ABSTRACT

AHMED, RAMIN. Optimizing Logistics and Supply Chain Designs through the Integration of New Technologies. (Under the direction of Dr. Michael Kay).

The supply chain of a firm is always dynamic, subject to changes in every possible form of disruption. The disruptions can be a result of pandemics, the introduction of new technologies in the market, geopolitical instability, cyber threats, and so on. In this dissertation, we analyze and optimize the performance of an existing supply chain and its logistics operations, incorporating the introduction of new technologies.

We first analyze the impact of introducing additive manufacturing (AM) to an existing supply chain. For a medium to small scale production environment, we position AM as a recourse in case of shortages as well as a localized facility. We develop an analytical allocation rule based on cost differentials, which provides optimal sourcing decisions through sequential demand replenishment and facilitates an efficient performance evaluation of possible network configurations. We first model the scenario as a three-stage stochastic optimization problem. We then solve it using the allocation rule and present an illustration of our analysis and the optimal supply chain network configuration. Furthermore, we derive some insights as to how different problem characteristics affect the value and usage of AM.

We then move onto a metal-casting context, where AM — specifically 3D Sand-Printing (3DSP) has been gaining a lot of attention lately. Though 3DSP has been offering unique advantages like lead time reduction and the ability to directly print complex cores/molds without expensive hard tooling, it has been limited in its adoption in foundries due to high capital costs, lack of in-house 3DSP expertise, and evolving demand/realization of 3DSP. However, as the demand for more complex castings grows, 3DSP can address the need for highly complex, low-volume, and highly customized products. The current 3DSP capacity in the U.S. is relatively low, and, along with the fragile nature of the sand molds during transportation, the ability to satisfy the demand for 3DSP will become increasingly difficult. So, we discuss a system of strategically located 3DSP hubs to serve the U.S. metalcasting industry using the North American Industry Classification System (NAICS) data for foundries in the U.S.

We then move away from AM and propose and analyze a new platform, “Public Logistics Networks (PLN)”, as an alternative to private logistics network for ground transport which has massive potential in alleviating several existing concerns in the freight transportation industry ranging from under-utilization of trucks and excessive emission levels on the supply side to disgruntled customers (because of continuous price hikes) on the demand side. In this study, apart from designing the protocols and the decision-making problem of each entity, we study a localized network to specifically look into the demand side to study and analyze the behavior of the packages, especially agent controlled smart packages where, instead of being price takers, all the packages bid for transportation services. We analyze a smart bidding mechanism where the agents use all the system information to predict (i) bids of other packages and, (ii) trucks' potential decision (accept or reject a set of packages). We evaluate the performance of these smart packages against other packages. We further compare the smart bidding policy of the agents against a clairvoyant policy. We observed that smart packages save lower while spending considerably lesser time in the system compared to dumb packages. Moreover, the smart packages almost always resort to the clairvoyant policy. On the other hand, we notice that, on average, in contrast to honest packages, the smart packages are considerably saving on their bids while spending a bit longer in the system. Moreover, the smart packages almost reach 93% of the clairvoyant policy in terms of its spend while spending much lesser time in the system than the clairvoyant policy. We also discuss the effect of such smart bidding mechanism on the dynamics of a PLN.

Optimizing Logistics and Supply Chain Designs through the Integration of New Technologies

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Industrial Engineering

Raleigh, North Carolina
2021

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DEDICATION

To my parents who are my source of inspiration.

To my wife who has been my constant support throughout this journey.

BIOGRAPHY

Ramin Ahmed is a doctoral student in the Edward P. Fitts Department of Industrial and Systems Engineering at North Carolina State University. He holds a Masters in Industrial and Systems Engineering from North Carolina State University, and a Bachelor of Science degree in Industrial Engineering and Management from Khulna University of Engineering and Technology, Bangladesh. His research interests are Supply Chain, Production and logistics systems analysis, modeling, and optimization. He primarily focuses on analyzing the integration of new technologies to optimize supply chain performance.

ACKNOWLEDGMENTS

The whole PhD journey, for me, was filled with a roller coaster of emotions. In all its phases, even in the toughest of times, some extraordinary people helped me get through every single transition and guided me selflessly. I am extremely privileged to have had them in my life and had the pleasure of knowing them closely.

First, I would like to extend my deepest gratitude and appreciation to my advisor, Dr. Michael G. Kay, for his continuous support and guidance. His mentorship and encouragement helped me conduct research in new, challenging, and diverse fields and be an independent researcher. He has set a bar, in my mind, as a role model for his ethics, dedication, mentorship and management skills which, in future, I would strive to reach.

I am also grateful to Dr. Hans Sebastian Heese for his endless support and invaluable guidance. He has been providing me guidance and motivation for research since the day I first met him. I am also thankful to Dr. Reha Uzsoy for his feedback and suggestions regarding my research and teaching. I would also like to express my gratitude to Dr. Guha Manogharan for his support and guidance on my research. My thanks also go to Dr. Russell King for his support and feedback on my research and graduate studies.

I truly feel honored and blessed to be a part of the Department of Industrial and Systems Engineering at NCSU. I am thankful to Dr. Yahya Fathi for always addressing all the questions and concerns I had regarding the graduate program. I am grateful to each and every member of this department for their support starting from all the faculty members to the wonderful staff members like Christina, Karen and Justin, providing me all sorts of administrative and IT support whenever I needed.

I will forever be indebted to my parents: My father, my superhero since childhood, for being there, providing me every sort of support and preparing me for the life ahead through sharing his life and abroad experiences, and my mother, for her endless shower of love and blessing. They truly have been the source of inspiration for me.

Finally, I would like to thank my lovely wife, Fahriba Tasnim. I cannot thank her enough for all her support, struggle, and understanding during this journey, and taking a different direction in her career just to help me, support me and be a true companion throughout this journey. I am grateful to have her as my better half and cannot wait to embrace together all the challenges that life will bring our way.

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1

INTRODUCTION

The ever-competitive marketplace leads organizations to focus on streamlining their supply chain, enhancing its effectiveness and responsiveness. Over the years, this practice has led companies to innovate in the form of new technology introduction and its continual improvement. Examples of such technologies are 3D printing, Internet of Things (IoT), robotics, data analytics, and artificial intelligence. The introduction of such technologies in a supply chain comes with significant difficulties in determining their appropriate incorporation, optimal level of acquisition, deciding on their specific roles and so on. This dissertation consists of three parts: (i) The potential role of additive manufacturing (AM) in optimizing the supply chain network under uncertain demand, (ii) The role of AM in revitalizing the sand casting supply chain and its implications, and (iii) Proposing and analyzing Public Logistics Network (PLN) as an alternative to private logistics network for ground transport.

In the first part, we investigate the effects of using AM as flexible and/or reactive capacity for an existing traditional manufacturing (TM) setting, where AM starts production only after the demand is realized. Adequate implementation of such reactive capacities is necessary to address the uncertainties in demand, which have always been a major threat to the efficient performance of a supply chain. We consider a firm that has several existing TM facilities (EF) catering to various demand locations in their respective designated regions is considering incorporating AM in their supply chain configuration. The firm can choose from some candidate locations as well as decide to facilitate in-house AM establishment, i.e., co-location with an EF. The firm needs to take the decisions on locating the AM capability, production quantities at EF and demand allocation. We believe that the decisions should be taken sequentially as each subsequent decision depends on the former and hence we model the decision making process as a three-stage optimization problem where stage 1 determines the optimal locations of the AM capacity, stage 2 determines the optimal production levels at each EF and stage 3 determines the optimal allocation of demand to each of the resources. We developed an allocation rule which provides optimal sourcing decisions through sequential demand replenishment in case of both regular demand and shortages. We then use backward induction to determine the optimal production decisions at each EF, and the optimal locations of these AM hubs in terms of financial viability. We then illustrate the performance of our model through numerical analysis.

In the second part, we discuss the role of AM in revitalizing the sand casting supply chain, proposing and analyzing a network of strategically located 3DSP hubs to support the metal casting industry. Recent research has determined that 3D sand printing (3DSP) allows for an increase in casting complexity, casting quality, and weight reduction of finished parts, ensuring shorter manufacturing lead time, minimal product and development delays, and reduced need for inventory. While these benefits are well documented and apparent to the metal casting industry, traditional manufacturers are still not willing to adopt AM at a mass level due to its high fixed cost, lack of in-house expertise, allowable mold size limitations, and its economical unattractiveness for low-complexity, high-volume production. However, as the demand for more highly complex metal castings continues to grow, the need to use alternative approaches such as 3DSP becomes inevitable to address the need for highly complex, low-volume, and highly customized products. The growing demand for AM along with the distribution of foundries all over the U.S., will make it extremely difficult for only a handful of dedicated AM firms to satisfy the demand points across the entire U.S. metal casting industry. In order to address the current state of 3DSP and traditional sand casting, this study proposes a network of 3DSP hubs spaced throughout the United States which would be able to support the existing foundries to meet their 3DSP demand without having to invest their own time, effort and space for the technology. In this system, the foundries would send the demand that qualifies for 3DSP to a nearby AM hub that would be responsible for producing the molds and cores using AM and shipping them back to the foundries for casting and post-processing. This work aims to determine the optimal 3DSP hub locations in the US and their allocations based on the demand estimated from 2018 NAICS data, and associated production and operating structures based on AM service bureau data. This study employs the uncapacitated facility location (UFL) procedure to search for independent locations as a first cut and then modifies the UFL procedure to accommodate the ever-growing AM demand over time, obtaining an evolving network of 3DSP hubs. This paper aims to demonstrate a decision-making model for both: (1) AM organizations that can use this model to search for optimal locations for operating AM hubs and (2) metal foundries that can exploit the benefits of AM by working in conjunction with such AM organizations.

In the third part, we propose and analyze a new platform, “Public Logistics Networks (PLN)”, as an alternative to private logistics network for ground transport which has massive potential in alleviating several existing concerns in the freight transportation industry ranging from under-utilization of trucks and excessive emission levels on the supply side to disgruntled customers - because of continuous price hikes - on the demand side. We envision PLN to be operating analogous to packet transmission through Internet: a package sent from a public distribution center (DC) would get routed through a sequence of DCs over a network and get delivered to its destination. Here, the DCs would function like routers in the internet. The PLN design focuses on three independent entities: DCs, packages and trucks. The DCs are basically a platform used for holding the packages for pickup and dropoff, and for facilitating the transaction between the package and the trucks. The packages, instead of being price-takers, bid for services of the trucks to reach to its destination upon arriving at a DC and pay each DC a fraction of the accepted bid and a per-unit time cost of waiting at the DC, akin to a holding cost in a typical inventory setting. These bids can be accessed and seen by all the involved agents. Trucks see these packages, their associated requirements and bids, and then decide which, if any, package to accept in order to maximize their profit. In PLN, unlike a private logistics network, the entities of the network are independent and hence, no single firm or entity can provide centralized control of the entire network. This, along with several other issues resulting from the synergies of each entity, makes the coordination of a PLN very difficult. In this study, we first extend the necessary protocols of a PLN as discussed by Kay(2004) which, we believe, would enable efficient coordination and performance of a PLN in the bigger picture, that is, for a large network. However, since the coordination of the operation of such a PLN is very complex and there is no prior work on which each of the pieces can be analyzed, we conduct a limited study — yet an interesting one — on a small network (with 3 DCs) to perform a feasibility analysis and gain insights on different trade-offs among the entities. We specifically look into the demand side to study and analyze the behaviour of the packages, especially agent controlled smart packages, for a localized network segment with N DCs ($N = 3$) and provide recommendations regarding larger implementation by illustrating a scenario (for $N = 4$). We analyze a smart bidding mechanism where the agents uses all the system information to predict (i) bids of other packages and, (ii) trucks' potential decision (accept or reject a set of package). We evaluate the performance of these smart packages against a clairvoyant policy.

CHAPTER

2

MANUFACTURING NETWORK CONFIGURATION WITH ADDITIVE MANUFACTURING UNDER DEMAND UNCERTAINTY

Manufacturing Network Configuration with Additive Manufacturing under Demand Uncertainty

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Abstract

Two of the major problems Traditional Manufacturing (TM) supply chains face are setting requisite reactive strategies to address the uncertainties in demand and the optimal placement of these buffering capacities in order to be both responsive and cost-effective. Additive Manufacturing (AM) facilities can act as a recourse to the TMs and, also, as a dedicated source providing responsive and cost-effective sourcing alternatives. We develop an analytical allocation rule based on cost differentials, which provides optimal sourcing decisions through sequential demand replenishment and facilitates an efficient performance evaluation of possible network configurations. We model the scenario as a three-stage stochastic optimization problem, solve it using the allocation rule and present an illustration of our analysis and the optimal supply chain network configuration. Furthermore, we derive some insights as to how different problem characteristics affect the value and usage of AM.

Keywords: production, additive manufacturing, facility location, logistics, inventory

1 Introduction

Additive manufacturing (AM), or 3D printing, has been increasingly considered as the most revolutionary manufacturing technology today with companies using it to a great extent for a variety of applications.

Currently, 52% of the manufacturing firms use AM for parts production (that is an increase of 25% over two years), of which 40% use AM to produce at least 25% of their end-use parts (Dulchinos, 2020). With the advancement of this technology and its increasing acceptance in industry, 3D printing is expected to quickly become more mainstream.

The General Electric Company (GE) uses AM to produce the intricate tip of the engine fuel nozzle while automotive manufacturers like Ford, General Motors, Local Motors (an Arizona Startup) and Divergent (a Los Angeles based startup) use additive manufacturing to varying extent from parts production to fully 3D printed cars (Warburg, 2018; Ford Corporate, 2019; Hannon, 2018). Siemens tackled its low volume production problem for the armrests of train driver seats by incorporating AM in their workflow which enabled them to better meet customer needs without incurring unnecessary inventory while reducing production time from weeks to days (Hannon, 2018). With the increased popularity of AM, companies like Voodoo Manufacturing, Met L Flo, and Slant 3D are emerging as additive manufacturing firms who specialize in low-volume, high-value parts for aerospace and medical uses (Naitove, 2018; Formlabs, 2020; Roberts, 2018). Recent developments in AM technology have also enabled different manufacturers to use AM for the mass production of their products (Zahnd, 2018).

