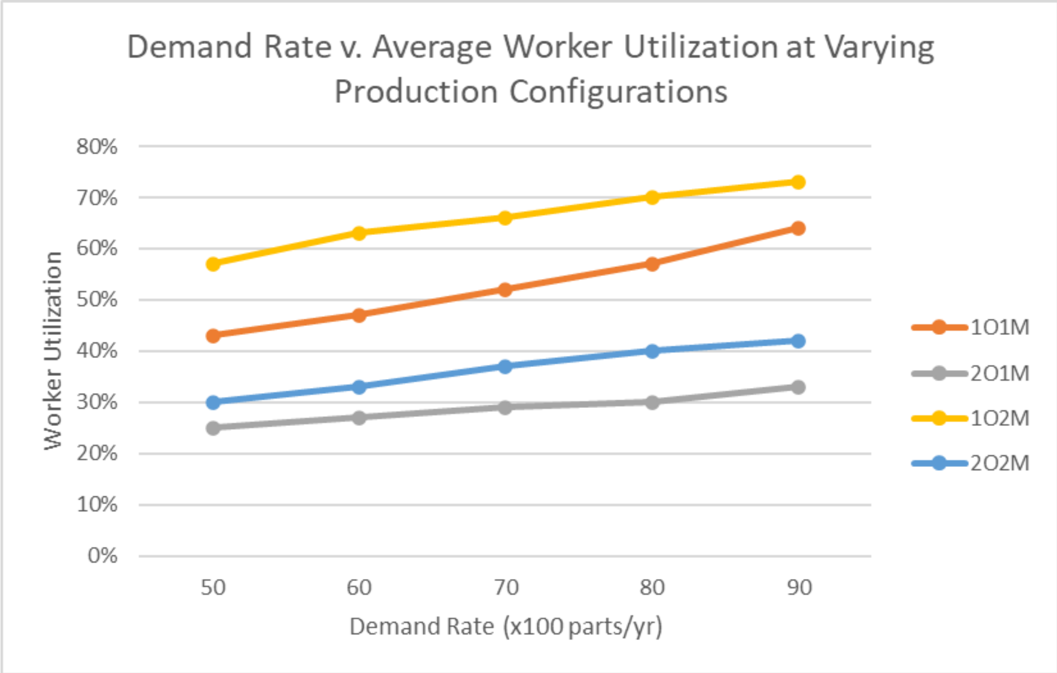

Figure 23. Average Worker Utilization for Various AM Production Configurations.

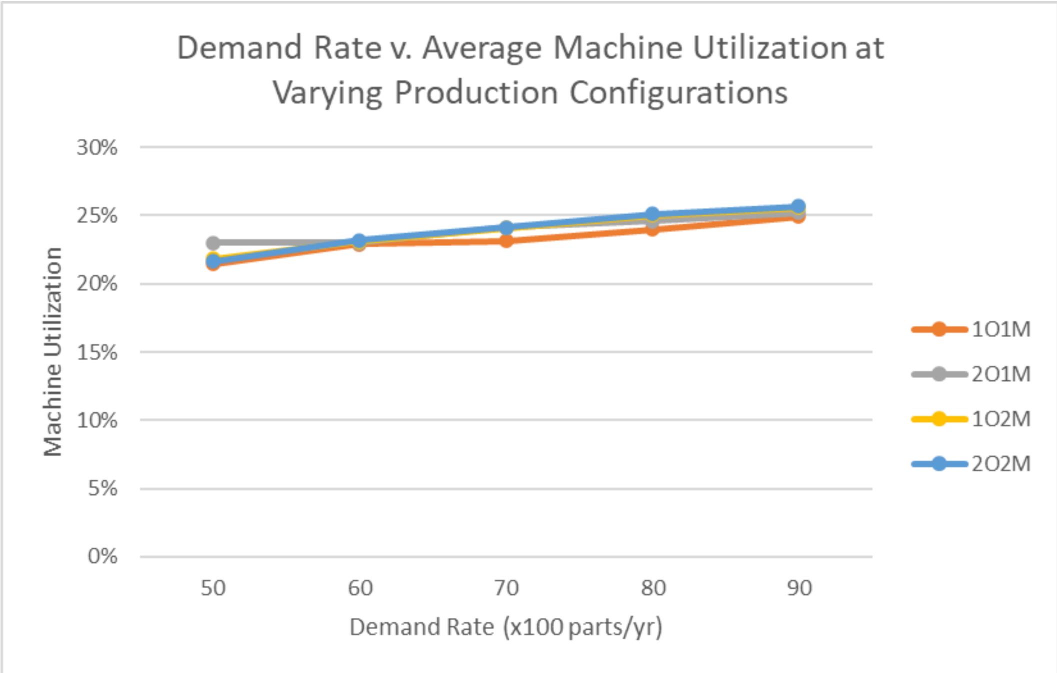

Figure 24. Average Machine Utilization for Various AM Production Configurations.

Although machine utilization appears lower than worker utilization, it should be noted that the machine utilization is calculated as the portion of time that machine is used in actual production.

This does not include the additional time spent waiting for an operator between machine steps such as setup, calibration, pre-heating, and post-processing. The latter, however, based on the observations in Experiment 2 account for roughly 30-50% of the total production time of the machine. Additional data analysis was conducted in order to find the average percentage of time a delay was caused by a worker or machine for each of the production configurations (Figure 25). The results show that machine capacity is the bottleneck of the production system. However, as demand rate increases and as worker utilization also increases (Figure 23) the percentage of delays begin to shift towards the worker. This is seen in all four configurations. When considering adding an additional worker or increasing the number of machines this data shows that the only significant difference in the percentage of delays is a decrease in worker attributable delays with the addition of a second worker.

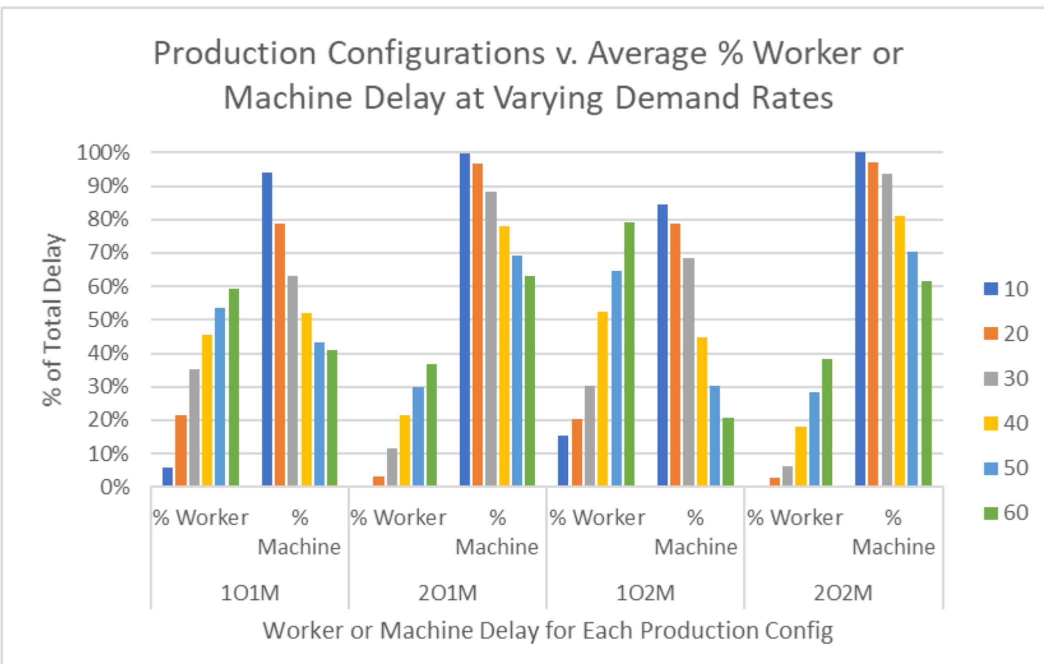

Figure 25. Average Percent of Delays Attributed to Workers or Machines for Various AM Production Configurations

Table 8 shows the total time in hours for these attributable worker or machine delays under each configuration at varying demand rates. Smaller demand rates show the capacity limitation of 1 machine configurations, as the attributable hours of machine related delays are significantly higher. Similarly, for the 2 operators and 2 machines configuration at all demand rates, worker attributed delays make up the majority of waiting times, though for a smaller cumulative amount.

Table 8. Worker and Machine Attributable Hours Delayed for Various AM Production Configurations.

	1O1M		2O1M		1O2M		2O2M	
Demand Rate	Worker	Machine	Worker	Machine	Worker	Machine	Worker	Machine
10	0.28	4.38	0.01	5.14	0.62	3.46	0.00	3.35
20	1.31	4.81	0.15	4.59	1.16	4.46	0.11	4.12
30	3.37	6.01	0.67	5.18	1.59	3.61	0.26	4.06
40	7.25	8.25	1.77	6.44	3.12	2.67	0.67	3.02
50	17.92	14.42	3.66	8.52	4.66	2.20	1.06	2.63
60	78.61	54.14	7.54	12.88	6.85	1.79	1.40	2.25

Throughput is another output given as parts out from the model and is averaged with five replications. Figure 26 shows how these system performances affect the actual production (throughput) of the system. It was noted that the waiting time in queue began to resemble exponential growth following a demand of 5,000 parts per year under the one operator and one machine configuration, resulting in a decrease in throughput. The two operator and one machine setup also seem to slope off around a demand of 7,000 parts per year. Based on the option of improving throughput by adding an additional worker or increasing the number of machines, while both increase throughput at higher demands, the larger benefit in average throughput is demonstrated with an additional machine with only marginal benefits for an additional worker.

