

Economic Feasibility of Adopting Additive Manufacturing for Low-volume Demand

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

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May 2020

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Dedication

I dedicate this work to

*The Republic of Turkey Ministry of National Education that has given me a golden
opportunity to pursue my graduate studies in the USA;*

*My beautiful wife, Pakize Cokyasar, who has sacrificed her youth years for my academic life
by leaving all her family behind and put up with their longings;*

*My little baby son, Alparslan Cokyasar, who has not been aware of what was going on but
has tremendously supported me and my family by bringing joy and happiness.*

Acknowledgments

I would like first and foremost thank to my academic advisor and dissertation committee chair, Dr. Mingzhou Jin, for his mentorship and support throughout my doctoral years. He has created a warm learning environment, been a leader rather than a boss, and supported me to achieve my career goals. Thanks to his teaching and mentoring, I did not only learn how to solve challenging optimization problems but also learned how to be a responsible person for the community and the environment and how to become a successful academician.

I would like to express my gratitude to the committee members, Dr. Sean P. Willems, Dr. Xueping Li, and Dr. James Ostrowski, for their valuable comments and contributions. Without their support, I would not be able to present this publication.

I would like to sincerely thank to my friends, Dr. Franco van Wyk, Huseyin Kose, Jeremy Hale, Dr. Masoud Barah, Dr. Mohammad Ramshani, Mohammad Arsalan Tariq, Rui Li, Wenquan Dong, for their friendship and support throughout my doctoral years. Obtaining a doctoral degree without them would be too boring.

I would also like to thank to Dr. Jeffrey Larson and Dr. Todd Munson of Mathematics and Computer Science Division at Argonne National Laboratory for helping me improve my knowledge in operations research. I also appreciate Dr. Aymeric Rousseau, Dr. Joshua Auld, and Dr. Omer Verbas of Energy Systems Division at Argonne National Laboratory for providing me an opportunity to apply my operations research knowledge on different application areas.

Lastly, I appreciate to the Stack Exchange, Stack Overflow, and Gurobi Google Forum communities for providing platforms to support researchers enhance their knowledge and encourage them to do better.

Abstract

Additive manufacturing (AM - also known as 3-D printing) is in its infancy. Although 3-D printers have been long existed as an alternative manufacturing technology to the conventional manufacturing (casting, molding, etc.), they were being used to prototype products rapidly; hence, the technology was referred to rapid prototyping. Recently, the AM technology has been adopted by enterprises to source low-volume demand products, such as spare parts and obsolete parts. Although the economic benefits of the technology for such products have not been theoretically measured, many enterprises started to adopt the technology with cost reduction expectations. Under this research framework, we partially fill the gap in the literature and propose mathematical models and their sound solution methods to address the economic feasibility of AM adoption for low-volume demand. To this end, we first focus on a single enterprise and propose a mathematical model to determine the optimal amount of investment by partitioning products into two sourcing options, namely, AM option and inventory option. Then, we extend our research to answer more questions for a multi-facility enterprise. In this extended version, we determine the optimal location to deploy AM capacity while still assessing the viability and extent of the investment. Our study contributes to the literature by providing a generally applicable solution approach to mixed integer nonlinear programs involving queueing nonlinearity. On the other hand, we present useful managerial insights to aid practitioners in decision-making about AM adoption.

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Introduction

As a rising manufacturing technology, additive manufacturing (AM), is a production process where objects are built by stacking materials (e.g., metal, plastic, ceramic, etc.) one on the top of another. The technology is also commonly known as three-dimensional (3-D) printing. AM has been available for nearly more than 30 years but mostly used for prototyping. The enhancement in the technology allowed the use of AM for regular production purposes though still limited with size and design of the products. Although some studies investigated the use of AM for mass production, AM was proposed as a low-volume demand supply source in the literature due to its current capabilities (Campbell et al., 2011). Even with industrial AM machines, build times can be up to several days depending on the product's size and geometric complexity.

In practice, many enterprises (e.g., Ford, General Electric, BMW, etc.) have begun using AM to produce fully functional parts and took advantage of the technology's freedom of design, low lead time for the first unit, and lightweight features (Campbell et al., 2018). On the other hand, prices of these machines (for industrial use) starting from approximately \$500,000 cause contemplation for most enterprises in terms of adoption decisions. Many enterprises traditionally met their low-volume product need by outsourcing or producing through conventional manufacturing (CM) methods. They often kept inventories for these products to be responsive and do not miss a profitable opportunity. The AM adoption decision for such enterprises is complicated because the trade-off between two options is not clearly visible. The literature provided some operational decision-making tools for the use of AM instead of CM. But, the actual question: "Should we adopt AM?" has not been quantitatively answered yet. Thus, in this study, we partially filled the gap in the literature by answering the question in a comprehensive and quantitative manner.

In Chapter 1, we focused only on spare parts sourcing through AM. To initiate our research, we developed a nonlinear mathematical model to assign spare parts to three sourcing options, namely AM, inventory, and emergency purchasing. We assessed the economic feasibility of adopting a single AM machine at a facility. We considered the long-term queueing times as a cost driver. The study was published in the Institute of Industrial and Systems Engineering Annual Conference Proceedings and received the Best Track Paper Award from the Logistics and Supply Chain Track.

In Chapter 2, we considered the economic feasibility of AM adoption for a single enterprise operating a single-facility. We created a generic mathematical model to solve the AM adoption problem. By comparing two sourcing options, namely AM and inventory as CM, the model creates an optimal long-term sourcing plan indicating which products should be sourced through AM and which from CM. Furthermore, the model provides the optimal AM capacity (i.e., optimal number of AM machines) to invest in so as to minimize the long-term expected sourcing cost of low-volume demand products. To make the decision, we consider AM machine costs, product costs through both AM and CM, inventory costs, and some opportunistic cost components (e.g., time value of a product).

In Chapter 3, we focused on enterprises operating multiple-facilities and created a mathematical model to solve AM adoption problem with a network optimization approach. With multiple-facilities, another cost dimension is inherently introduced to the problem: the transportation cost. This cost component also brings in increased lead times to source the product. Since AM machines are quite expensive, multi-facility enterprises face with another challenge of AM location selection. In this study, the model determines the optimal location and capacity of AM machine(s). In addition, the long-term network product flow is provided by the model. One of the goals of the study is to investigate whether AM capacity should be deployed centrally or distributed.

The summaries of the methods developed in these chapters to solve the AM adoption problem are provided below.

Chapter 1. We developed a nonlinear model to assign spare parts to sourcing options. Since the problem was difficult to solve numerically, we used an agent-based simulation model to obtain a near-optimal solution.

Chapter 2. We developed a mixed-integer nonlinear programming model incorporating queueing theory nonlinearities to solve the problem. Since build times are long, product orders were assumed to form an imaginary queue to consume the AM capacity. Further, following the literature, we assumed the demand follows a Poisson process, while the build time for each product type is deterministic. We used $M/G/k$ queueing theory to account for the average queue waiting time of product orders. The term k determined the optimal AM machines to invest in. To account for the inventory cost of products sourced through CM, we used $(S-1,S)$ inventory policy with backlogging. We first introduced techniques to linearize the model as much as possible and then provided unique solution approaches, i.e., cut generation, static allocation, and greedy algorithm to solve the problem. In the end, we carried out a sensitivity analysis to aid decision-makers.

Chapter 3. We used network optimization literature to form a stochastic queue median-like model that involves nonlinear terms due to queueing considerations. In this model, the product procurement lead time plays a vital role in the sourcing decision. For an enterprise operating multiple-facilities, the model determines where and how many machine(s) should be located to minimize the overall low-demand network cost. To calculate the long-term average cost of a product sourced through AM produced at any location, we considered the material, transportation, lead time, and machine costs. On the other hand, we use $(S-1,S)$ inventory policy with backlogging to determine the optimal target inventory level at any location for any product and estimated the long-term average cost. The model incorporates these two cost components and makes a sourcing decision.

Chapter 1

An Agent-Based Simulation Model for Optimization of Spare Parts Sourcing with Additive Manufacturing

Disclosure: This chapter is based on a paper published by Cokyasar et al. (2018) in IIE Annual Conference Proceedings.

My contributions to this paper include: (i) the development of the problem and methodology to investigate the problem, (ii) reviewing the appropriate literature, (iii) the identification of study objectives, (iv) collection of data, (v) design and conducting of the numerical experiments, (vi) majority of the writing responsibilities of the manuscript.

Abstract

The demand of spare parts is usually met from stocking and/or through emergency purchasing. In other words, companies either stock these parts in their inventory to respond to failures quickly or order them from spot market when they are needed to avoid inventory holding costs while accepting some additional costs and lead time due to emergency needs. Studies on the trade-offs between these two options have found their place in the literature for a long time. The advantages of additive manufacturing, e.g., cost-effectiveness with low-batch size, shorter lead times, and more flexible design, make it an alternative sourcing option for spare parts. This option can potentially minimize inventory costs resulting from spare parts as well as decrease emergency procurement costs. In this chapter, the cost comparisons of these three options, namely additive manufacturing, stocking, and emergency purchasing were analyzed using an agent-based simulation model. The objective of the study is to determine the optimal sourcing option for each part type that minimizes the overall acquisition cost. The cost of additive manufacturing was calculated with the $M/G/1$ queueing principle to consider the waiting time during the printing process, while $(S-1, S)$ policy was used to model the cost of stocking option.

1.1 Introduction

Additive manufacturing (AM), also known as three-dimensional (3-D) printing, rapid prototyping (RP), layered manufacturing (LM), and solid freeform fabrication (SFF), is a relatively new manufacturing technology that creates objects via a 3-D computer-aided design (CAD) model by sticking materials with a *layer-upon-layer* way (Bandyopadhyay and Bose, 2015). 3-D machines use several different materials including but not limited to polymer, metal, ceramic, superalloy, composite, resin, and paper to form an object. From a user's perspective, 3-D machines can be categorized into two: personal 3-D machines and industrial 3-D machines. The price of the personal machines has tremendously decreased over time; however, industrial level 3-D machines have always been very expensive. Hence, many enterprises that currently use conventional manufacturing (CM) have had hesitations to invest in the new technology. In this chapter, an agent-based simulation model was created based on a non-linear programming model to aid enterprises for the decision of an AM machine purchase to the use of spare parts sourcing. Additionally, the model assists users to optimally source their spare parts via a cost-benefit analysis perspective. Spare parts have been a special focus of this chapter as the current specifications of AM exactly match with their supply chain nature.

Contrary to CM, AM enables manufacturers to produce geometrically complex parts while reducing the waste of the raw material. Geometrical freedom allows custom and more futuristic design (Emelogu et al., 2016). The production via CM often requires a pre-planning to assemble the individually produced parts. So, one should produce the components of a product in such a way that will ease the assembly process, which means the production process requires pre-calculations on how to combine separately molded parts. Contrarily, AM does not require such a pre-planning because it divides an object into layers with the assistance of a 3-D slicing software and eventually prints these layers to form the final product. By producing parts as a concrete, without requiring assembly, AM has a high potential to lower production costs. As another benefit of AM, Pérès and Noyes (2006) mention that it can significantly reduce production lead times. Due to long mold preparation times of CM, AM is often faster for the first unit. AM also has a high potential to decrease

transportation costs by decentralizing the production. Because of all these advantages, AM is a cut out technology for spare parts sourcing.

This chapter is organized as follows. In Section 1.2, the existing literature is presented while distinguishing the work from similar studies. The mathematical model underlying the simulation approach is introduced and adapted methodologies are justified in Section 1.3. In Section 1.4, a case of study with its results is demonstrated to illustrate the use of the model. Finally, the Section 1.5 summarizes how the study has been carried out and future works that are needed to be done to enhance the approach.

1.2 Literature Review

AM has been an attractive research topic for the last few decades. Many research papers have been published to address both the capabilities and the deficiencies of the layer-by-layer manufacturing process. Although additive manufacturing is still in its development phase and may not be readily a one-to-one substitution for the CM due to its inconsistent quality issues (Cheng et al., 2018), copyright protection, and high machinery acquisition costs, it is widely discussed in many articles that it can potentially decrease spare part sourcing costs (Thomas and Gilbert, 2014). Recently, many enterprises use dual-sourcing to obtain their spare parts. Song and Zipkin (2009) define a dual-sourcing inventory as a system in which one supplier is faster but more expensive, while the other is slower but cheaper. For a spare parts inventory management system, parts can be purchased from the slower supplier to stock in the inventory and the faster supplier can be used in a stock-out case as an emergency supplier.

There are many papers that were subjected to dual-sourcing in the literature. The first paper mentioning the use of dual-sourcing with the single period case was authored by Barankin (1961). Daniel (1963) extended the study by proposing the multiple periods version of the same study. Ramasesh et al. (1991) compared single-sourcing with dual-sourcing and stated that the dual-sourcing can be cost effective especially for products that have low ordering cost and high uncertain lead times. Allon and Van Mieghem (2010) created a model to share the demand to a close source and an offshore source with a tailored

base-surge policy. Xin and Goldberg (2017) provided asymptotic optimality conditions of a tailored base-surge policy.

With the introduction of the *third-dimension* into the dual-sourcing problem, the new problem can be studied as *triple-sourcing*. Even though Song and Zipkin (2009) provided a multiple sources model for the problem, the use of AM brings in different considerations and thus disables the direct use of their model. The existing literature considers a linear structure for the problem, however, printing spare parts with a queueing principle causes the problem to be non-linear. Therefore, a different approach to solve the problem is required. A few working papers address the problem from different point of views. Song and Zhang (2019) presented a dual-sourcing model by providing AM and inventory options to the spare parts sourcing problem. Their paper approaches the problem in a similar way as in this paper. However, they do not consider emergency purchasing as an option and create their formulations based on two options. Knofius et al. (2017) compared AM and CM for spare parts sourcing. Different from Song and Zhang (2019), they considered that the sourcing option can affect the lifespan of spare parts. For a given type of spare part, they used Markov decision process combined with linear programming to optimize the sourcing policy. Dong et al. (2017) carried out a similar study that compares AM and CM. They concluded that AM does not only increase the profitability but gives an opportunity to an enterprise to have a higher product variation. Different than the literature, this paper aims to solve the problem as a triple-sourcing problem in a dedicated way.

1.3 Problem Description

This section is devoted to explaining the mathematical background of the simulation model. As mentioned earlier, this paper aims to create and solve an assignment problem that will determine the optimal sourcing option for each spare part type of a given set, where a part type refers to the geometric shape of a part, e.g., a bleed air valve and a pressure switch of an F-16 are two different part types. In the rest of the paper the terms parts and part types are used interchangeably. To optimally select the sourcing option for a given set of parts, cost functions for three options, namely additive manufacturing (A), inventory (I),

and spot market emergency purchasing (P) were created. Before illustrating the notations, j is defined as the index of the set of spare parts, where $j \in J$ and the set J^A represents the set of spare parts decided to be sourced through the option A as a result of the optimization. Parameters and variables used to form the cost functions and the assignment model are provided in Table 1.1.

Table 1.1: Parameters and continuous variables.

Parameter	Meaning
f	amortized worth of fixed cost to obtain and maintain a 3-D machine.
C_j^A	unit production cost of part type j through option A .
C_j^I	unit purchasing cost of part type j through option I .
C_j^P	unit purchasing cost of part type j through option P .
h_j	unit inventory holding cost of part type j per unit time.
d_j	unit downtime cost of part type j per unit time.
τ_j^I	acquisition lead time of part j through I .
τ_j^P	acquisition lead time of part j through P .
λ_j	failure rate of part j per unit time.
μ_j	service rate of part j per unit time.
S_j^*	optimal target inventory level for part j .
B_j	expected number of backorders for part j .
Continuous Variable	Meaning
W	average time a spare part spends in the queue of 3-D machine prior to printing.
V	second moment of the service time for parts in J^A , where $V = \lambda^{-1} \sum_{j \in J^A} \frac{\lambda_j}{\mu_j^2}$.
λ	aggregate failure rate for parts in J^A , where $\lambda = \sum_{j \in J^A} \lambda_j$.
μ	aggregate service rate for parts in J^A , where $\mu = \lambda \left(\sum_{j \in J^A} \frac{\lambda_j}{\mu_j} \right)^{-1}$.
ρ	aggregate traffic intensity, where $\rho = \frac{\lambda}{\mu}$.

Based on these notations, the cost function TC_j^A , which is the first component of the assignment model, for the option A was created as follows.

$$TC_j^A = \lambda_j \left[C_j^A + d_j \left(\frac{1}{\mu_j} + W \right) \right], \quad (1.1)$$

where,

$$W = \frac{\lambda V}{2(1 - \rho)}. \quad (1.2)$$

Equation (1.1) calculates the production cost and the downtime cost of a part considering the average waiting time in the queue to be served in (1.2). It should be noted that (1.2) is a performance measurement of the $M/G/1$ queueing principle. Based on this principle, the order arrivals of spare parts for each part type j follow Poisson distribution with the rate of λ_j and the service times are deterministic for each part type j with a value of μ_j , i.e., each part needs a constant time to be printed and variations are neglected. By using the queueing theory, the cost function can accurately calculate the cost of using the option A for a given part type set of J and a specific planning horizon, say one year. The derivation procedure of W and a lot more about queueing theory can be found in Gautam (2012). The second component of the model, the cost function TC_j^I , was formed by using $(S-1, S)$ policy as follows.

$$TC_j^I = C_j^I \lambda_j + h_j (S_j^* - \lambda_j \tau_j^I) + B_j (h_j + d_j), \quad (1.3)$$

where

$$B_j = \lambda_j \tau_j^I P(S_j^* - 1) - S_j^* P(S_j^*), \quad (1.4)$$

and the probability of having n number of demands during the lead time is

$$P(n) = 1 - \sum_{k=0}^{n-1} \frac{(\lambda_j \tau_j^I)^k}{k!} e^{-\lambda_j \tau_j^I}. \quad (1.5)$$

Furthermore, the optimal target inventory level, S_j^* is

$$S_j^* = \min_S \left\{ \sum_{k=0}^S \frac{(\lambda_j \tau_j^I)^k}{k!} e^{-\lambda_j \tau_j^I} \geq \frac{d_j}{d_j + h_j} \right\}. \quad (1.6)$$

The first summation in (1.3) represents the purchasing cost of the parts, while the second and third account for the average inventory holding and backorder costs, respectively. Based on $(S-1, S)$ inventory policy, a product is replenished as soon as it is demanded. This policy is suitable for spare parts as they are not frequently consumed products. Many enterprises usually stock a few spare of each type. The details of the inventory policy can be found in Hadley and Whitin (1963) as a special case of (Q, r) policy with $Q = 1$. Lastly, the cost

function TC_j^P was created to calculate the annual cost of option P .

$$TC_j^P = \lambda_j (C_j^P + d_j \tau_j^P). \quad (1.7)$$

For the option P , there is not much to consider. Basically, (1.7) calculates the purchasing and the downtime cost, the cost owing to the elapsed time from the demand occurrence to the replacement moment of the spare part. In addition to the variables, W , V , λ , μ , and ρ denoted previously, the following binary variables in Table 1.2 are created to assign part types to sourcing options.

Table 1.2: Binary variables.

Binary Variable	Meaning
y_j^A	$\begin{cases} 1, & \text{if part } j \text{ is sourced through option } A, \\ 0, & \text{otherwise.} \end{cases}$
y_j^I	$\begin{cases} 1, & \text{if part } j \text{ is sourced through option } I, \\ 0, & \text{otherwise.} \end{cases}$
y_j^P	$\begin{cases} 1, & \text{if part } j \text{ is sourced through option } P, \\ 0, & \text{otherwise.} \end{cases}$
x	$\begin{cases} 1, & \text{if a 3-D machine is purchased,} \\ 0, & \text{otherwise.} \end{cases}$

After creating all the necessary functions and defining the variables, the objective function of the assignment model was created as provided below.

$$\min \quad fx + \sum_{j \in J} (TC_j^A y_j^A + TC_j^I y_j^I + TC_j^P y_j^P) \quad (1.8)$$

The first part of (1.8) represents the investment cost of the 3-D machine. The cost of each option is considered in the summation, thus, assigning one part type to one of the options will increase the overall objective function value. As this is a minimization problem, part types will be assigned to the least costly option all the time. To ensure yielding optimal assignments and to create boundaries for the feasible region, the objective function is subjected to the

following constraints and non-negativity conditions.

$$y_j^A + y_j^I + y_j^P = 1 \quad \forall j \in J \quad (1.9)$$

$$\sum_{j \in J} y_j^A \leq |J|x \quad (1.10)$$

$$\sum_{j \in J} \lambda_j y_j^A = \lambda \quad (1.11)$$

$$\sum_{j \in J} \frac{\lambda_j}{\mu_j} y_j^A = \rho \quad (1.12)$$

$$\sum_{j \in J} \frac{\lambda_j}{\mu_j^2} y_j^A = \theta \quad (1.13)$$

$$\rho \leq 0.99 \quad (1.14)$$

$$x, y_j^A, y_j^I, y_j^P \in \{0, 1\}, W, \lambda, \rho, \theta \geq 0$$

Constraint set (1.9) ensures to assign each part type to exactly one sourcing option. Constraint (1.10) makes sure to calculate the cost of the 3-D machine if there is at least one part type assigned to the option A . Here, $|J|$ denotes the cardinality of the set J . The aggregate demand, traffic density, and θ (nominator of W equation) are calculated by (1.11), (1.12), and (1.13) respectively. Constraint (1.14) assures that the traffic density, $\rho < 1$. This constraint is necessary for the queue to meet the steady state condition. The average waiting time depends on the part types selected to be sourced through the option A which is not known before solving the problem, thus, the model is nonlinear and difficult to solve. For this reason, a simulation modeling approach, which is presented in the next section, was adopted to solve the problem in a reasonable time frame.