Additive manufacturing not only provides different manufacturing solutions but also offers scope for innovation and competitive advantages in this realm. Several companies like Siemens, Ford and GE have started building their business plans centering on the possibilities of AM while others are partnering or outsourcing their additive manufacturing activities. Having comprehended the increasing additive demand in several sectors, many startups like Zverse, SOLS, Formlabs, Nano Dimensions, and Desktop Metal are providing 3D printing as a service to different industries (Paine, 2017). Such inclusion of AM in a supply chain comes with significant difficulties in determining the optimal level of capacity acquisition, proper demand allocation, appropriate implementation and placement of these additional capacities.

In AM, although a considerable fixed cost is involved, the variable cost does not vary much with scale, and hence, the payback period of the up-front investment can be allowed to have a wide horizon. The basic cost trade-off between AM and TM in terms of production of a batch of parts is between fixed and variable cost, where TM has a high fixed cost of setting up a production run, followed by low variable costs, whereas AM has a comparatively lower setup cost and a comparatively higher variable cost. This, along with AM's localization of production, leads to considerably lower lead times and often has the potential to work as a make-to-order setting in a make-to-stock environment (Arbabian & Wagner, 2020). Moreover, AM, with its inherent traits of flexible manufacturing (see Eyers et al. (2018)) is often referred to as a viable mode of flexible manufacturing in the literature. In this paper, we investigate the effects of using AM as a flexible and/or reactive capacity to an existing TM setting where AM starts production once demand is realized. Moreover, AM, working in conjunction with TM, is more flexible in terms of capacity adjustments to demand since capacity can be bought in smaller increments.

Adequate implementation of such reactive capacities is necessary to address the uncertainties in demand that have always been a major threat to the efficient performance of a supply chain. Several survey results have confirmed that mastering demand variability for devising accurate product forecasts is the biggest supply chain challenge (CSCMP's Supply Chain Quarterly, 2011). Such estimates will, inherently, have forecasting errors in several periods, if not all, which creates a burden for businesses that strive to minimize stock-outs while avoiding the high cost of holding excess inventory. With the fluctuations in demand, a traditional manufacturing (TM) facility runs the risks of one of these happening. Over the years, this dilemma has been addressed in many ways by many researchers. Most works emphasize reactive or buffering strategies where the firms react to demand uncertainty in an attempt to maintain a prescribed customer service level through safety stock, safety lead times, extra capacity, and other internal reactions. In this paper, we propose AM to be used as a reactive strategy in addition to the relative cost advantages it might offer based on its placement. We address this proposal through the following scenario.

We consider a firm that has several existing TM facilities catering to various demand locations in their respective designated regions and that is considering incorporating AM into its supply chain configuration. The firm can choose from some candidate locations as well as decide to facilitate in-house AM establishment, that is, co-location with an existing TM facility. The firm needs to take the following decisions:

- Whether to incorporate AM based on financial viability, and if so, where to locate AM capacity.
- How much to produce at each existing TM facility.
- How to satisfy demand, and what to do in case of shortages.

In this paper, we model the decision making process as a three-stage optimization problem where stage 1 determines the optimal locations of the AM facilities (if any), stage 2 determines the optimal production quantities at each existing TM facility, and stage 3 determines the optimal allocation of demand to each of the resources. We develop an allocation rule which provides optimal sourcing decisions through sequential demand replenishment in case of both regular demand and shortages. This rule then effectively allows us to reduce the three-stage optimization problem to a two-stage optimization problem. We illustrate the performance of our model through numerical analysis.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. In Section 3, we discuss our model and the sequence of events. In Section 4, we develop our allocation rule, reformulate the production and location problems, and discuss a numerical illustration of our model. In Section 5, we perform a sensitivity analysis to obtain additional insights into the role of various factors. Section 6 presents our discussion and concluding remarks.

2 Literature Review

Our research draws on three areas of literature: managing demand uncertainty through flexible capacity, facility location, and AM working in conjunction with TM.

2.1 Managing demand uncertainty through flexible capacity

AM is often described as flexible capacity due to its different flexibility capabilities (see Eyers et al. (2018)) to respond to dynamic requirements in an uncertain and competitive economic environment. In this paper, we position AM as a reactive/flexible capacity to the existing TM facilities in order to buffer against demand uncertainty and analyze the performance of such a supply chain. Here, we mainly focus on managing demand variability using flexible capacity as a hedge against demand uncertainty and the associated investment decisions in a monopolistic environment.

Many researchers such as Fine & Freund (1990), Röller & Tombak (1993), Lee & Tang (1997), Van Mieghem (1998), Aviv & Federgruen (2001), Buxey (2005), Malhotra & Mackelprang (2012), Georgiadis & Athanasiou (2013) and, more recently, Wang et al. (2019) studied flexible capacity strategy as an effective means for a firm to manage demand variability and increase the overall supply chain effectiveness. Having reactive capacities in a supply chain can facilitate a firm to better match supply with uncertain demand and, thereby, gain significant economic and operational improvements (Li & Ha, 2008). Several researchers have explored the benefits of positioning a flexible or reactive capacity in their supply chain and have tried to optimize its performance in different contexts. Lin & Parlaktürk (2012), Mutha et al. (2016), Fisher & Raman (1996), Fisher et al. (1997), Moreno & Terwiesch (2015), Gerwin (1993) studied the benefits a firm can derive by incorporating different versions of flexible capacities in their supply chain. These authors investigate the benefits in different contexts like generating additional savings by reducing inventory levels, reducing expected stockouts and markdowns, producing more through such reactive capacities, and so on. In this paper, we investigate a supply chain with the inclusion of flexible capacity, AM, and study the benefits a firm can derive by reducing expected levels of inventory and backorders as well as due to the savings generated by AM's localized service. Our allocation rule, based on relative cost benefits, facilitates the optimal use of a mix of inventory and the AM service. Like several researchers (see Lücker et al. (2019), Simchi-Levi et al. (2018), Huang et al. (2016)), we also investigate the supply chain performance under varying mixes of inventory and flexible capacities.

In addition to the use of reactive capacities along with finished good inventory, the investment decisions regarding the placement of such reactive capacities are also of interest in this paper. Several researchers (see Yang & Ng (2014), Van Mieghem (2003), Chod & Rudi (2005), Goyal & Netessine (2007), and Anand & Girotra (2007)) have investigated the investment decisions concerning the inclusion of flexible capacities in different supply chains in order to optimize different performance measures. Boonman et al. (2015) investigate dedicated versus flexible capacity investment decisions and derived equilibrium conditions of an incumbent and a potential entrant in an uncertain economic environment. Yang et al. (2014) study technology investment decisions under flexible capacity with uncertain demand and determine the optimal conditions and levels of such capacity inclusion under different associated cost structures. They use a three-stage optimization model for making sequential decisions on the technology level, capacity, and production quantity respectively. This is similar to our study in terms of the setting and objective. In our work, we use AM as a dedicated source to exploit localization benefits and, also, as a flexible recourse for the TM. Under uncertain demand and based on the relative cost advantages, we formulate a three-stage stochastic optimization problem for making sequential decisions on the placement of capacity, production quantity at each existing TM facility, and demand allocation across the modes. We determine the optimal investment decisions and further determine the impact of such decisions across varying levels of cost structures.

2.2 Facility location

The facility location problem has been widely studied and is one of the major strategic decisions for optimizing a supply chain network. Over the years, researchers have studied various models that incorporate different levels of complexity. Some of the most basic models used for supply chain network design include the uncapacitated facility location and p-median problems, which can be extended to include capacitated facilities and, when the transportation network is explicitly included, the hub location model. While these models are widely used, they fail to capture the supply chain uncertainties. Owen & Daskin (1998) discussed facility location under uncertainty, which was further studied in detail by Snyder (2006) and, more recently, by Correia & da Gama (2015).

Stochastic optimization is one of the most prominent approaches to deal with uncertainties when some knowledge is available about the probability distribution of the random variables. This approach makes use of mathematical programming to find the configuration that optimizes expected performance. In this paper, variability in customer demand is of interest. Many papers consider demand uncertainty and use a two-stage stochastic optimization model to solve the problem. Louveaux & Peeters (1992) determine the size and location of the sites in the first stage and customer allocation in the second whereas Snyder et al. (2007) additionally consider safety stock levels and risk measures. Laporte et al. (1994) determine location and assignment decisions in the first stage and observe customer revenues in the second stage. We consider a three-stage optimization model where we determine the location in the first stage, production decisions in the second stage, and allocation decisions once demand is realized in the third stage.

When the uncertainty does not have a probabilistic description, robust optimization is a useful technique in solving such problems (Kchaou Boujelben & Boulaksil, 2018). Jakubovskis (2017) uses robust optimization to determine optimal facility locations and resource mode acquisition. The author studies a combination of types of capacity acquisition options and examines their effects under demand uncertainty. This work aligns with the motivation and scenario of our paper in terms of the location and capacity decisions. However, instead of making a complete set of decisions to design the complete network, we develop an allocation rule based on cost differentials between AM and TM and investigate the optimal location decision using stochastic optimization under an existing network design.

2.3 AM working in conjunction with TM

Additive manufacturing (AM) is a manufacturing process of producing a part by depositing material layer by layer to obtain a net shape unlike the subtractive processes/traditional manufacturing (TM) where the final shape is obtained through the removal of material (ASTM Committee F42 on Additive Manufacturing Technologies, 2012).

Both AM and TM offer many unique benefits and several researchers have investigated the optimal choice of such modes from different points of view. Some researchers (Thomas, 2016; Knofius et al., 2016) have used different cost factors to determine when to use AM, while some other studies (Weller et al., 2015; Kleer & Piller, 2013) used production volumes and magnitude of the fixed cost to decide on the optimal production mode. Sasson & Johnson (2016) assert that TM with heterogeneous bills-of-material might include AM capabilities to separate low-volume production from scalable mass production. Such incorporation of AM in the TM supply chain has been found to be advantageous, and many researchers have advocated the role of AM in simplifying the complexity of supply chains (Strong et al., 2017; Hur et al., 2002; Xiong et al., 2009). According to Petrick & Simpson (2013), with a complementary TM, AM would localize both production and sourcing activities, facilitating reduced logistics costs.

AM, with its wide range of capabilities, provides manufacturers huge scope and flexibility, which is increasingly becoming vital for business successes (Chan, 2001; Chan et al., 2006; Groover, 2013; Wadhwa et al., 2005) and more so when utilized complementarily to existing TM methods (Thomas & Gilbert, 2014).

Several researchers (see Song & Zhang (2019); Dong et al. (2016); Knofius et al. (2020); Westerweel et al. (2018)) have studied the complementarity of AM and TM in different supply chains, and analyzed the allocation of supply to the demand stemming from partition decisions based on different parameters. While these works deal with a one-to-one correspondence between a unit of demand and its optimal production mode, we propose to place AM in a TM supply chain to exploit localization benefits and more importantly, as a recourse for TM under demand uncertainty. Our allocation rule provides an optimal partitioning/catering decision based on demand realization, production size at TM and, of course, the respective costs of meeting a particular demand.

The closest paper to ours in terms of motivation and structure is Arbabian & Wagner (2020). They study the impact of placing AM in manufacturer-retailer supply chains, focusing on the interaction between a manufacturer and a retailer when deciding on placing AM in-house or in either of their sites and addressing the uncertainties in demand through AM. However, our paper studies the impact of incorporating AM in a centrally owned supply chain, and analyzes the AM location and TM production decisions by addressing the uncertainties in demand based on relative cost differentials.

To the best of our knowledge, our paper is the first to study and propose AM as such a reactive buffering strategy.

3 Model

In this section, we formally describe the firm's problem and introduce the model used to optimize the supply chain network configuration. We first present the problem definition in terms of inputs, parameters, assumptions, and objectives. We then state the sequence of events in the decision-making problem.

3.1 Problem definition

We consider a supply chain in which a firm has a set of existing TM facilities (EFs), M, each producing products at a unit cost v_T to cater to a set of demand points N. Demand shortages are backordered, which costs b per part per period, and any leftover units cost h per part per period to store. We assume the products that the EFs produce can also be produced using AM (just like present-day plastic toys or Siemens' armrest), and the firm is looking into whether to incorporate AM capabilities, if any, to one or some sites from a set of candidate sites K; we use a binary variable θ_k to indicate whether an AM facility is opened at site $k \in K$. Each selected AM site $k \in K$ has a periodic cost of F_k, including the cost of the facility, 3D printers, and developing 3D schematics, and prints the products at a unit cost v_A. We assume $v_A > v_T$ which is reflective of actual industry standards, often due to TM's economies of scale. The firm is responsible for the delivery of the orders to the customers and bears the transportation costs. It costs t per unit per mile to transport. The unit transportation cost is the product of the distance and t, where the distance is denoted by d with origin-destination subscripts — d_{ij} and d_{kj} denote the distances from EF i and AM k to demand point j, respectively. For tractability and simplicity of the analysis, we assume each demand point $j \in N$ is assigned to its nearest EF, forming separate designated regions for the EFs, in order to optimize the supply chain transportation cost. Since any different demand point–EF associations would result in higher transportation costs, we assume transshipments between EFs are not allowed. Hence, each EF $i \in M$ is restricted to only respond to the demand points in its designated region — the EF and demand point associations do not change. Note however, this restriction is not applicable to AM sites, which can be used across these designated regions and hence, link the problems of the different EFs and do not allow us to separate the problems. In addition, we have assumed that AM capacity can be easily added to a facility in terms of addition of machines or access to additional capacity which, in case of high utilization, can be accessed by the firm.

With the possible inclusion of AM in its supply chain configuration, the firm needs to decide on the EF production quantities, Q_i, and how to satisfy demand, once realized. Specifically, the firms decides on the allocation of demand to the available modes, denoted by X with origin-destination as subscripts and the optimal mode as a superscript — the available modes are inventory, backorder and AM which are denoted by superscripts I, B and A, respectively. For example, X_{ij}^B denotes the amount of demand at point j to be satisfied using backorder at EF i. Table 1 provides a comprehensive summary of notation.