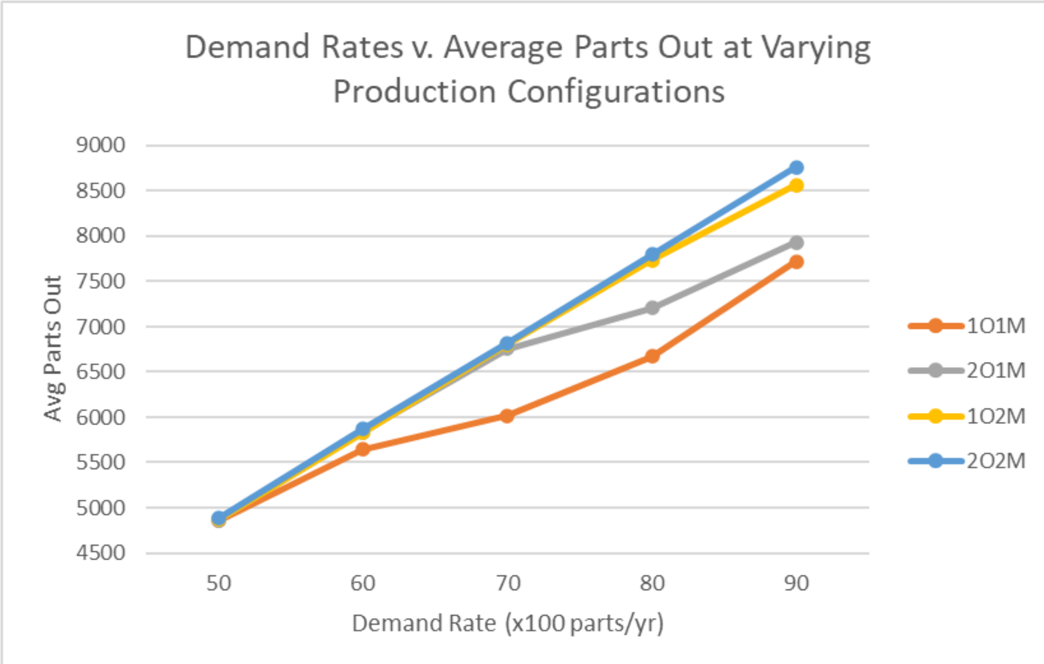

Figure 26. Average Throughput for Various AM Production Configurations

We also evaluate how four configurations ultimately affect the average cost per part, which is the important bottom line for any service provider. An operator's salary is different than the cost of purchasing and maintaining a machine. In addition, the penalty cost associated with these delayed parts significantly affect the cost of production, especially under high penalty scenarios being modeled here.

The AM costs represent the same values used in Experiment 1. The same penalty cost calculations are used as before for the 1x (low) and 10x (highest) penalty scenarios (Equation 7). The other costs are $100,000 per operator salary (1 or 2), $1,000,000 per purchased machine (1 or 2), $25,000 per machine for maintenance (1 or 2), $0.2 per gram of material and $0.02 per kWh of energy used in production (Equation 8).

Figure 27 shows the average cost per part for the four configurations under a 1x penalty. For the one operator and one machine setup, the lost throughput and increased penalty for late orders, significantly increase average cost per part. In order to lower cost an additional worker can be added. Even with the added salary the two operator and one machine configuration provide a lower average cost for higher demand rates, when the original configuration is burdened. The two machine options only become cost beneficial at the highest demand rates, when the one machine configuration assumes larger penalties. In addition, the combination of two operators and two machines yields very little benefit in comparison to the 1 operator and 2 machines configuration.

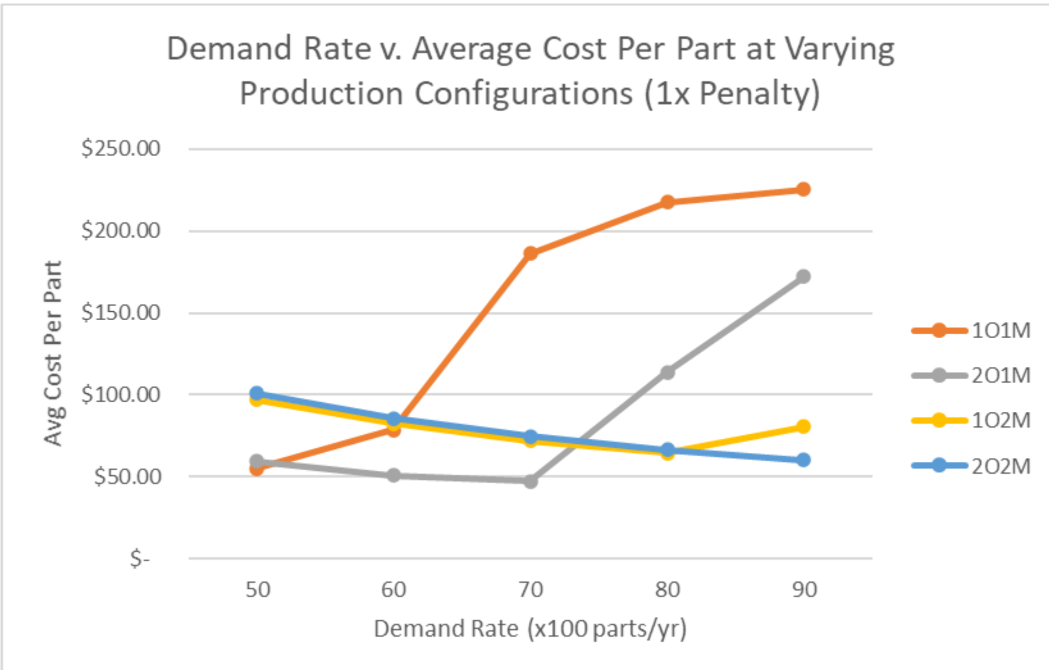

Figure 27. Average Cost Per Part for Various AM Production Configurations (1x Penalty)

A similar effect is seen in Figure 28 when the penalty cost of delayed cost is set to be ten times the baseline penalty. In this case, the benefit of adding a second machine appears to have an equivalent effect for higher penalty levels as an additional operator and becomes the better option at the highest demand rates. This implies that the two machine configurations are cost effective for a larger range of expected demands and might be the best option when considering expanding production capacity in anticipation for higher demands and higher penalty for late delivery.

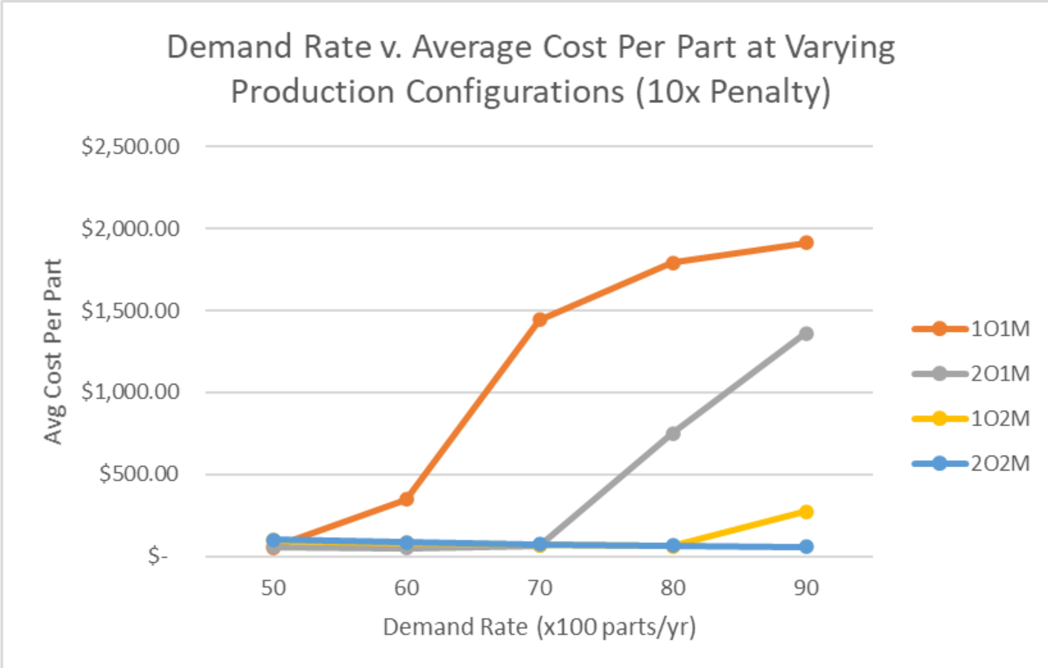

Figure 28. Average Cost Per Part for Various AM Production Configurations (10x Penalty)

C. Experiment 3:

For this experiment the goal was to evaluate three different prioritization strategies for orders waiting in queue: FCFS, earliest due date, and highest current penalty. Recall that in the experiment setting, emergency part orders arrive as a Poisson process and are assigned low demands and low allowed manufacturing times in order to mimic the demand and attributes associated with a part failure for the aerospace industry. All other demand takes on the characteristics of normally scheduled maintenance part orders, where the arrivals follow a normal distribution and part attributes range significantly in value, volume, and allowed manufacturing time. These emergency part orders are unique and of the most interest as their arrivals are highly disruptive to the manufacturing flow because they occur randomly, and because the system must provide them higher priority in order to meet their allowed manufacturing times. The cost per part for each of these prioritization strategies under our baseline production settings is shown in Figure 29. Average Cost Per Part for Various

Prioritization Strategies.. Reordering parts based on current highest penalty showed the largest reduction in cost (roughly $6 per part) compared to FCFS. Sorting by earliest due date also saw a large improvement (roughly $5 per part). The total improvement was nearly $1 million in savings. This outcome is expected. Penalty is the highest cost factor under these conditions and therefore it provides the largest cost savings to prioritize parts based on their expected penalty.

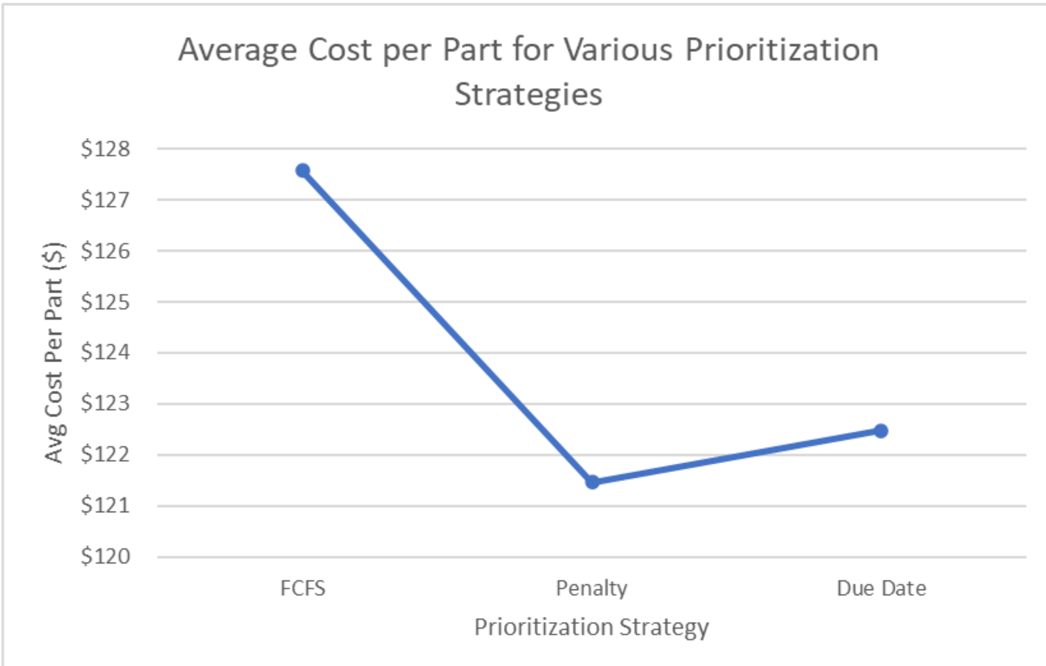

Figure 29. Average Cost Per Part for Various Prioritization Strategies.