1.4 Simulation Model and Preliminary Results

An agent-based simulation model was developed to obtain the optimal solution in a reasonable time frame. The model was built in the commercial software, Anylogic that uses JAVA programming language. Three agent types were created to simulate the sourcing

process. The flow logic of the model can be observed in Figure 1.1. The functioning state represents the system with machines working flawlessly. Once a failure occurs, the order of the spare part goes to one of the three sourcing options based on the cost-effectiveness of the option for that specific part, which is optimized using the model. If the AM option is selected, a new part would be produced with the 3-D machine and replace the failed one. If the inventory option is selected, the replacement procedure is performed unless there is a stock-out. In the stock-out case, the replenishment lead time is accounted as a loss so that the options can be compared fairly. The outsourcing option works quite straightforward as it is only composed of the emergency purchase of the needed part.

Due to the constraint limits of the software, six part types were considered in the hypothetical case. In this small case, annualized service rate (μ) is considered to be uniformly distributed among part types between 91 and 876 parts, which converts to 10 – 96.3 hours of printing. Due to stochastic demand, arrival rates (λ), annual spare part demands, are generated with uniform distribution ranging as shown in Table 1.3. Four different scenarios for the demand were investigated to better understand the properties of the problem. Other parameters are generated in such a way that large-size products require more time and more resources to be printed. To evaluate the efficiency of the model over time, the simulation model was run for three different time periods – 10, 20, and 30 years. The assignment solutions for different demand scenarios and different planning horizons are provided in Table 1.3.

Table 1.3: Results with $\mu_j = U(91, 876)$ and different scenarios for λ_j .

Part Type #	Planning Horizon (Years)											
	10 $\lambda_j = U(0.01, 0.1)$	20	30	10 $\lambda_j = U(0.09, 0.1)$	20	30	10 $\lambda_j = U(0.1, 0.5)$	20	30	10 $\lambda_j = U(0.5, 0.9)$	20	30
1	I	I	A	I	A	I	A	I	A	A	I	A
2	I	I	A	I	I	A	I	I	A	A	A	A
3	I	I	I	I	A	A	A	A	I	I	I	I
4	I	I	I	I	A	A	I	A	I	I	A	I
5	I	P	P	I	I	P	A	I	P	P	P	A
6	I	A	A	I	I	A	A	I	A	I	A	I

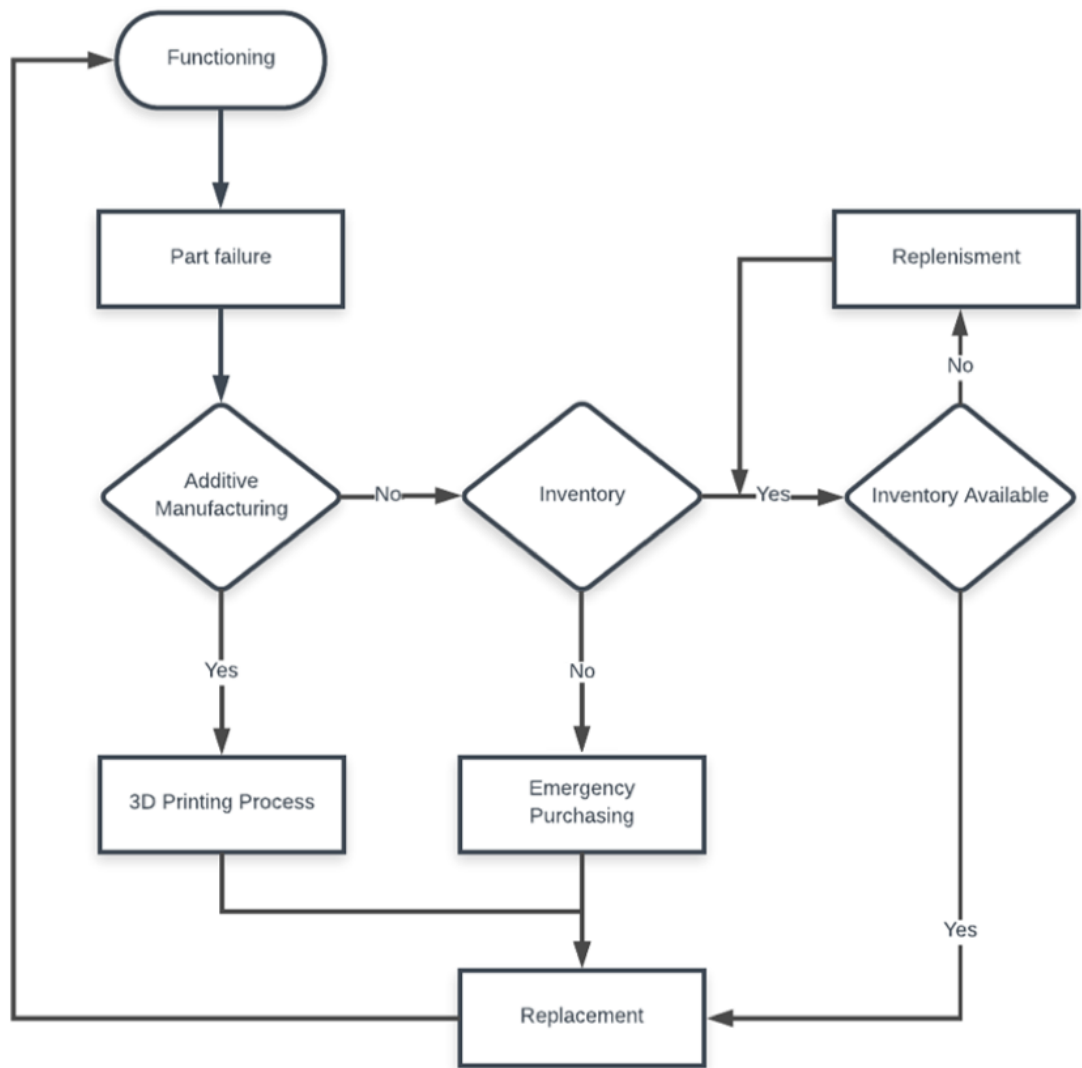


Figure 1.1: Simulation model flow logic.

As seen in Table 1.3, the demand rate distribution significantly affects the sourcing decision. When arrival rate was relatively smaller, part types were assigned mainly to the inventory sourcing option in short time periods. The underlying reason for this assignment is that the expensive initial 3-D machine investment may not be compensated in such a short time period and the emergency purchases were considered to be costlier. Once the decision is made based on a longer time period, it can be seen that some part types were assigned to the AM option. On the other hand, the high arrival rate yields AM and emergency purchasing as alternative options even for the short time periods because the expenses made for spare parts outweigh the initial investment cost.

1.5 Summary, Conclusion, and Future Work

In this chapter, a new approach to the sourcing of spare parts was presented. A non-linear assignment model that aids to the decision making for the spare parts sourcing was created and solved using optimization via simulation. This study is only the first step for investigating the possible advancements of the new manufacturing technology in the spare parts industry. The number of different spare part types are usually much higher than the given case for large size enterprises. Hence, the provided case in regard to the problem size is not satisfactory, yet, it elucidates the potential of the model to deal with the problem.

This chapter studies the problem within the minimal case, which involves only one 3-D machine, one enterprise, and one location. The scope of the study is to create more robust mathematical models and solution procedures to deal with the same problem for 1) larger size problems, 2) multiple printers, 3) multiple enterprises, 4) multiple locations. Additionally, this study considered a long-term decision-making plan, where the decisions are made on an annual basis. In reality, a dynamic assignment with a Markovian modeling approach can be more helpful for enterprises to make the decision instantaneously. Therefore, more comprehensive methodologies are planned to be developed to fully capture the AM revolution on spare parts industry.

Chapter 2

Strategic Adoption Decision of Additive Manufacturing for Low-volume Demand

Disclosure: This chapter is based on a paper submitted/will be submitted by Cokyasar et al. (2020) to Management Science.

My contributions to this paper include: (i) the development of the problem and methodology to investigate the problem, (ii) reviewing the appropriate literature, (iii) the identification of study objectives, (iv) collection of data, (v) design and conducting of the numerical experiments, (vi) majority of the writing responsibilities of the manuscript.

Abstract

Problem definition: Considering the proliferation of the additive manufacturing (AM) technology, we study the economic feasibility of adopting AM for low-volume demand products. *Academic/practical relevance:* The industrial level AM machines are quite expensive causing small and medium enterprises contemplate about its adoption. Although some studies answered which products are economically better to occupy the AM capacity, they did not answer some key questions (e.g., how many AM machines are optimal) and did not provide exact solution methods. We use the procurement lead time of a product as a cost driver and create cost functions to estimate the long-term average costs of using AM and conventional manufacturing (CM) with stocking. Since AM technology has a limited capacity to build all products, we select the most economically suitable ones and determine the optimal number of AM machines to purchase. *Methodology:* For modeling purposes, we use $M/G/k$ queueing theory due to the shared capacity in AM use and $(S-1, S)$ inventory policy with backorders for the conventional stocking because of the low and stochastic features of the demand. In this light, we create a mixed-integer nonlinear program and present three solution algorithms one of which promises the global optimum. The solution method we derive does not only allow us to find the globally optimal solution but also solves similar queueing nonlinearity involved optimization problems. *Managerial implications:* To aid enterprises with strategic decision of AM adoption, our study answers: 1) How many AM machines would be optimal? and 2) Which products are suitable for AM? A detailed analysis is presented while distinguishing the focus areas of AM end-users and original equipment manufacturers.

2.1 Introduction

It is widely known that *additive manufacturing* (AM), also known as three-dimensional (3-D) printing, has a considerable potential to reduce energy and raw material consumption, inventory cost, product weight, production lead time, and transportation cost. Allen (2006) stated that AM brings in 30% energy savings for a typical aerospace alloy. Campbell et al. (2011) mentioned the extensive amount of spare parts inventory that the U.S. military keeps on ships, foreign bases, and battle front and pointed AM as a viable solution to reduce this amount. SpaceX produced main oxidizer valves via AM for their Falcon 9 rockets in less than two days, which used to be produced in months with conventional casting (Wohlers and Caffrey, 2015). NASA published a summary report on results from the 3-D printing in zero gravity that indicates how AM can be adopted in isolated work environments (Prater et al., 2016). Many enterprises, such as Adidas, Airbus, Boeing, DIY Rockets, Ford, General Electric, Nike, Stryker, and Toyota adopted AM technology to produce parts more efficiently (Campbell et al., 2018). Only in a single facility, General Electric and Ford house more than 75 and 23 AM machines, respectively (Kellner and Bovalino, 2019, Iftikhar, 2018). Wohlers Report estimated that 1,768 metal AM machines were sold in 2017 (Campbell et al., 2018). These progresses support the validity of the motto: “AM technology revolutionizes the industry” (The Economist, 2012). Furthermore, high number of AM capacity deployment examples justify the reason why this study was devoted to strategic adoption decision of these machines. Briefly, optimizing the AM machine purchase/sale quantity is quite useful for end-users and original equipment manufacturers (OEMs) of AM.

The time spent on the procurement of low-volume demand is often critical owing to the margin loss either during the idle time of a halted machine or an impatient customer. The AM technology is in its infancy and industrial level AM machines are still priced starting with six-digit. Since one cannot afford infinite amount of AM machines, the impact of build time on the overall adoption cost requires an attention while making the adoption decision. Low-volume, stochastic, and non-critical products are the most suitable candidates that can maximize the advantage taken out of AM (Huang et al., 2013). Contrarily, many low-volume demand are often critical and require high responsiveness (i.e., short procurement lead time).

Therefore, determining products that are economically the most viable to be produced by AM in a strategic decision-making layout is vital.

Traditionally, low-volume demand products are often stocked due to their criticality, if either their design or themselves are available in the market. In the exiguity of a supply base (e.g., obsolete products), AM can be inevitable to adopt. In this study, we consider only the products that are available in the market and can be readily outsourced from a third-party supplier because we desire to have two economically competitive sourcing options for products. We compare the long-term average procurement cost of a given low-volume demand product with its AM production cost and assign it to either AM or the conventional inventory sourcing option, which will be henceforth referred to as *AM option* and *inventory option*, respectively. We use the term “inventory” because we assume products outsourced will be inventoried (if necessary) to quickly respond the demand.

To make the long-term AM adoption decision, assign products to sourcing options, and determine the optimal number of AM machines to purchase, we created a mixed-integer nonlinear program (MINLP) and tailored robust solution techniques. Our contribution to the literature is twofold. First, we extended the model — though our methodological approaches are different — in Song and Zhang (2019) by optimizing the number of AM machines and provided a quantitative interpretation to the recent AM adoption trends. Second and more importantly, we developed an exact solution method to find the globally optimal solution. Our method can be applied to similar MINLPs involving convex queueing nonlinearity with assignment dependency (e.g., Cokyasar et al., 2019, Mak et al., 2013, Xie et al., 2018).

The rest of this paper is organized as follows. We thoroughly review the literature and discuss the similarities and differences in Section 2.2. We provide the problem description and present the MINLP in Section 2.3. In Section 2.4, we share our findings about the model and present three solution approaches based on unique properties. We conduct numerical experiments and present our remarks in Section 2.5. After mentioning our data layout, we show performance comparisons for our solution methods and emphasize the important performance metrics a decision-maker should focus on. Our comparison chart provides the solution gap and computational time based on 1,555 problem instances. Briefly, we note that one should solve the problem using the exact solution algorithm if the solution quality is

the concern. Otherwise, the heuristic solutions can be adopted to reduce the computational burden with a cost of slight deviation from the global optimality. In Section 2.5, we also conduct experiments to provide managerial insights. We can briefly list our findings as follows.

- Our model brings in approximately 26-34% savings for low-volume product sourcing.
- Number of AM machines has an undeniable impact on AM production lead times and hence the long-term sourcing costs.
- Low AM adoption rates of small-and-medium businesses are commonly attributed to high AM machine prices. However, rather than high machine prices, our analysis shows that the AM production quality (i.e., the lifetime of additively manufactured products) is the most influential factor for the long-term sourcing costs.
- We identify AM material (e.g., metal powder) and machine costs as the key determinants for OEMs to increase machine sales to their existing customers.
- Our experiments illustrate that AM production quality is not a high priority concern of OEMs because improving the quality too much will indeed reduce the sales to existing customers. This finding supports the reality as the technology could not have totally replaced the CM in the last 30 years.

Finally, we conclude the study and emphasize extension possibilities in Section 2.6.

2.2 Literature Review

Hax and Meal (1975) explained why planning and scheduling should be made hierarchically. AM adoption decision is as complicated as the problem they described. Thus, based on their framework, this study embraces a strategic decision-making approach. Due to considering high cost machine adoption, this paper is similar to Fine and Freund (1990). They created a two-stage stochastic program to first, make an investment decision in manufacturing capacity and second, make production decisions. In our model, however, we incorporated both decisions in a single-stage modeling framework.

Most related studies focused on spare parts which is a sub-group of the low-volume demand products. Westerweel et al. (2018) focused on printing spare parts at remote locations, especially for army use purposes. They assumed fixed time intervals to replenishing the spares and considered the poor quality of parts manufactured with AM. They proposed a temporary use of additively manufactured parts to mitigate quality and intellectual property concerns. As they collaborated with Royal Netherlands Army (RNLA) and RNLA used an AM machine with an approximate value of €30,000, they focused only on general-purpose AM machines. Adversely, in this study, the quality and the price of the AM technology plays a key role in the decision-making through waiting time consideration. Usually, machine prices are highly correlated with their speed and yield quality. The model presented in this study capture these aspects of AM.

One of the ideologically most related studies was presented by Song and Zhang (2019). Similar to our model, they also determined the optimal partition of products to be sourced through the given two options: AM and inventory. Unlike ours, they focused on a single AM machine purchase decision. They used heuristics to solve the problem. In our study, although our problem settings are similar, we used slightly different modeling approaches. As the most distinguishing feature, we provided an exact solution algorithm to solve the problem in addition to our heuristic approaches. Our model setting enabled us to provide insights on the importance of the number of AM machines to purchase.

Another study for a similar problem was carried out by Knofius et al. (2016) with a completely different approach. Instead of deciding on the sourcing option for each product, they used a top-down ranking method to identify the spare parts that are characteristically suitable for AM. However, they did not cover the effect of downtime costs occurring due to long AM build times. In another article, Knofius et al. (2017) presented a dual-sourcing model for spare parts, while considering CM and AM as sourcing options. They accounted for the failure behaviors of identical parts, one produced with CM and the other with AM, i.e., the sourcing choice can affect the lifetime of the product. For a single type of spare part, they found the optimal sourcing policy using Markov Decision Process with linear programming. Their concern on the final product quality shed light on the formulation process of this study, hence, we penalized AM option by multiplying the demand with a

weight parameter. Similar to their study, Dong et al. (2017) compared the use of AM and CM on a firm that used CM and had a potential to switch to AM and assessed the profit of the firm under three different scenarios. They concluded that AM technology does not only increase profitability but also allows the firm to have higher product variety.

Sirichakwal and Conner (2016) used $(S-1, S)$ inventory policy to quantify the effect of AM on the management of spare parts inventory. They presented the effect of reduced holding cost and shorter lead time on inventory cost. The main difference of these studies from ours is the lack of downtime cost consideration. To sum up with, this paper contributes to the literature by presenting an optimization model to quantify the economic measures of acquiring AM technology for low-volume demand. We also built sound solution approaches that can benefit researchers dealing with queueing nonlinearity in linear programs.

2.3 Methodological Approach and the Model

We consider an enterprise willing to take advantage of the emerging AM technology and hesitant to make investment in the AM machines as they are quite expensive. Assume, the enterprise occasionally needs a set of low-volume demand products $\mathcal{P}$ and their stochastic demand rate, λ_p , follows a Poisson distribution. Unavailability of $p \in \mathcal{P}$ incurs a downtime cost of d_p per time unit. The enterprise has two options to source product p , namely, AM option and inventory option. We assume, each product $p \in \mathcal{P}$ can be supplied through a single source during the planning horizon. The problem is to optimally partition the set $\mathcal{P}$ by assigning products to $\mathcal{A}$ and $\mathcal{I}$ such that the long-term average sourcing and AM machine investment costs are minimized. The sets $\mathcal{A}$ and $\mathcal{I}$ includes products sourced through AM and inventory options, respectively. We use the set notations, $\mathcal{A}^*$ and $\mathcal{I}^*$, to denote the optimal set partitions and differentiate them from a sub-optimal/feasible solution denoted by $\mathcal{A}$ and $\mathcal{I}$. We note that our system design is similar to the *hybrid system* described in Song and Zhang (2019). Since inventory option costs are more stable and straightforward, we begin with providing the dynamics for this option.

2.3.1 Inventory Option Costs

We assume products sourced through inventory option are available in the market and they can be purchased from a third-party supplier ahead of the demand occurrence. In case of a stock-out, the order is backlogged. Within this option, the enterprise does not have to keep any unit unless it is economically better to keep. We use the $(S-1, S)$ inventory policy with backlogging to calculate the long-term average sourcing cost of product $p \in \mathcal{P}$. This inventory policy is widely used for low-volume demand (e.g., Feeney and Sherbrooke, 1966, Muckstadt and Thomas, 1980). Hadley and Whitin (1963) studied the model comprehensively and provided a closed-form solution to compute the long-term average system costs under this policy.