The total supply chain cost is given by:

$$TC = \sum_{k \in K} C_k^F + \sum_{i \in M} C_i^I + \sum_{i \in M} C_i^B + \sum_{j \in N} C_j^T + \sum_{k \in K} C_k^A - \sum_{i \in M} C_i^S \tag{1}$$

where

$$C_k^F = F_k \theta_k \tag{2}$$

$$C_i^I = v_T Q_i \tag{3}$$

$$C_i^B = (v_T + b) \sum_{j \in N} X_{ij}^B \tag{4}$$

$$C_j^T = t \left[\sum_{i \in M} X_{ij}^I d_{ij} + \sum_{k \in K} X_{kj}^A d_{kj} + \sum_{i \in M} X_{ij}^B d_{ij} \right] \tag{5}$$

$$C_k^A = v_A \sum_{j \in N} X_{kj}^A \tag{6}$$

$$C_i^S = (v_T - h) \left[Q_i - \left(\sum_{j \in N} X_{ij}^I \right) \right]^+ \tag{7}$$

Here, C_k^F is the fixed cost of the newly added facilities at site k, C_i^I is the cost of regular production at EF i, C_i^B is the cost incurred due to backordering at EF i that includes the backordering cost b and the production cost for the backordered units, C_j^T is the transportation cost associated with shipments to demand point j, C_k^A is the total production cost at AM facility k and C_i^S is the salvage value derived by storing a unit at a cost of h, thereby reducing next period's production cost by v_T per unit held. Here, $[\cdot]^+$ denotes $\max(\cdot, 0)$.

Table 1: Notation

Sets:	
N	Set of demand points, $N = \{j\}, j = 1, 2, ...\vert N\vert$.
M	Set of EFs, $M = \{i\}, i = 1, 2, ...\vert M\vert$.
K	Set of candidate sites, $K = \{1, 2, ..., l, l+1, l+2, ..., l+\vert M\vert\}$, where l is the number of independent AM candidate sites, so the total number of AM candidate sites (with co-location) is $l+\vert M\vert$.
Parameters:	
d_{ij}, d_{jk}	Distance from EF i and AM k to demand point j, respectively, $\forall i \in M$, $\forall j \in N$ and $\forall k \in K$.
F_k	Periodic fixed cost of an AM facility, $\forall k \in K$.
D_j	Realized demand at demand point j, $\forall j \in N$, with support of $[0, \overline{D}]$.
$\boldsymbol{D}$	Vector of all realized demand.
$\boldsymbol{\xi}$	Vector of all demand random variables.
v_T, v_A	Unit production cost at TM and AM, respectively.
h	Unit inventory holding cost per period.
b	Unit backordering cost per period.
t	Per-mile per unit transportation cost.
Decision variables:	
θ_k	If an AM facility is established at k, $\theta_k = 1$, otherwise it equals 0, $\forall k \in K$.
Q_i	Production quantity at EF i, $\forall i \in M$.
X^I_{ij}	Amount of demand at point j that is satisfied from Q_i, $\forall i \in M$ and $\forall j \in N$.
X^B_{ij}	Amount of demand at point j that is satisfied using backorder at EF i, $\forall i \in M$ and $\forall j \in N$.
X^A_{kj}	Amount of demand at point j that is satisfied using AM at site k, $\forall k \in K$ and $\forall j \in N$.

Going forward, as a short hand, we will use $\boldsymbol{\Theta}$, $\boldsymbol{Q}$ and $\boldsymbol{X}$ to define the vector of locations decisions (θ_k), the vector of production decisions across the EFs (Q_i) and the matrix of allocation decisions across the modes ($X^I_{ij}, X^B_{ij}, X^A_{kj}$), respectively.

3.2 Sequence of decisions

The firm needs to make three decisions, as discussed in Section 1. The decisions should be taken sequentially as each subsequent decision depends on the former. Hence, the firm's decision-making process consists of the following sequential stages:

Stage 1: In anticipation of the optimal production quantity decision, $\boldsymbol{Q}^*$, and allocation decision, $\boldsymbol{X}^*$, determined in stages 2 and 3 respectively, in this stage, we set the AM facility locations so as to

$$\begin{aligned}\underset{\boldsymbol{\Theta}}{\text{minimize}} \quad & \sum_{k\in K} C_k^F + \sum_{i\in M} C_i^I(\boldsymbol{Q}^*(\boldsymbol{\Theta})) + E_{\boldsymbol{\xi}}\Bigg[\sum_{i\in M} C_i^B(\boldsymbol{Q}^*(\boldsymbol{\Theta}), \boldsymbol{X}^*(\boldsymbol{Q}^*,\boldsymbol{\Theta})) + \sum_{j\in N} C_j^T(\boldsymbol{Q}^*(\boldsymbol{\Theta}), \boldsymbol{X}^*(\boldsymbol{Q}^*,\boldsymbol{\Theta})) \\ & + \sum_{k\in K} C_k^A(\boldsymbol{Q}^*(\boldsymbol{\Theta}), \boldsymbol{X}^*(\boldsymbol{Q}^*,\boldsymbol{\Theta})) - \sum_{i\in M} C_i^S(\boldsymbol{Q}^*(\boldsymbol{\Theta}), \boldsymbol{X}^*(\boldsymbol{Q}^*,\boldsymbol{\Theta}))\Bigg]\end{aligned} \tag{8}$$

Stage 2: Given $\boldsymbol{\Theta}$ and in anticipation of the optimal allocation decision, $\boldsymbol{X}^*$, determined in stage 3, we set the production decisions in order to

$$\begin{aligned}\underset{\boldsymbol{Q}\geq 0}{\text{minimize}} \quad & \sum_{i\in M} C_i^I(\boldsymbol{Q}) + E_{\boldsymbol{\xi}}\Bigg[\sum_{i\in M} C_i^B(\boldsymbol{Q}, \boldsymbol{X}^*(\boldsymbol{\Theta},\boldsymbol{Q})) + \sum_{j\in N} C_j^T(\boldsymbol{Q}, \boldsymbol{X}^*(\boldsymbol{\Theta},\boldsymbol{Q})) + \sum_{k\in K} C_k^A(\boldsymbol{Q}, \boldsymbol{X}^*(\boldsymbol{\Theta},\boldsymbol{Q})) \\ & - \sum_{i\in M} C_i^S(\boldsymbol{Q}, \boldsymbol{X}^*(\boldsymbol{\Theta},\boldsymbol{Q}))\Bigg]\end{aligned} \tag{9}$$

Stage 3: Given $\boldsymbol{\Theta}$, $\boldsymbol{Q}$ and the demand realizations, we set the allocation decisions so as to

$$\begin{aligned}\underset{\boldsymbol{X}\geq 0}{\text{minimize}} \quad & \sum_{i\in M} C_i^B(\boldsymbol{X}) + \sum_{j\in N} C_j^T(\boldsymbol{X}) + \sum_{k\in K} C_k^A(\boldsymbol{X}) - \sum_{i\in M} C_i^S(\boldsymbol{X}) \\ \text{subject to} \quad & \sum_{j\in N} X_{ij}^I \leq Q_i, \ \forall i \in M \\ & \sum_{i\in M}\left(X_{ij}^I + X_{ij}^B\right) + \sum_{k\in K} X_{kj}^A = D_j, \ \ \forall j \in N \\ & X_{kj}^A \ \leq \overline{D}\theta_k, \ \ \forall j \in N, \ \forall k \in K\end{aligned}$$

4 Results and Illustration

In this section, we solve our three-stage optimization problem through backward induction.

4.1 Allocation rule

Every demand point is characterized by t_{T_j} and t_{A_j}, that is, the unit transportation costs from the nearest TM and AM, respectively (if no AM capacity is established, then $t_{Aj} = \infty$). We define the transportation cost differential for demand point j, $\Delta t_j = t_{A_j} - t_{T_j}$, and the product cost differential, $\Delta v = v_A - v_T$.

By comparing the costs of satisfying any given unit of demand through each of the different available modes, namely through existing inventory, I, additive manufacturing, A, or by backordering of demand, B, we can derive the following general allocation rule.

Theorem 1. *It is optimal to allocate inventory in decreasing order of* Δt_j *as long as* $\Delta t_j \geq -\Delta v - h$.
Proof: Demand can be satisfied through three modes with the following per unit costs.

- Using inventory (I) at a cost $c_j^I = t_{T_j} + (v_T - h)$.

- Using backordering at EF (B) at a cost $c_j^B = v_T + t_{T_j} + b$.
- Using AM (A) at a cost $c_j^A = v_A + t_{A_j}$

Comparing these costs it can be easily established that:

- For $\Delta t_j > b - \Delta v$: $\quad c_j^I < c_j^B < c_j^A$, $\quad$ and $\quad c_j^B - c_j^I = b + h$,
- For $-\Delta v - h \leq \Delta t_j \leq b - \Delta v$: $\quad c_j^I < c_j^A < c_j^B$, $\quad$ and $\quad c_j^A - c_j^B = \Delta t_j + \Delta v + h \leq b + h$, $\quad$ and
- For $\Delta t_j < -\Delta v - h$: $\quad c_j^A < c_j^I < c_j^B$, $\quad$ so using inventory is not optimal.

The benefit of using inventory, thus, is non–negative and weakly decreasing in Δt_j for all demand points with $\Delta t_j \geq -\Delta v - h$, and it is negative otherwise. ■

Using the results of Theorem 1 for all demand points with respect to their nearest EF and AM facilities, we define three sets. We use Ω_1 to denote the set of demand points where, in case of shortages, backordering at the EF is preferred over using AM to satisfy demand (i.e., $c_j^I < c_j^B < c_j^A$) :

$$\Omega_1 := \{j \in N \mid \Delta t_j > b - \Delta v\} \tag{10}$$

We use Ω_2 to denote the set of demand points where, for shortages, AM is preferred over backordering at EF to satisfy demand (i.e., $c_j^I \leq c_j^A \leq c_j^B$ — we use I if $c_j^I = c_j^A$ and AM if $c_j^A = c_j^B$) :

$$\Omega_2 := \{j \in N \mid -\Delta v - h \leq \Delta t_j \leq b - \Delta v\} \tag{11}$$

Finally, we let Ω_3 denote the set of demand points where AM is the dedicated preferred mode for satisfying demand (i.e., $c_j^A < c_j^I < c_j^B$) :

$$\Omega_3 := \{j \in N \mid \Delta t_j < -\Delta v - h\} \tag{12}$$

For ease of exposition, we use $D(\Omega_i)$ to denote the total realized demand over Ω_i. These sets of demand points for each catering method along with the general allocation rule in Theorem 1 imply the following optimal allocation actions for the firm.

Corollary 1: *Given θ, Q, and demand realization for each demand point, D_j, the following are the optimal allocation actions for the firm:*

(a) Satisfy the demand in Ω_1 using inventory (arbitrarily). If inventory is not sufficient, satisfy any remaining demand (i.e., $[D(\Omega_1) - Q]^+$) by backordering.

(b) If inventory is available after satisfying demand points in Ω_1, use this excess inventory to satisfy demand in Ω_2 in the decreasing order of Δt_j and satisfy any remaining demand (i.e., $[D(\Omega_2) - \{Q - D(\Omega_1)\}^+]^+$) using AM as a recourse.

(c) If inventory is available after satisfying all the demand points in Ω_1 and Ω_2, keep this excess inventory (i.e., $[Q - D(\Omega_1, \Omega_2)]^+$) in inventory for next period.

(d) Satisfy all the demand in Ω_3 using AM.

From Theorem 1, it is evident that using existing inventory, if available, is always optimal for the first two sets of demand points, that is, Ω_1 and Ω_2. We use backordering to satisfy the excess demand in (a) because here the additional transportation cost AM would incur outweighs the benefit it would offer ($c_j^B < c_j^A$). So, for Ω_1, in the case when inventory runs out, it is cheaper to backorder the excess demand from the EF instead of using AM. However, in (b), if the existing inventory is already depleted, it is optimal to use AM as a recourse since $c_j^A \leq c_j^B$. Here, different from (a), the benefit of using AM is justified after accounting for the transportation cost differential, product cost differential and the backorder cost which EF would otherwise incur. Finally, actions (c) and (d) call for using AM to satisfy an incoming demand while storing the existing inventory, if any, since $c_j^I > c_j^A$. Here, the benefit of storing the existing inventory for the next period outweighs the cost of satisfying it using AM.

Now that we have characterized the optimal allocation decisions, laid out by Theorem 1 and Corollary 1, in section 4.2, we determine the optimal production and allocation decisions.