Next was to determine if the other strategy of earliest due date would ever become preferred over the penalty prioritization strategy. This was analyzed by increasing the arrival rate of emergency part orders by decreasing interarrival time from exponential with a mean of 400 hours down to 300 hours (1.5x) and finally 200 hours (2x), see Figure 30. As arrival rates increased for emergency orders, the average cost per part for the penalty strategy also increased linearly. In contrast, FCFS and earliest due date began to exhibit a concave curve. This indicates that although parts were entering the system at a faster rate than before these two strategies were able to accommodate them. This would make sense as emergency part orders are very small, always falling in the range of low part demand (1-10 parts per order) and requiring the quickest manufacturing times (24-48 hours). If these parts are prioritized, they can be completed in time of their due dates and save on penalty costs. The penalty strategy on the other hand, prioritizes not just on due date but also factors in order size and part value. These factors do not prioritize the emergency orders with low part demands, but instead prioritize large orders with high value parts.

The difference shows a dramatic increase (roughly $32 per part, or $5 million total) between the earliest due date and the penalty prioritization strategies. It also noted that FCFS performed well under these conditions. The slope of this curve indicates that parts are still arriving relatively infrequently (normal mean of 100 hours, exponential rate of 200 hours) and parts are already entering the queue in order by their allowed manufacturing time (earliest due date). Therefore, this strategy is also preferred over the penalty prioritization.

If emergency order rates increase, there will be a point where the best strategy for order prioritization becomes sorting orders in queue by their earliest due date.

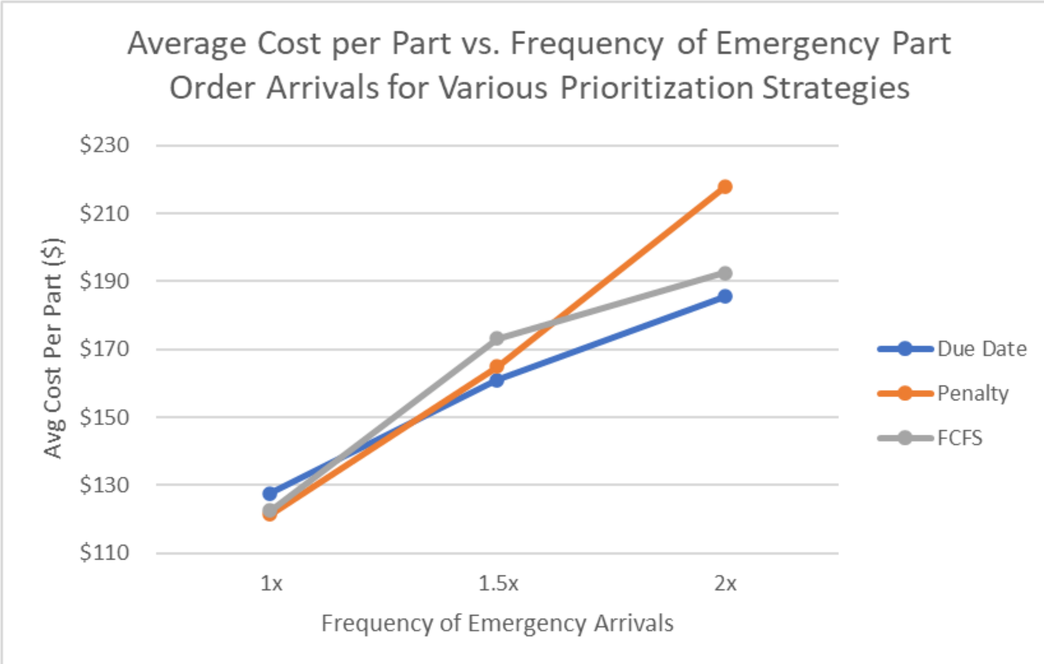

Figure 30. Average Cost Per Part versus Emergency Arrival Rates for Various Prioritization Strategies.

If emergency orders are arriving at a higher rate, then to understand when penalty will once again become the preferred prioritization strategy, the part value of emergency parts was increased to the highest value ($1,000 per part), see Figure 31. This increase resembles the high penalty cost for aerospace spare parts for a part failure and the results provide a good argument for penalty prioritization.

As the arrival rate of emergency parts increases FCFS and earliest due date slope downward once again, but this time the penalty strategy also curves. From Figure 31, when arrival rate of emergency orders increases to twice the baseline, a larger reduction in cost (roughly $20 per part, or $2 million total) occurs with the penalty strategy than those with the FCFS and earliest due date strategies. This indicates that the part value of emergency orders now outweighs the large size and values of regular orders and the penalty strategy is better able to prioritize emergency orders.

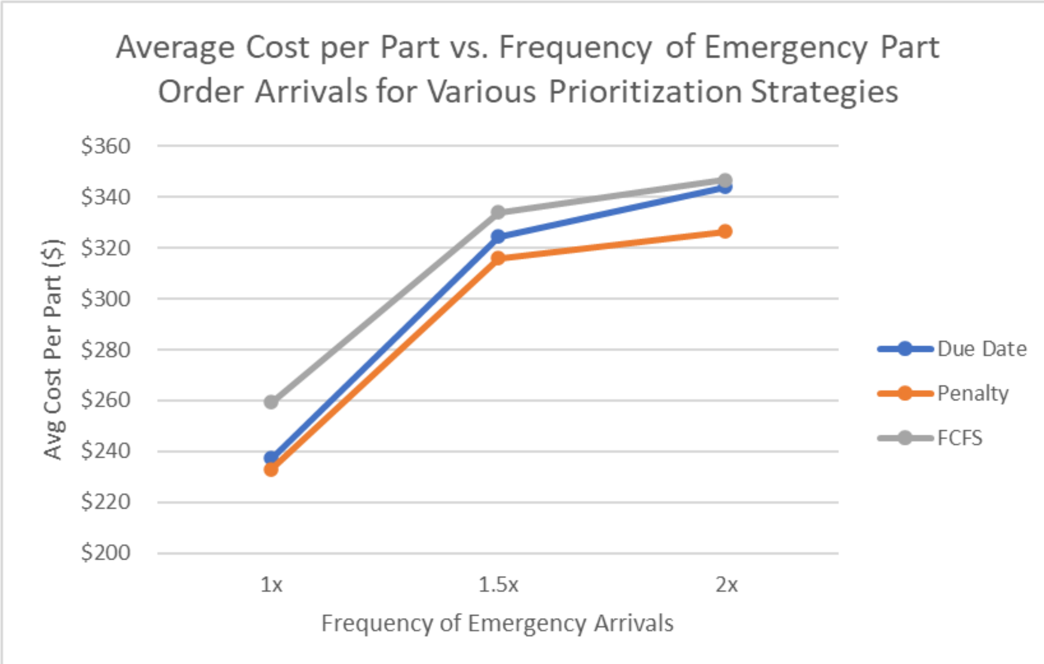

Figure 31.Average Cost Per Part versus Emergency Arrival Rates for Various Prioritization Strategies with High Emergency Part Penalty.

These strategies indicate that for low demand orders with short lead times (emergency parts), prioritizing by earliest due date will reduce cost per part. However, in cases were the distribution gap of part value and/or demand widens prioritizing by highest expected penalty is preferred.

VI. Conclusions

The development of the simulation model and the results of three main experiments provide a better understanding on the operational characteristics of AM and its impacts on the overall logistics at the plant-level for high-impact spare parts such as aerospace parts. The model was able to capture the microscopic operational aspects of the AM production considering key AM operation resources (e.g. AM system, operator) and attributes (e.g. AM manufacturing speed, individual part characteristics and demands). They address the four objectives of this thesis.

Objective 1) The ability of analyzing tradeoffs between cost and customer responsiveness was successfully demonstrated. This includes an analysis of each cost factor and the relationship between cost and various service levels at three different penalty rates (1x, 2x, and 10x).

Experiment 1 showed between these the two approaches to supplying spare parts, i.e., AM and warehousing, AM is especially favorable with higher penalty scenarios like those exhibited in the aerospace supply chain. AM penalty costs are less severe at lower service levels where parts are still manufactured quicker than they can be delivered in the warehousing solution. In addition, Experiment 1 demonstrated how decreased production rates significantly increased cost per part and decreased output for the AM approach. In order to achieve lower costs and compete with the warehousing solution, AM users will need to ensure their demand, like most production facilities, does not to exceed the capacity of production.

Objective 2) AM-based production characteristics (e.g. waiting time in queues, worker and machine utilization, throughput rate, and cost per part) were captured under four different production configurations: 1 operator and 1 machine, 2 operators and 1 machine, 1 operator and 2 machines, and 2 operators and 2 machines.

Results indicated the model represented a queueing system as waiting times grew exponentially at increasing demand rates. In addition, Experiment 2 showed a large reduction in waiting times with an additional worker, but an even larger reduction with an additional machine. Furthermore, the doubling of workers and machines showed a synergetic effect by more than doubling the system's capacity.

For utilization, better (higher) worker utilization was obtained when an additional machine is used. This implies workers completed more orders under the 2 machines configuration, which is reflected in the additional throughput for these scenarios. In contrast, machine utilization showed little difference between the four configurations. We attribute this to the batching strategy in place in the AM production model, which helps to reduce burden placed on this resource.

Throughput was also highest in the two machine configurations and this is consistent with the results of the queueing times and conclusions on utilization. Workers were better utilized, and orders spent less time in queues leading to increased output.

Cost per part under low (1x) and high (10x) penalty factors demonstrated the cost savings for the investment of an additional worker and/or machine when capacity is beyond the 1 operator and 1 machine limits. In addition, under the higher penalty scenario the 2 operators and 2 machines configuration provided the largest range of cost benefit.