Following Hadley and Whitin (1963), we introduce C_p^I , τ_p^I , and h_p that represent the unit purchasing cost, procurement lead time, and holding cost of $p \in \mathcal{P}$ for inventory option, respectively. The function $I_p(S_p^*, B_p)$, where

$$I_p(S_p^*, B_p) = C_p^I \lambda_p + h_p (S_p^* - \lambda_p \tau_p^I) + B_p (h_p + d_p), \quad (2.1)$$

accounts for the long-term average inventory option costs (including purchasing, inventory holding, and backlogging) for a given product $p \in \mathcal{I}$ and a planning horizon. The inputs, S_p^* and B_p , denote the optimal target inventory level and the expected number of backlogging during the procurement lead time, respectively. Hadley and Whitin (1963, Chapter 4, pp. 204-212) provide the following equations to calculate these constants. In (2.2), $prob(n_p, \lambda_p \tau_p^I)$ is the probability mass function of the Poisson distribution. The optimal target inventory level, S_p^* , is the largest S_p (inventory level for $p \in \mathcal{I}$) in (2.3).

$$B_p = \sum_{n_p=S_p^*}^{\infty} (n_p - S_p^*) prob(n_p, \lambda_p \tau_p^I). \quad (2.2)$$

$$S_p^* = \max_{S_p} \left\{ \sum_{n_p=S_p}^{\infty} \frac{(\lambda_p \tau_p^I)^{n_p}}{n_p!} e^{-\lambda_p \tau_p^I} > \frac{d_p}{d_p + h_p} \right\}. \quad (2.3)$$

In some cases (e.g., demand is too low and/or procurement lead time is too short), $S_p^* = 0$. For such cases, we still keep inventory option as a sourcing channel for $p \in \mathcal{P}$ but assume the product is purchased from the third-party supplier on-demand rather than being kept in the inventory. Hadley and Whitin (1963) also provide the system stability condition $\lambda_p \tau_p^I < 1$ for the policy to properly function.

2.3.2 Additive Manufacturing Option Costs

In AM option, the procurement of the products are made on-demand. Once the demand for a unit of $p \in \mathcal{A}$ arrives, the AM machine(s) build (3-D print) the order. To simplify the problem, we assume that an AM machine can build only one unit at a time. The build time, $1/\mu_p$, is constant/deterministic and it generally depends on the product volume (dimensions). Since, the deterministic build time for each $p \in \mathcal{A}$ corresponds to a general service rate distribution for the whole system, we use the multi-class $M/G/k$ queueing theory with non-homogeneous demand and a first come first served rule to approximate the long-term average AM sourcing cost of $p \in \mathcal{A}$. The parameter k in $M/G/k$ denotes the number of servers (AM machines).

An exact closed form formulation to calculate the average queue waiting time in $M/G/k$ queues unfortunately does not exist. On the other hand, a vast amount of approximations to calculate this performance metric reside in the literature (e.g., Boxma et al., 1979, Crommelin, 1934, Cosmetatos, 1976). Most of these formulations consider $M/M/k$ and $M/D/k$ queues to derive an approximation for $M/G/k$. Kimura (1994) and Bolch et al. (2006) summarize the work done regarding $M/G/k$ queues. We adopted the formulations in Bolch et al. (2006, Chapter 6, pp. 267-269) and they are exact for $M/G/1$. Based on their formulation, we define the function, $W^q(V, \lambda, k, \rho)$, the average queue waiting time (excluding the build time) and it is

$$W^q(V, \lambda, k, \rho) = \begin{cases} \frac{V\lambda(k\rho)^k}{2k!k^2\rho(1-\rho)^2 \left[\sum_{n=0}^{k-1} \frac{(k\rho)^n}{n!} + \frac{(k\rho)^k}{k!(1-\rho)} \right]}, & k\rho > 0, \\ 0, & k\rho = 0. \end{cases} \quad (2.4)$$

The inputs of $W^q(V, \lambda, k, \rho)$ are the second moment of service (build) time, aggregate demand rate, number of AM machines, and traffic intensity, respectively. Except for k , these inputs are variables in $\mathcal{A}$. The aggregate demand and average aggregate service time for the AM machine(s) are denoted by λ and μ , respectively. We define λ , μ , V , and ρ in terms of $\mathcal{A}$ in (2.5). We note that $\rho \in \mathbb{R}_{\geq 0}$ and $\rho \in [0, 1)$.

$$\lambda = \sum_{p \in \mathcal{A}} w_p \lambda_p, \quad \mu = \lambda \left(\sum_{p \in \mathcal{A}} \frac{w_p \lambda_p}{\mu_p} \right)^{-1}, \quad V = \lambda^{-1} \sum_{p \in \mathcal{A}} \frac{w_p \lambda_p}{\mu_p^2}, \quad \rho = \frac{\lambda}{\mu k}. \quad (2.5)$$

To reduce the number of inputs in $W^q(V, \lambda, k, \rho)$, we define $\zeta = V\lambda$ and note $W^q(\zeta, k, \rho) \equiv W^q(V, \lambda, k, \rho)$. Based on these, we create the function $A_p(W^q(\zeta, k, \rho))$ to calculate the long term average AM sourcing cost (including build and downtime costs) of product $p \in \mathcal{A}$ and

$$A_p(W^q(\zeta, k, \rho)) = w_p \lambda_p \left[C_p^A + d_p \left(\frac{1}{\mu_p} + W^q(\zeta, k, \rho) \right) \right]. \quad (2.6)$$

The parameters, C_p^A and w_p , in (2.6) denote the unit build cost (involving material, energy consumption, labor, post-processing, and quality control) and the weight factor of product $p \in \mathcal{G}$. As Knofius et al. (2017) and Westerweel et al. (2018) pointed out, the lifespan of products produced by AM machines may be shorter than the conventionally produced counterparts depending on the AM machine quality, material type used, and geometrical complexity of products. For this reason, we use w_p to reflect the increase in λ_p when a product is sourced through AM instead of inventory. More clearly, the parameter w_p can be considered as a *demand multiplier* in case AM option is used to source product $p \in \mathcal{P}$. Song and Zhang (2019) also considered this parameter as a trivial extension to their model. Though it is trivial, we use this parameter in our model because it represents the AM quality which is one of the biggest concerns in the relatively slow AM adoption rates. We also provide useful insights based on this simple extension.

2.3.3 The Mathematical Model

We introduce the binary decision variables, y_p , where $y_p \in \{0, 1\} \forall p \in \mathcal{P}$, to partition the set $\mathcal{P}$ into $\mathcal{A}$ and $\mathcal{I}$. When $y_p = 1$, product $p \in \mathcal{A}$; otherwise, $p \in \mathcal{I}$ (where $\mathcal{I} = \mathcal{P} \setminus \mathcal{A}$). We also define f to account for the investment cost of a single AM machine during a given planning horizon (e.g., annualized worth of the investment). Song and Zhang (2019) considered the machine cost inside C_p^A . Unlike them, we isolate this cost because we want to find how many AM machines would be optimal (where, $k=0$ may also be the optimal solution) and we also want to easily identify the system cost given different machine specifications with varying prices. Thus, the objective of our mixed-integer nonlinear program is to

$$\min_{y, W^q, \zeta, \rho, k} C(k) = fk + \sum_{p \in \mathcal{P}} A_p(W^q) y_p + \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p) (1 - y_p), \quad (2.7)$$

$$\text{subject to } \rho = \sum_{p \in \mathcal{P}} \frac{w_p \lambda_p}{\mu_p k} y_p, \quad \zeta = \sum_{p \in \mathcal{P}} \frac{w_p \lambda_p}{\mu_p^2} y_p, \quad \sum_{p \in \mathcal{P}} y_p \leq \mathbb{M}_1 k, \quad W^q = W^q(\zeta, k, \rho), \quad (2.8)$$

$$y_p \in \{0, 1\}, W^q, \zeta, \rho \in \mathbb{R}_{\geq 0}, \rho < 1, k \in \mathbb{Z}_{\geq 0}.$$

The objective function (2.7) minimizes the long-term average sourcing cost of all products in $\mathcal{P}$ and AM investment costs. The first two constraints in (2.8) calculate the values for ρ and ζ for a given optimal partition $\mathcal{A}$. The third constraint in (2.8) ensures that no products can be supplied through AM option when $k = 0$. We define $\mathbb{M}_1 = |\mathcal{P}|$. The introduced model is nonlinear due to the component $W^q(\zeta, k, \rho)$ appearing in the objective function (2.7). Although we provide solution approaches in the next section, we briefly show how we linearize the objective function (2.7). We break the function $A_p(W^q(\zeta, k, \rho))$ into two pieces and let A_p represent the long-term average AM sourcing cost of a given product $p \in \mathcal{P}$ independent from $W^q(\zeta, k, \rho)$. Hence, we define $A_p = w_p \lambda_p (C_p^A + d_p / \mu_p)$ and $\alpha_p = w_p \lambda_p d_p W^q(\zeta, k, \rho) y_p$ and replace objective function (2.7) with objective function (2.9) subject to (2.10).

$$\min_{y, W^q, \zeta, \rho, k, \alpha} C(k) = fk + \sum_{p \in \mathcal{P}} (A_p y_p + \alpha_p) + \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p) (1 - y_p), \quad (2.9)$$

$$\alpha_p \geq w_p \lambda_p d_p W^q - \mathbb{M}_2 (1 - y_p) \quad \forall p \in \mathcal{P}. \quad (2.10)$$

In (2.10), $\mathbb{M}_2$ is a big number satisfying $\mathbb{M}_2 > \max_{p \in \mathcal{P}} \{w_p \lambda_p d_p W^q(\zeta, k, \rho)\}$. In the next section, we derive solution approaches to surpass the nonlinearity issue and present an exact solution algorithm to solve the problem.

2.4 Model Analysis and Solution Approaches

To derive a solution procedure, we first isolate the ζ term from the function in (2.4) and redefine $W^q(\zeta, k, \rho) \equiv \zeta \psi(k, \rho)$. The isolated portion, $\psi(k, \rho)$, provides an opportunity to derive a cut generation algorithm through Theorem 2.1.

Theorem 2.1. *Let $k \in \mathbb{Z}_{\geq 0}$ and $\rho \in [0, 1)$. Then, the function $\psi(k, \rho)$ is monotonically increasing and convex in ρ .*

In Section 2.4.1, we provide cut generation algorithm to provide an exact solution method to the problem. This algorithm computationally performs well in small size instances (e.g., $|\mathcal{P}| \leq 100$) but becomes inefficient in large size due to high computational complexity which is thoroughly explored in Section 2.5.2. Following this solution method, we provide heuristic solution approaches in Section 2.4.2 and Section 2.4.3 to be able to solve the large instances of the problem. We develop two heuristic solutions: one provides a quick but low quality solution and the other is not as much quick as the other but provides near-optimal solutions.

2.4.1 Exact Solution with Cut Generation Algorithm

Theorem 2.1 (see Appendix A for all proofs) implies that a linear function $a + b\rho$ supports $\psi(k, \rho)$ at $\rho = \tilde{\rho}$ where $a = \psi(k, \tilde{\rho}) - b\tilde{\rho}$ and $b = \frac{d\psi(k, \tilde{\rho})}{d\tilde{\rho}}$. By expanding ζ and ρ provided in (2.8), $W^q \geq \sum_{p \in \mathcal{P}} \frac{w_p \lambda_p}{\mu_p^2} y_p \left(a + b \sum_{p' \in \mathcal{P}} \frac{w_{p'} \lambda_{p'}}{\mu_{p'k}} y_{p'} \right)$ is a valid cut due to Theorem 2.1. The only nonlinearity we need to deal with turns out to be a quadratic one with $y_p y_{p'}$, which can be linearized with additional variables and constraints. Based on these findings, we introduce the binary variables $z_{pp'} \equiv y_p y_{p'}$, where $z_{pp'} \in \{0, 1\} \forall p, p' \in \mathcal{P}$ and (2.11).

$$z_{pp'} \geq y_p + y_{p'} - 1, \quad z_{pp'} \leq y_p, \quad z_{pp'} \leq y_{p'} \quad p, p' \in \mathcal{P}. \quad (2.11)$$

Assume we get a solution y_p^r at iteration r by solving program formed by (2.8)—(2.11) with r cuts and obtain the solution $(y_r, W_r^q, \zeta_r, \rho_r, \alpha_r)$ and $\psi_r = W_r^q / \zeta_r$ with optimal objective value $C_r(k)$ as a lower bound. Based on these solutions, we also obtain the upper bound: $\hat{C}_r(k) = fk + \sum_{p \in \mathcal{P}} A_p(W^q(\zeta_r, k, \rho_r)) y_{p,r} + \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p)(1 - y_{p,r})$. A new cut constraint (2.12) with $a_r = \psi_r(k, \rho_r) - b_r \rho_r$, $b_r = \frac{d\psi(k, \rho_r)}{d\rho}$ is introduced into the program until $\hat{C}_r(k) = C_r(k)$ (i.e., $\psi_r(k, \rho_r) = \hat{\psi}_r$) is satisfied. For practicality purposes, we stop generating cuts when the gap between $\hat{C}_r(k)$ and $C_r(k)$ is less than the maximum allowed optimality gap (ϕ) .

$$W^q \geq a_r \sum_{p \in \mathcal{P}} \frac{w_p \lambda_p}{\mu_p^2} y_p + b_r \sum_{p, p' \in \mathcal{P}} \frac{w_p w_{p'} \lambda_p \lambda_{p'}}{\mu_p^2 \mu_{p'} k} z_{pp'}. \quad (2.12)$$

We provide Figure 2.1 to visualize the logic flow of the algorithm. First, for a constant k , we solve the program (2.8)—(2.11) that yields the solution (ρ_1, ψ_1) and the corresponding lower and upper bounds, i.e., $\psi_1(k, \rho_1)$ and $\hat{\psi}_1(k, \rho_1)$. ($\psi_1 = 0$ because ψ is only constrained by non-negativity at the first iteration and the program minimizes it.) Then, we introduce a linear cut that is tangent to the curve $\psi(k, \rho)$ at the point $(\rho_1, \hat{\psi}_1)$ using (2.12). The program (2.8)-(2.12) yields the next solution (ρ_2, ψ_2) and the corresponding lower and upper bounds. We keep introducing more cuts via (2.12) until $\hat{C}_r(k) = C_r(k)$ is satisfied.

Note that cut generation method (see Appendix B for algorithm details) finds the optimal solution, denoted by $C^*(k)$, for a given k . Once the problem is solved for $k \in \mathcal{K}$, $C^*(k^*) \equiv \min_{k \in \mathcal{K}} C^*(k)$ yields the globally optimal solution to the problem. Here, $\mathcal{K} = \{0, 1, 2, \dots\}$ is the set for possible number of AM machines to purchase and $|\mathcal{K}|$ is often not too large for practical applications. For a given k , the worst case complexity of the method is $\mathcal{O}(2^{|\mathcal{P}|})$ which is equivalent to a total enumeration. Briefly, we may need to generate (2.12) for each combination of $y_p y_{p'}$, $p, p' \in \mathcal{P}$. Practically, we have not observed such a performance and our problem instances were solved after a few cut generations.

2.4.2 Heuristic Solution with Static Allocation Algorithm

In this section, to propose a solution approach with better (compared to the previous one) computational performance (but worse solution quality), we further investigate the properties

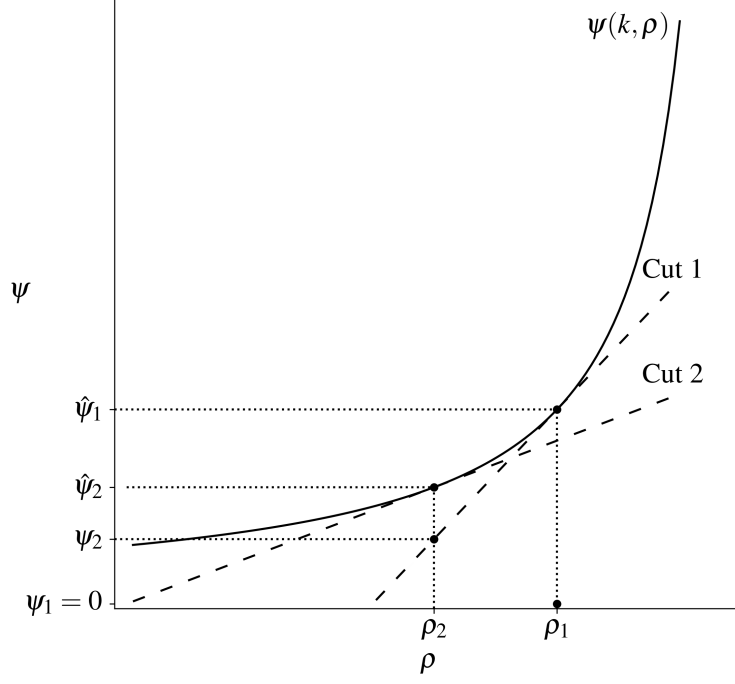


Figure 2.1: An example application for the cut generation method.

of $W^q(\zeta, k, \rho)$ and ρ with their relation to $\mathcal{A}^*$. First, we introduce new notations with $W^q(\{\cdot\}, k) \equiv W^q(\zeta, k, \rho)$ and $\rho(\{\cdot\}, k) \equiv \rho$, where $\{\cdot\}$ is the input set of product(s) and $k \in \mathbb{Z}_{\geq 0}$ is the number of AM machines.

Lemma 2.2. *For a given $p \in \mathcal{P}$ and $k \in \mathbb{Z}_{\geq 0}$, $p \in \mathcal{I}^*$, if*

$$\rho(\{p\}, k) < 1, \quad \theta_p = A_p(W^q(\{p\}, k)) - I_p(S_p^*, B_p) > 0. \quad (2.13)$$

In Lemma 2.2, the described queueing system reduces to an $M/D/k$ queue. Hence, we use the formulation derived in Bolch et al. (2006, Chapter 6, pp. 268, equation 6.102) to calculate $W^q(\{p\}, k)$. Here, $A_p(W^q(\{p\}, k))$ is calculated for each product individually (i.e., assuming only product p is sourced through AM option). If the AM sourcing cost of product $p \in \mathcal{P}$ (ignoring f) is strictly greater than inventory option cost, this product should not be sourced through AM option. Adding one more product to $\mathcal{A}$ will not decrease the sourcing cost of $p \in \mathcal{A}$. Though quite clear, we provide the following property to support the argument.

Lemma 2.3. *Let $\mathcal{A}_1 \subset \mathcal{A}_2 \subseteq \mathcal{A}$ and $k \in \mathbb{Z}_{\geq 0}$. Then, $\rho(\mathcal{A}_1, k) < \rho(\mathcal{A}_2, k)$ and $W^q(\mathcal{A}_1, k) < W^q(\mathcal{A}_2, k)$.*

Theorem 2.1 and Lemma 2.3 support the argument provided in Lemma 2.2. This property implies that $\rho(\{\cdot\}, k)$ and $W^q(\{\cdot\}, k)$ will increase when more products are assigned to the set $\{\cdot\}$ (e.g., assume $\mathcal{A}_2 := \mathcal{A}_1 \cup \{p\}$, where p is an additional product). The properties provided so far only ensures $p \in \mathcal{G}^*$ under some conditions; the following property shows a condition for $p \in \mathcal{A}^*$.

Lemma 2.4. *For a given $p \in \mathcal{P}$ and $k \in \mathbb{Z}_{\geq 0}$, $p \in \mathcal{A}^*$, if*

$$\begin{aligned} \rho(\mathcal{P}, k) < 1, \quad \gamma_p = A_p(W^q(\mathcal{P}, k)) - I_p(S_p^*, B_p) \\ + \sum_{p' \in \mathcal{P}, p' \neq p} d_{p'} \left[W^q(\mathcal{P}, k) - W^q(\mathcal{P} \setminus \{p\}, k) \right] < 0. \end{aligned} \quad (2.14)$$

Lemma 2.4 considers a case where all products in $\mathcal{P}$ are assigned to AM option when $\rho(\{\cdot\}, k)$ for a given $k \in \mathcal{K}$ and set $\mathcal{P}$ satisfy the queue equilibrium constraint $\rho(\{\cdot\}, k) < 1$. If the AM sourcing cost of $p \in \mathcal{P}$ is strictly less than its inventory option cost, it must be sourced through the AM capacity. This is because $W^q(\{\cdot\}, k)$ is maximized for the given set $\mathcal{P}$ and it cannot further increase by setting $y_p = 1$ for any $p \in \mathcal{P}$. Based on these properties, we develop the static allocation algorithm (see Appendix C for details) to reach a sub-optimal solution without spending much computational time. The algorithm yields a feasible solution that may not always be near-optimal because it does not fully consider the interaction (i.e., the effect of sourcing a collection of products to the average waiting time) between products. Although the solution quality of this algorithm may not always be close to the cut generation algorithm, in practice, it is quite useful to obtain a sub-optimal solution to a very large instance in a very reasonable time, possibly in seconds. The worst case complexity of the algorithm is $\mathcal{O}(k'n \log n)$. (Note that we use k' and $C'(k')$ to denote the best k and the lowest system cost found by the heuristic algorithms.)