4.2 Reformulation of the production and allocation problems using the allocation rule

We first define the set of demand points associated with EF i as $N_i \subset N$ and for each of these demand points, we define Δt_j as the transportation cost differential between the closest AM (i.e., the smallest $t_{A_j}^i$) and the associated EF (i.e., the smallest $t_{T_j}^i$). We define the Ω's for each EF i as $\Omega_1^i := \{j \in N_i \mid \Delta t_j > b - \Delta v\}$, $\Omega_2^i := \{j \in N_i \mid -\Delta v - h \leq \Delta t_j \leq b - \Delta v\}$ and $\Omega_3^i := \{j \in N_i \mid \Delta t_j < -\Delta v - h\}$, and without loss of generality, we index the points in each N_i in increasing order of Δt_j

In Section 4.1, we defined the optimal actions for the firm and thereby, the allocation decisions, $\boldsymbol{X}$. We have also seen that the magnitude of these variables depend on $\boldsymbol{Q}$ and $\boldsymbol{D}$. Since demand points in Ω_1^i and Ω_3^i are always going to be catered from EF i (backorder and regular) and AM (dedicated), respectively, the transportation cost for satisfying each of these points is always going to be the same. However, in Ω_2^i the allocation decision depends on the available inventory, the distance from the nearest AM and, of course, the realized demand. We define the available inventory for Ω_2^i, that is, the remaining inventory, if any, after satisfying all the demand in Ω_1^i, as

$$I_i^+ = \left[Q_i - \sum_{j \in \Omega_1^i} D_j \right]^+$$

Using the allocation rule in Theorem 1 and Corollary 1, we rewrite the cost components in equations (4) to (7), denoting each of them with an additional prime ($'$).

$$C_i^{B'} = (v_T + b)\left[\left(\sum_{j\in\Omega_1^i} D_j\right) - Q_i\right]^+ \tag{13}$$

$$C_i^{T'} = \sum_{j\in\Omega_1^i} D_j t_{T_j} \tag{14a}$$

$$+ \sum_{j\in\Omega_2^i} min\{(I^+ - \sum_{p=|\Omega_1^i|+2}^{j} D_{p-1})^+, D_j\} t_{T_j} \tag{14b}$$

$$+ \sum_{j\in\Omega_2^i} \{D_j - (I^+ - \sum_{p=|\Omega_1^i|+2}^{j} D_{p-1})^+\}^+ t_{A_j} \tag{14c}$$

$$+ \sum_{j\in\Omega_3^i} D_j t_{A_j} \tag{14d}$$

$$C_i^{A'} = v_A \sum_{j\in\Omega_3^i} D_j \tag{15a}$$

$$+ v_A \sum_{j\in\Omega_2^i} \left[D_j - (I^+ - \sum_{p=|\Omega_1^i|+2}^{j} D_{p-1})^+\right]^+ \tag{15b}$$

$$C_i^{S'} = (v_T - h)\left[Q_i - \sum_{j\in(\Omega_1^i \cup \Omega_2^i)} D_j\right]^+ \tag{16}$$

$C_i^{B'}$ refers to the cost of backordering and production at EF i in the next period in order to satisfy any excess demand in Ω_1^i after allocating all of Q_i. Each of the expressions of $C_i^{T'}$ refers to the transportation cost for a set of demand points where (14a) refers to the demand points in Ω_1^i, (14b) refers to the demand in Ω_2^i to be catered from existing inventory if $I_i^+ > 0$, (14c) refers to the excess demand, if any, in Ω_2^i after the existing inventory is depleted and (14d) refers to the demand points in Ω_3^i. The expressions in $C_i^{A'}$ refer to the AM production cost for a set of demand points where (15a) refers to the demand points in Ω_3^i and (15b) refers to the excess demand, if any, in Ω_2^i after the existing inventory is depleted. $C_i^{S'}$ refers to the salvage value of the leftover inventory, if any, after satisfying the demand in Ω_1^i and Ω_2^i, since it is cost effective to store it in inventory and use AM to satisfy the demand in Ω_3^i as per Theorem 1.

Note that, different from the previous stage 2 cost function, these cost components with primes no longer contain the variable $\boldsymbol{X}$. This is because the way they are structured already encompasses the optimal allocation rule and thus avoids the need to further consider the stage 3 problem. Hence, with these simplified cost components, (8) can be rewritten as:

$$\underset{\boldsymbol{Q}\geq 0}{\text{minimize}} \quad \sum_{i\in M} C_i^I(\boldsymbol{Q}) + E_{\boldsymbol{\xi}}\left[\sum_{i\in M} C_i^{B'}(\boldsymbol{Q},\boldsymbol{\Theta}) + \sum_{i\in M} C_i^{T'}(\boldsymbol{Q},\boldsymbol{\Theta}) + \sum_{i\in M} C_i^{A'}(\boldsymbol{Q},\boldsymbol{\Theta}) - \sum_{i\in M} C_i^{S'}(\boldsymbol{Q},\boldsymbol{\Theta})\right] \tag{17}$$

Similarly, anticipating the quantity decisions and using the simplified cost components, (9) can be rewritten as follows:

$$\begin{aligned}\underset{\boldsymbol{\Theta}}{\text{minimize}} \quad & \sum_{k\in K} C_k^F + \sum_{i\in M} C_i^I(\boldsymbol{Q}^*(\boldsymbol{\Theta})) + E_{\boldsymbol{\xi}}\Bigg[\sum_{i\in M} C_i^{B'}(\boldsymbol{Q}^*(\boldsymbol{\Theta})) + \sum_{i\in M} C_i^{T'}(\boldsymbol{Q}^*(\boldsymbol{\Theta})) + \sum_{i\in M} C_i^{A'}(\boldsymbol{Q}^*(\boldsymbol{\Theta})) \\ & - \sum_{i\in M} C_i^{S'}(\boldsymbol{Q}^*(\boldsymbol{\Theta}))\Bigg]\end{aligned} \tag{18}$$

4.3 Illustration

In this section, we first consider a base case scenario, that is, the existing state without AM. We then study the case of the possible inclusion of AM and compare its performance against the base case.

As our base case, we consider an exemplary configuration of a firm whose supply chain is based on North Carolina, USA. We consider 30 randomly generated demand points ($|N| = 30$) from the 84 cities of North Carolina having a population of at least 10,000 (using random stream 'mcg16807' in MATLAB with default seed) and 5 EFs ($|M| = 5$) at Durham, Greensboro, Rocky Mount, Salisbury and Concord (as EF1, EF2, EF3, EF4, and EF5, respectively). Each EF serves demand points in their designated region — the region being constructed based on closest distance from the demand points. EFs do not serve outside their designated region, and no transshipments occur between them. We assume the demand at each demand point to be zero with probability p and non-zero with probability $(1-p)$. We consider the non-zero demand to follow a symmetric distribution with three points: $\mu(1-\alpha)$, μ and $\mu(1+\alpha)$ with probabilities 25%, 50% and 25%, respectively, where μ is the mean of non-zero demand and α (variability measure) is the fraction by which the non-zero demand can vary from its mean. In order to facilitate the derivation of insights, we consider μ to be the same for all demand points. EF i sets its production quantity decision Q_i so as to

$$\underset{Q_i\geq 0}{\text{minimize}} \quad v_T Q_i + E_{\boldsymbol{\xi}}\left[(v_T+b)\left(\sum_{j\in N_i} D_j - Q_i\right)^+ + \sum_{j\in N_i} D_j t_{T_j} - (v_T-h)\left(Q_i - \sum_{j\in N_i} D_j\right)^+\right] \tag{19}$$

Here, each EF chooses a production quantity that minimizes the sum of production cost, expected backorder cost and expected transportation cost, netting out the expected salvage value.

Next, we assume the firm is considering the inclusion of AM and has identified four sites as potential standalone locations for AM establishments — Sanford, Warsaw, Lowesville, Lexington, marked as AM1, AM2, AM3 and AM4; we use AM5 to AM9 to denote the option of co-locating at the EFs (hence, $K = \{1,2,\ldots,9\}$). Further, the periodic cost of establishing an AM at an independent site is F_A and that of establishing AM at an EF co-located site is γF_A, where $0 < \gamma < 1$, as less investment is required in an already established facility.

$$F_k = \begin{cases} F_A & \forall k = 1,2,...,l \\ \gamma F_A & \forall k = l+1, l+2, \ldots, l+|M| \end{cases}$$

We set F_A as \$20,000 (high end performance printer/low end industrial printer (Fusion 3 Blog, 2020) along with associated operating and maintenance cost) and γ at 0.6.

We first solve (19) for our base case for each EF i and then solve the case with the inclusion of AM. We present the results of both cases in Table 2 where "Base case (Without AM)" represents the former scenario and "With AM" the latter. In the table, we use $E[B]$, $E[I]$, $E[C]$ and Θ^* to denote expected backorders, expected inventory, expected cost and optimal AM sites, respectively. Note that, $E[C]$ does not include the fixed costs for operating an EF (considered as sunk) and the periodic fixed costs for AMs (i.e. F_k). The savings column denotes the excess profit derived from using AM, which includes the fixed cost of establishing the AMs.

Table 2: Results of the Analysis ($\mu = 134$, $v_T = \$240$, $v_A = \$300$, $b = \$150$, $h = \$60$ and $p = 10\%$)

α	Base case (Without AM)					Θ^*	With AM				Savings
	EF	Q^*	$E[B]$	$E[I]$	$E[C]$		Q^*	$E[B]$	$E[I]$	$E[C]$	
10%	1	938	4.6	98.4	\$349,830	1, 2	536	0.0	58.3	\$307,970	\$93,664
	2	402	4.5	44.7	\$125,911		402	0.0	44.7	\$125,800	
	3	938	4.6	98.4	\$490,906		402	4.5	9.3	\$399,213	
	4	536	4.7	58.3	\$168,436		536	4.7	58.3	\$168,436	
	5	1193	7.2	114.8	\$420,232		1193	7.2	114.8	\$420,232	
	Total	4007	25.5	414.5	\$1,555,315		3069	16.3	285.3	\$1,421,651	
50%	1	938	25.9	119.7	\$354,309	1, 2, 3	536	0.8	78.0	\$311,281	\$100,548
	2	402	22.9	63.1	\$129,786		402	0.0	63.1	\$129,216	
	3	938	25.9	119.7	\$495,385		402	22.9	18.4	\$402,969	
	4	536	24.4	78.0	\$172,569		536	0.8	78.0	\$170,844	
	5	1206	25.9	146.5	\$424,923		670	0.0	0.9	\$402,114	
	Total	4020	124.9	526.9	\$1,576,972		2546	24.5	238.3	\$1,416,424	
90%	1	938	55.4	149.2	\$360,497	1, 2, 3	536	10.0	101.1	\$315,524	\$110,763
	2	402	43.0	83.2	\$134,005		402	5.5	83.2	\$133,073	
	3	938	55.4	149.2	\$501,573		415	39.6	42.1	\$407,168	
	4	536	47.5	101.1	\$177,413		536	10.0	101.1	\$174,675	
	5	1206	58.3	178.9	\$431,741		657	0.0	6.2	\$404,026	
	Total	4020	259.4	661.4	\$1,605,229		2546	65.0	333.5	\$1,434,466	

With $\alpha = 90\%$, the addition of AM generates the largest saving at EFs 1, 3, and 5. This stems from their nature and magnitude of utilization of AM. Here EFs 1 and 3 are using AM both as recourse (over Ω_2^i) and as dedicated source (over Ω_3^i) whereas EFs 2, 4 and 5 are using AM only as a recourse, that is, $|\Omega_3^1|, |\Omega_3^3| > |\Omega_3^2|, |\Omega_3^4|, |\Omega_3^5|$. Further, among the EFs that are using AM only as a recourse, EF 5 is generating the most savings since $|\Omega_2^5| >> |\Omega_2^2|, |\Omega_2^4|$. With the average demand level (μ) being same for each demand point, $|\Omega|$ is also representative of $D(\Omega)$, the size of demand over Ω.

Regardless of their level of utilization of AM, the presence of AM drastically reduces the expected number of backorders and inventory and, as a result, generates considerable savings for the supply chain. The extent of such savings increases as the variability in demand increases because of AM's capability, in this context, to address larger fluctuations in demand as a recourse and eventually, allowing the EFs to keep lower levels of inventory. As variability increases ($\alpha = 50\%$ and 90%), it pays to establish an additional AM facility in its configuration to obtain larger savings.

5 Sensitivity Analysis

In this section, we discuss the effect of different parameters on the optimal supply chain configuration. First, we consider how varying the parameters v_T, v_A, b, h, and t, affects the partition conditions, that is, Ω_1, Ω_2, and Ω_3, which, in turn, affects the optimal supply chain configuration. The following proposition outlines some structural insights.

Proposition 1: *Assume customer locations (Δt_j) are uniformly distributed in space. Then:*

(a) As Δv decreases, $|\Omega_1|$ decreases, $|\Omega_2|$ remains unchanged and $|\Omega_3|$ increases.

(b) As b increases, $|\Omega_1|$ decreases, $|\Omega_2|$ increases and $|\Omega_3|$ remains unchanged.

(c) As h increases, $|\Omega_1|$ remains unchanged, $|\Omega_2|$ increases and $|\Omega_3|$ decreases.

(d) As t increases, $|\Omega_1|$ increases, $|\Omega_2|$ decreases and $|\Omega_3|$ increases.

Proof: For (a), as Δv reduces, the right-hand sides of the inequalities defining Ω_1 in (10) and Ω_3 in (12) reduce, leading to a smaller $|\Omega_1|$ and a larger $|\Omega_3|$. While the conditions in (11) change similarly, the uniformly distributed customer locations imply that $|\Omega_2|$ remains unchanged. The proofs of (b) and (c) can be derived from inspection of (10), (11) and (12), and from similar observations of the associated intervals.

For (d), when the unit transportation cost t increases, the partition conditions in (10), (11) and (12) are not explicitly affected, but the demand point associations change. To demonstrate this, consider the transportation cost differential to be $\Delta t'_j$ upon an increase in t, where this $\Delta t'_j$ is essentially a constant times Δt_j. (10), (11) and (12) then imply that $|\Omega_1|$ and $|\Omega_3|$ increase and conversely, $|\Omega_2|$ decreases. ■

The changes in each of $|\Omega_1|$, $|\Omega_2|$ and $|\Omega_3|$ affect the value and usage of AM, where, given Theorem 1 and Corollary 1, an increase in $|\Omega_2|$ implies that more demands points use AM as a recourse and an increase in $|\Omega_3|$ suggests that more demand points use AM as a dedicated source. Each of these scenarios effectively translates to the EFs saving on backorders, inventory and transportation, incurring less costs. Consequently, from Proposition 1, we see that the most value of AM as a recourse is derived when b and/or h increases, and the most value for AM as a dedicated source is derived when Δv and/or t increases and/or h decreases. While we assumed uniformly distributed customer locations to obtain the structural results in Proposition 1, numerical experiments — based on the data set created before (section 4.3) — are consistent with what we observed in Proposition 1 (see Appendix A.1 to A.4).

We next consider the parameters directly related to the investment decisions, F_A and γ. Based on the potential savings an AM can generate, F_A provides a cut-off for the independent AM facility establishment decision — and a combination with γ providing for EF–AM co-location. As a consequence, consistent with intuition, as F_A decreases more AM sites are likely to be added and, as γ decreases, EF co-located AMs become relatively more attractive.

In the numerical study of our model, we have considered demand uncertainty in terms of the parameters p and α, where p is the probability of zero demand, and α is the fraction of demand spread relative to its mean. In our analysis, we considered $p = 10\%$. With the non-zero demand being a three-point symmetric distribution, an increase in p causes an increase (from $p = 10\%$) and then a decrease in the demand variability, depending on the reference p and the α level. However, for the same level of p, as α increases, the uncertainty in demand always increases, which causes the expected inventory levels and expected backorder numbers to grow. In this situation, AM can generate maximum benefit as a recourse. Table 2 presents the analysis of the effect of demand variability on the usage of AM in a network configuration.