For the AM spare part supply chain, these results demonstrate a benefit in applying a conservative approach to matching production with demand, by investing in personnel and machines, especially when dealing with a high penalty supply chain like the aerospace spare parts industry.

Objective 3) Three prioritization strategies (e.g. FCFS, earliest due date, and highest penalty) were successfully simulated and a trade-off between each was created. The results showed earliest due date was optimal for cost reduction with an increasing rate of low demand orders that allow short lead times (emergency parts). However, prioritizing based on highest expected penalty was optimal for cases with a wide distribution gap between part value and/or demand. The latter being a good representation of the aerospace spare parts supply chain with high penalty for late emergency parts. Overall, the significance in prioritization strategies was demonstrated with total savings of millions for the operation.

VII. Future Research

This research studies, on the microscopic level, operational characteristics of AM-based production at the plant-level for aerospace spare parts, so that the efficiency on cost and customer responsiveness for AM can be evaluated against the warehousing alternative. Key AM operation resources (e.g. machine, operator) were accounted for in the modeling of various configurations. A benchmark warehouse inventory model was also established separately based on classic inventory theories, which was subsequently utilized to create a cost/benefit analysis for the AM based part supply strategies versus the traditional warehousing strategy.

Experiments demonstrated the cost versus service level trade-off between warehousing and AM solutions to the aerospace spare parts supply chain. The current thesis used a simplistic Monte Carlo simulation for modeling the costs of the warehouse solution. Future may develop a simulation model for warehousing operations so that inventory measures such as demand rate, lead time, stock level and service level can be analyzed in more detail. Also, of interest is the effect of various transportation and inventory policies in the aerospace spare parts supply chain.

The characteristics of the AM production model under the four configurations of varying operators and machines demonstrated the waiting time, utilization, throughput, and cost trade-offs between adding additional operators and/or machines. This could be expanded with the inclusion of stochastic order demands and order prioritization.

Likewise, the conclusions on order prioritization strategies for varying stochastic order lists could also be expanded to evaluate other operational strategies such as postponement, machine selection, operator scheduling, among others. These strategies, or policies, are common in production facilities, and will become increasingly important as AM-based on-demand production is adopted as an alternative to warehousing solutions.

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Appendix I. Algorithms for Creating Stochastic Part Orders

Algorithm 1: Creating Regular Spare Part Orders with Attributes

START

1) Create Regular spare part entities with interarrival time following N(μ,σ) hours, where "N"=Normal
   a) Generate Allowed Manufacturing Time attribute
      i) Route 5% of the entities to the Low range of Allowed Manufacturing Time
         (1) Assign the part an Allowed Manufacturing Time ~U(24,48) hours, where "U"=Uniform
      ii) Route 20% of the entities to the Medium range of Allowed Manufacturing Time
         (1) Assign the part an Allowed Manufacturing Time ~U(72,120) hours, where "U"=Uniform
      iii) Route 75% of the entities to the High range of Allowed Manufacturing Time
         (1) Assign the part an Allowed Manufacturing Time ~U(168,336) hours, where "U"=Uniform
   b) Generate Priority Level Attribute considering correlation with allowed manufacturing time
      FOR entities with an Allowed Manufacturing Time in the Low range
         (1) Assign 80% a Priority Level of 1
         (2) Assign 10% a Priority Level of 2
         (3) Assign 10% a Priority Level of 3
      END FOR
      FOR entities with an Allowed Manufacturing Time in the Medium range
         (1) Assign 10% a Priority Level of 1
         (2) Assign 80% a Priority Level of 2
         (3) Assign 10% a Priority Level of 3
      END FOR
      FOR entities with an Allowed Manufacturing Time in the High range
         (1) Assign 10% a Priority Level of 1
         (2) Assign 10% a Priority Level of 2
         (3) Assign 80% a Priority Level of 3
      END FOR
   c) Generate Volume attribute considering correlation with part volume
      i) Route 75% of the entities to the Low range of Volume
         (1) Assign the part a Volume ~U(1000,10000) mm^3, where "U"=Uniform
      ii) Route 20% of the entities to the Medium range of Volume
         (1) Assign the part a Volume ~U(10001, 500000) mm^3, where "U"=Uniform
      iii) Route 5% of the entities to the High range of Volume
         (1) Assign the part a Volume ~U(500001, 1000000) mm^3, where "U"=Uniform
   d) Generate Value attribute
      FOR entities with a Volume in the Low range
      i) Route 80% of the entities to the Low range of Value
         (1) Assign the part a Value ~U(10,50) USD, where "U"=Uniform
      ii) Route 10% of the entities to the Medium range of Value
         (1) Assign the part a Value ~U(51,200) USD, where "U"=Uniform
      iii) Route 10% of the entities to the High range of Volume

(1) Assign the part a Value ~U(201,1000) USD, where "U"=Uniform

END FOR

FOR entities with a Volume in the Medium range

i) Route 10% of the entities to the Low range of Value
   (1) Assign the part a Value ~U(10,50) USD, where "U"=Uniform
ii) Route 80% of the entities to the Medium range of Value
   (1) Assign the part a Value ~U(51,200) USD, where "U"=Uniform
iii) Route 10% of the entities to the High range of Volume
   (1) Assign the part a Value ~U(201,1000) USD, where "U"=Uniform

END FOR

FOR entities with a Volume in the High range

i) Route 10% of the entities to the Low range of Value
   (1) Assign the part a Value ~U(10,50) USD, where "U"=Uniform
ii) Route 10% of the entities to the Medium range of Value
   (1) Assign the part a Value ~U(51,200) USD, where "U"=Uniform
iii) Route 80% of the entities to the High range of Volume
   (1) Assign the part a Value ~U(201,1000) USD, where "U"=Uniform

END FOR

e) Generate Demand attribute
   i) Route 5% of entities to the Low range of Demand
      (1) Assign the part a Demand ~U(1,10) parts, "U"=Uniform
   ii) Route 20% of the entities to the Medium range of Demand
      (1) Assign the part a Demand ~U(11,30) parts, where "U"=Uniform
   iii) Route 75% of the entities to the High range of Demand
      (1) Assign the part a Demand ~U(31,50) parts, where "U"=Uniform

END

Algorithm 2: Creating Emergency Spare Part Orders with Attributes

START

1) Randomly generate Emergency spare part entities with interarrival time following E(λ) hours, where "E"=Exponential
   a) Assign Priority Level attribute value of 0
   b) Assign the part an Allowed Manufacturing Time ~U(24,48) hours, where "U"=Uniform
   c) Generate Volume attribute
      i) Route 75% of the entities to the Low range of Volume
         (1) Assign the part a Volume ~U(1000,10000) mm^3, where "U"=Uniform
      ii) Route 20% of the entities to the Medium range of Volume
         (1) Assign the part a Volume ~U(10001,500000) mm^3, where "U"=Uniform
      iii) Route 5% of the entities to the High range of Volume
         (1) Assign the part a Volume ~U(500001,1000000) mm^3, where "U"=Uniform
   d) Generate Value attribute considering correlation with part volume

      FOR entities with a Volume in the Low range

      i) Route 80% of the entities to the Low range of Value
         (1) Assign the part a Value ~U(10,50) USD, where "U"=Uniform

ii) Route 10% of the entities to the Medium range of Value
   (1) Assign the part a Value ~U(51,200) USD, where “U”=Uniform
iii) Route 10% of the entities to the High range of Volume
   (1) Assign the part a Value ~U(201,1000) USD, where “U”=Uniform

END FOR

FOR entities with a Volume in the Medium range

i) Route 10% of the entities to the Low range of Value
   (1) Assign the part a Value ~U(10,50) USD, where “U”=Uniform
ii) Route 80% of the entities to the Medium range of Value
   (1) Assign the part a Value ~U(51,200) USD, where “U”=Uniform
iii) Route 10% of the entities to the High range of Volume
   (1) Assign the part a Value ~U(201,1000) USD, where “U”=Uniform

END FOR

FOR entities with a Volume in the High range

i) Route 10% of the entities to the Low range of Value
   (1) Assign the part a Value ~U(10,50) USD, where “U”=Uniform
ii) Route 10% of the entities to the Medium range of Value
   (1) Assign the part a Value ~U(51,200) USD, where “U”=Uniform
iii) Route 80% of the entities to the High range of Volume
   (1) Assign the part a Value ~U(201,1000) USD, where “U”=Uniform

END FOR

e) Assign the part a Demand ~U(1,10) parts, where “U”=Uniform

END

Appendix II. Simio Order Generation Model

The Simio model for generating spare part orders, shown in Figure 32 below, links two source nodes to a network of servers that assign attributes to the order, before the order is finally destroyed at the sink node. It's at the final sink node that part order data is captured in an output table.

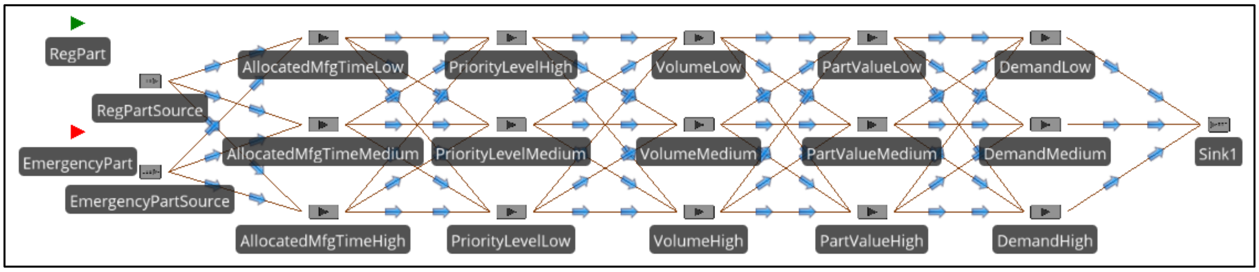


Figure 32. Simio model for generating spare part orders.

Arrivals

The two source nodes; "RegPart" and "EmergencyPart", are associated with the type of part (regular or emergency) being created. Since, these part order types follow a different arrival rate, they are separated. The random function is used for both source nodes to generate the arrival time of these parts. An example source node for a regular spare part order with interarrival times that follows a Normal distribution with a mean (μ) of 75 hours and a standard deviation (σ) of 5 hrs, is shown in Figure 33. The math function, maximum, is used to ensure any randomly generated value less than zero will not be assigned, as this is possible with normal distributions with a range of ($-\infty$, ∞), and would result in an error in the model. Likewise, Figure 34, shows an example emergency part source node that follows a Poisson distribution with a mean (λ) of 75 hours. The Poisson distribution is always positive, so there is no need to include the maximum function.