2.4.3 Heuristic Solution with Greedy Algorithm

In this section, we benefit from the properties in Section 2.4.2 and Lemma 2.5 to develop a greedy heuristic to solve the problem with a higher solution quality (compared to the static allocation) but a lower computational time requirement (compared to the cut generation algorithm). We omit providing every detail of the heuristics because they are self-explanatory due to the properties provided.

Lemma 2.5. *Let $\mathcal{A}_1 \subset \mathcal{A}_2 \subseteq \mathcal{A}$, $p \in \mathcal{A} \setminus \mathcal{A}_1 \setminus \mathcal{A}_2$, and $k \in \mathbb{Z}_{\geq 0}$. Then, $\rho(\mathcal{A}_1 \cup \{p\}, k) - \rho(\mathcal{A}_1, k) < \rho(\mathcal{A}_2 \cup \{p\}, k) - \rho(\mathcal{A}_2, k)$ and $W^q(\mathcal{A}_1 \cup \{p\}, k) - W^q(\mathcal{A}_1, k) < W^q(\mathcal{A}_2 \cup \{p\}, k) - W^q(\mathcal{A}_2, k)$.*

From Lemma 2.5, we know that the marginal increase in $\rho(\{\cdot\}, k)$ and $W^q(\{\cdot\}, k)$ for products in $\mathcal{A}_2$, which spans another set of products $\mathcal{A}_1$, is strictly greater than the spanned set $\mathcal{A}_1$, when an additional product $p \in \mathcal{A} \setminus \mathcal{A}_1 \setminus \mathcal{A}_2$ is added to both sets. Using this property, we can observe the interaction between products when an additional one is assigned to AM option and the marginal increase in the total sourcing cost can be computed. Hence, we rank the products based on their marginal increase every round a product is assigned to $\mathcal{A}$ and always choose the product with the lowest marginal increase. We provide the greedy algorithm details in Appendix D and note that the worst case computational complexity is $\mathcal{O}(k'n^2)$. Further, we emphasize this algorithm is the best for practical applications due to its high computational performance and solution quality. Yet, to ensure finding the globally optimal solution which can be quite valuable in a strategic decision-making environment, one should consider the computationally expensive cut generation algorithm.

2.5 Numerical Experiments

In this section, we provide details about our data settings to present reproducible insights. Then, we present important findings to researchers and practitioners (end-users and OEMs).

2.5.1 Data Layout

Wohlers and Caffrey (2015) predicted the value of an industrial level AM machine to be \$780,000 with \$20,000 annual maintenance cost and 7-year lifespan. After considering economic factors (e.g., amortizement), we determined $f \cong 120,000$ (annual fixed AM machine cost). We considered the estimations mentioned in Knofius et al. (2017) and used $\lambda_p = U(0.05, 0.3)$ and $w_p = U(1, 5)$, where U denotes the uniform distribution.

Values of C_p^A and μ_p mainly depend on the physical volume of a product and the material type deposited. Atzeni and Salmi (2012) presented a cost model to calculate C_p^A given C_p^M (material cost of product p), V_p (volume of product p in cm^3), D_p (density of product p in g/cm^3), and some processing costs (e.g., machine operator and heat treatment). To consider wide variety of products, we use $V_p = U(10^3, 10^5)$ and $D_p = U(2.68, 8.9)$. Here, the density bounds are based on Al and Ni (Wohlers and Caffrey, 2015). For the processing costs and C_p^M , we adopt the cost values in Atzeni and Salmi (2012), calculate C_p^A and convert the currency to the USD with the exchange rate: Euro=1.13×USD. We also estimate μ_p based on V_p and the deposition rate (70 cm^3/h) for a laser metal fusion machine provided by Brockmann et al. (2015).

We estimate $C_p^I = \beta_p C_p^A$, where $\beta_p = U(0.1, 10)$ because the literature mentions C_p^A could be ten times cheaper or more expensive compared to C_p^I (Atzeni and Salmi, 2012, Knofius et al., 2017, Thomas and Gilbert, 2014). We use $\tau_p^I = U(20, 40)$ in units of days and estimate $h_p = 0.25 C_p^I$ following Deshpande et al. (2006). Khajavi et al. (2014) estimated the downtime cost (d_p) of an F-18 Super Hornet fighter jet to be \$255 per hour. Since not all the products can have such important roles, we use $d_p = U(25, 255)$. In the end, we convert all time units into annual and use this data layout unless otherwise stated.

2.5.2 Computational Performance

The number of products considered in the program is the most critical parameter influencing the computational complexity because the number of feasible solutions is $2^{|\mathcal{P}|}$. As the number of feasible solutions exponentially increases in $|\mathcal{P}|$, solving the problem via the cut generation algorithm for very large but realistic instances (e.g., $|\mathcal{P}| = 1,000$) becomes a challenge. Thus,

an acceptable sub-optimal solution can be obtained by using the other two algorithms. In this section, the complexity of the problem is discussed and numerical cases comparing the performances of the algorithms are provided.

To begin with, the parameters affect neither the quality nor the applicability of the proposed mathematical model, but they can tremendously impact the problem complexity, and thus the computational time. Based on our numerical experiments, we found that the problem is the most complex and time consuming when $|\mathcal{A}^*|/|\mathcal{P}| \approx 0.5$ for an iteration of the cut generation algorithm. When this ratio is relatively smaller or larger, e.g., 0.3 or 0.7, the problem is usually solved momentarily for relatively small instances, e.g., $|\mathcal{P}| \leq 100$. Thus, we observed a bell-shaped-like curve when we plotted a graph with the ratio $|\mathcal{A}^*|/|\mathcal{P}|$ on the x-axis and the solution times on the y-axis for a given set of problem instances with $|\mathcal{P}| = 100$. When we attempted to create a similar figure for a larger case with $|\mathcal{P}| = 500$, we have seen that problems with $|\mathcal{A}^*|/|\mathcal{P}| = (0.2, 0.8)$ took several days to converging the desired optimality gap ($\phi = 0.0001$). We omit providing these figures since our attempt was quite exploratory and we do not have any proven theories to fully address the fact.

However, we can deduce why we observed a bell-shaped-like curve. Assume, the model initializes with $|\mathcal{A}^*|/|\mathcal{P}| = 1$ and needs to eliminate 30% of the products in a combinatorial way to find the optimal ratio, $|\mathcal{A}^*|/|\mathcal{P}| = 0.7$. Thus, it is intuitive that the solver spends more time to eliminate 30% of the products compared to e.g., 20% with such an initialization rule. Now, consider an adverse case and assume the program initializes with $|\mathcal{A}^*|/|\mathcal{P}| = 0$. For instance, reaching $|\mathcal{A}^*|/|\mathcal{P}| = 0.4$ would take more time than reaching $|\mathcal{A}^*|/|\mathcal{P}| = 0.1$. It is also clear that having a large problem size would make the bell-shape wider leaving more problems in the intermediary of the curve unsolved in a reasonable time frame due to the combinatorial complexity.

The properties provided in Lemma 2.2 and Lemma 2.4 also play an important role towards the computational performance of the algorithms. In cut generation, the solver converges to the optimality faster when the majority of $\mathcal{P}$ can be partitioned based on the properties. In the other two algorithms, these properties hasten the computations because less comparisons are needed to be made.

We carried out numerical experiments with four different $\mathcal{P}$ sizes to compare the solution quality and the computational performances of the algorithms. Table 2.1 illustrates the solution statistics of the experiments while addressing average quality and average computational times of the replications. For all three algorithms, we allocated up to one hour computational time per replication. The average solution gap of the replications for the cut generation algorithm was denoted by $\bar{\phi}$ and the average deviation between the solution of cut generation algorithm and the other two algorithms were represented by $\bar{\Delta}_S$ and $\bar{\Delta}_G$. Negative values for $\bar{\Delta}_G$ indicate that the greedy algorithm provides a better solution than the cut generation algorithm while the positive ones show the adverse. Since we can obtain the best bound through the cut generation algorithm, we used other two as benchmarks. The average solution time of replications in seconds were denoted by $\bar{t}$ in seconds.

Table 2.1: Solution statistics comparing the performance of the three algorithms.

$ \mathcal{P} $	Replications	Cut Generation		Static Allocation		Greedy	
		$\bar{\phi}$	$\bar{t}$ (s)	$\bar{\Delta}_S$	$\bar{t}$ (s)	$\bar{\Delta}_G$	$\bar{t}$ (s)
50	1000	4.4×10^{-6}	0.18	7.4×10^{-5}	0.01	2.2×10^{-7}	0.08
100	100	1.6×10^{-5}	0.72	1.2×10^{-4}	0.07	7.2×10^{-7}	1.50
200	5	1.9×10^{-5}	3,600	1.7×10^{-4}	0.28	-1.5×10^{-6}	29.1
400	5	4.1×10^{-5}	3,600	1.5×10^{-4}	1.70	-1.1×10^{-5}	936.95

Naturally, $\bar{t}$ increases when $|\mathcal{P}|$ increases. In general, the greedy algorithm outperforms the other two by providing near-optimal solutions in a reasonable amount of time. On average, it provides better solutions than the cut generation algorithm, though we stated several times that cut generation algorithm finds the globally optimal solution. The reason lies under the provided time limitation. Allocating unlimited time to the cut generation method ensures convergence to optimality. Although the static allocation algorithm does not usually provide the best solution, its computational performance dominates the other two algorithms and it could be a handy solution approach if computational time is a concern. Considering that our approach can also be used for quite large cases, e.g., $|\mathcal{P}| = 1,000$ for the U.S. Navy (Kosowatz, 2019), and for shorter time intervals to make approximate operational decisions, we can justify the reason why we develop such an algorithm.

In Table 2.2, we report key statistics about another set of cases. We used the greedy algorithm to solve these instances due to its computational speed and acceptable solution quality. The table provides average results for: k' , partition ratio ($|\mathcal{A}'|/|\mathcal{P}|$), aggregate annual demand rate (λ), traffic intensity ($\rho(\mathcal{A}', k')$), and the queue waiting time in hours ($W^q(\mathcal{A}', k')$). Note that we use $\mathcal{A}'$ to denote the (economically) best set of products occupying the AM capacity. We refrain using $\mathcal{A}^*$ due to our algorithm choice.

Table 2.2: Solution statistics based on the greedy algorithm.

$ \mathcal{P} $	k'	$ \mathcal{A}' / \mathcal{P} $ (%)	λ units/year	$\rho(\mathcal{A}', k')$	$W^q(\mathcal{A}', k')$ (hours)
50	2	44	23.3	0.10	0.41
100	3	63	69.9	0.19	0.41
200	4	57	123.7	0.27	0.42
300	4	51	172.1	0.35	1.07
400	5	53	235.3	0.37	0.69
500	6	55	312.9	0.41	0.56
1,000	10	52	590.9	0.51	0.41

2.5.3 Managerial Insights

In this section, we provide insights for OEMs and end-users of AM. Based on the 1,555 replications used in Section 2.5.2, we compute the sourcing costs assuming $\mathcal{A} = \mathcal{P}$ and $\mathcal{I} = \mathcal{P}$ and compare these costs to $C'(k')$ (provided by the greedy algorithm). Our model brings in 25.5% and 33.5% savings compared to sole-AM-source and sole-inventory-source systems, respectively. Further, we provide Figure 2.2 and Figure 2.3 to illustrate why k is an important factor to consider. The saving percentages and Figure 2.2 justify the reason why the AM technology along with the optimization model is economically better to be used for low-volume demand.

For an instance with $|\mathcal{P}| = 500$, Figure 2.2 shows the system costs on a component-basis. We consider variable AM costs under two categories: *build* ($w_p \lambda_p C_p^A$) and *downtime* ($w_p \lambda_p d_p (1/\mu_p + W^q(\zeta, k, \rho))$) costs, and inventory costs under three: *purchasing* ($\sum_{p \in \mathcal{G}} C_p^I \lambda_p$), *holding* ($\sum_{p \in \mathcal{G}} h_p (S_p^* - \lambda_p \tau_p^I)$), and *backlogging* ($\sum_{p \in \mathcal{G}} B_p (h_p + d_p)$) costs. We also use the linear *fixed AM* (fk) cost and the total cost ($C(k)$) to provide a complete picture.

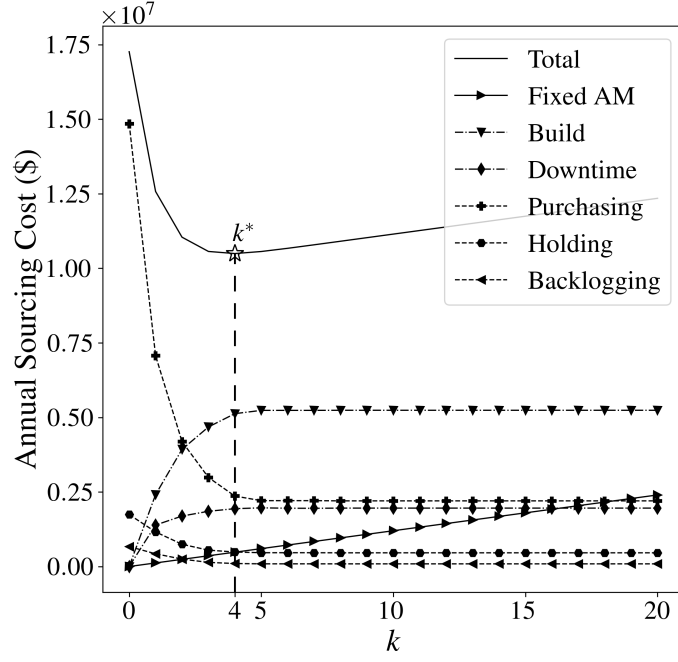


Figure 2.2: Impact of k on $C(k)$ for a case with $|\mathcal{P}| = 500$.

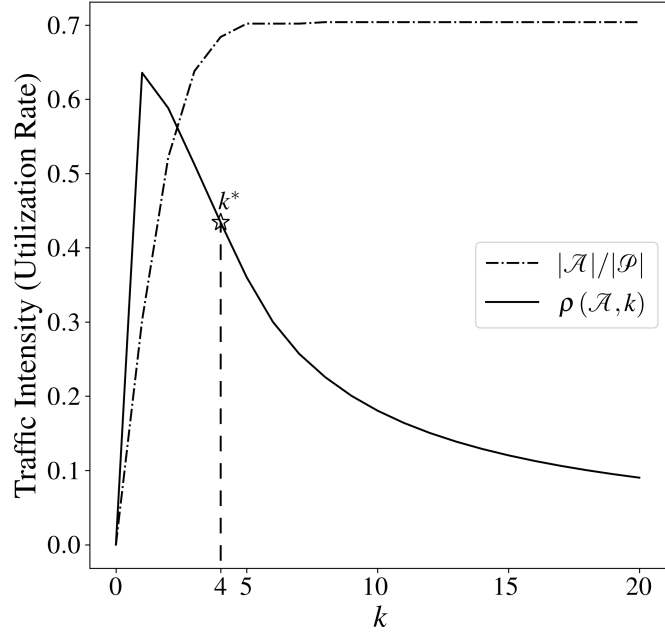


Figure 2.3: Impact of k on $\rho(\mathcal{A}, k)$ for a case with $|\mathcal{P}| = 500$.

In Figure 2.2, we observe that key components highly affecting the curve of the total cost based on k are purchasing, build, and downtime costs. Increasing k , until it reaches to k^* , exponentially pulls the purchasing cost down and pushes the build costs up. Though downtime costs may not reflect a high increase along k , the rate of its increase is higher than the rate of decrease in holding and backlogging, which highlights why we deem AM queueing as a vital factor to consider while assessing the economic feasibility of the new technology. Along with Figure 2.3, we can see that although $k < 4$ can readily satisfy $\rho(\mathcal{A}, k) < 1$, purchasing more AM machines decrease the total system cost. On the other hand, $k > 4$ causes a higher system cost because of the linearly increasing fixed AM machine cost and non-increasing $|\mathcal{A}|/|\mathcal{P}|$ ratio. Hence, finding k^* is indeed important in minimizing the system cost to fully take advantage of the technology.

Next, we consider the impact of w_p , C_p^M , f and μ_p on $C^*(k^*)$ and its associated k^* since they steer the AM adoption decision. The parameter, C_p^M , denotes the AM material cost for a given $p \in \mathcal{P}$ and determines the value for C_p^A in our settings. In the baseline case, we set $w_p = 5 \forall p \in \mathcal{P}$ and use $|\mathcal{P}| = 100$ data replications to better observe and interpret the AM quality concerns. Later, we improve the quality up to 80% (i.e., set $w_p = 1 \forall p \in \mathcal{P}$) by incrementally decreasing w_p from five to one with a step size 0.5 to observe how it affects the sourcing cost and the optimal number of AM machines. To denote the average sourcing cost and the average number of AM machines of 100 replications, we use $[\bar{C}(k) | w_p]$ and $[\bar{k} | w_p]$, respectively. Furthermore, we investigate the effects of improving C_p^M , f , and μ_p in the total sourcing cost and the optimal number of AM machines in a similar manner, use similar notations to the ones of w_p , and plot Figure 2.4 and Figure 2.5.

In Figure 2.4, we also include $\bar{C}^*(k = 0)$ so that we can observe the viability of adopting AM based on the value of w_p . Figure 2.4 shows that AM is an economically feasible option for all the cases with different improvement levels. Yet, in some undocumented experiments, we have also observed that increasing w_p (i.e., lowering the quality) or C_p^M makes the AM adoption economically infeasible. From Figure 2.4, we can also deduce w_p is the most critical parameter for an end-user to make an adoption decision because it affects the sourcing cost with the highest degree. Although low AM adoption rates are commonly attributed to machine investment costs (f), our results indicate it is not a highly influencing factor.

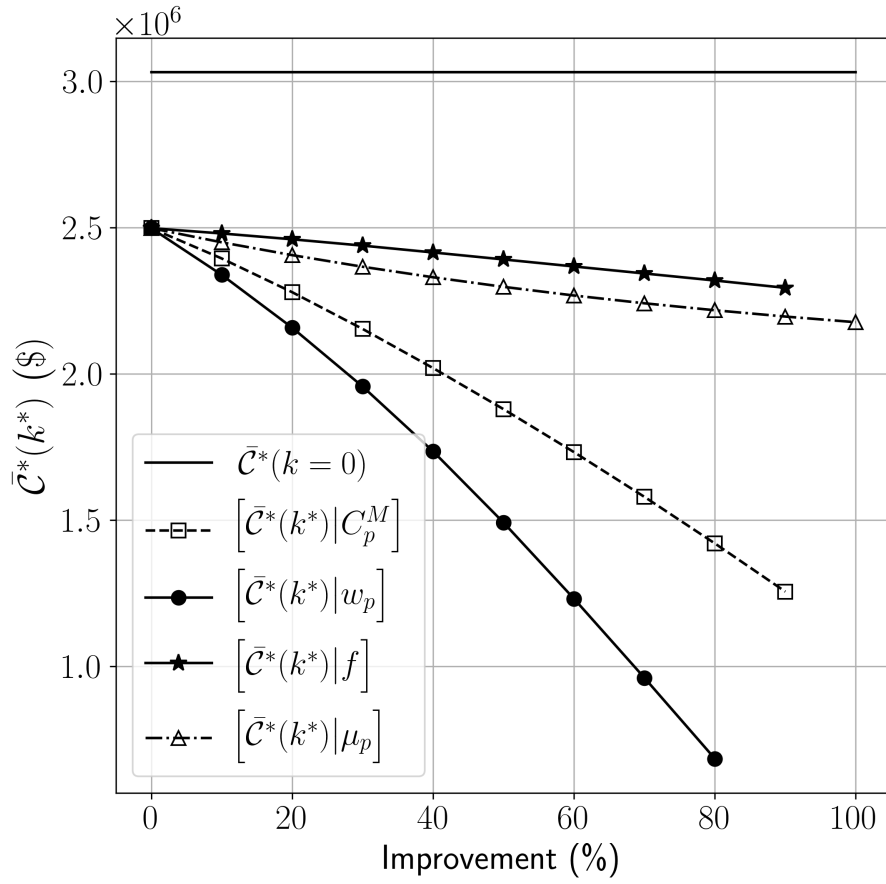


Figure 2.4: Impact of improvement in C_p^M , w_p , f , and μ_p on $\bar{C}^*(k^*)$ for $|\mathcal{P}| = 100$ and 100 replications.