6 Conclusion

We analyze the role of AM both as a recourse as well as a dedicated source in a TM network setting. We consider the problem of a firm that is evaluating whether to incorporate AM capabilities into its supply network. We model the firm's problem as a three-stage stochastic optimization problem, where in stage 1 the firm decides on locations (if any) for new AM facilities, stage 2 involves decision making regarding the production quantities at each EF under the new configuration, and stage 3 addresses the problem of allocating realized demand to each production mode. In this context, we derive an optimal allocation rule, effectively allowing us to reduce the three-stage optimization problem to a two-stage optimization problem. We study when AM creates the most value. We structurally characterize, for the case of uniformly distributed customer locations, how the value is created in different settings, and numerically confirm our structural insights. Specifically, our results suggest that AM creates most value as a recourse when backorder costs and/or holding costs are high whereas it creates the most value as a dedicated source when holding costs are low, transportation costs are high, and/or when the difference in the production costs between AM and traditional manufacturing is low.

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A Appendix

A.1 Sensitivity analysis on Δv at $p = 0.1$ and $\alpha = 0.9$

v_A	Base Case (Without AM)					θ^*	With AM				Savings
	EF	Q^*	$E[B]$	$E[I]$	$E[C]$	index	Q^*	$E[B]$	$E[I]$	$E[C]$	
\$241	1	938	55.4	149.2	\$360,497	1, 2, 3, 6	523	0.0	93.9	\$291,561	\$202,293
	2	402	43.0	83.2	\$134,005		26	0	0.2	\$122,908	
	3	938	55.4	149.2	\$501,572		402	5.5	83.2	\$377,915	
	4	536	47.5	101.1	\$177,413		389	0.0	34.6	\$168,411	
	5	1206	58.3	178.9	\$431,741		402	0.0	16	\$370,140	
	Total	4020	259.4	661.4	\$1,605,228		1742	5.5	227.7	\$1,330,935	

A.2 Sensitivity analysis on b at $p = 0.1$ and $\alpha = 0.9$

b	Base case (Without AM)					θ^*	With AM				Savings
	EF	Q^*	$E[B]$	$E[I]$	$E[C]$	index	Q^*	$E[B]$	$E[I]$	$E[C]$	
\$300	1	1059	23.7	238.5	\$364,647	1, 2, 4	536	0.0	101.1	\$315,784	\$127,042
	2	523	11.1	172.3	\$136,207		402	0.0	83.2	\$133,856	
	3	1059	23.7	238.5	\$505,723		523	0.0	93.9	\$407,556	
	4	657	15.1	189.7	\$180,141		536	0.0	101.1	\$175,108	
	5	1327	27.5	269.1	\$436,654		657	0.0	6.2	\$404,026	
	Total	4625	259.4	661.4	\$1,623,372		2654	0.0	385.3	\$1,436,330	

A.3 Sensitivity analysis on h at $p = 0.1$ and $\alpha = 0.9$

h	Base case (Without AM)					θ^*	With AM				Savings
	EF	Q^*	$E[B]$	$E[I]$	$E[C]$	index	Q^*	$E[B]$	$E[I]$	$E[C]$	
\$240	1	804	116.2	76.0	\$378,906	1, 2, 4, 8	523	11.1	9.5	\$321,212	\$160,472
	2	281	109.3	28.5	\$145,791		268	0.0	24.9	\$135,664	
	3	804	116.2	76.0	\$519,981		402	43.0	16.0	\$411,818	
	4	415	109.5	42.1	\$190,765		389	0.0	34.6	\$182,179	
	5	964	179.2	57.8	\$452,998		644	0.0	5.6	\$405,096	
	Total	3268	259.4	661.4	\$1,688,441		2226	54.1	90.5	\$1,455,969	

A.4 Sensitivity analysis on t at $p = 0.1$ and $\alpha = 0.9$

t	Base case (Without AM)					θ^*	With AM				Savings
	EF	Q^*	$E[B]$	$E[I]$	$E[C]$	index	Q^*	$E[B]$	$E[I]$	$E[C]$	
$15	1	938	55.4	149.2	$782,407	1, 2, 3, 4	536	47.5	101.1	$556,131	$783,786
	2	402	43.0	83.2	$241,207		402	5.5	83.2	$237,757	
	3	938	55.4	149.2	$1,346,709		402	43.0	83.2	$902,047	
	4	536	47.5	101.1	$322,807		268	0.0	63.6	$292,533	
	5	1206	58.3	178.9	$887,053		523	11.1	93.9	$727,929	
	Total	4020	259.4	661.4	$3,580,183		2131	106.9	424.8	$2,716,397	

CHAPTER

3

REVITALIZING THE SAND-CASTING SUPPLY CHAIN IN THE UNITED STATES – A STUDY ON LOCATING 3D SAND PRINTING HUBS TO SUPPORT THE METALCASTING INDUSTRY

Revitalizing the Sand-Casting Supply Chain in the United States – A Study on Locating 3D Sand Printing Hubs to Support the Metalcasting Industry

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Abstract:

Additive manufacturing (AM), specifically 3D sand-printing (3DSP) is gaining attention from the metalcasting industry where sand casting is the most widely used process in foundries. 3DSP offers unique advantages, including lead time reduction and the ability to directly print complex cores/molds without expensive hard-tooling. Currently, 3DSP has been limited in its adoption due to high capital costs, lack of in-house 3DSP expertise, and evolving demand/realization of 3DSP. However, as the demand for more complex castings grows, 3DSP can address the need for highly complex, low-volume, and highly customized products. The current 3DSP capacity in the U.S. is relatively low, and along with the fragile nature of the sand molds during transportation, the ability to satisfy the demand for 3DSP will become increasingly more difficult. In this research, a system of strategically-located 3DSP hubs to serve the U.S. metalcasting industry using the North American Industry Classification System (NAICS) data for foundries in the U.S. is presented. The uncapacitated facility location (UFL) procedure is utilized to determine the optimal locations for 3DSP hubs based on geographic data, demand, and a calculated fixed cost of production. Results from this study have identified (a) candidate US counties for 3DSP hubs and (b) total cost (investment, operational, and transportation). Evolving demand growth for 3DSP cores-molds is incorporated into the model through a dynamic analysis over various levels of demand to study its implications on the 3DSP supply chain. Findings from this study can help 3DSP/AM firms and the traditional manufacturers in determining the strategic hub locations to most efficiently serve the metalcasting industry to establish a profitable and sustainable 3DSP supply chain.

Keywords: 3D Sand-Printing, Sand Casting, Additive Manufacturing (AM), Facility Location, Supply Chain, Logistics.

Paper Type: Research paper

1. Introduction:

Sand casting is considered the oldest manufacturing process, where molten metal is poured into a sand mold to solidify the melt into desired geometry [1]. It is the most widely used casting process due to its size versatility, lower operating costs, and the ability to cast metal parts of a broad range of alloys. Metal casting plays a role in 90% of all manufactured goods and is a $33 billion industry in the U.S. [2]. The U.S. ranks third in global production behind China and India and produced 11.5 million tons of castings in 2016 across 1,950 facilities [2]. Almost 70% of metal castings are produced using the sand casting process [3]. Patterns, cores, and mold making are the foundation of the traditional casting process. Without efficient and viable patterns, foundries cannot produce the desired product. However, there are a number of concerns with the traditional sand casting process, including minimum wall thickness, elimination of undercuts, sharp corners, draft angle, part complexity level, and associated costs [4]. Due to these issues, a customer usually ends up deviating from their original design considerations [5]. This is where the technique of additive manufacturing (more specifically, three-dimensional sand printing or 3DSP) comes into play. Additive manufacturing (AM) or 3D Printing, by ISO/ASTM definition, is a process of joining materials to make parts from 3D model data, usually layer by layer [6].

Recent developments in additive manufacturing (AM) have brought innovation to the 5,000-year-old practice of metal casting, including the sand casting process. AM has been a rapidly growing area of research during the last twenty years, with publications increasing exponentially in number [7]. Researchers have continued to expand upon the techniques, materials, complexity, quality, size, and reduce the cost of AM.

The traditional sand casting process requires a custom-built pattern and core boxes that may take anywhere from weeks to months to manufacture. After patterns are manufactured, sand molds can be made in minutes to seconds depending on the level of automation within a foundry. In contrast, 3DSP does not require the production of hard tooling (i.e., pattern and core box); each individually printed mold needs to be printed in sections, cleaned, and assembled. This process often takes hours to complete. The comparison in pattern time and cost versus printing time and cost is at the heart of the sand printed process versus traditional sand casting process debate. The more complex the tooling (pattern and coring) needed for the job, the longer and costlier the pattern making stage will be. This is the window of opportunity for 3-D printed molds that offer a faster way to print and assemble molds and cores. If the number of units to be produced is on the order of hundreds, or thousands, the traditional sand casting process will likely be the most cost-effective. Deciding between printed and traditional comes down to part complexity and quantity. Printed molds will be cheaper and faster for high complexity, low quantity orders.

Recent research has also determined that 3D sand printing (3DSP) allows for an increase in casting complexity, casting quality, and weight reduction of finished parts, ensuring shorter manufacturing lead time, minimal product and development delays, and reduced need for inventory [8]. While these benefits are well documented and apparent to the metalcasting industry, traditional manufacturers are still not encouraged to adopt AM at a mass level due to its high fixed cost, lack of in-house expertise, allowable mold size limitations, and economical unattractiveness for low-complexity, high-volume production. However, as the demand for more highly complex metal castings continues to grow, the need to use alternative approaches such as 3DSP becomes inevitable to address the need for highly complex, low-volume, and highly customized products [9]. The growing demand for 3DSP along with the distribution of foundries all over the U.S. will make it extremely difficult for only a handful of dedicated AM firms to satisfy the demand points across the entire U.S. metalcasting industry.

In order to address the current state of 3DSP and traditional sand casting, this study proposes a network of 3DSP hubs spaced throughout the United States to support the existing foundries to meet their 3DSP demand without having to invest their own time, effort and space for the technology. In this system, the foundries would send the demand that qualifies for 3DSP to a nearby AM hub that would be responsible for producing the molds and cores using AM and shipping them back to the foundries for casting and post-processing.

This work aims to determine the optimal 3DSP hub locations in the US and how their capacities are allocated among the foundries based on the demand estimated from 2018 NAICS data, and associated production and operating structures based on AM service bureau data. This study employs the uncapacitated facility location (UFL) procedure to search for a set of independent locations initially and then modifies the UFL procedure to accommodate the growing AM demand over time, obtaining an evolving network of 3DSP hubs. The study facilitates the latter by assuming that AM capacity can be easily added to a facility in terms of addition of machines or access to additional capacity which, in case of high utilization, can be accessed by the facility.

This paper aims to demonstrate a decision-making model for both (1) AM organizations that can use this model to search for optimal locations for operating AM hubs and (2) metal foundries that can exploit the benefits of AM by working in conjunction with such AM organizations. Further, such a configuration would facilitate improved logistics in the additive manufacturing environment, which, in turn, might very well answer to the recent concerns regarding Marine and Airforce Aircraft Service [10].

This paper is structured as follows: Section 2 presents the literature review on facility location in AM, AM in sand casting and AM working in conjunction with traditional processes. Section 3 discusses the methodology applied for the facility location model, followed by the results of the study in Section 4. Section 5 includes the discussions, benefits of such a supply chain, and key insights obtained from this study. Finally, Section 6 presents the conclusions, summarizes the work, discusses its contribution to the existing literature, limitations and future direction for such a sand casting supply chain.

2. Literature Review

This research expands the following areas in the literature: facility location in AM, AM in sand casting, and AM working in conjunction with traditional manufacturing (TM).

2.1 Facility Location in AM

In this study, we assume that once the foundries receive their casting order and decide on their manufacturing mode, they order the sand molds and cores from AM sand printing hubs. Different foundries would have different AM hubs assigned to them based on economic attractiveness. The optimal demand allocations are based on the proximity of the AM hub establishments; hence hub locations are the main drivers for the allocation decisions. Alumur and Kara [11] discussed a review of several hub location and allocation problems such as hub with fixed cost, hub centering, and hub covering using both single and multiple allocations. Farahani et al. [12] further added p-hub median location, p-HLP with limited capacity, continuous and multi-objective in their review study. Campbell and O'Kelly [13] presented a survey of the hub location literature where they discuss the evolution of the hub location problem (HLP), evaluating from the origin to its current state. Daskin and Dean [14] discussed the importance of facility location models where poorly located facilities or too many or too few facilities will increase expenses and diminish customer service. According to Chen et al. [15], optimally located sites can improve operational performance and help gain competitive advantages in both the short term and long term. Moreover, the location of facilities with respect to their competitors, as well as customers, have a significant impact on a firm's ability to run and deliver efficiently [16].

Several facility location models are commonly used, including those for p-hub median, uncapacitated hub, capacitated hub, and uncapacitated facility location problems. Snyder and Daskin [17] presented some classical facility location models such as the uncapacitated fixed-charge location or uncapacitated fixed-charge location (UFL) problem, which choose optimal locations and potential customers in order to minimize the sum of fixed cost and transportation costs. UFL allows a decision-maker to determine optimal locations with any physical, technological, and monetary restrictions. Though, in most cases, fixed capacity level and additional capacity constraints make it logical to use the capacitated facility location (CFL) problem, this paper employs the UFL procedure since it is assumed and also intuitive that the AM hubs would make provisions for expanding their capacity to address the growth of AM demand.

Facility location in AM, more specifically the study of locating AM service establishments to improve supply chain performance, is a relatively a new field that only a few papers have investigated, yet it poses a ripe opportunity for its integration to the existing supply chain in order to exploit the AM benefits. Barz et al. [18, 19] talked about the relocation of TM sites after being replaced by AM and used a two stage capacitated facility location model to study the impact of AM location decisions. Strong et al. [20] have used UFL and p-median heuristics to locate AM hubs optimally to support TM, but an overestimation of the fixed cost resulted in too few being established. This work addresses this problem by estimating the fixed cost via random-intercept multi-level modelling.