Entity Arrival Logic	
Entity Type	**RegPart**
Arrival Mode	Interarrival Time
Time Offset	0.0
Interarrival Time	**Math.Max(Random.Normal(75,5),0)**
Units	**Hours**
Entities Per Arrival	1
Stopping Conditions	
Maximum Arrivals	**1000**
Maximum Time	Infinity

Figure 33. An example regular part source node.

Entity Arrival Logic	
Entity Type	**EmergencyPart**
Arrival Mode	Interarrival Time
Time Offset	0.0
Interarrival Time	**Random.Poisson(75)**
Units	**Hours**
Entities Per Arrival	1
Stopping Conditions	
Maximum Arrivals	**1000**
Maximum Time	Infinity
Stop Event Name	

Figure 34. An example emergency part source node.

Attribute Level Proportioning

Once a part is created the entity, will follow a connector (shown by the red lines with blue arrows) to a server node. This is where the proportions of total entity flow are introduced. Figure 35, shows how an example of a connector from the low level allowed manufacturing time server to a high priority level server. Following the two algorithms defined above, these attributes share a correlation, where 80% of total entities assigned a low allowed manufacturing time should be given a high priority level. This 80% proportion is specified in the routing logic, under selection weight.

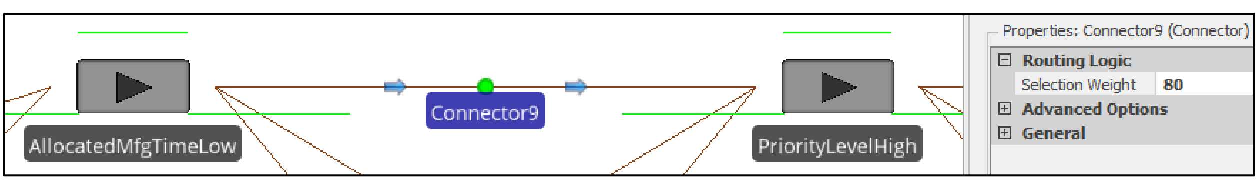


Figure 35. An example of the routing logic between two attribute servers.

The model uses these connections to route entities based on the proportions and correlations specified in Algorithms 1 and 2 and shown in Tables 1-5.

Assigning Attribute Value

When an entity is being processed by a server, it will trigger an add-on process that will then be assign an attribute value for that entity based on a given distribution. An example of the server add-on process associated with the high level allowed manufacturing time is shown in Figure 36 below. All these add-on processes assign a value using the random function and a uniform distribution with the lower and upper limits, as outlined in Algorithms 1 and 2, and shown in Tables 1-5.

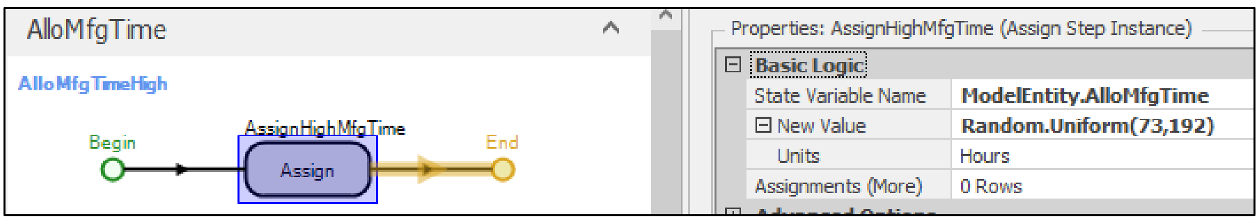


Figure 36. An example of a server with the assign attribute add-on process.

Output

Once the entity (part order) has passed through the network, it is finally sent to the sink node. When the entity enters this node, it triggers the final add-on process that adds a row to an output table and displays the entity's attributes. Figure 37, shows the add-on process for this step, and Figure 38 shows the output table that is generated after simulating the model.

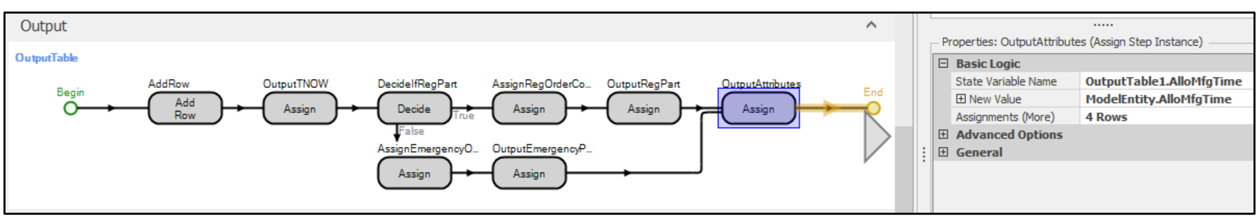


Figure 37. The add-on process for collecting final outputs.

Output Table1

	Index	Timestamp (Hours)	Part Type	Priority Level	Allo Mfg Time (Hours)	Volume (Cubic Meters)	Part Value (USD)	Demand
1	1	0.0000	Reg Part	3	134.1912	0.0000	47.9893	4
2	1	0.0000	Emergency Part	0	154.4169	0.0000	11.5445	8
3	2	60.0000	Emergency Part	0	68.3008	0.0000	10.3019	10
4	2	72.1748	Reg Part	3	95.7831	0.0000	47.7971	19
5	3	129.0000	Emergency Part	0	118.6902	0.0000	35.2200	17
6	3	148.7745	Reg Part	3	110.1566	0.0000	18.0008	30
7	4	198.0000	Emergency Part	0	94.6240	0.0001	36.9848	3
8	4	226.8745	Reg Part	3	82.6725	0.0000	45.9365	43
9	5	279.0000	Emergency Part	0	112.3801	0.0001	97.7381	9
10	5	303.8337	Reg Part	3	132.1506	0.0000	45.1268	2
11	6	360.0000	Emergency Part	0	83.4946	0.0000	48.8850	28
12	6	373.0709	Reg Part	1	41.3861	0.0000	15.2227	10
13	7	441.0000	Emergency Part	0	169.2476	0.0000	21.8639	5
14	7	456.0514	Reg Part	3	181.2415	0.0000	49.4874	5

Figure 38. An example output table showing part orders and their attributes.

For each simulation 1000-part orders are created of both regular and emergency parts and exported from the output table to a .csv file to be used in the AM Supply Chain model.

Appendix III. ARENA AM Production Model

Order Creation

For this model it was decided to use ARENA's random variable expressions to create entities following our desired distributions, typically normal r.v. for regular parts and Poisson r.v. for emergency parts. This entity generation is done through a create step, shown in Figure 39.

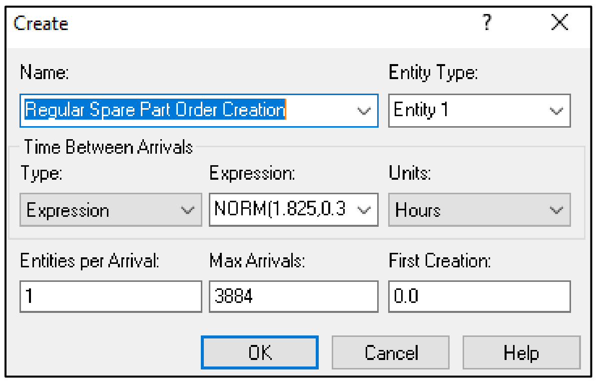
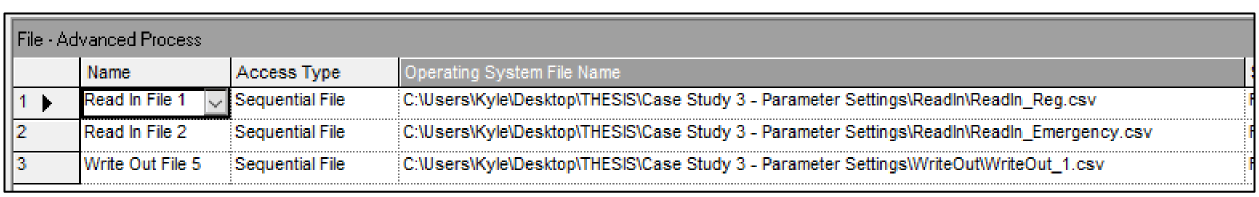


Figure 39. An example create step for regular part orders.

Since part attributes are pre-generated via a Simio file, this ARENA model simply pulls attribute data from the input file (.csv). This input file is the same output from the part order generation model, the only difference is that regular and emergency parts are separated into two files first. Figure 40 below, shows the linkage to the two Simio input file paths.



File - Advanced Process

	Name	Access Type	Operating System File Name
1	Read In File 1	Sequential File	C:\Users\Kyle\Desktop\THESIS\Case Study 3 - Parameter Settings\ReadIn\ReadIn_Reg.csv
2	Read In File 2	Sequential File	C:\Users\Kyle\Desktop\THESIS\Case Study 3 - Parameter Settings\ReadIn\ReadIn_Emergency.csv
3	Write Out File 5	Sequential File	C:\Users\Kyle\Desktop\THESIS\Case Study 3 - Parameter Settings\WriteOut\WriteOut_1.csv

Figure 40. Read In file links.

A Read Write step then provide the link of a specific part order's attribute to a newly created entity. The assigning of these attributes can be seen in Figure 41 below.

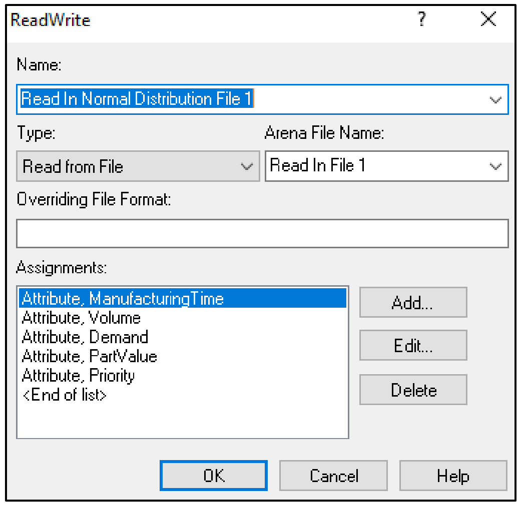


Figure 41. An example Read Write step.