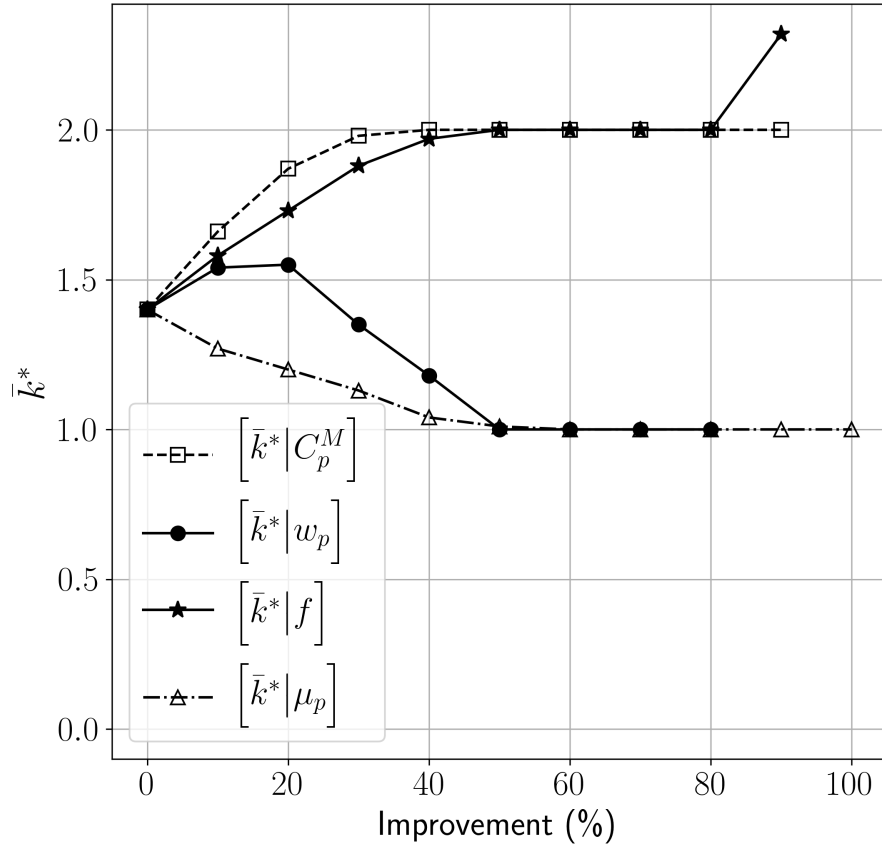


Figure 2.5: Impact of improvement in C_p^M , w_p , f , and μ_p on $\bar{k}^*$ for $|\mathcal{P}| = 100$ and 100 replications.

Figure 2.5 shows that w_p has a critical role to adjust the sales volume. While improving the AM product quality by 20% helps an OEM to increase AM machine sales, further improvement hurts sales. Such a behavior can be easily explained by the change in the magnitude of demand. When w_p increases up to 20%, a lower queue waiting time with an additional AM machine (in some cases) allows more products to be assigned to the AM capacity. The supplemental figures in Appendix E support the reasoning. In Figure A.1, we can observe that the average queue waiting time, $\bar{W}^q(\mathcal{A}, k)$, fluctuates between 0 (baseline case) and 20% improvements and Figure A.2 shows a symmetry in the average aggregate demand ($\bar{\lambda}$). In other words, when more products are sourced through AM, $\bar{W}^q(\mathcal{A}, k)$ becomes lower under a 10% improvement in w_p compared to the baseline because of the additional AM machine. The explanation does not hold when w_p is improved by more than 20% because $\bar{\lambda}$ decreases too much (refer to Figure A.2) and the end-user needs fewer AM machines to justify economic feasibility of using AM. Briefly, improving w_p helps an OEM up to a certain point and begins to harm the AM machine sales when too much improvement is made. We also provide Figure A.3 and Figure A.4 in Appendix E to further support the discussion.

All of the above facts can also be reinterpreted considering two different end-user segments: *new customers* and *existing customers*. Since Figure 2.4 shows that w_p is the most critical parameter for end-users, a substantial improvement may attract more new customers to adopt the technology. Further, existing customers can purchase an additional AM machine under the conditions aforementioned.

Figure 2.5 illustrates that the most critical parameters for an OEM to increase sales are C_p^M and f . The material cost, C_p^M , affects the cost trends of an end-user more than f . Considering this fact, an OEM may allocate most of the time and resources to improve C_p^M . On the other hand, letting aside other concerns, f is one of the most important reasons why AM has not yet dominated CM. For this reason, new customers can be considered very sensitive to f while the existing ones follow the changes in C_p^M more meticulously. An OEM should consider these two types of customers while making enhancement in these two parameters. In Figure 2.5, we can also observe that improving μ_p decreases sales. In other words, the build rate affects the sourcing cost of an end-user quite slightly. However, it is also

a known fact that low build speed (i.e., build rate) of AM is another factor highly affecting the adoption decision in reality. These two figures very well explain one of the many reasons why end-users usually complain about the quality and slow build speed disadvantage of AM compared to CM. Based on the figures, it should be understandable that OEMs may not desire to invest a lot on the drastic improvement of AM quality and speed because hastening the technology improvement process may not payoff at least for the existing customers. Therefore, reaching to the quality excellence level of the AM technology may take some time. Supplemental figures conveying more information to practitioners can be found in Appendix E.

To provide more insights, we used the cut generation algorithm and plotted the partition results of a case with $|\mathcal{P}| = 100$ in Figure 2.6. We intentionally created a grid based on the given axis ranges to map the optimality regions of the sourcing channels. AM is dominant in the region below the solid line, while inventory is chosen in the region above the dashed line. The ambiguity of sourcing choice in the region between the lines is the reason why we need to use an optimization tool. On the other hand, this figure will also aid decision-makers by providing a rubric to make near-optimal decisions without implementing the model.

2.6 Conclusions and Future Work

In this paper, we present an MINLP model, its linearization procedure, and unique solution approaches to solve the low-volume demand sourcing problem considering AM. The model finds an answer to the question: *Is AM technology economically feasible to produce low-volume products, if yes, how many AM machines will be the optimal to purchase and which products are economically suitable for the technology?* from a cost-benefit analyst’s perspective. To form an optimization tool, we use the procurement lead time of a product as a cost driver. The article touches on the problem complexity, illustrates numerical experiment results, carries out sensitivity analysis to identify key parameters for different entities, and provides a comprehensive guide for practitioners and researchers.

It should be noted that the study only focuses on a single-enterprise and a single-facility with a long-term planning horizon. So, this model only provides an estimate for a strategic

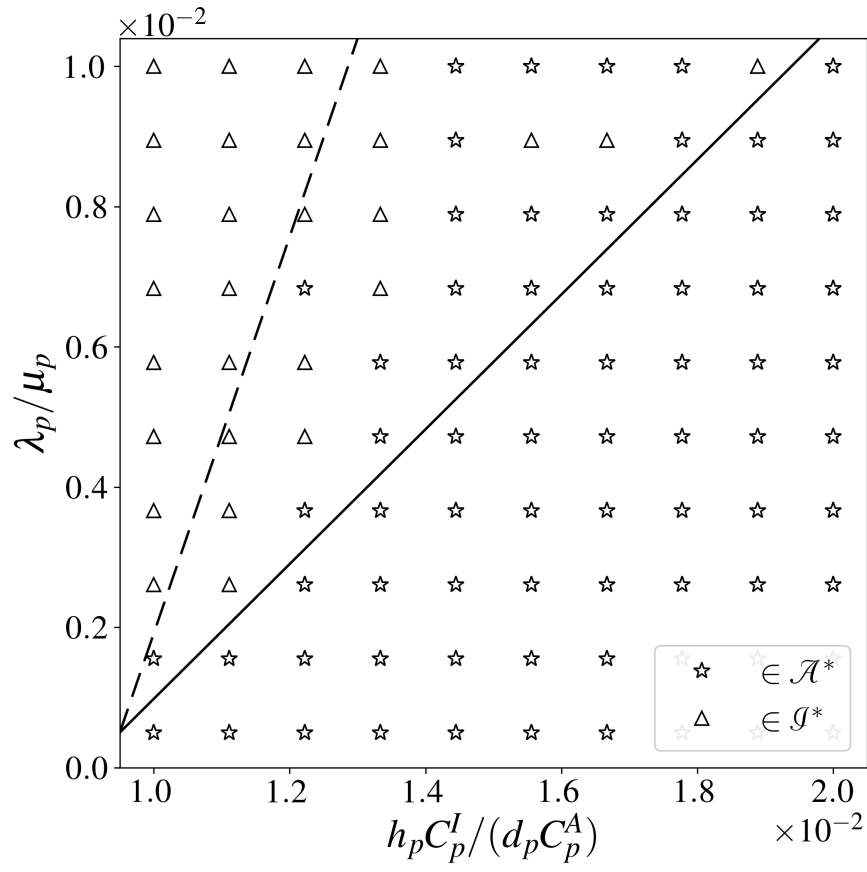


Figure 2.6: Partition results for a case with $|\mathcal{P}| = 100$ to show the optimality regions.

decision. In reality, enterprises tend to change their decisions during the implementation. For example, a more dynamic model considering the operational (day-to-day) decisions based on Markov Decision Processes could be a strong supporter of the proposed one to allow the enterprise shift options depending on the availability of the AM machine(s). The model can also consider producing multiple products at one build and potentially save more energy, time, and, raw material by answering the question: *given a product order, should we wait for the second order and build them together or only build the existing one?* It is clear that there are numerous research opportunities that will benefit both practitioners and researchers.

The introduced models are projected to be extended with a single-enterprise-multi-facility case by creating a network optimization model and a multi-enterprise-multi-facility case on the basis of a game theoretic approach. The big picture of the problem can be imagined as a sourcing consortium using AM, where multiple enterprises come together with a contract to invest on the best AM technology available to source their low-volume demand. In such a consortium idea, the per unit time cost of the AM machines should be calculated and participant enterprises may invest according to the time they occupy the machine(s). The location of the AM machine(s), which would be a highly important concern, can also be determined by using a game theoretic network optimization model. All these problems should be handled considering strategic, tactical, and operational decision-making. Each of these models with different timelines provide rather useful benefits for both researchers and practitioners.

Chapter 3

The Multiple Additive Manufacturing Machine Location Problem

Disclosure: This chapter is based on a paper submitted/will be submitted by Cokyasar and Jin (2020) to IISE Transactions.

My contributions to this paper include: (i) the development of the problem and methodology to investigate the problem, (ii) reviewing the appropriate literature, (iii) the identification of study objectives, (iv) collection of data, (v) design and conducting of the numerical experiments, (vi) majority of the writing responsibilities of the manuscript.

Abstract

The use of Additive Manufacturing (AM) for low-volume demand, such as spare parts have recently attracted quite considerable attention from researchers and practitioners. Although several studies investigated the economic benefits of using AM, some questions remain to be unanswered, e.g., how should a multi-facility enterprise adopt the AM technology to maximize its benefit from the technology and which products among a given set are the most suitable for AM production? In this study, we introduce the multiple additive manufacturing machine location problem (MAMMLP). The MAMMLP seeks answers for the following: *Which facilities should host AM machines? How many AM machines should be obtained? Which products are economically suitable for AM production and which should be kept to be supplied through conventional supply channels?* To answer these questions, we use mixed-integer nonlinear programming to model the MAMMLP and present an *exact* solution method that can also be used for similar queue involving stochastic location problems. We also share managerial implications for practitioners by analyzing different network configurations.

3.1 Introduction

Additive manufacturing technology is expanding in many industries day by day. Medical industry adopted it to save millions of lives by manufacturing functional human organs. Construction industry uses it to build a more efficient and sustainable environment. In this study, we focus on additive manufacturing usage in the manufacturing industry, specifically for enterprises in need of low-volume demand products, such as spare parts either to maintain their production lines operational with minimal interruption or to serve a customer with urgent need without the necessity of keeping units in stock. The current state of the AM technology is not yet competitive with conventional manufacturing (CM) methods for mass production but quite suitable for low-volume (infrequent demand) and physically small products. As low-volume demand fit quite well into this definition, AM was proposed as a supply option by several studies (Khajavi et al., 2018, Westerweel et al., 2018, Knofius et al., 2019).

Large enterprises have already adopted the AM technology. For example, BMW Group owns around 50 AM machines distributed globally and produced a million parts in the last ten years (Seidel, 2018). General Electric produces aircraft parts using nearly 90 AM machines in its Additive Technology Center (Anusci, 2018). Ford invested \$45 million in 23 AM machines, additional equipment, and operators at a single facility (Advanced Manufacturing Center) in Redford, MI (Goehrke, 2019). There are many other enterprises taking advantage of the advancing technology. In addition to the private industry, government agencies also benefit using AM for low-volume demand. U.S. Navy has used AM to print 135 fully functional components and targeted to extend this number to 1,000 by the end of 2018 (Lai, 2018). U.S. Army aims to fit a portable AM machine into the toolbox of soldiers and allow them use it at the point of need (Sarantinos-Perrin, 2016). The Royal Netherlands Army also use the technology in remote locations (Westerweel et al., 2018).

The companies investing on the technology and gathering AM machines at one location usually operate globally and need to transport additively manufactured products to the point-of-use. Adversely, AM is a key enabler of localized production and remove the necessity of long-distance transportation. Although there is still not enough evidence that AM is

an economically feasible replacement for some categories of conventionally manufactured products, the following questions arise: *Where should we deploy AM machines? Should we centralize or decentralize AM capacity? How many AM machines would be optimal given the stochastic features of demand? In long run, which products are economically better to be supplied through AM?* For AM investors, answers to these questions are critical.

Our contribution to the literature can be summarized as follows. We propose a mixed-integer nonlinear programming (MINLP) model to solve the multiple additive manufacturing machine location problem (MAMMLP) which is explained in Section 3.3. We provide an exact solution method for a type of stochastic queue median (SQM) problem that can be applied to other MINLP models involving convex queueing nonlinearity. Further, since (to the best of our knowledge) there is not any study answering the questions aforementioned with a quantitative approach, we partly fill the gap in the literature with our model. To reveal the capability of our solution approach and validate the functionality, we run computational experiments and conduct a case study. Moreover, we assess sensitivity analysis to show the impact of important parameters on the solution properties.

Our model is designed to make strategic (long-term) AM adoption decisions for enterprises with multiple facilities. For a given network of facilities, it finds the optimal number of AM machines to deploy with their location information and creates a long-term supply plan for a set of low-volume products by minimizing the supply cost. The plan involves the assignment of each product type to one of the two supply options: AM and outsourcing. In the AM option, when the demand occurs, the product is built at one of the facilities that are optimally designated to host AM machines and then transported to the location of need. In the outsourcing option, the product is purchased from a third-party supplier ahead of time, stocked at the location of need, and used when demand occurs. Since outsourcing involves stocking, we will refer to this option as the *inventory option* in the following sections.

The rest of this paper is organized as follows. We provide a comprehensive literature review in Section 3.2. We thoroughly describe the MAMMLP and present the model in Section 3.3. We describe the solution method in Section 3.4. We provide data description and

numerical findings in Section 3.5. We conclude the study and emphasize future extensions in Section 3.6.

3.2 Literature Review

Our study can be positioned into two different research streams. Based on the root of the problem, our study is close to the ones investigating the optimal supply chain (SC) configurations for AM. From a modeling point of view, our paper is similar to studies presenting models and solution methods for SQM problems. Hence, we provide the literature review by focusing on these two segments. Further, our model is a SC strategic decision model as explained in Chopra et al. (2013).

3.2.1 Supply Chain Analysis for Additive Manufacturing

Although AM technology has been available for 30 years, only a few studies concerning their economic and SC implications have been published. However, in recent years, the advancements in the technology lead researchers to begin filling this gap. Emelogu et al. (2019) provides a brief review on SC cost analysis by categorizing the field based on solution approaches, i.e., qualitative and quantitative. A more comprehensive review on the subject can also be found in Verboeket and Krikke (2019).

Among the qualitative ones, Oettmeier and Hofmann (2016) provides a systematic analysis for AM effects on SC processes. They found that AM adoption affects supply and demand structure of enterprises. Thomas (2016) provided a cost-benefit analysis of adopting AM from a SC perspective. Knofius et al. (2016) used a top-down ranking method to identify spare parts that are characteristically suitable for AM. Though there are a few more qualitative studies, we omit listing them as they are not closely relevant.

By focusing on the aerospace industry, Liu et al. (2014) used an SC operation reference model to analyze the impact of AM in the aircraft spare parts SC. They concluded that AM can reduce safety inventory for aircraft spare parts. They used AM lead time as a variable but did not consider the queueing effect of products with different characteristics on the overall system. Emelogu et al. (2019) considered AM adoption for biomedical implants.

They found optimal AM facility locations that serve multiple hospitals. Instead of using a discrete model they employed a continuous approximation. Since we do not find alternative locations but allot AM machines to existing facilities, we do not use such a method. As a downside, similar to many AM studies, they also did not consider the dynamically changing AM service time, i.e., the nonlinear effect of building different sets of products on the average production time.

Chung et al. (2018) created two mathematical models to support strategic and operational decision-making of AM usage in connected smart factories. Their model determines where a particular AM process should be performed. Although they use similar cost objectives, they do not aim to determine optimal machine numbers and locations. Strong et al. (2018) used uncapacitated facility location problems to decide the nationwide locations of AM hubs. They also did not consider optimizing the number of AM machines and the variable production lead time due to the stochastic feature of demand. More relevant to our study, Song and Zhang (2019) presented a nonlinear model to determine the optimal partition of a given set of spare parts into AM and inventory. From many perspectives, our study is quite similar to theirs, however, their model is bounded by a single AM machine and single location. Furthermore, they use heuristic solution techniques, while our exact solution can also be applied to their problem if their queueing formulation is slightly altered by refusing product build priority.

Simulation approaches were also proposed in the literature. Zhang et al. (2019) used discrete event simulation to observe a similar problem layout to this study. They also considered two supply channels for products and made their assignments for orders based on AM machine availability. In addition to the Poisson following demand products, they also included maintenance products which usually follow a normal distribution. Not only their methodological approach but also their objective differs from ours. Rather than optimizing AM machine locations and determining their numbers, they focused on the trade-off between AM and traditional stocking. Cokyasar et al. (2018) also used simulation to make similar observations. But, their study was limited by a single location and did not consider the purchase of multiple AM machines.

3.2.2 Stochastic Queue Median Problems

Hakimi (1964) laid the foundations of locating facilities in a network. In this section, we focus on the so-called “stochastic location models” (Berman and Drezner, 2007), e.g., stochastic demand and queue involving facility location problems (FLPs), as they are relevant to our modeling approach. Although our model is somewhat similar to SQMs, in MAMMLP, we allocate AM machines to readily operating facilities and do not consider opening/closing a facility.

The first queue involving FLP proposed by Larson (1974) partitions areas into districts to achieve best level of service. He found the optimal locations for service providers, such as ambulances or police patrol, while the providers are idle (not responding to calls). He assumed a Poisson demand arrival and exponential service time with s servers which corresponds to an $M/M/s$ queue system. The reason behind the choice of exponential service time distribution is to ignore variations in travel times. Similarly, Berman et al. (1985) optimized the location of a single server (such as an ambulance or police patrol serving to a community) considering Poisson demand arrival and generally distributed service times which forms an $M/G/1$ queue. Chiu and Larson (1985) extended these models and used an $M/G/s$ loss system to represent the problem. They found that the optimal location reduces to the minisum location of Hakimi (1964). Later, Berman et al. (1987) proposed an SQM model and two heuristic methods to solve the problem described in Larson (1974) with a more realistic $M/G/s$ system. Note that SQM problems usually find a single depot/garage to host the servers. From this perspective, our problem is not similar, however, our model can also be considered as an extension of this literature because we consider multi-servers and multi-locations.

Batta (1989) carried the continuously allowed location space of Berman et al. (1985) into a discrete network layout by allowing a set of candidate nodes to locate the servers. The author provided an exact algorithm to solve this problem. Soon after, Batta and Berman (1989) extended this model by considering s servers in an $M/G/s$ queueing layout. Although we can consider this model close to ours, there are several differences. Firstly, in their problem layout, servers are *mobile* meaning that they are dispatched to customer locations and called

back to the optimally designed locations until the next demand/call arrives. Whereas, in our problem, servers are *stationary* (immobile). Secondly, as they also explain, their model considers a *single location* with multiple servers. In our study, we consider multiple servers (AM machines) and multiple locations. These differences differentiate our model from the SQM literature and considerably change our modeling and solution derivation processes.