2.2 Additive Manufacturing in Sand Casting

Recent advancements in additive manufacturing have added more design and production freedom to the sand casting industry. Today’s 3D binder jet sand printers can simply print sand molds and cores without the need for hard tooling. A 3D computer-aided design (CAD) model combined with a 3D binder jet sand printer can rapidly produce mold and core designs of various complexities.

The first commercial sand printer was released in 2001 by Generis GmbH of Germany. This printer used the same binder jetting process used by today’s printers. In 2005, Ex One released its first “S-Print” sand printer at the cost of $500,000 [21]. Today, companies such as Ex One, Voxeljet, and Envisiontec produce sand printers in a variety of sizes ranging from research to full-scale production units. Most commercially available 3D sand printers use the AM technique of binder jetting, a powder bed printing technique. Through this technique, a print head spreads a controlled-height layer of sand across the area of the build box. Binder is applied to the exact areas where the sand is desired to be bonded. The process is repeated, building up layers of bonded sand that together form a completed mold [7]. The workflow for casting a part through 3D Sand Printing (3DSP) is shown in Figure 1.

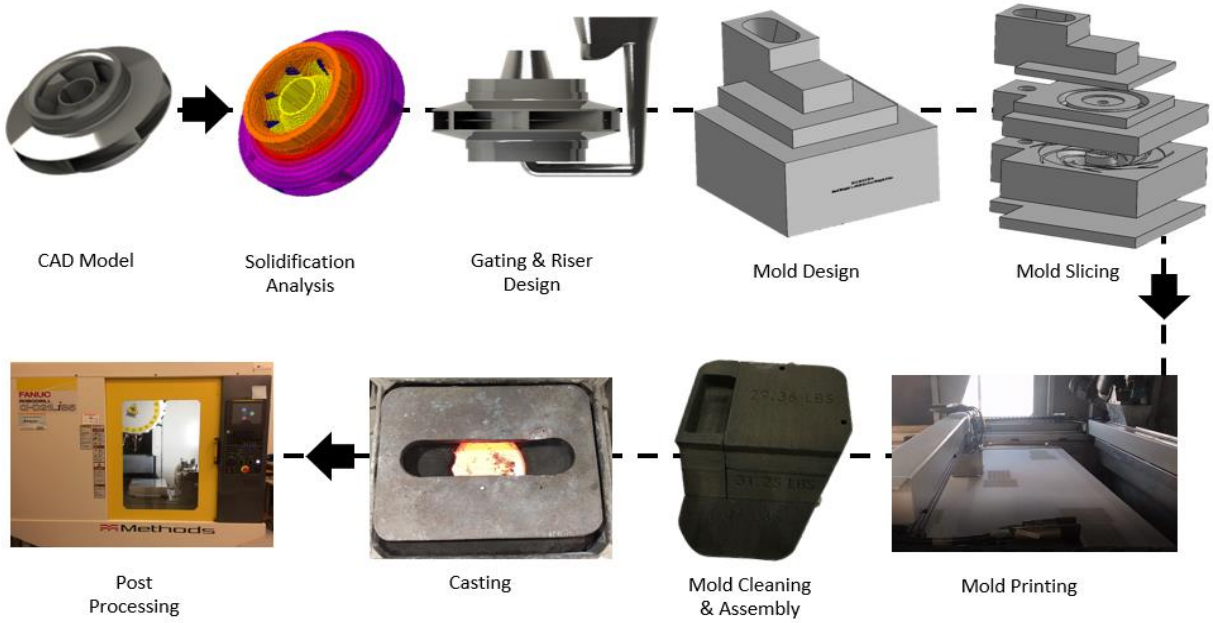


Figure 1: 3D sand casting mold printing work flow

Previously, all castings have been subject to a single parting line constriction where a pattern plate can be inserted. Because of this, the casting of parts with overhang geometries or geometries that curve back on the part required the use of custom-designed, resin-bonded sand cores. Cores require their own hard tooling, which, in addition to the pattern plate, increases the cost and likelihood of defects in the casting. 3DSP eliminates the need for patterns while also potentially eliminating cores. Through the binder-jetting process, the entire mold can be built, leaving the necessary cavities inside. This is a freedom to not only the design of the casting, but also to the gating system (channels through which the molten metal flows to the mold cavity). Recent studies have also shown how 3D printed sand molds can lead to a reduction in melt turbulence through the use of complex gating geometries [22]. Several papers also discuss the impact of binder saturation and curing time on chemical and mechanical properties, upon investigation, in the form of strength, permeability and dimensional conformance [7, 23-25].

3DSP is a maturing technology that is currently not well suited for all areas of the metal casting industry. Printed molds are limited to the size of the printer bed. The largest commercially available printers feature build volumes of just over 300 ft^3 and maximum build heights of around 3 ft. This places limits on the maximum size of a mold or how many molds may be completed in a single print. Furthermore, all unbonded sand needs to be removed from the print bed prior to the next print. Unbonded sand must also be removed from the printed mold, which often requires each mold to be printed in pieces and bonded together after cleaning. Failure to properly clean a mold of loose sand or failure to assemble the mold properly will cause defects in the casting. These factors do not currently make 3DSP an economical option for low complexity, high volume production. Moreover, high purchasing costs, operating costs, and large installation volumes can make 3D sand printing integration prohibitive for smaller manufacturers. Though 3DSP provides considerable advantages in terms of mold complexity, the printing rate is slow compared to traditional molding processes for large scale production [7].

The current state of 3DSP lends itself to be most useful to small quantity, high complexity castings [7]. As investigated by this paper, this niche in the U.S. metalcasting industry may best be filled by a network of 3DSP hubs spaced throughout the United States to service-specific regions. These hubs would be able to help multiple foundries meet the needs of customers who may require 3DSP without having to invest the time and space in the technology.

2.3 AM working in conjunction with Traditional Manufacturing (TM)

Additive manufacturing (AM) involves manufacturing a part by depositing material layer-by-layer until a net-shape or near net-space is achieved. This differs from conventional processes such as subtractive processes/traditional manufacturing (TM) (i.e., milling, drilling, cutting, grinding) where the material is removed to obtain a final shape [26]. Both AM and TM offer several unique advantages, but concerns still remain as to when to use a given mode of production. Several researchers have explored the notion from different points of view and identified a mode based on different decision parameters. Thomas [27] used operational cost data for motor vehicle components to determine when AM is cost-effective and operationally more efficient over TM. Knofius et al. [28] presented several cost factors that help in determining the nature of AM adoption in the spare parts supply chain. Some studies [29, 30] have discussed the scenarios where small batch size production and low fixed cost will allow AM to be adopted widely.

Manners-Bell and Lyon [31] observed that AM adoption would enable the shift of facilities towards the customer, which would reduce the involvement of logistics suppliers in the supply chains. They proposed that several logistics suppliers would come forward to help the AM facility in the storage and movement of materials.

Many researchers have emphasized the importance of AM in the conventional supply chain, especially about how AM would simplify the complexity of the supply chains [32]. For instance, Petrick and Simpson [33] asserted that AM would localize both production and sourcing activities but noted there is a need for complementary traditional manufacturing. Over time, several research works have highlighted the need and advantages of integrating AM and machining processes [34, 35]. Such hybrid strategies have been developed for the environment where additive and subtractive operations are repeated in a cycle until the final part is created [35, 36]. Strong et al. [32] contended that hybrid manufacturing has the potential to improve the capabilities of traditional manufacturing by integrating AM where traditional machining would post-process the AM metal parts. Sasson and Johnson [37] recognize that existing manufacturers with heterogeneous bills-of-material may develop AM capabilities to isolate disruptive, low-volume production from scalable mass production.

AM and TM are often viewed as alternatives when it comes to manufacturing setup in several industries where the manufacturers have been seen to remain fixated on only one form of production (TM or AM). In doing so, TM based firms will generate less revenue if they cannot exploit the economies of scale advantage, they have over AM based facilities hampered by high variable cost and low production capabilities. In this work, a supply chain is proposed where both TM and a network of AM hubs coexist, mutually benefiting each other through various interactions and transactions.

3. Methodology

This study applies the uncapacitated facility location (UFL) procedure based on total demand, foundry locations, UFL fixed cost, operation cost, and transportation cost in an effort to identify candidate U.S. locations where AM hubs, when located, could support foundries with their additive capabilities.

3.1 Model Parameters

The analysis makes use of two types of datasets: a foundry dataset and an AM service bureau dataset. The foundry dataset was obtained from the North American Industry Classification System (NAICS) Association for 2144 foundries containing various information of which the following were of significance to this work: foundry addresses and annual sales volume of each foundry. Using Geocode API and Matlab capabilities, the exact longitude and latitude of each foundry were determined. To estimate the demand, the approximate sales price per part had to be obtained. The current market price was determined from actual quotes provided by a local AM service provider. Quotes were provided for five sample CAD drawings of mold designs of various complexities. Table 1 shows the part drawings, dimensions, weights, volumes, and price quotes for sand molds of each part. Such molds had a geometric mean unit price of \$ 387.84 per unit with a geometric mean weight of 135.95 lbs. per part and geometric mean volume of 2873.16 in^3 per unit. Throughout this analysis, we assumed the same pricing structure (as of Table 1) all over the U.S.

The AM bureau data obtained from a local AM service provider and a thorough literature search contained representative investment cost structures for an AM facility that helped in designing AM hub facilities for the analysis. The data used to calculate hub costs includes annual machine costs, machine capacities, building rent and utilities, employee (mechanical engineering technology skill set) salaries and benefits, annual software and hardware costs and requirements, direct and indirect consumables. Table 2 provides a summary of the data, the justification and reference of the data.

This work first investigates an independent search method (determining optimal locations from scratch) where the model conservatively assumes 5%, 10%, and 25% of current demand as candidates for 3D sand printing. The study next moves on to a dynamic search method (determining optimal locations and capacity adjustments incrementally over time), where the demand level continues to increase gradually.

Table 1: Mold designs, properties and quotes surveyed from existing AM service bureaus

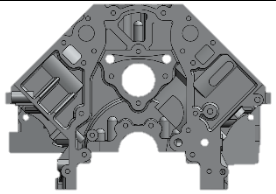
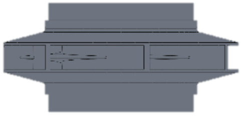
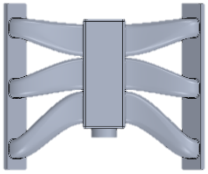
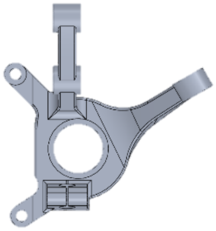
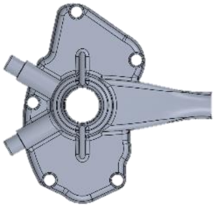
Part Name	Figure	Weight (lbs)	Bound Volume (in^3)	Quote
Engine Block		492	11,709	$1,581
Intake Manifold		191.8	4,794	$647
Pump Turbine		169	3,235	$437
Steering Knuckle		56	1,075	$145
Pump Housing		52	1,003	$135

Table 2: Measure, justification and reference of the investment cost components

Component	**Measure**	**Justification and Reference**
Working Hours	4160 Hours/ Year	- Standard Assumption: 52 weeks/ year at 5 days per week at 16 hours per day
Machine Capacity	3661 in^3/hr 4424 in^3/hr 5187 in^3/hr	- Equipment Provider Data Sheet [38].
Annual Machine Costs	$ 1M/5 years or $ 750K/5 years	- Used equal annual payment series calculation with interest rate (Current Market Rates- Small Business Loan): 6% annual - Purchase Price: Estimation Based on Industry and Academic Feedback. - Company will charge depreciation expenses on financials for the machine according to IRS standards.
Rent and Utilities	$ 10.4/ sq ft/year	- Average U.S. Commerical/ Industrial Rent References [39, 40].
Floor Capacity	4000 sq ft (2 machines) and 750 sq ft (for each additional machine)	- Data from industry feedback
MET Salaries and Benefits	$ 70,560/year/ employee	- Average MET Salary: ($56,000/ Year) [41, 42]. - Overhead Costs: 26% of Salary ($14,560) [42].
Employee Capacity	2 employees for first 2 machines 1 employee for two additional machines	- Data from industry feedback
Indirect Consumables (Packaging)	$ 0.015/in^3	- Data from Industry Feedback

Table 2 (continued)

Machine Software Cost	$ 5000/year/ machine	- Based on Academic and Industry Feedback
Machine Hardware Cost	$ 5000/year/ machine	- Based on Academic and Industry Feedback
Machine Maintenance	5% of machine cost/year	- Companies commonly sell maintenance contracts on large capital purchase equipment. This is approximately 5% of the machine cost for all-inclusive maintenance contract each year per machine.
Direct machine consumables (sand and binder costs)	$\$ 0.02/in^3$ $\$ 0.04/in^3$ $\$ 0.06/in^3$	- Cost of Sand, Binder, Catalyst: Industry Feedback- This price could fluctuate significantly depending on demand for sand. A cost analysis was done with available industry prices (domestic and international) [43-47]. - Communication with Industry/ Foundry Sand Supplier: Currently around $0.02/ in^3 is an accurate estimate. The study also looks at $0.04/ in^3 and $0.06/ in^3 to account for the fluctuation in the direct consumable cost. (e.g. natural gas industry influence on the foundry industry).

3.2 Model Assumptions

Sets of assumptions applied in the UFL procedure are summarized in Table 3, while scenarios such as time sensitivity of products, accumulation of queues, incorporation of time delay, local and state taxes and state of AM investment market are not taken into consideration for this work.

Table 3: Summary of model assumptions

	Justification
Locations	Existing traditional metal foundries to remain fixed at their current locations
Demand	A fraction of the total demand in metal foundries is an indicator of the demand for AM hubs
Hub Capacity	All hubs operating under same utilization rate.
AM organization	The AM hubs will strive to exploit economies of scale.
Independent Search (IS)	The UFL searches for optimal hub locations from scratch using the knowledge of current 3DSP demand rates.
Dynamic Search (ES)	The UFL keeps adding hubs and/or additional capacities to existing hubs with the evolution of 3DSP demand rates over time.
Supply Chain Integration	Traditional metal foundries receive orders that need to be manufactured using AM capabilities → Send CAD models to AM hubs → AM hubs produce 'near net' sand molds→ AM hubs ship them to traditional metal foundries → fulfill orders to customers.