Reception

After a part order (entity) has been created it will arrive at reception. The processing time for receiving part orders follows a triangular distribution with a range of 0.05 to 0.15 hours and a mode of 0.1 hours. Before processing, a worker is requested. If no operator is available at the time of the request the order must wait to be processed. The reception server is shown in Figure 42 below. The reception time is recorded for further calculation of operator cost. The next module "Route To AM" sends the order to the next step of order distribution.

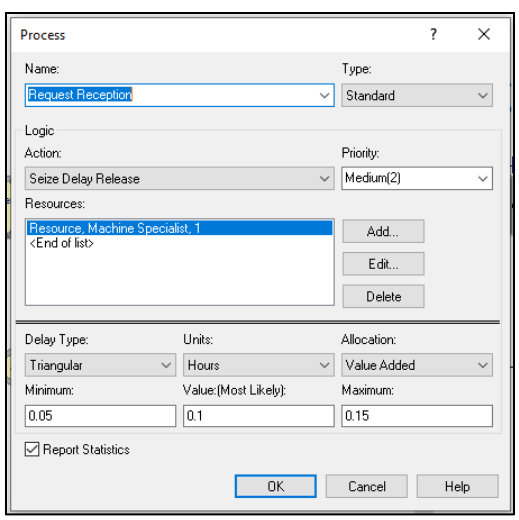


Figure 42. Reception process.

Queueing

Next the entity is routed to the preparation station. This model exhibits the characteristics of a queueing system. Due to the variability of arrivals and service times, a queue is inevitable. At the AM routing station, entities will go through logic steps to decide if they must be queued. Figure 43 below shows the decision steps (diamonds).

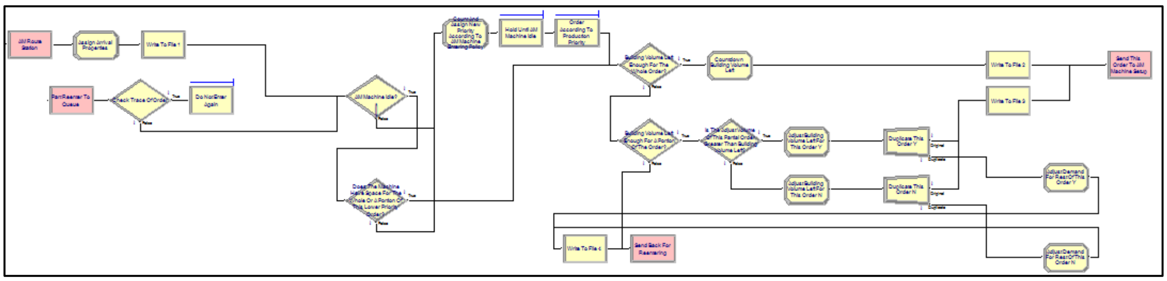


Figure 43. AM preparation station routing logic.

Prioritization Strategy

If the machine is busy, then entities are given new priority levels and placed in a queue. Figure 44 shows how the priority attribute is changed for orders entering the queue. This is a crucial step in the model, allowing the system to make decisions on how to prioritize parts that will reduce late orders.

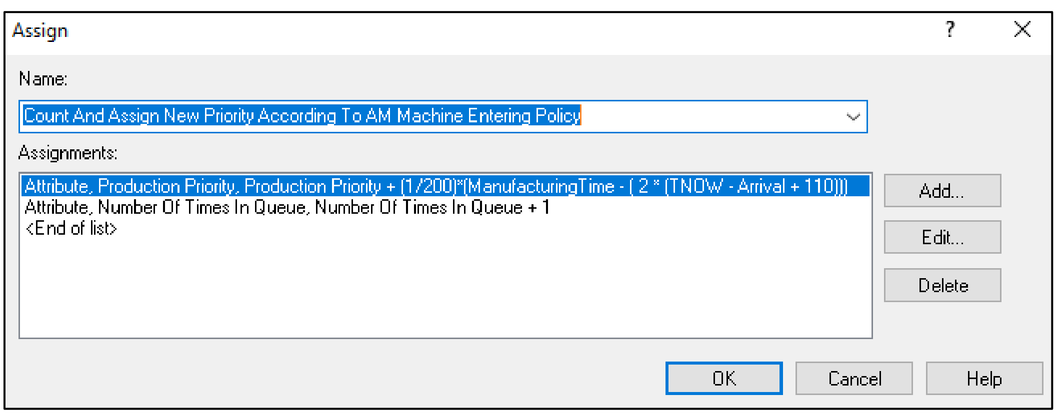


Figure 44. An example assign priority step.

Batching / Order Separation

Once the machine is idle again, part orders will go through another series of decisions to fill the printer. These steps ensure enough space for the orders entering the printer. First, the model will check to see if the building volume left is enough to accommodate the whole order (Figure 45). If the building volume left inside the AM machine has enough to fulfill an entire order, the building volume left inside the AM machine is adjusted by subtracting the product of volume and demand for the order. If the printer's capacity is reached the model will instead attempt to split the order. This smaller order will be routed to the printer, while the remaining parts reenter the queue and wait to be prioritized for the next batch. These steps are shown in more detail in Figure 46 below.

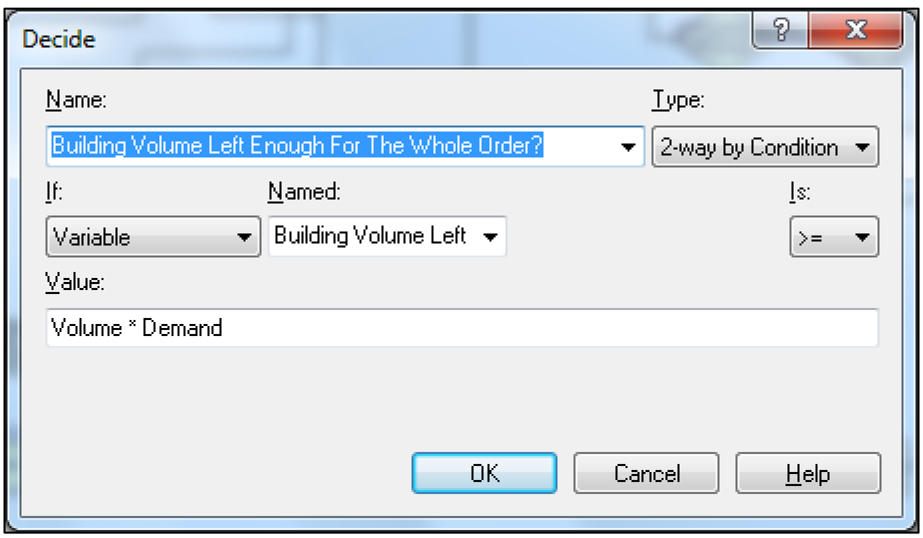


Figure 45. An example building volume left decision step.

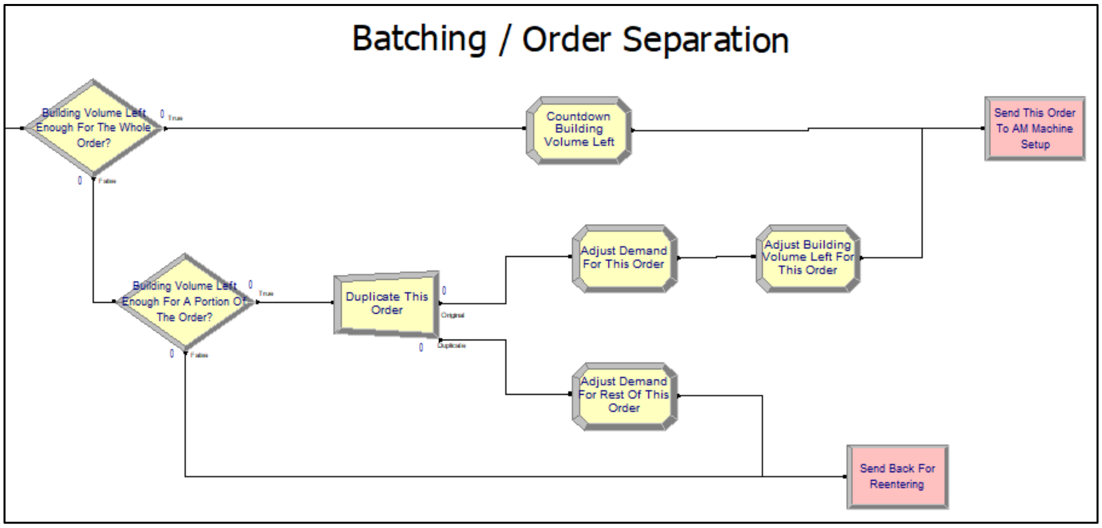


Figure 46. Batching and order separation steps.

AM Setup, Calibration, and Preheating

The next phase in the AM process involves waiting to activate the AM Machine, running calibration and setting up parameters, and preheating the machine. At this point, all orders are combined in order to calculate the value of the order, and the order setup time (Figure 47). The module "Hold To Activate AM Machine Setup", shown in Figure 48, ensures not only the parameters setup and preheating steps are not currently running before sending out a new order for processing but also the queue here is sorted by production priority attribute for each order (lowest production priority attribute value first).

The AM machine calibration and parameters setup is performed by the same operator as in previous reception process. The setup time is recorded for further calculation of operator cost. "AM Machine Preheating" is time (hrs) in which it takes to preheat the machine in order to run the AM process. Prior experience has found that a machine has volume 8,000,000 mm^3 will take approximately one hour to finish preheating. To ensure this ratio is kept depending on the size of the machine, the preheating time is expressed as $\frac{1}{8{,}000{,}000\ mm^3} * AM\ Machine\ Volume$. The baseline AM Machine volume is 9,000,000 mm^3, which would result in a preheating time of 1.125 hrs for a full build. In this study, we define the total order setup time as the summation of each order setup time and each order setup time is proportional to the demand for each order and a triangular expression which takes the order setup time anywhere from 0.008 to 0.024 hrs, with a mode time of 0.016 hrs. After the machine has finished preheating, the actual manufacturing process can begin. These steps are shown in Figure 49 below.