From an *immobility* perspective, our model is similar to the one of Wang et al. (2002). They consider locating automated teller machines (ATMs) using an $M/M/1$ queueing theory. Hence, their problem is a single-server and multi-facility type (immobile) SQM. They proposed three heuristic algorithms to solve the problem. Berman and Drezner (2007) extended this model by allowing facilities to host more than one ATM making the queue system an $M/M/s$. This extension makes the problem close to the MAMMLP layout due to considering multi-servers and multi-locations. The authors proposed four metaheuristic solution procedures to solve the problem. Due to the known convexity of $M/M/s$ queues under certain domains (refer to Dyer and Proll, 1977) and the properties provided in this study, indeed, we can also optimally solve the ATM location problem.

More recently, Hamaguchi et al. (2010) studied single-server and multi-location with an $M/G/1$. They also used heuristic solution methods and suggested the use of a total enumeration for highly utilized systems. Our solution approach can also help optimally solve this problem. SQM problems have been formulated for decades, yet the literature still has research gap to be filled. This paper helps fill this gap in part. For more details on queue involving FLPs, refer to Owen and Daskin (1998) or Snyder (2006).

3.3 Problem Description and Model

We can describe the MAMMLP as follows. A multi-facility enterprise runs its business in $|\mathcal{I}|$ facilities indexed by $i \in \mathcal{I}$. These facilities occasionally need product $p \in \mathcal{P}$. Each $p \in \mathcal{P}$ corresponds to a product type demanded by facility $i \in \mathcal{I}$. We assume the demand for product $p \in \mathcal{P}$ follows a Poisson distribution and only one unit is demanded at a time. Our assumption can be justified by the type of products being low and infrequent demand. Each facility is given two supply choices to meet the demand for $p \in \mathcal{P}$, namely AM and

inventory. In case AM is chosen, $p \in \mathcal{P}$ will be built on-demand at a selected facility $i \in \mathcal{I}$ with AM capabilities and transported to the demand location. Hence, the system will incur a procurement lead time cost which can be vital for critical products. To account for the average build time, we use $M/G/s$ queueing theory. In the inventory choice, $p \in \mathcal{P}$ is outsourced from a third-party supplier, locally kept in stock, and is allowed to be backlogged which was modeled as an $(S-1, S)$.

To simplify the problem, we assume the following. AM machines are considered to be identical and each AM machine builds one unit at a time. Products supplied by AM are directly transported and milk-runs are ignored. Once a supply option is chosen for $p \in \mathcal{P}$, the decision is assumed to remain intact over the planning horizon because considering the ramifications bring difficulty to tackle nonlinearity. Hence, we ignore switching between supply locations and supply options during the planning horizon. Inventory choice is locally evaluated and inventory sharing across facilities is not permitted.

The MAMMLP is to determine the optimal 1) facilities (locations) to deploy AM machines, 2) number of AM machines to own at each facility, 3) partition of the products into the two supply options, and 4) supply facility for product $p \in \mathcal{P}$.

The average Poisson demand rate (demand per time unit) for product $p \in \mathcal{P}$ is denoted by λ_p . The unavailability of one unit $p \in \mathcal{P}$ causes the enterprise to lose d_p USD per time unit. This loss can be related to an interruption in a production line because of a missing spare part or a price discount due to a delayed sale or any other reason causing the enterprise miss an opportunity because of product $p \in \mathcal{P}$ unavailability. The parameter, μ_p , represents the constant AM build rate (inverse of build time) for $p \in \mathcal{P}$ and does not depend on the supply location.

The unit AM build cost of product $p \in \mathcal{P}$ is denoted by C_p^A and it includes all processing (i.e., pre-processing, build, and post-processing) and material costs. The per unit time AM machine investment cost, including the repair and maintenance, is denoted by C^F . Transporting one unit of $p \in \mathcal{P}$ from facility $i \in \mathcal{I}$ incurs the logistics cost C_{pi}^L to the enterprise and requires a constant τ_{pi}^A transportation lead time. In case product $p \in \mathcal{P}$ is supplied through the inventory option, the enterprise is charged the unit purchasing cost

(C_p^I) and the inventory holding cost (h_p) per unit time. Further, the procurement lead time is a constant τ_p^I , $\forall p \in \mathcal{P}$.

The binary variable $y_{pi} = 1$, if the demand for product $p \in \mathcal{P}$ is supplied through the facility $i \in \mathcal{I}$; otherwise, $y_{pi} = 0$. In case $\sum_{i \in \mathcal{I}} y_{pi} = 0$ for a particular $p \in \mathcal{P}$, the demand must be supplied through the inventory option. The variable, s_i , denotes the number of AM machines at facility $i \in \mathcal{I}$. Further, we define some queueing performance metric variables as follows. The aggregate demand that will be supplied by facility $i \in \mathcal{I}$ is $\lambda_i = \sum_{p \in \mathcal{P}} \lambda_p y_{pi}$. The traffic intensity of AM machine(s) at facility $i \in \mathcal{I}$ is $\rho_i = \sum_{p \in \mathcal{P}} \lambda_p y_{pi} / (\mu_p s_i)$. The second moment of build time at facility $i \in \mathcal{I}$ is $V_i = \lambda_i^{-1} \sum_{p \in \mathcal{P}} \lambda_p y_{pi} / \mu_p^2$.

Based on the above definitions, the expected cost of supplying product $p \in \mathcal{P}$ from facility $i \in \mathcal{I}$ using the AM option is

$$A_{pi}^F(W_i^q(V_i, \lambda_i, s_i, \rho_i)) = \lambda_p \left[C_p^A + C_{pi}^L + d_p \left(\frac{1}{\mu_p} + W_i^q(V_i, \lambda_i, s_i, \rho_i) + \tau_{pi}^A \right) \right], \quad (3.1)$$

and the expected cost of supplying $p \in \mathcal{P}$ from the third-party supplier using the inventory option is

$$I_p(S_p^*, B_p) = C_p^I \lambda_p + h_p (S_p^* - \lambda_p \tau_p^I) + B_p (h_p + d_p). \quad (3.2)$$

For a given planning horizon, (3.1) accounts for AM build costs, logistic costs to transport the additively built products from $i \in \mathcal{I}$ to the corresponding demand facility of $p \in \mathcal{P}$, and downtime costs spanning the time duration including build time, average queue waiting time, and transportation time. The function, $W_i^q(V_i, \lambda_i, s_i, \rho_i)$, is the only variable in (3.1), constitutes to the average queue waiting time at the supplier facility $i \in \mathcal{I}$, and introduces nonlinearity to (3.1). The conditional equation in (3.3) calculates $W_i^q(V_i, \lambda_i, s_i, \rho_i)$ and it is an approximation for an $M/G/s$ queue adopted from Bolch et al. (2006, Chapter 6, pp. 267-269).

$$W_i^q(V_i, \lambda_i, s_i, \rho_i) = \begin{cases} \frac{V_i, \lambda_i (s_i \rho_i)^{s_i}}{2s_i! s_i^2 \rho_i (1 - \rho_i)^2 \left[\sum_{n_i=0}^{s_i-1} \frac{(s_i \rho_i)^{n_i}}{n_i!} + \frac{(s_i \rho_i)^{s_i}}{s_i! (1 - \rho_i)} \right]}, & s_i \rho_i > 0, \\ 0, & s_i \rho_i = 0. \end{cases} \quad (3.3)$$

While taking S_p^* and B_p as inputs, (3.2) calculates the cost of supplying product $p \in \mathcal{P}$ through the inventory option and it accounts for product purchasing, inventory holding, and backlogging costs for the demand of a given planning horizon. The equation is derived from the $(S-1, S)$ inventory policy that is commonly used for low-volume product inventory planning. The equation in (3.2) appears in Hadley and Whitin (1963, Chapter 4, pp. 204-212) with a slightly different form as they also considered a fixed backorder cost for replenishment. The input, S_p^* , denotes the optimal target inventory level for $p \in \mathcal{P}$ that is

$$S_p^* = \max_{S_p} \left\{ \sum_{n_p=S_p}^{\infty} \frac{(\lambda_p \tau_p^I)^{n_p} e^{-\lambda_p \tau_p^I}}{n_p!} > \frac{d_p}{h_p + d_p} \right\}, \quad (3.4)$$

and B_p is the expected number of backorders during replenishment lead-time for a given product $p \in \mathcal{P}$ which is

$$B_p = \sum_{n_p=S_p^*}^{\infty} (n_p - S_p^*) \text{prob}(n_p, \lambda_p \tau_p^I). \quad (3.5)$$

The term $\text{prob}(n_p, \lambda_p \tau_p^I)$ in (3.5) is the probability mass function of the Poisson distribution. Without loss of generality, we present the following MINLP to model the MAMMLP. The objective function (3.6) aims to minimize the AM machine investment and the total low-volume demand supply costs of the enterprise for a given planning horizon. The integrality in (3.7) satisfies that each product $p \in \mathcal{P}$ can be supplied through at most one facility $i \in \mathcal{I}$. Constraints (3.8) – (3.11) define ρ_i , $V_i \lambda_i$, W_i^q , and λ_i , respectively. The non-negativity constraints, integrality of s_i , and the upper bound of ρ_i are provided in (3.12).

$$\min \mathbf{C} = \sum_{i \in \mathcal{I}} C^F s_i + \sum_{p \in \mathcal{P}, i \in \mathcal{I}} A_{pi}^F (W_i^q) y_{pi} + \sum_{p \in \mathcal{P}} I_p (S_p^*, B_p) \left(1 - \sum_{i \in \mathcal{I}} y_{pi} \right), \quad (3.6)$$

$$\text{subject to} \quad \sum_{i \in \mathcal{I}} y_{pi} \leq 1 \quad \forall p \in \mathcal{P}, \quad (3.7)$$

$$\rho_i = \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p s_i} y_{pi} \quad \forall i \in \mathcal{I}, \quad (3.8)$$

$$V_i \lambda_i = \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p^2} y_{pi} \quad \forall i \in \mathcal{I}, \quad (3.9)$$

$$W_i^q = W_i^q(V_i, \lambda_i, s_i, \rho_i) \quad \forall i \in \mathcal{I}, \quad (3.10)$$

$$\lambda_i = \sum_{p \in \mathcal{P}} \lambda_p y_{pi} \quad \forall i \in \mathcal{I}, \quad (3.11)$$

$$y_{pi} \in \{0, 1\}, W_i^q, \rho_i, \lambda_i, V_i \in \mathbb{R}^+, \rho_i < 1, s_i \in \mathbb{Z}^+. \quad (3.12)$$

The model formed by objective function (3.6) – constraint set (3.12) is nonlinear and difficult to solve due to the term W_i^q . For an instance of the problem, we can have $2^{|\mathcal{P}|}$ feasible solutions. In the next section, we will investigate model properties and provide an exact solution method.

3.4 An Exact Solution Method

In this section, we present model properties, apply linearization techniques, and tailor an exact solution method to solve the problem. First, we define $\zeta_i = V_i \lambda_i$ to prepare partitioning (3.3) and eliminate the nonlinearity in (3.9). Further, by doing so, we can remove (3.11) because we do not explicitly use λ_i in the other constraints. Therefore, we can also define $\psi(\rho_i, s_i) = W_i^q(\zeta_i, s_i, \rho_i) / \zeta_i$, where $W_i^q(\zeta_i, s_i, \rho_i) \equiv W_i^q(V_i, \lambda_i, s_i, \rho_i)$.

In the queueing theory literature, convexity of W^q (average queue waiting time) with respect to s (number of servers) has been proven for $M/M/s$ and $M/D/s$ queues by Dyer and Proll (1977) and Rolfe (1971), respectively. Under certain conditions, Harel and Zipkin (1987) proved that reciprocal of $W = W^q + 1/\mu$ is concave in ρ and noted that the W should be convex. Lee and Cohen (1983) proved that W^q is convex in ρ for $M/G/s$ queues. However, we do not use the same approximation. Instead, we use the one given in Bolch et al. (2006) which is —ignoring the location factor— $W^q \approx \frac{P_s (1 + c_\mu^2)}{2s\mu(1 - \rho)}$. Here, P_s is the steady state probability that an arriving order has to wait in the queue and $P_s = \frac{(s\rho)^s}{s!(1 - \rho) \left[\sum_{n=0}^{s-1} \frac{(s\rho)^n}{n!} + \frac{(s\rho)^s}{s!(1 - \rho)} \right]}$. Also, c_μ^2 is the squared coefficient of variation in the service time (i.e., $c_\mu^2 = V\mu^2 - 1$). Since this approximation is not the same as the one in

Lee and Cohen (1983) and we do not need W_i^q to be convex to derive a solution approach, we prove convexity of $\psi(\rho_i, s_i)$ in ρ_i . (See Appendix A for proofs.)

Theorem 3.1. *The function $\psi(\rho_i, s_i)$ is convex in ρ_i in the domain of $\rho_i \in [0, 1)$ for a given $s_i \in \mathbb{Z}_{\geq 0}$.*

To eliminate nonlinearity in objective function (3.6), we partition (3.1) into A_{pi}^F and $\alpha_{pi} = \lambda_p d_p W_i^q$. Here, A_{pi}^F represents the portion of (3.1) isolated from the W_i^q input. Hence, we can present the linearized form of the objective function with its corresponding (nonlinear) constraint set (3.14) as follows. In (3.14), $\alpha_{pi} \in \mathbb{R}_{\geq 0}$ is a variable accounting for the downtime cost of queue waiting time at facility i and $\mathbb{M}_1$ is a big constant number satisfying $\mathbb{M}_1 > \max_{p \in \mathcal{P}, i \in \mathcal{G}} (\lambda_p d_p \bar{W}_i^q)$, where $\bar{W}_i^q = \max_{\rho_i} W_i^q(V_i, \lambda_i, s_i = 1, \rho_i) \quad \forall i \in \mathcal{G}$.

$$\min \mathbf{C} = \sum_{i \in \mathcal{G}} C^F s_i + \sum_{p \in \mathcal{P}, i \in \mathcal{G}} (A_{pi}^F y_{pi} + \alpha_{pi}) + \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p) \left(1 - \sum_{i \in \mathcal{G}} y_{pi}\right), \quad (3.13)$$

$$\alpha_{pi} \geq \lambda_p d_p W_i^q - \mathbb{M}_1 (1 - y_{pi}) \quad \forall p \in \mathcal{P}, i \in \mathcal{G}. \quad (3.14)$$

To prepare eliminating the nonlinearity caused by y_{pi}/s_i in (3.8), we may replace it with (3.15). First, we introduce the set $\mathcal{S} = \{0, 1, 2, \dots, S\}$ including the possible number of AM machines any facility can invest in. Next, we introduce binary variables, $x_{si} \in \{0, 1\}$ which holds $x_{si} = 1$ when we optimally allocate $s \in \mathcal{S}$ AM machines to facility $i \in \mathcal{G}$ as in (3.16). To satisfy our conditions, we introduce (3.15). Also, s_i in objective function (3.13) should be replaced with $\sum_{s \in \mathcal{S}} s x_{si}$ as in (3.15).

$$\sum_{s \in \mathcal{S}} s x_{si} \rho_i = \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p} y_{pi} \quad \forall i \in \mathcal{G}. \quad (3.15)$$

$$\sum_{s \in \mathcal{S}} x_{si} = 1 \quad \forall i \in \mathcal{G}. \quad (3.16)$$

$$\zeta_i = \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p^2} y_{pi} \quad \forall i \in \mathcal{G}. \quad (3.17)$$

As these new variables cause nonlinearity due to $x_{si} \rho_i$, we introduce $\phi_{si} \in \mathbb{R}_{\geq 0}$ where $\phi_{si} = x_{si} \rho_i$ and $\mathbb{M}_2$ satisfying $\mathbb{M}_2 > \max_{s \in \mathcal{S}, i \in \mathcal{G}} \phi_{si}$. To embed the new variables into the

model, we replace (3.15) with (3.18) – (3.19).

$$\sum_{s \in \mathcal{S}} s \phi_{si} = \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p} y_{pi} \quad \forall i \in \mathcal{I}. \quad (3.18)$$

$$\rho_i - \mathbb{M}_2(1 - x_{si}) \leq \phi_{si} \leq \mathbb{M}_2 x_{si}, \quad \phi_{si} \leq \rho_i \quad \forall s \in \mathcal{S}, i \in \mathcal{I}. \quad (3.19)$$

Due to Theorem 3.1, we know that $a + b\rho_i$ supports $\psi(\rho_i, s_i)$ at $\rho_i = \tilde{\rho}_i$ and a given s_i , where $a = \psi(\tilde{\rho}_i, s_i) - b\tilde{\rho}_i$ and $b = \frac{\partial \psi(\tilde{\rho}_i, s_i)}{\partial \tilde{\rho}_i}$. Hence, $W_i^q \geq \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p^2} y_{pi} \left(a + b \sum_{p' \in \mathcal{P}} \frac{\lambda_{p'}}{\mu_{p'} s_i} y_{p'i} \right) - \mathbb{M}_4(1 - x_{si})$ is a valid cut for any $i \in \mathcal{I}$ due to Theorem 3.1, (3.8), and (3.9) with a condition of s_i being a constant. Briefly, if $x_{si} = 1$, we set a lower bound for $W_i^q(\zeta_i, s_i, \rho_i)$ with a given s_i ; otherwise, our cut is passive. Here, $\mathbb{M}_3$ is a big positive real number. As we treat s_i as a constant, we only need to deal with nonlinearity caused by $y_{pi}y_{p'i}$. Therefore, we introduce $z_{pp'i} \equiv y_{pi}y_{p'i}$, where $z_{pp'i} \in \{0, 1\} \quad \forall p, p' \in \mathcal{P}, i \in \mathcal{I}$ and

$$z_{pp'i} \geq y_{pi} + y_{p'i} - 1, \quad z_{pp'i} \leq y_{pi}, \quad z_{pp'i} \leq y_{p'i} \quad \forall p, p' \in \mathcal{P}, i \in \mathcal{I}. \quad (3.20)$$

Cuts defined by (3.20) are added iteratively. At iteration r , solving the program formed by objective function (3.13) after replacing s_i with $\sum_{s \in \mathcal{S}} s x_{si}$ subject to (3.7), (3.12), (3.14), (3.17)–(3.21) from previous iterations yields a solution vector $(x, y, z, W^q, \rho, \zeta, \alpha)$, $\psi_r = W^q/\zeta$, and the objective value, $\mathbf{C}_r$, which is a lower bound for the whole problem. We can compute an upper bound $\hat{\mathbf{C}}_r = \sum_{i \in \mathcal{I}} C^F \sum_{s \in \mathcal{S}} s x_{si} + \sum_{p \in \mathcal{P}, i \in \mathcal{I}} A_{pi}^F(W_i^q(\zeta, \sum_{s \in \mathcal{S}} s x_{si}, \rho)) y_{pi} + \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p)(1 - \sum_{i \in \mathcal{I}} y_{pi})$. A new set of cuts (3.21) are created at this iteration with

$$W_{i'}^q \geq a_{ir} \sum_{p \in \mathcal{P}} \frac{\lambda_p}{\mu_p^2} y_{pi} + b_{ir} \sum_{p, p' \in \mathcal{P}} \frac{\lambda_p \lambda_{p'}}{\mu_p^2 \mu_{p'} s_r} z_{pp'i'} - \mathbb{M}_4(1 - x_{s_{i'}, i'}) \quad \forall i, i' \in \mathcal{I}. \quad (3.21)$$

Here, $a_{ir} = \psi(\rho_i, s_i) - b_{ir}\rho_i$ and $b_{ir} = \frac{\partial \psi(\tilde{\rho}_i, s_i)}{\partial \tilde{\rho}_i}$. Please note that a cut created from location i is applicable to all locations. It is a choice of preference how these cut constraints shall be introduced and this choice unpredictably affects the computational performance. For a given solution set, we may introduce: 1) a single cut to one location, 2) multiple cuts to all locations that were active at iteration $r - 1$, or 3) multiple cuts to all locations by cross-using (a_{ir}, b_{ir}) based on the active locations at iteration $r - 1$. Solving the new program with the

third option can break the symmetries and help the gap between $\mathbf{C}_r$ and $\widehat{\mathbf{C}}_r$ converge to zero faster. We present the algorithm details as follows. Note that ϕ denotes the maximum allowed gap between the bounds and $\mathbf{C}^*$ denotes the cost of the optimal solution.