3.3 Uncapacitated Facility Location Model

The uncapacitated facility location (UFL) procedure [16]. is one of the most widely used methods to solve facility location problems. It aims at locating an undefined number of new facilities in order to minimize the Total Logistics Cost (TLC), which is the sum of the fixed cost and cost of transporting products from each new facility to its desired demand point.

Given *I* set of existing facilities (EFs) and *J* set of sites available for new facilities (NFs), the following is the (strong) mixed-integer linear programming (MILP) formulation of the UFL problem:

$$\text{Minimize} \qquad \sum_{j\in J} k_j X_j + \sum_{j\in J}\sum_{i\in I} c_{ij} Y_{ij}$$

$$\text{Subject to} \qquad \sum_{j\in J} Y_{ij} = 1 \qquad \forall i \in I$$

$$Y_{ij} - X_j \leq 0 \qquad \forall i \in I,\ \forall j \in J$$

$$X_j \in \{0,1\} \qquad \forall j \in J$$

$$Y_{ij} \geq 1 \qquad \forall i \in I,\ \forall j \in J$$

Where

$k_j =$ fixed cost of establishing a new facility at site *j*.

$c_{ij} =$ variable transportation cost to serve all of EF *i*'s demand from site *i*.

$X_j = 1$, if NF is established at site *j*, 0, if not.

$Y_{ij} =$ fraction of EF *i*'s demand served from NF at site *j*.

This study employs the UFL procedure in Matlab using the Matlog Logistics Toolbox [48]. The determination of the associated fixed costs and variable transportation costs are discussed in the following subsubsections.

3.3.1 UFL fixed cost

The UFL fixed cost is the most critical parameter for such a location analysis. The UFL literature consists of mostly structured work where fixed costs are assumed to be a constant parameter. Some papers perform a data-driven analysis for the UFL fixed cost but there is no proper distinction among the cost components, merely summing over the assumed investment cost components. Strong et al. [20] shed some light on the way to estimate the fixed cost, but an overestimation of the fixed costs by summing all the direct and indirect costs led to misleading results when the UFL procedure was used.

Based on the data in Table 2, this study looks at six different combinations of scenarios based on the available machine cost estimates and sand and binder cost estimates. For each combination, total costs are calculated over a range of demand; where the upper bound of the demand is the sum of all demand across the U.S. and the lower bound being the localized demand, meaning the average demand of a single metal foundry. From Table 1, it is evident that all of the cost components are capacity dependent which, in turn, is demand dependent. We formulated a simple mixed-integer programming (MIP) model to determine the minimum capacity required for several levels of demand and obtained the associated total cost structures based on the cost components in Table 2. Due to the economies of scale, the total cost behaves in a concave manner over the range of demand. A simple regression analysis over the curve would provide the *y*-intercept and slope where the *y*-intercept was used as the UFL fixed cost. This makes sense since this would be the annual expenditure of an AM hub (strictly facility level costs), even with a zero scale of production. The variable cost (slope) is unimportant in the context of this problem since it is not going to affect the location decisions and will have the same impact wherever it is established. Table 4 presents the summary of the sensitivity analysis on the fixed cost estimates for each of the six scenarios and Figure 2 provides the plot for UFL fixed costs for each sand and binder cost measure across both the machine cost scenarios.

Table 4: Summary of sensitivity analysis for the fixed cost estimates

Annual Machine Cost	**Direct Consumable ($/inch^3)**	**Annual Fixed Cost ($/year)**
$178047 (5 years/ $750K)	$0.02	$424,450
	$0.04	$515,750
	$0.06	$612,500
$237396 (5 years/ $1M)	$0.02	$453,878
	$0.04	$548,575
	$0.06	$640,334

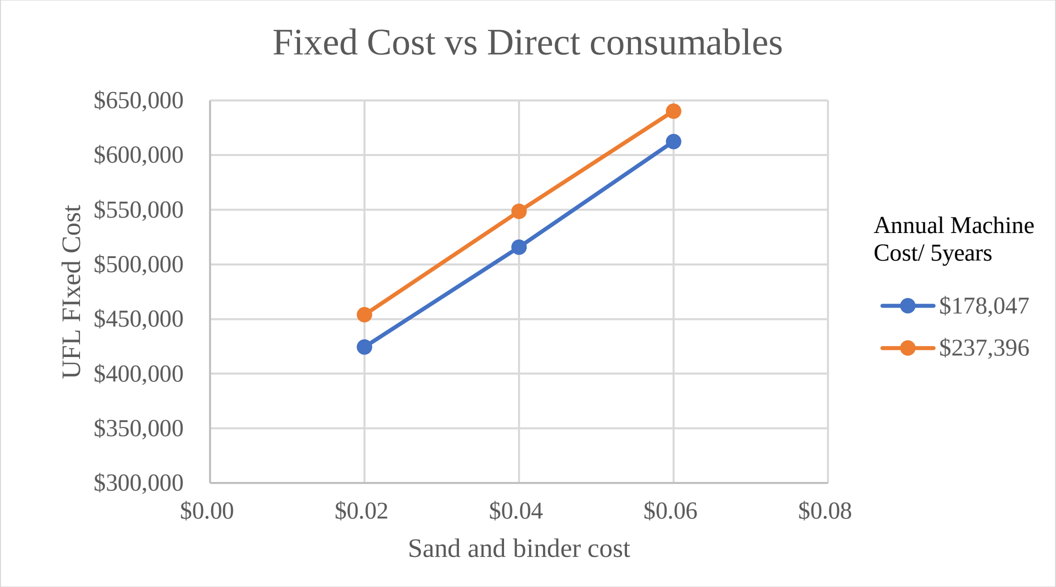


Figure 2: UFL fixed cost versus direct consumables across the machine costs.

From Table 4, it is evident that sand and binder costs more significantly impact the fixed costs. In a more volatile market, sand and binder costs should be the main decision variable for any further analysis. On the other hand, machine costs tend to have a lesser impact and can be assumed to take on a constant value for any such analysis as well as for any structured analysis.

Since the data in Table 4 are nested and the intercept estimate varies for each estimate, we use Random-Intercept Multi-level Modelling to estimate the final intercept i.e. the final fixed cost. This encompasses the idea of going over all the combinations as well as factoring in the impact of the trend and behavior of each of them. This resulted in a fixed cost (y-intercept) of $ 532,581.21 and an operating cost (OC) (slope) of $ 0.0668/in^3. For UFL problems, only the fixed cost and transportation costs are used because the OC is not a decision parameter since it has no impact on such a location analysis, meaning it will continue to incur the same cost regardless of the location.

3.3.2 Transportation Cost

There are three most widely used modes of transportation: truckload (TL), less than truckload (LTL), and small package. Less Than Truckload (LTL) is the preferred mode of transportation for this study as a result of the following reasons: shipment size (falling into LTL optimal range), deals with a fragile product, intermittent demand from foundry shops (certain fraction of demand from each shop is not enough to fill up a truckload), and frequent shipments allow better prices to be obtained through negotiation (negotiation based on product class). The selection of LTL as the preferred mode of transportation was validated after communicating with current sand printing AM service providers. Further, products are transported using a 32” × 32” × 30” inch container that holds an average of 10 parts per shipment which also confirms the use of LTL. The following estimation formula was used to determine the LTL rate [49] :

$$\text{Minimum charge, } MC_{LTL} = \left(\frac{PPI_{LTL}}{104.2}\right)\left(45 + \frac{d^{\frac{28}{19}}}{1625}\right)$$

$$\text{LTL transport rate, } r_{LTL}(q) = PPI_{LTL}\left[\frac{\frac{s^2}{8}+14}{\left(q^{\frac{1}{7}} d^{\frac{15}{29}} - \frac{7}{2}\right)\left(s^2+2s+14\right)}\right]$$

$$\text{LTL charge, } c_{LTL}(q) = r_{LTL}(q)\,qd$$

$$\text{Transport charge, } c_0(q) = \max\left\{c_{LTL}(q), MC_{LTL}\right\}$$

where

PPI_{LTL} = Producer Price Index for LTL.

d = distance over which the items are to be shipped.

q = shipment size.

s = density of the product.

This study uses the Matlog Logistics Toolbox [48] to estimate the LTL rates to obtain the c_{ij} matrix. Though the geometric mean of the physical density is 81.76 $\mathrm{lb/ft^3}$, after communicating with current sand printing

AM service providers it was found that they have negotiated with the LTL carriers and obtained a rate for class 60, meaning the monetary density is 32.16 $\mathrm{lb/ft^3}$. Intuitively, it seems that the AM service provider is overpaying since a comparatively dense product is likely to incur less LTL transportation cost but that is not the case. The estimation of LTL transportation rates depends on two components: product density and product fragility. Since there is no proper and proven scale to incorporate the fragility factor, class rate negotiation factors into the product fragility in terms of special handling care.

Upon obtaining the fixed and transportation costs, as an independent search, the UFL [16] heuristic is used to determine the optimal hub numbers and their locations where the variable x represents the site indices for positioning a hub and variable y represents the fraction of demand allocated to the hub.

3.4 Dynamic Search Analysis

The percentage of AM demand in the metalcasting industry has seen a significant increase in recent years, and there are no signs of this trend changing in the years to come. In order to account for this increasing demand, dynamic analyses are included in this study. This study investigates a series of evolutionary scenarios where the UFL gradually factors in 5, 8, 10, 15, 20, and 25% 3DSP demand rates. This is what the paper calls a dynamic search, which is different from an independent search in modeling terms. The independent search treats the problem as a new scenario and sets up optimal locations, allocating hubs based on the demand, whereas the dynamic search facilitates the AM organization to account for and locate additional capacity buffers the system would need for over time.

Specifically, for such a dynamic analysis, the idea here is to initially use an independent search for the initial demand volume and find optimal hub locations. As the demand increases, this study modifies the UFL procedure to search for additional capacities and/or hub locations, keeping the initial locations fixed, in order to address the additional demand.

To summarize, using the current data on the existing foundries and cost of AM sand mold production, this study aims to determine the optimal locations and total costs for 3DSP AM hubs at various demand levels, and also, perform dynamic analyses to address potentially growing demand.

4. Results and Analysis

While performing the logistics analysis, this paper ignores raw material procurement and inbound transportation for AM. On the basis of monetary weight, inbound transportation would be significantly cheaper than that of outbound, in other words, cost per ton-mile out would significantly outweigh cost per ton-mile in. The inbound transportation is not as time-sensitive, which would allow the organization to choose the least expensive transportation mode available. Moreover, the raw material packages are dense and compact, thereby outbound transportation and inbound transportation forms a 5:1 ratio in terms of weight. This then becomes a monetary weight gaining activity with respect to freight transport and location theory, under such scenario, suggests the outbound transportation (i.e., delivering printed cores and molds to foundries) dictates the location decisions. One might still incorporate the inbound transportation and raw material procurement, but it is expected that there might be very little (if any) deviation to the location decisions.

4.1 Independent Search

The independent search of the UFL procedure determines optimal hub numbers to be 31, 58 and 103 for 5, 10, and 25 % demand, respectively. Their respective heat maps are presented in Figures 3, 4, and 5, where the red points represent AM hub locations, and the biggest hubs are labeled.

Table 5 presents the summary of the Independent Search results containing the average hub demand, total system cost excluding the operating cost (OC), total system cost including the OC, average hub cost excluding OC, and average hub cost, including OC. OC contains all the variable characteristics of the cost components, meaning it accounts for all the costs contributing to the production of one unit of product. Figure 6 represents the plot of average hub cost across various demand percentages.

Tables 6, 7 and 8 (in Appendix) present additional detailed information on all hub locations for 5, 10, and 25% demand respectively which contain the following information: hub location, county, largest nearby city (with a population of at least 100K) and nearest metropolitan area. Appendix A1, A2 and A3 contains their respective hub level demand, cost of transporting from each location, and total hub cost (fixed cost + transportation cost + operating cost).