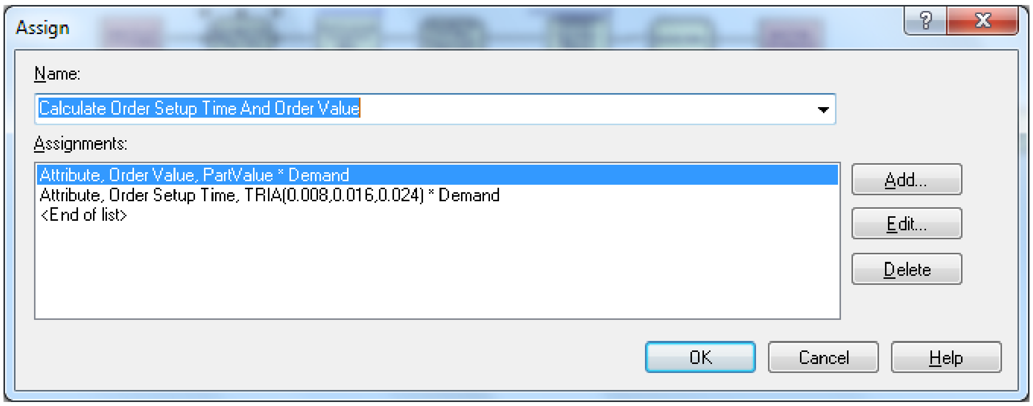


Figure 47. Assign order value and setup step.

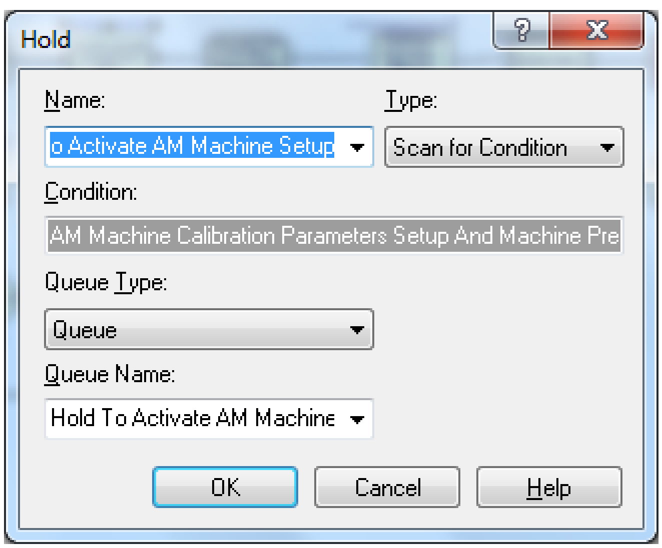


Figure 48. Hold to activate AM machine setup step.

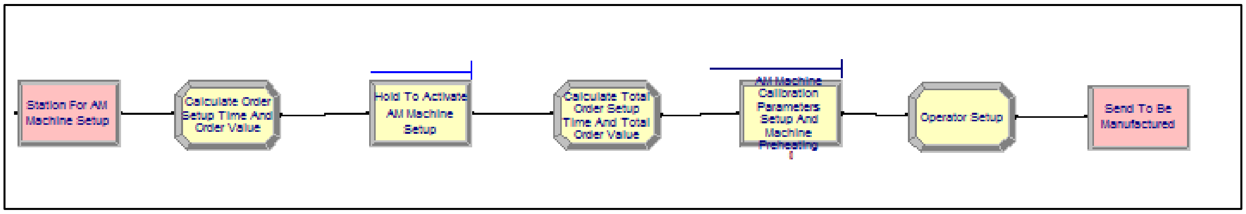


Figure 49. Order setup, calibration, and preheating steps.

Printing and Cool Down

The time it takes to complete the manufacturing process is calculated as the volume of the machine that is filled by the orders divided by the building speed (Figure 50). The less building volume left for AM machine, the longer it will take to finish the manufacturing process. If the machine is at full capacity, the manufacturing process will be significantly longer. After the AM machine has finished its process, a Hold module is added in order to mimic the batch processing of AM machine and a cool down period occurs before the machine is ready for more orders. The time of cool down process follows a normal distribution with a mean of 5 hrs and a standard deviation of 1 hr (Figure 51).

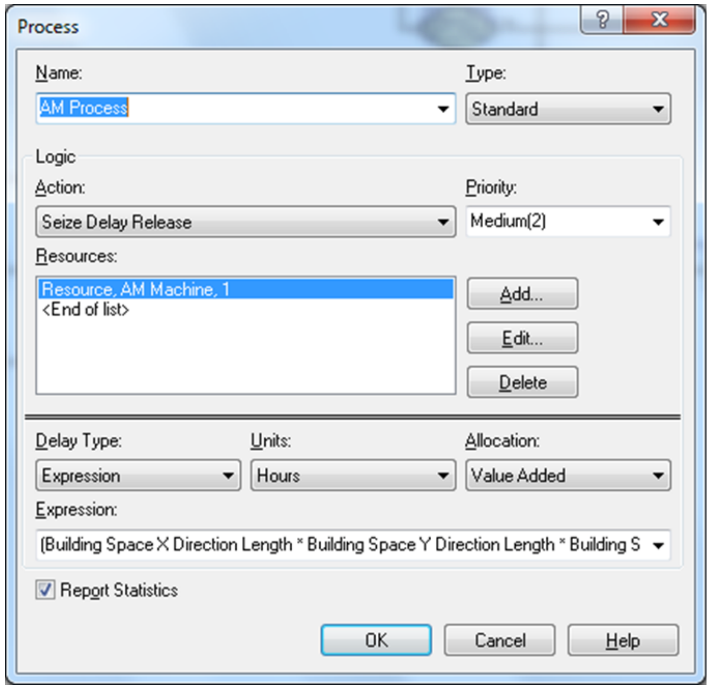


Figure 50. AM Printing step.

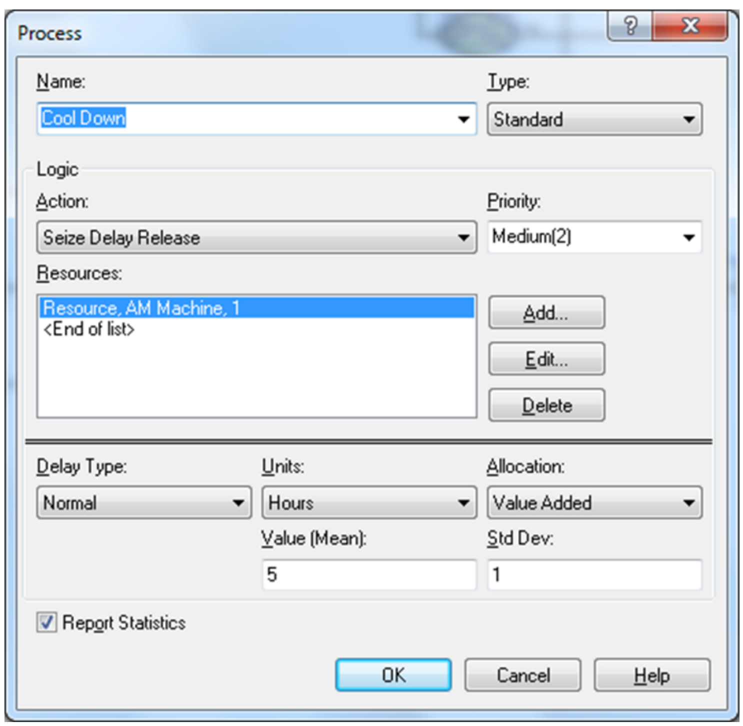


Figure 51. AM cool down step.

Post-Processing

Once the machine has finished cooling down, it is marked as idle. The operator then performs a post-processing quality check on the batch of parts. The post processing process follows a triangular distribution where the minimum time is 0.08 hrs and maximum time is 1.2 hrs with a mode time of 0.5 hrs (Figure 52). Once the post-processing is complete, more orders can be sent to the AM machine for processing and results can be calculated per batch produced. Figure 53 shows the process of AM manufacturing and post-processing.

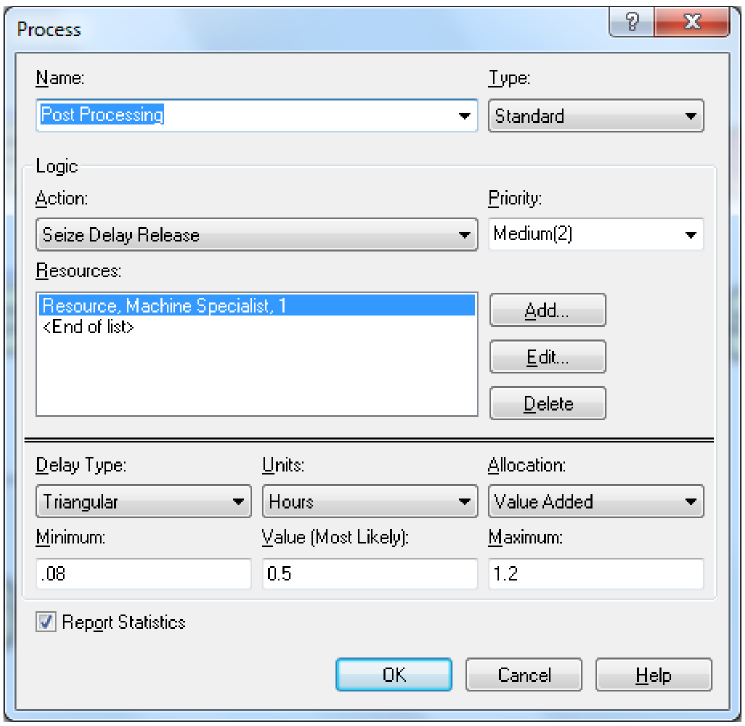


Figure 52. Post-processing step.

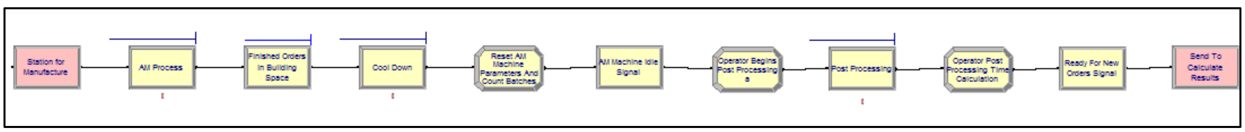


Figure 53. AM printing, cool down, and post-process routing logic.

Output

If the manufacturing time is less than the time it took to fulfill the order from order creation, there will be a late delivery. This results in a penalty for the order (Figure 54). If a portion of order is not delivered on time, the penalty will be applied to only this portion of order but not the entire order. The penalty for late delivery is by user. In this study, we set the value of penalty proportional to the order demand, part value and duration in the AM process. The greater the part value in order, the higher the demand of order and the longer duration the order exists in the AM process, the higher the penalty for the late delivery. Similar as production priority, the formula for calculating the penalty needs additional studies to determine the validity of such treatment in real-world.