Algorithm 1: MAMMLP Cut Generation Algorithm

Initialize with $r = 0$, solve the program formed by objective function (3.13) after replacing s_i with $\sum_{s \in \mathcal{S}} s x_{si}$ subject to (3.7), (3.12), (3.14), (3.17)–(3.20), obtain $\mathbf{C}_{r=0}$, and compute $\widehat{\mathbf{C}}_{r=0}$.

while $(\widehat{\mathbf{C}}_r - \mathbf{C}_r) / \widehat{\mathbf{C}}_r \geq \phi$, **do**

Set $r = r + 1$, introduce constraint set (3.21), resolve the extended program, obtain $\mathbf{C}_r$, and compute $\widehat{\mathbf{C}}_r$.

end

Set $\mathbf{C}^* = \widehat{\mathbf{C}}_r$.

3.5 Numerical Results

In this section, we share results of our numerical experiments. First, we provide the baseline parameter settings that were used in these experiments. Next, we show the results for our computational experiments revealing the solution quality for given problem sizes and model capabilities. Following, we illustrate a case study to highlight the economic benefit of our model by investigating different network configurations that are commonly practiced. Lastly, we denote how a change in key parameters affect important solution metrics.

3.5.1 Data Layout

To ease solution interpretation, we assume all AM machines at all locations are identical and their fixed costs are the same. In a realistic case, this assumption may not be valid as AM machine prices highly vary depending upon the quality of output, capability of different types of material deposition, and build speed. Hence, a user of our model can easily remove this assumption by replacing C^F with C_i^F , where C_i^F denotes the fixed AM machine cost per unit time (e.g., year) involving machine purchase, maintenance, and operation.

To estimate C_p^A , we use the cost model of Atzeni and Salmi (2012) and their model takes the following inputs: C_p^M (material cost of p), V_p (physical volume of p in cm^3), D_p (density of p in g/cm^3), and processing costs. For cost model details, please refer to their study. To estimate μ_p , we use V_p and the deposition rate ($70 \text{ cm}^3/\text{h}$) for a laser metal fusion machine provided by Brockmann et al. (2015). Using C_p^A , we generate $C_p^I = \beta_p C_p^A$, where β_p is a weight parameter. For the inventory cost, we use $h_p = 0.25 C_p^I$ which is a common assumption as in Deshpande et al. (2006). Downtime cost, d_p is quite subjective and highly product dependent. For some parts, such as a critical component in a manufacturing facility, cost of system interruption can be thousands of dollars per hour.

Except from τ_{pi}^A and C_{pi}^L , we use the parameters in Table 3.1 to conduct our experiments, unless otherwise expressed. In the following sections, we will mention how we approximate τ_{pi}^A and C_{pi}^L . For product dependent parameters, we use uniform distribution so that we can better simulate real-life instances. We also randomly (using uniform distribution) distribute $\mathcal{P}$ into $|\mathcal{G}|$ locations. Hence, numbers of products demanded at each facility are not necessarily the same. Note that all the time units were converted to yearly units as the analysis is conducted on an annual basis.

Table 3.1: Baseline parameter layout.

C^F (\$/year)	V_p (cm^3)	D_p (g/cm^3)	λ_p (units/year)	τ_p^I (hours)	d_p (\$/hour)	β_p
120,000	$U(10^2, 10^4)$	$U(2.68, 8.9)$	$U(8, 10)$	$U(20, 60)$	$U(250, 10^3)$	$U(0.1, 10)$

3.5.2 Computational Experiments

In this section, we use randomly (from a uniform distribution) selected cities from a publicly available dataset as a network configuration (Parmer, 2014). Based on coordinates, we obtain real-time transport lead times from Google Cloud Platform (2020) and travel cost estimates from United States Postal Services (USPS, 2020) shipping calculator. Although these parameters may not be rather accurate for τ_{pi}^A and C_{pi}^L in realistic applications, they provide a test bed for our experiments. For the rest, we use the parameters demonstrated in

Table 3.1. For each instance, we limit the computational time by an hour. All computations were carried out on an Intel® Core™ i9 CPU@2.3 GHz laptop with 32GB of RAM and problem instances were solved using the Python 3.7 interface to the MIP solver Gurobi 9.0 (Gurobi Optimization, LLC, 2020).

The optimality gap and computational time results based on the problem sizes are demonstrated in Table 3.2. Considering the gap and time, we can deduce that $|\mathcal{P}|$ has higher impact on the computational performance compared to $|\mathcal{G}|$. This is an expected result as the number of possible combinations at each location exponentially grows with $|\mathcal{P}|$. The gap percent of instances with $|\mathcal{P}| < 50$ also supports this argument as these instances could be solved to optimality in a reasonable time frame for all sizes of $|\mathcal{G}|$.

The table also reveals the limitations of our solution approach. Although our algorithm can provide optimal solutions, the computational time for large size problems is considerably high. For this reason, we recommend solving problems with up to $|\mathcal{P}| = 100$ and $|\mathcal{G}| = 40$ if computational time is a limitation.

3.5.3 A Case Study

In this section, we consider a case study for U.S. Marine Bases. The coordinate locations of the bases are publicly available (Military.com, 2020). Given 14 base locations in the U.S., a predicted $|\mathcal{P}| = 50$, and aforementioned baseline parameter layout supported with Google Cloud Platform (2020) and USPS (2020) data, we solve the problem under different scenarios. (We exclude Hawaii and geographically too close bases to ease visualization.) The scenarios are based on common new technology deployment practices. In some cases, managers can completely replace AM with CM. In others, they may want to totally centralize or decentralize the AM machines to maximize some managerial objectives. To this respect, we analyze six scenarios listed and explained as follows.

Scenario 1. Optimal sourcing: In this scenario, we adopt the model without any alteration and find the optimal network configuration.

Scenario 2. Complete centralization: We allow only one facility to house all AM machines and keep inventory as an alternative supply channel. The choice of the central location is

Table 3.2: Solution statistics for computational experiments.

$ \mathcal{G} $	$ \mathcal{P} $	Gap (%)	Time (s)
2	25	5.2×10^{-3}	1.02
	50	5.2×10^{-3}	3.54
	75	5.7×10^{-3}	48.51
	100	4.7×10^{-3}	99.28
	150	5.8×10^{-3}	868.84
	200	1.2	3600
5	25	1.7×10^{-2}	2.33
	50	5.0×10^{-3}	20.16
	75	3.9×10^{-3}	733.01
	100	7.0×10^{-3}	731.41
	150	1.9	3600
	200	4.8	3600
10	25	4.8×10^{-2}	8.95
	50	3.6×10^{-3}	61.26
	75	1.5	3600
	100	2.5	3600
	150	2.7	3600
	200	2.9	3600
20	25	5.2×10^{-3}	13.15
	50	3.0×10^{-3}	116.1
	75	2.9	3600
	100	1.8	3600
	150	16	3600
	200	5.1	3600
30	50	8.0×10^{-4}	319.9
	75	3.7	3600
	100	3.3	3600
	150	8.8	3600
	200	13	3600
40	50	5.0×10^{-4}	1430
	75	3.7	3600
	100	2.6	3600
	150	5.4	3600
	200	12	3600

determined by the model by replacing (3.16) with (3.22).

$$\sum_{s \in \mathcal{S}, i \in \mathcal{I}} x_{si} \leq 1. \quad (3.22)$$

Scenario 3. Complete decentralization: We locate at least one AM machine to each location, forbid capacity sharing between facilities, and keep inventory as the alternative supply option. We use the model by introducing (3.23) and replacing (3.7) with (3.24). Note that i_p in (3.24) denotes the specific demand location of product $p \in \mathcal{P}$.

$$x_{0i} = 0 \quad \forall i \in \mathcal{I}. \quad (3.23)$$

$$\sum_{i \in \mathcal{I}, i \neq i_p} y_{pi} = 0 \quad \forall p \in \mathcal{P}. \quad (3.24)$$

Scenario 4. Complete centralization with sole AM supply: In addition to allowing only one facility to house all AM machines, we eliminate the inventory alternative. We use the model by replacing (3.16) and (3.7) with (3.22) and (3.25), respectively.

$$\sum_{i \in \mathcal{I}} y_{pi} = 1 \quad \forall p \in \mathcal{P}. \quad (3.25)$$

Scenario 5. Complete decentralization with sole AM supply: Each facility should house at least one AM machine, capacity sharing is not allowed, and inventory is not an option. We use the model by introducing (3.23) and (3.26).

$$y_{pi_p} = 1 \quad \forall p \in \mathcal{P}. \quad (3.26)$$

Scenario 6. Sole inventory supply: We only allow inventory option to be used. In this scenario, the optimal solution is quite straightforward with $\mathbf{C}^* = \sum_{p \in \mathcal{P}} I_p (S_p^*, B_p)$.

Table 3.3 provides the key solution metrics. For each scenario, we provide the total number of machines located at the 14-bases, total number of products supplied through AM capacity, average utilization rate (ρ_i) and average queue waiting time (W_i^q) in units of hour for the locations that house at least one AM machine, and percent cost increase in

scenarios with respect to the optimal scenario 1. We also provide Figure A.5 — Figure A.10 to visualize the solutions in Appendix E. In the figures, we illustrate candidate locations to deploy AM machines (which are also demand locations with randomly shared $\mathcal{P}$) and the number of optimal AM machines next to location names inside the parentheses.

Table 3.3: Solution statistics for different scenarios.

Scenario	Number of machines located	Number of AM sourced products	Average ρ_i	Average W_i^q (hour)	Percent cost increase with respect to scenario 1
1	5	17	0.22	1.44	-
2	3	11	0.48	374.03	6.33
3	15	16	0.09	2.85	6.88
4	8	50	0.28	0.57	48.16
5	23	50	0.12	2.53	39.44
6	-	-	-	-	19.95

Due to the distribution of the 14-bases (see Figure A.10 for the problem layout), even without solving the problem, we could expect an optimal solution to involve one central AM capacity at both east and west coasts. Surely, our model provides more information than that by pointing out the economically best locations within the coasts and the optimal numbers of AM machines at each of these locations.

In Table 3.3, we can see that five strategically-well located AM machines can be enough to justify the economic benefit of AM. In scenario 1, 17 out of 50 products are sourced through AM while utilizing AM machines at an average 22% and causing an order to wait the build queue on average 1.44 hours. As scenario 2 limits the AM deployment to a single location, the number of AM sourced products decline and the existing AM capacity becomes considerably congested. A complete decentralization as in scenario 3 causes quite low average utilization but allows sourcing more products compared to scenario 2. Note that Washington, D.C. has the highest number of product demand and hence the model allocates two AM machines at this location. Further, this location becomes a sole AM supply source in scenarios 2 and 4. In scenario 5, our model allocates the highest number of AM machines to reduce W_i^q and hence the total cost. When we consider the percent cost increase of the scenarios with respect to the optimal configuration, we can observe that even the traditional inventory

sourcing is economically better than using AM solely. To maximize the savings obtained by AM adoption, one should consider benefiting from our methodology rather than following the common practices.

3.5.4 Impact of Parameters on the Optimal Network Configuration

In this section, we analyze the system cost and the optimal network layout under a percent improvement in key parameters. Due to the continuous development in AM, machine prices and build speed are expected to improve over time. Hence, a percent price drop in C^F or a percent increase in μ_p are possible scenarios to consider. Further, in some cases, λ_p can increase over time. For a single instance with $|\mathcal{P}| = 50$ and $|\mathcal{G}| = 10$ with the previously mentioned baseline parameter layout, we investigate how the number of AM machines and the optimal system cost ($\mathbf{C}^*$) are impacted with respect to percent improvement in C^F , λ_p , and μ_p .

Figure 3.1 shows the total number of optimally allocated AM machines and the total system costs with respect to percent improvement in C^F . We use conditional notations such as $[\mathbf{C}^*|C^F]$ and $[\sum_{s \in \mathcal{S}, i \in \mathcal{G}} sx_{si}|C^F]$ to denote the system cost and the total number of AM machines allocated given the corresponding parameter, respectively. We also follow this notation convention for μ_p and λ_p and omit explicitly defining them. As seen in the figure, the total number of AM machines increases as C^F decreases. At 100% improvement (i.e., $C^F = 0$), the model allots a total of 119 AM machines to 10 locations because such allocation provides a convergence to zero for W_i^q , i.e., $W_i^q \rightarrow 0 \forall i \in \mathcal{G}$. We also observe a steep decline in $\mathbf{C}^*$ as C^F improves.

We could predict that being able to build more products (i.e., increasing/improving μ_p or equivalently increasing the build speed) will lead to decrease the number of machines allotted because less number of machines may provide an equivalent supply with faster building machines. However, in AM allocation, this prediction is indeed not valid. In Figure 3.2, we can observe that improving μ_p first increases the number of AM machines but decreases it later, though $\mathbf{C}^*$ constantly drops down along the improvement. We observe this behavior

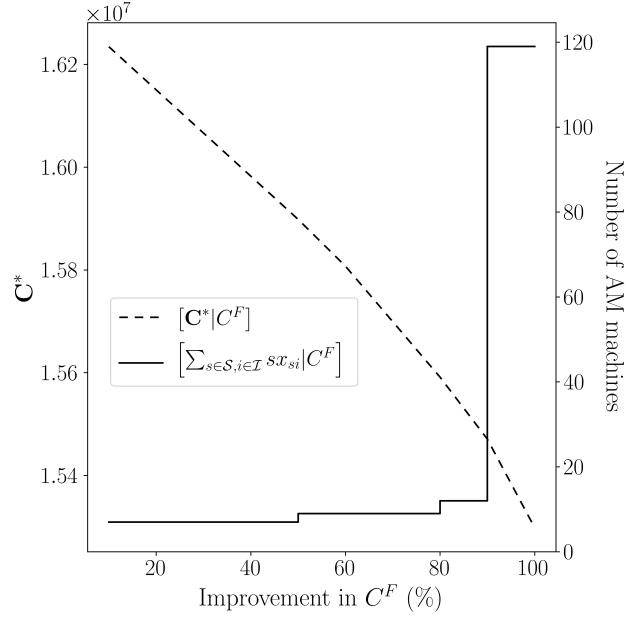


Figure 3.1: Impact of percent improvement in C^F on C^* and the number of AM machines.

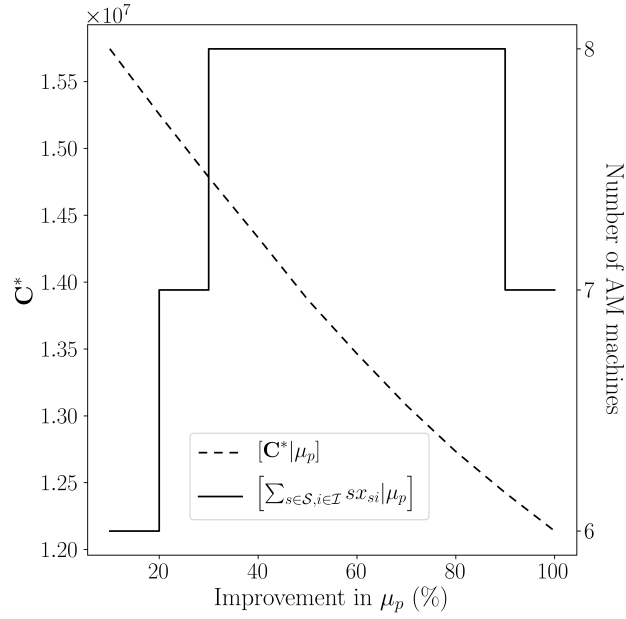


Figure 3.2: Impact of percent improvement in $\mu_p \forall p \in \mathcal{P}$ on C^* and the number of AM machines.

because having faster machines can lead to shorter queue waiting times and having more number of faster machines can help even further. Hence, the model selects to obtain more AM machines up to some point and maximizes the savings gained by the AM technology. At extreme levels of improvement in mu_p , the system saturates and obtaining one less AM machine becomes optimal.

Lastly, we investigate the optimal network layout under an increase in λ_p for a given instance. Note that in the optimal case with a given set of λ_p , we allocate seven AM machines. Figure 3.3 shows that doubling $\lambda_p \forall p \in \mathcal{P}$ leads to obtaining only one more AM machine. We illustrate this example to highlight the nonlinear relationship between λ and the total number of allocated AM machines. Although $\mathbf{C}^*$ almost doubles at 100% improvement compared to the baseline case, we cannot observe a similar pattern with the number of AM machines. From this example, we deduce that inventory also plays a role in the optimal decision. When demand surges, AM may not be an economical choice for some products anymore. For this reason, some products can be sourced through inventory and the demand assigned to AM may not require very high number of machines to justify its economic feasibility.

3.6 Conclusions and Future Research

In this study, we present the MAMMLP, provide a comprehensive literature review, create an MINLP model to optimally allocate AM machines to a set of locations, propose an exact solution method, and illustrate numerical results including computational experiments, a case study, and a sensitivity analysis.

We describe the MAMMLP as a problem that requires answers for optimal: 1) locations to deploy AM machines, 2) number of AM machines to house at each facility, 3) products to be supplied through AM capacity, and 4) supply facilities to source a given set of products. To solve the problem, we create an MINLP model inspired from the stochastic location analysis literature and form an exact solution algorithm with cut generations based on convexity properties of the queueing functions employed. We analyze the capability of our model by

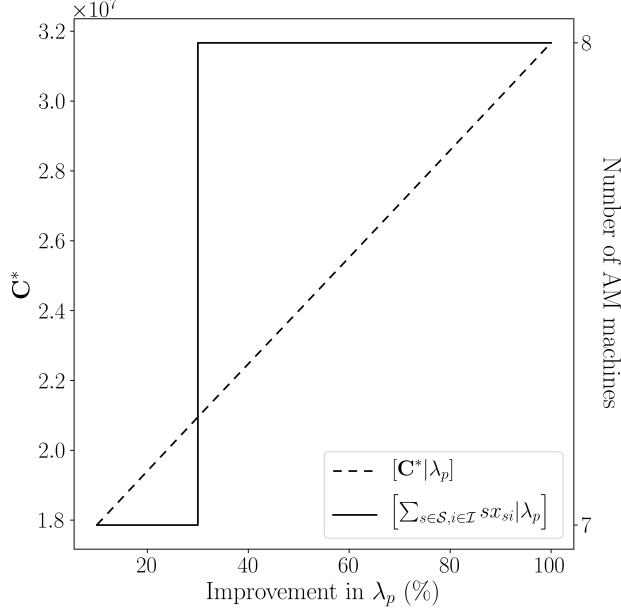


Figure 3.3: Impact of percent improvement in $\lambda_p \forall p \in \mathcal{P}$ on C^* and the number of AM machines.

running problem instances with different sizes and address that our model is the most useful (due to reasonable computational time requirements) in problem sizes with $\mathcal{P} < 100$ and $\mathcal{I} < 40$. We consider a case study for U.S. Marine Bases and optimally locate AM machines to supply their low-volume demand. We provide analysis for different network configurations managers can implement and share the economic savings of our model with respect to these possible implementations. Lastly, we focus on three key parameters (C^F , μ_p , and λ_p) and illustrate figures showing how the number of AM machines and the total system cost can be impacted due to improvement in these parameters.

The AM supply chain analysis literature lacks quantitative approaches to answer many questions. In this study, we partially filled the gap in the literature by providing a macro-scale analysis. However, there are many more questions to be answered on a micro-level to fully benefit from the technology. For example, we assume supply decisions cannot be altered during the planning horizon. A more detailed, operational model, could refuse this assumption and allow decision changes during the implementation. Such a model could bring in higher savings as more dynamics of the AM machine working mechanisms would be

observed. Yet, again, such a model would not be appropriate for location analysis which is carried out in this study.

Industrial level AM machines are expensive and many small- and medium-sized enterprises may not afford purchasing an AM machine to supply low-volume demand. For this reason, a quantitative game-theoretic model focusing on a shared-economy version of our problem could be useful. Apart from this, a more comprehensive model could also consider the inventory cost of AM materials and even a make-to-stock option for the AM supply. Such models surely add a high level complexity to both the modeling approach and solution derivation. This study simplifies the decision-making by disregarding some of the system details to make the problem solvable.

Conclusion

In this study, we investigate the economic feasibility of adopting additive manufacturing (AM) for low-volume demand. We categorize the study into three chapters based on the methodology and scope.

In Chapter 1, we focus on spare part supply with AM and create an agent-based simulation to assess the long-term feasibility of AM by assigning part orders into three options: AM, inventory, and outsourcing. Within this study, we share the simulation model flow logic and results with different demand and supply levels. The study can be considered as a first step towards the investigation of AM economic feasibility. In the following chapters, we generalize the context by focusing on a broader level of products.

In Chapter 2, we create a mixed-integer nonlinear program (MINLP) to model the AM adoption problem. Within this study, we provide a comprehensive literature review, denote mathematical formulation notations, develop three solution algorithms, namely, cut generation algorithm, static allocation algorithm, and greedy algorithm. We provide the algorithm details and computational complexity. In the numerical experiments, we share the data layout used, provide computational performance results by comparing the performance of the three algorithms, and document managerial insights with figures showing the impact of key parameters on decision variables. Considering both AM users and AM original equipment manufacturers, we share suggestions towards assumption decisions.

In Chapter 3, we extend the model provided in the previous chapter by considering multiple facilities and introducing the multiple additive manufacturing machine location problem (MAMMLP). Such an extension considerably changes the corresponding literature, model, and solution approach to be adopted. In the literature section, we focus on supply chain analysis for AM and stochastic queue median problems. Then, we thoroughly describe

the MAMMLP and provide mathematical formulations. We provide an exact solution algorithm that is based on the solution from the previous chapter. As a difference, in this study, we integrate the “number of machines” variable into the model and improve the algorithm convergence. Additionally, we incorporate the “multiple locations” factor into the modeling and consider the transportation lead time and costs in between the facilities. In the numerical experiments, first, we assess the computational capabilities of our solution methodology, then, we provide a case study considering U.S. Marine Bases and sensitivity analysis based on key parameters. We conclude the study by addressing the challenges in AM adoption and future research to be conducted.

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Appendices

A Proofs of Theorem and Lemmas

Proof of Theorem 2.1 To prove the monotonic increase and convexity, we take partial derivatives of $\psi(k, \rho)$ for a given $k \in \mathbb{Z}_{\geq 0}$. When $d\psi(k, \rho)/d\rho \geq 0$ and $d^2\psi(k, \rho)/d\rho^2 \geq 0$, we can respectively conclude that the function is monotonically increasing and convex in the domain, $\rho \in [0, 1)$ and $k \in \mathbb{Z}_{\geq 0}$.

$$\begin{bmatrix} \frac{d\psi(k=1, \rho)}{d\rho} \\ \frac{d\psi(k=2, \rho)}{d\rho} \\ \frac{d\psi(k=3, \rho)}{d\rho} \\ \vdots \end{bmatrix} = \begin{bmatrix} \frac{1}{2(1-\rho)^2} \\ \frac{1+\rho^2}{4(\rho^4-2\rho^2+1)} \\ \frac{\rho(3\rho^3+2\rho+4)}{18\rho^6+12\rho^5-22\rho^4-32\rho^3+16\rho+8} \\ \vdots \end{bmatrix}$$

$$\begin{bmatrix} \frac{d^2\psi(k=1, \rho)}{d\rho^2} \\ \frac{d^2\psi(k=2, \rho)}{d\rho^2} \\ \frac{d^2\psi(k=3, \rho)}{d\rho^2} \\ \vdots \end{bmatrix} = \begin{bmatrix} \frac{1}{(1-\rho)^3} \\ -\frac{\rho(\rho^2+3)}{2(\rho^2-1)^3} \\ -\frac{27\rho^8+36\rho^7+72\rho^6+204\rho^5+230\rho^4+112\rho^3+24\rho^2+16\rho+8}{(\rho-1)^3(9\rho^4+24\rho^3+28\rho^2+16\rho+4)} \\ \vdots \end{bmatrix}$$

Since $d\psi(k, \rho)/d\rho \geq 0$ and $d^2\psi(k, \rho)/d\rho^2 \geq 0$ hold for $k = \{1, 2, 3, \dots\}$, by induction, we prove the function is monotonically increasing and convex in ρ . $\square$

Proof of Lemma 2.2 Ignoring the fixed cost of AM machine(s), assume a sourcing decision only for a single product p is made. The corresponding $W^q(\{p\}, k)$ of this product can be easily computed using a closed form formulation of an M/D/k queueing model. Afterwards, using equation (2.6), $A_p(W^q(\zeta, k, \rho))$ can be computed and compared to $I_p(S_p^*, B_p)$. If AM option is costlier than inventory option, product p should be in $\mathcal{G}^*$. Further, assigning more products to $\mathcal{A}$ will not help product p to be assigned to AM option because the product causes queue waiting time rise hence the total sourcing cost increase. Lemma 2.3 supports this argument. $\square$

Proof of Lemma 2.3 For two sets one of which is a subset of the other, $\mathcal{A}_1 \subset \mathcal{A}_2$, the traffic intensity, $\rho(\{\cdot\}, k)$, and the average queue waiting time, $W^q(\{\cdot\}, k)$, for the covering set $\mathcal{A}_2$ must be strictly higher than the other one because $\mathcal{A}_2$ not only contains the products

in $\mathcal{A}_1$, but also more. Theorem 2.1 supports this argument through monotonicity and convexity. $\square$

Proof of Lemma 2.4 Since $A_p(W^q(\zeta, k, \rho))$ is minimized, product p should be in $\mathcal{A}^*$. Similar to the case in Lemma 2.2, ignoring the fixed cost of AM machine, assume all products in $\mathcal{P}$ are in the optimal set $\mathcal{A}^*$. In this case, $W^q(\{\cdot\}, k)$ possesses its maximum value. With the highest waiting time, if product p is still less costly than the other option, this product should be sourced through AM option. From Lemma 2.3 it can be deduced that $\rho(\{\cdot\}, k)$ and $W^q(\{\cdot\}, k)$ decrease when products are removed from $\mathcal{A}^*$. Removing products from $\mathcal{A}^*$ will not make product p increase its sourcing cost through AM option. $\square$

Proof of Lemma 2.5 The proof of this lemma is in part provided by Lemma 2.3. To further clarify, let $\mathcal{A}_2 = \mathcal{A}_1 \cup \{p\}$, where $\{p\}$ represents the set of additional products. We can rewrite the lemma for $\rho(\{\cdot\}, k)$ portion as $\rho(\mathcal{A}_1 \cup \{p'\}, k) - \rho(\mathcal{A}_1, k) < \rho(\mathcal{A}_1 \cup \{p\} \cup \{p'\}, k) - \rho(\mathcal{A}_1 \cup \{p\}, k)$. Due to Lemma 2.3, we have already proven that $\rho(\mathcal{A}_1 \cup \{p\} \cup \{p'\}, k) > \rho(\mathcal{A}_1 \cup \{p'\}, k)$ and $\rho(\mathcal{A}_1 \cup \{p\}, k) > \rho(\mathcal{A}_1, k)$. Hence, we can prove that $\rho(\mathcal{A}_1 \cup \{p\} \cup \{p'\}, k) - \rho(\mathcal{A}_1 \cup \{p\}, k) - \rho(\mathcal{A}_1 \cup \{p'\}, k) + \rho(\mathcal{A}_1, k) > 0$. Since the proof for the $W^q(\{\cdot\}, k)$ portion follows a similar structure, we omit providing it. $\square$

Proof of Theorem 3.1 See the proof of Theorem 2.1. $\square$

B Cut Generation Algorithm

Algorithm 2: Cut Generation Algorithm

Initialize with $C^*(k=0) = C^*(k=-1) = \infty$ and $k=0$.

while $C^*(k-1) \geq C^*(k)$, **do**

$k = k + 1$.

 Set $r = 1$ and compute $C_r(k)$ and $\hat{C}_r(k)$ by solving constraint

 set (2.8)-constraint set (2.11). Here, r is an iteration counter.

while $1 - C_r(k) / \hat{C}_r(k) \geq \phi$, **do**

 | Set $r = r + 1$, solve the program (2.8)-(2.12), and compute $C_r(k)$ and $\hat{C}_r(k)$.

end

 Set $C^*(k) = \hat{C}_r(k)$.

end

Set $k = k - 1$.

Update $C^*(k=0) = \sum_{p \in \mathcal{D}} I_p(S_p^*, B_p)$. If $C^*(k=0) \leq C^*(k)$, $k^* = 0$ and

$C^*(k^*) = \sum_{p \in \mathcal{D}} I_p(S_p^*, B_p)$. Otherwise, $k^* = k$ and $C^*(k^*) = C^*(k)$.

C Static Allocation Algorithm

Algorithm 3: Static Allocation Algorithm

Initialize with $C'(k=0) = C'(k=-1) = \infty$ and $k = 0$.

while $C'(k-1) \geq C'(k)$, **do**

$k = k + 1$.

for $p \in \mathcal{P}$, **do**

| If p satisfies equation (2.13), $p \rightarrow \mathcal{I}$; end.

end

for $p \in \mathcal{P} \setminus \mathcal{I}$, **do**

| If p satisfies equation (2.14), $p \rightarrow \mathcal{A}$; end.

end

Sort $p \in \mathcal{P} \setminus \mathcal{I} \setminus \mathcal{A}$ ascending in θ_p based on equation (2.13).

for $p \in \mathcal{P} \setminus \mathcal{I} \setminus \mathcal{A}$, **do**

| If $\rho(\mathcal{A} \cup \{p\}, k) < 1$, $p \rightarrow \mathcal{A}$.

end

Assign the remainder of products in $\mathcal{P}$ to $\mathcal{I}$, compute $C(k)$, and set

$C'(k) = C(k)$.

end

Set $k = k - 1$.

Update $C'(k=0) = \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p)$. If $C'(k=0) \leq C'(k)$, $k' = 0$ and

$C'(k') = \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p)$. Otherwise, $k' = k$ and $C'(k') = C'(k)$. Here, k' and

$C'(k')$ are the best solutions found by this algorithm.

D Greedy Algorithm

Algorithm 4: Greedy Algorithm

Initialize with $C'(k=0) = C'(k=-1) = \infty$ and $k = 0$.

while $C'(k-1) \geq C'(k)$, **do**

$k = k + 1$.

for $p \in \mathcal{P}$, **do**

| If p satisfies equation (2.13), $p \rightarrow \mathcal{I}$; end.

end

for $p \in \mathcal{P} \setminus \mathcal{I}$, **do**

| If p satisfies equation (2.14), $p \rightarrow \mathcal{A}$; end.

end

while $\mathcal{P} \setminus \mathcal{A} \setminus \mathcal{I} \neq \emptyset$, $\Delta C_p(k) < 0 \forall p \in \mathcal{P} \setminus \mathcal{A} \setminus \mathcal{I}$, and $\rho(\mathcal{A}, k) < 1$, **do**

Compute $C_p(k)$ for any additional product $p \in \mathcal{P} \setminus \mathcal{A} \setminus \mathcal{I}$ using

$$\Delta C_p(k) = A_p(W^q(\mathcal{A} \cup \{p\}, k)) - I_p(S_p^*, B_p) + \sum_{p' \in \mathcal{A}} w_{p'} \lambda_{p'} d_{p'} \left[W^q(\mathcal{A} \cup \{p\}, k) - W^q(\mathcal{A}, k) \right].$$

Assign $p \in \mathcal{P} \setminus \mathcal{A} \setminus \mathcal{I}$ to $\mathcal{A}$ with $\min_{p \in \mathcal{P} \setminus \mathcal{A} \setminus \mathcal{I}} \Delta C_p(k)$ satisfying $\Delta C_p(k) < 0$, compute $C(k)$, and set $C'(k) = C(k)$.

end

end

Set $k = k - 1$.

Update $C'(k=0) = \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p)$. If $C'(k=0) \leq C'(k)$, $k' = 0$ and

$C'(k') = \sum_{p \in \mathcal{P}} I_p(S_p^*, B_p)$. Otherwise, $k' = k$ and $C'(k') = C'(k)$. Here, k' and

$C'(k')$ are the best solutions found by this algorithm.

E Supplemental Figures

The following figures are provided to further guide practitioners by pointing out the parameters need to be focused to achieve a specific goal. For example, regardless of finding an optimal solution, a practitioner may only focus on producing more units by utilizing AM. In this case, C_p^M seems to be the most critical parameter to focus on as seen in Figure A.2.

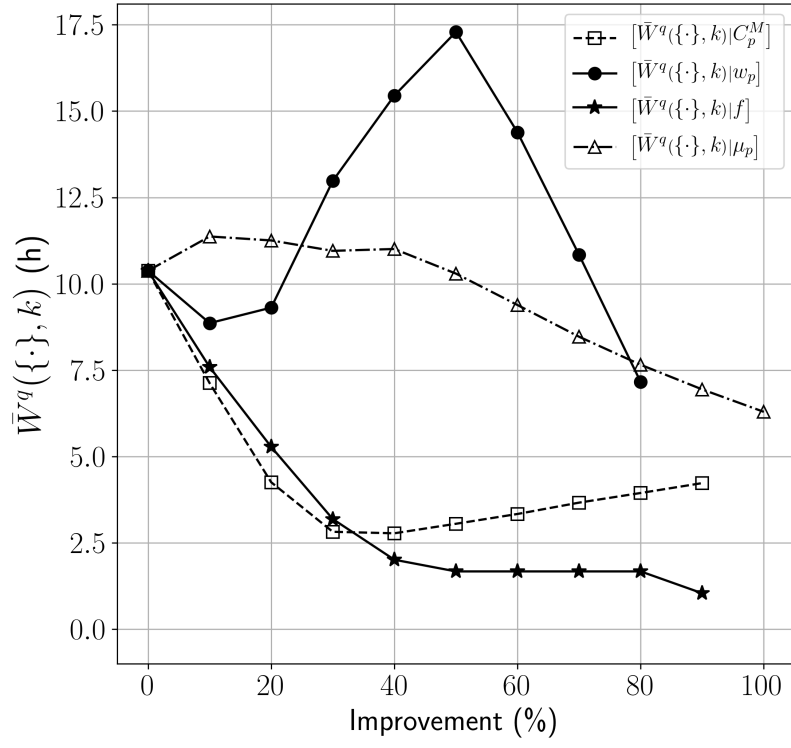


Figure A.1: Impact of improvement in C_p^M , w_p , f , and μ_p on $\bar{W}^q(\{\cdot\}, k^*)$ for $|\mathcal{P}| = 100$ and 100 replications.

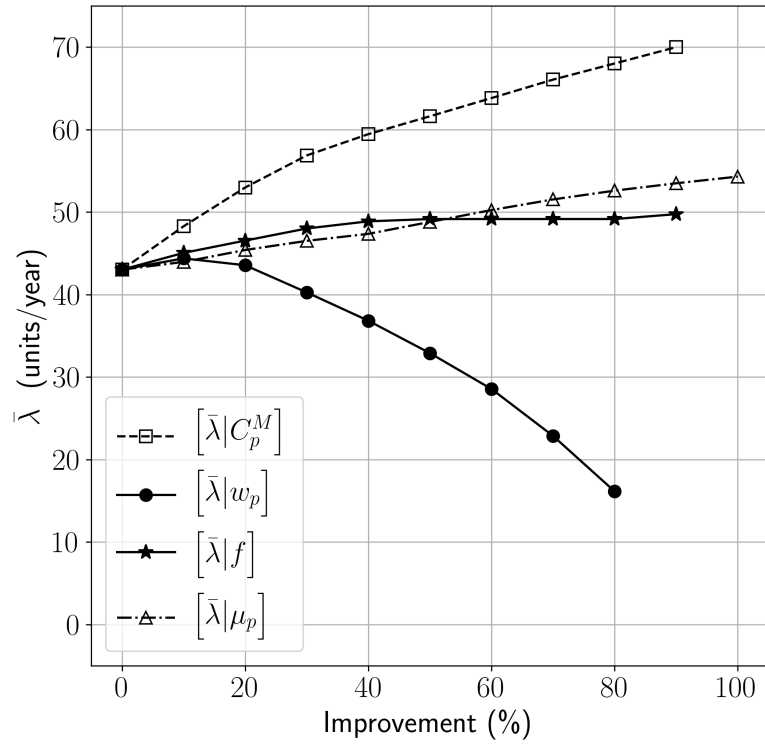


Figure A.2: Impact of improvement in C_p^M , w_p , f , and μ_p on $\bar{\lambda}$ for $|\mathcal{P}| = 100$ and 100 replications.

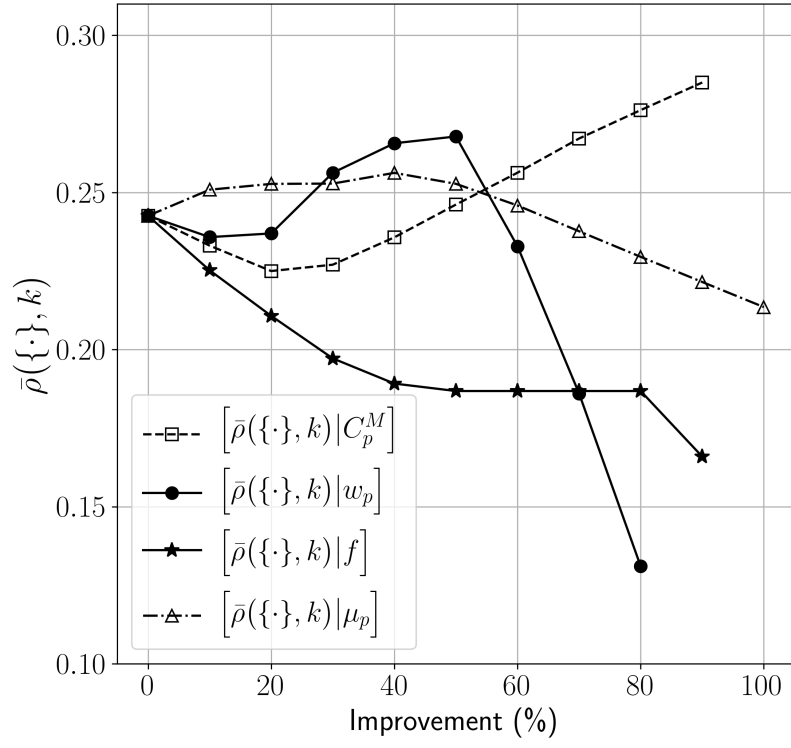


Figure A.3: Impact of improvement in C_p^M , w_p , f , and μ_p on $\bar{\rho}(\{\cdot\}, k^*)$ for $|\mathcal{P}| = 100$ and 100 replications.

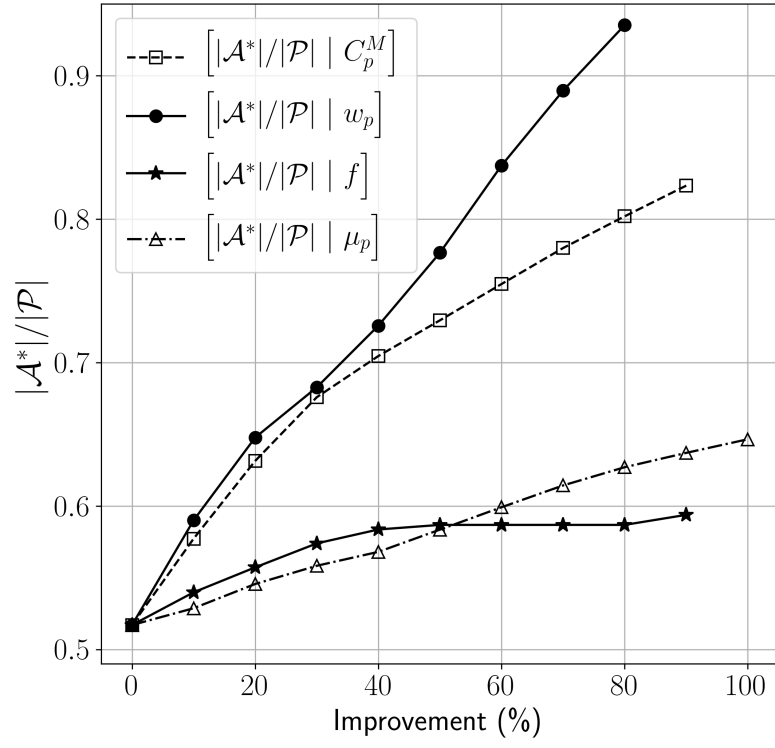


Figure A.4: Impact of improvement in C_p^M , w_p , f , and μ_p on $|\mathcal{A}^*|/|\mathcal{P}|$ for $|\mathcal{P}| = 100$ and 100 replications.



Figure A.5: Solution visualization for scenario 1.



Figure A.6: Solution visualization for scenario 2.



Figure A.7: Solution visualization for scenario 3.



Figure A.8: Solution visualization for scenario 4.



Figure A.9: Solution visualization for scenario 5.



Figure A.10: Solution visualization for scenario 6.

Vita

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