The "Consumption And Cost Update" module calculates several results such as total penalty, total operator cost, total maintenance cost, machine depreciation and total AM cost, etc. After the calculations are complete, the order is sent out for delivery and exits the system. The constant values and expression for attributes and variables in this study can be found in next part.

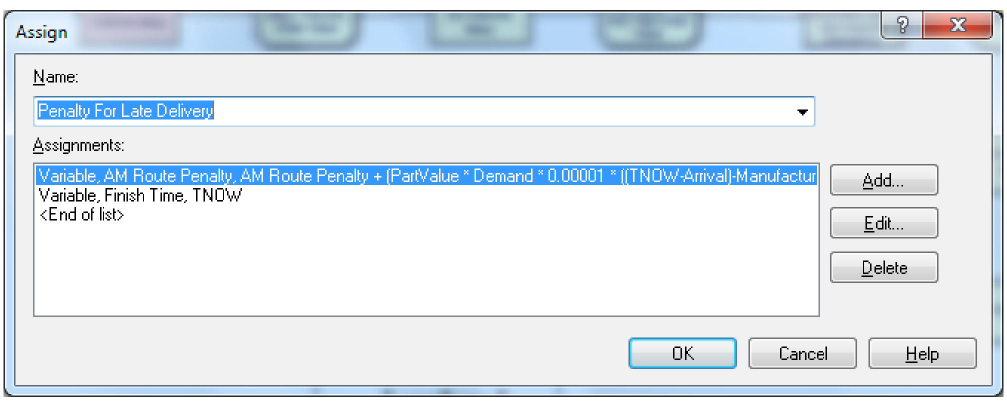


Figure 54. Assign penalty step.

Appendix IV. Excel Warehouse Model

The Excel Warehouse Model, shown in Figure 55, defines 100 SKUs, where 80% are manually classified as regular parts and 20% are categorized as emergency parts. Additionally, part value, inventory holding cost, penalty rate, predicted demand, and the standard deviation of that demand are all initially set, as well as the lookup table of the distribution of penalty days and . The service level is set through a Scenario Manager to test the resulting costs of various service levels. All other sells are calculated as follows.

Part Value ($)	50		Penalty Days					
Inventory Cost ($/unit/yr)	5		R.V.	Days		Total Cost		
Penalty Cost ($/day)	1000		0	2		Service Level	80%	
Predicted Demand of Each SKU (parts/yr)	100		0.25	3				
Normal Inventory	117		0.5	4				
Poisson Inventory	108		0.75	5		Total Penalty	Total Purchase	Total Inventory
								$ 58,500.00
SKUs	Type	Actual Demand	Stockouts	Late RV	Days Late	Penalty Cost	Purchase Cost	Inventory Cost
1	Emergency			0.258304776	3			$ 585.00
2	Emergency			0.879540016	5			$ 585.00

Figure 55. Excel Warehouse Model example trial.

Inventory

The demand distribution for regular part SKUs follows a normal distribution with a mean (μ) of 100 parts/yr and a standard deviation (σ) of 20 parts. To create a function in Excel for calculating normal inventory based on the indicated service levels, the following function is used "=NORM.INV(probability, mean, standard deviation)", where probability is the desired service level, mean is predicted demand, and the standard deviation of that demand.

Emergency part SKUs follow a Poisson distribution with a rate (λ) of 100 parts/yr. Excel, however, does not contain an inverse Poisson function, so a macro was created to achieve this purpose. Credit for the code created by MrExcel MVP who posted the original code on the site, https://www.mrexcel.com/board/threads/reverse-poisson.507508/ on April 15, 2015, see below.

```
' shg 2011, 2012, 2014, 2015-0415
```

```
' For a Poisson process with mean Mean, returns a three-element array:
'   o The smallest integer N such that POISSON(N, Mean, True) >= Prob
'   o The CDF for N-1 (which is < Prob)
'   o The CDF for N (which is >= Prob)

' E.g., POISSON(5, 10, TRUE) returns 0.067085962
' PoissonInv(0.067085962, 10) returns 5

' Returns a descriptive error if Prob <= 0 or Prob >= 1
' If Mean >= 100, then uses a normal approximation

Dim N            As Long     ' number of events
Dim CDF          As Double   ' cumulative distribution function at N
Dim CDFOld       As Double   ' CDF at N-1

' These two variables are used to simplify the probability mass
' function summation CDF = CDF + Exp(-Mean) * Mean ^ N / N!

Dim dExpMean     As Double   ' =Exp(-Mean)
Dim dK           As Double   ' incremental power & factorial

If Prob <= 0 Or Prob >= 1 Then
PoissonInv = "Prob ]0,1["

ElseIf Mean < 100 Then
dExpMean = Exp(-Mean)
dK = 1#
CDF = dExpMean

Do While CDF < Prob - 0.000000000000001
CDFOld = CDF
N = N + 1
```

```
dK = dK * Mean / N
CDF = CDF + dExpMean * dK
Loop

PoissonInv = Array(N, CDFOld, CDF)

Else
' Plan B, for large means; approximate the Poisson as a normal distribution
' http://en.wikipedia.org/wiki/Continuity_correction#Poisson
Dim iInv       As Long

With WorksheetFunction
iInv = .Ceiling(.Norm_Inv(Prob, Mean, Sqr(Mean)) - 0.5, 1)
PoissonInv = Array(iInv, _
.Norm_Dist(iInv - 0.5, Mean, Sqr(Mean), True), _
.Norm_Dist(iInv + 0.5, Mean, Sqr(Mean), True))
End With
End If
End Function
```

The result is the function “=PoissonInv(probability, mean)”, where the probability is the desired service level, and mean is predicted demand. This value is used to calculate the inventory levels for emergency parts.

Stockouts

In order to provide actual demands, a random number generator following the same distributions described for regular and emergency SKUs is used. For normal the following function is used, “=NORM.INV(RAND(), mean, standard deviation)”, where this time the rand function is used to produce a random value for probability between 0 and 1. Likewise the Poisson function using the macro above is, “=PoissonInv(RAND(), mean)” with the same rand function used for probability.

Now the model can calculate stockouts, or the difference between the actual demand and *SS* if the demand is greater than inventory (See **Error! Reference source not found.**). For calculating days late based on the distribution provided a random value (r.v.) between 0 and 1 is used to refer to the days associated with that probability in “Penalty Days” lookup table. This is done using the following function, “VLOOKUP(lookup_table, table_array, col_index_num, TRUE)”, where the lookup_table is the “Penalty Days” table, the table array is the r.v., the col index num is the days column, and the TRUE range lookup is specified to find approximate matches.

Cost Calculations

Using the previously calculated stockout days, a penalty cost is assessed by multiplying days late and the penalty rate (**Error! Reference source not found.**). For purchasing costs the calculated SS for each SKU is multiplied by part value (**Error! Reference source not found.**). Inventory holding is calculated by taking SS and multiplying by the inventory holding (**Error! Reference source not found.**). Finally, a total cost for the scenario is calculated by summing up all these costs (**Error! Reference source not found.**).

Replications

Now the spreadsheet can be replicated in a Monte Carlo Simulation. This model takes the average costs of 100 replications to determine the outputs of various service levels under the penalty settings (Figure 56).

Replications	Penalty Cost	Purchase Cost	Inventory Cost	Total Cost
1			$ 58,500.00	
2			$ 58,500.00	
3			$ 58,500.00	
4			$ 58,500.00	

Based on 100 Replications	
Avg Penalty Cost	
Avg Purchase Cost	
Avg Inventory Cost	$ 58,500.00
Avg Total Cost	

Figure 56. Replication list for the Monte Carlo Simulation.

Scenarios

Finally, to test the results of multiple scenarios of service level Excel's Scenario Manager is used, where the service level cell is changed and the results of the 100 replications is provided in a report. Figure 57 shows the dialog box used to enter scenarios and an example summary report is shown in Figure 58.

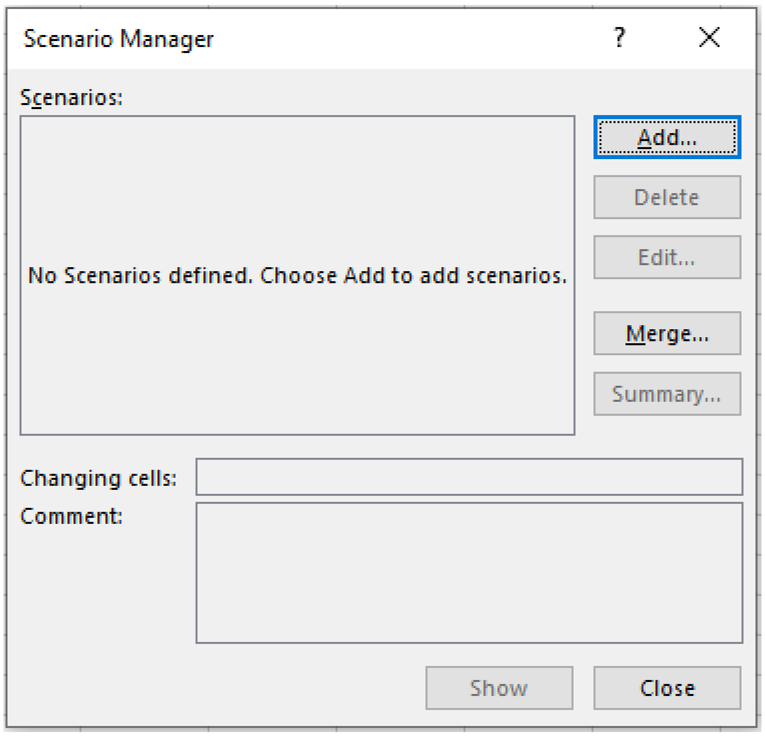


Figure 57. Excel Scenario Manager dialog box.

Scenario Summary	B2			
	Current Values:	50%	55%	60%
Changing Cells:				
J3	80%	50%	55%	60%
Result Cells:				
T2	$ 696,410.00	$ 2,464,860.00	$ 2,095,800.00	$ 1,787,290.00
T3	$ 594,339.50	$ 535,324.00	$ 543,711.50	$ 550,338.00
T4	$ 2,925,000.00	$ 2,500,000.00	$ 2,575,000.00	$ 2,625,000.00
T5	$ 4,234,233.00	$ 5,606,009.50	$ 5,193,999.00	$ 4,970,188.00

Figure 58. Excel Scenario Summary example.