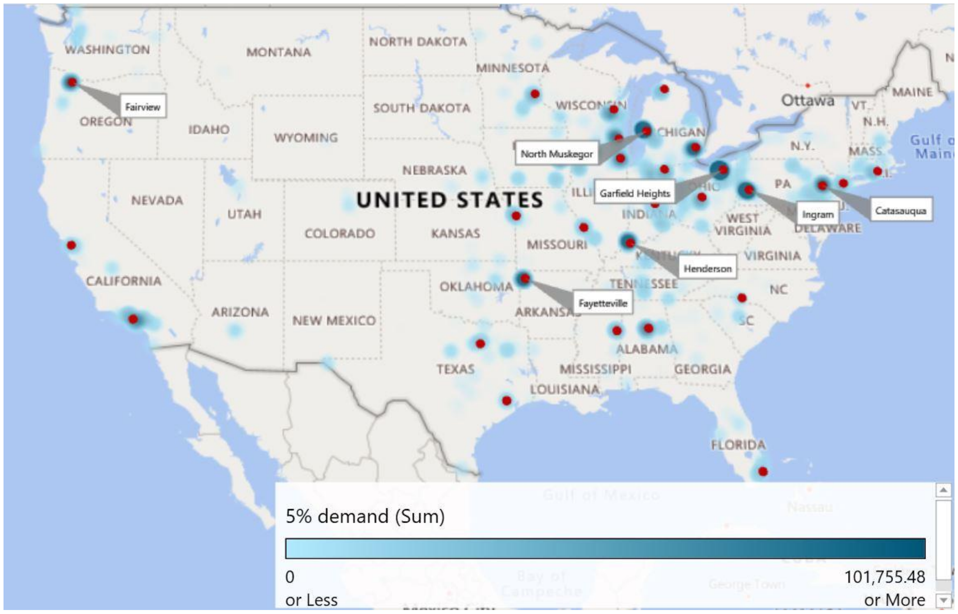


Figure 3: Independent Search results for Optimal AM hub locations at 5% Demand

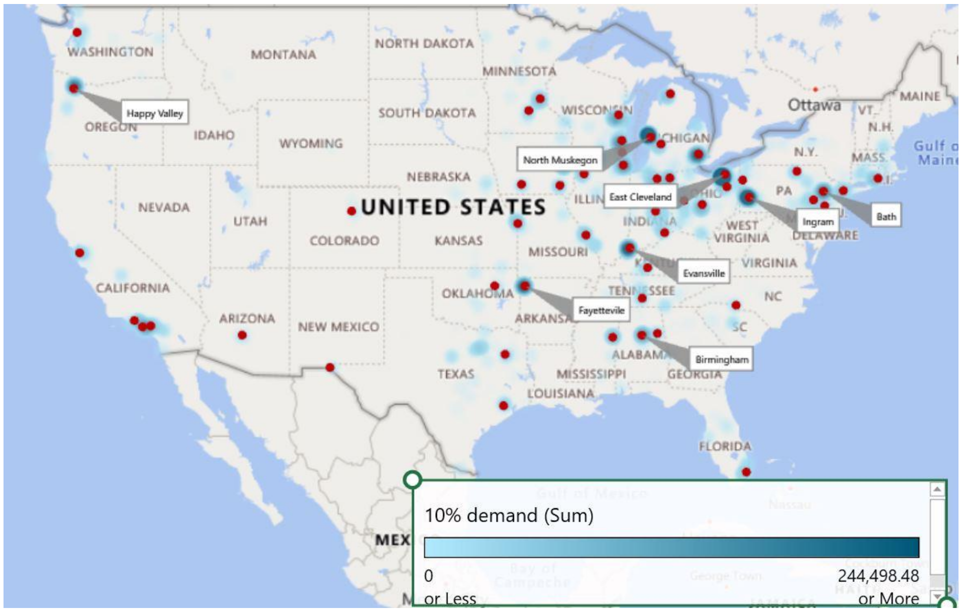


Figure 4: Independent Search results for Optimal AM hub locations at 10% Demand

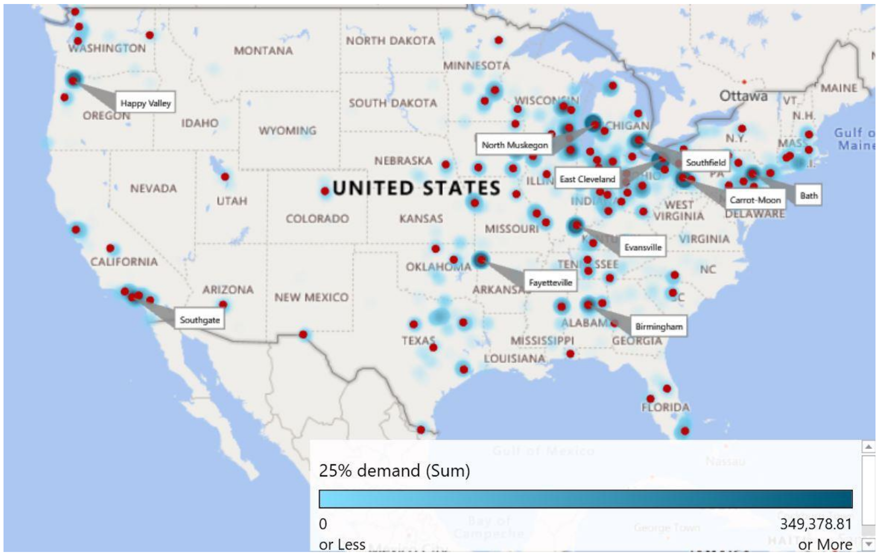


Figure 5: Independent Search results for Optimal AM hub locations at 25% Demand

Table 5: Summary of Independent Search Analysis

Independent Search						
Demand Percent	No. of hubs	Average Demand (units)	System: Total Annual Cost without OC	System: Total Annual Cost including OC	Hub: Average Annual Cost without OC	Hub: Average Cost including OC
5%	31	144270	$77,650,288	$936,268,657	$2,504,848	$30,202,215
10%	58	154220	$132,610,890	$1,849,845,899	$2,286,395	$31,893,895
25%	103	217105	$269,578,212	$4,562,661,030	$2,617,265	$44,297,680

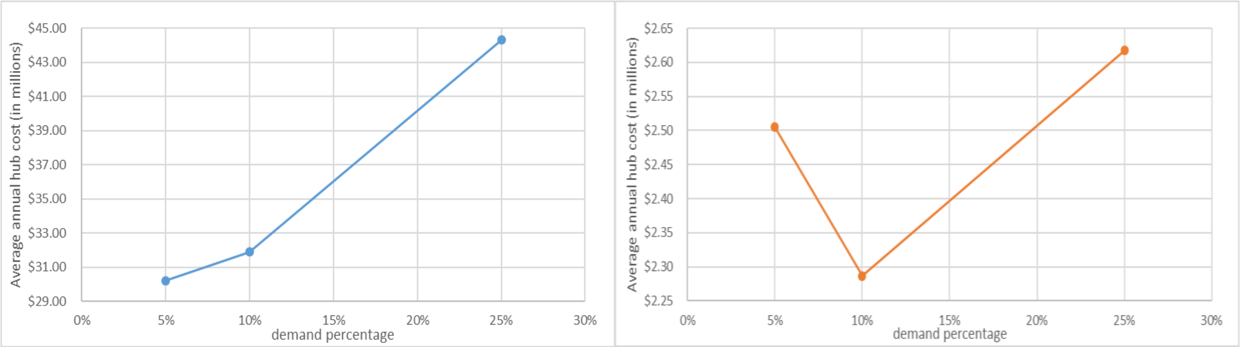


Figure 6: Annual average hub costs versus demand percentage with including OC (left) and excluding OC (right)

For 5% demand, it is observed that the largest AM hub is located in Garfield Heights, OH, which means this AM hub will face the most demand of 568,724 units with a total hub cost of approximately $115.16 M. The smallest hub is located in Boyne City, MI, facing a demand of 37,753 units with a total hub cost of approximately $8.076 M.

Further, the analysis for 10% demand shows that the largest AM hub should be located in East Cleveland, OH that with a demand of approximately 2.5 M units and a total hub cost of approximately $505.5 M. The smallest hub should be located in Fort Bliss, TX with a demand of 20,358 units and a total hub cost of approximately $4.36 M.

For 25% demand, it is observed that the largest AM hub should remain located in East Cleveland, OH with a demand of 1,009,990 units and a total hub cost of approximately $202.16 M while the smallest hub is located in Granjeno, TX with a demand of 36,306 units and a total hub cost of roughly $7.78 M. Interestingly, throughout the independent search analysis, it has been seen that Pennsylvania, Ohio, Michigan and Oregon contain the largest hubs. This shows that these states have concentrated demand and have the potential for establishing shared user hubs with the ability to accommodate foundries by efficiently transporting printed molds and cores relatively short distances.

4.2 Dynamic Search

As stated in section 3.4, a dynamic search aims to address the potential growth in 3DSP demand by increasing the hub capacity and/or establishing additional AM hubs to facilitate optimal logistic operations where an increase in hub capacity can be easily addressed by either procuring additional 3D printers or gaining additional access to subcontracting. This study investigates the evolution of such a network through gradual increases in foundry 3DSP demand over time. The 5% demand scenario was obtained using an independent search model where the optimal number of hubs was found to be 31. Using the data for the 5% demand scenario and an dynamic search analysis, 8, 10, 15, 20, and 25% demand scenarios were studied and used to demonstrate the effects in terms of hub locations, hub capacity and associated costs. Table 9 presents the additional hub numbers and their locations, and Figure 7 depicts the hub locations obtained through dynamic search analysis.

Table 10 outlines the summary of the Dynamic Search results containing the average hub demand, total system cost excluding the operating cost (OC), total system cost including the OC, average hub cost excluding OC, and average hub cost, including OC. The average hub costs have been shown to increase; however, this increase is a result of the need to address the increase in demand over time. The Dynamic Search model both adds capacity to the existing AM hubs and locates the optimal place to establish additional hubs. Through each level of demand increase, the percentage increase in hub capacity is presented in Table 11.

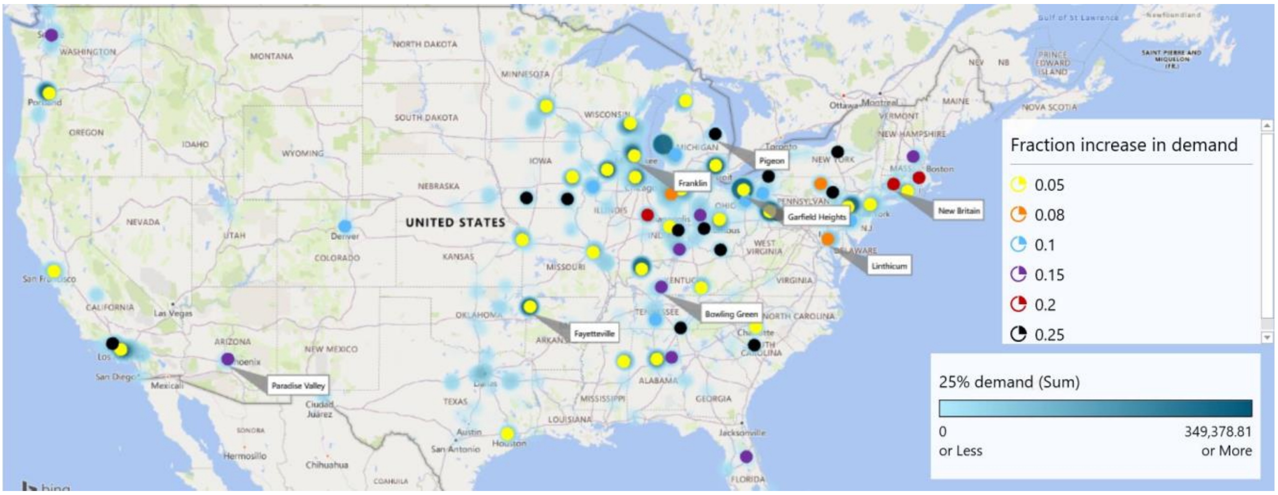


Figure 7: Dynamic Search results for Optimal AM hub locations

Table 9: Newly added hubs and their locations throughout Dynamic Search Analysis

Demand Percentage	Newly added hub number	City	State
8%	4	Blossburg	PA
		Sinking Spring	PA
		Linthicum	MD
		Warsaw	IN
10%	7	Sharpsville	PA
		Bryn Mawr	PA
		Green	OH
		Lewisburg	TN
		East Grand Rapids	MI
		Riverdale	IA
		Lakeside	CO
15%	8	Amherst	NH
		Lockhart	FL
		Hobson City	AL
		Bowling Green	KY
		Sidney	OH
		Madison	IN
		Paradise Valley	AZ
		Picnic Point	WA
20%	3	Attleboro	MA
		New Britain	CT
		Attica	IN
25%	13	East Syracuse	NY
		Greensburg	PA
		McKean	PA
		Jamison City	PA
		Blythewood	SC
		Chattanooga	TN
		Xenia	OH
		South Shore	KY
		Rushville	IN
		Pigeon	MI
		Creston	IA
		Fairfield	IA
		Simi Valley	CA

Table 10: System Cost and Hub Cost throughout the Dynamic Search Analysis

Demand percentage	System: Total Cost without OC	System: Total Cost including OC	Hub: Average Demand (units)	Hub: Average Cost without OC	Hub: Average Cost including OC
5%	$77,650,000	$936,256,465	144,268	$2,504,839	$30,201,822
8%	$113,610,000	$1,487,403,383	204,452	$3,246,000	$42,497,240
10%	$135,340,000	$1,852,572,130	212,970	$3,222,381	$44,108,861
15%	$187,730,000	$2,763,568,595	268,340	$3,754,600	$55,271,372
20%	$239,860,000	$3,674,247,465	337,529	$4,525,661	$69,325,424
25%	$284,760,000	$4,577,888,318	338,819	$4,314,546	$69,361,945

Table 11: Average hub capacity increment throughout Dynamic Search Analysis

Demand percentage	number of Hubs	Hub: Average minimum increase in capacity (%)
5%	31	N/A
8%	35	40.71%
10%	42	3.79%
15%	50	25.31%
20%	53	25.43%
25%	66	0.05%

5. Discussion

The results of this study propose that a network of AM hub establishments strategically and optimally placed across the United States can address the increase in demand by U.S. metalcasters for 3D printed sand molds and cores that is anticipated in years to come. The proposed method would revitalize the sand casting supply chain by bringing AM technology and required technical support within reach of existing traditional foundries without causing foundries to invest significant capital, time, effort, and space for the technology. The introduction of such AM hubs into the sand casting supply chain will allow foundries to enhance their product offerings and part complexities while accelerating the current AM adoption in sand casting as well as might continue to increase the amount of AM demand. The paper presents a decision-making model for (1) existing AM organizations seeking to locate new sites or an investor looking to establish an AM service providing facility and (2) foundries that can capitalize on the benefits of AM by working in conjunction with such AM organizations. Further, this work might also influence the existing AM organizations, having excess capacity, to approach nearby foundries as potential customers in order to obtain such a 3DSP arrangement. The results from this study provide insights into such a network, and the findings demonstrate a means of studying the appropriate location candidates and associated costs.

For the various demand percentages investigated, it was observed that the analysis resulted in an annual UFL annual fixed cost of 1.2-1.7%, annual transportation cost of 4.7-6.5% and annual production costs of 91.8-94.1% of the total average AM hub costs. Though the fixed cost and transportation costs constitute the minor share, they are the major drivers of such a logistics study since production cost would be relatively the same regardless of the location. In addition, it is important to optimize the number of hubs and their location because the network fixed costs depend on how many hubs are located, and the transportation costs depend on where the hubs are located.

With an increase in demand, it has been noticed that building new hubs alone is not going to optimize the production system configuration. In that case, all the new demand needs to be allocated to the new hubs which may not justify the transportation expenses. Hence, adding additional capacities (i.e., adding more AM machines) to the existing hubs as well as installing new hubs can optimally address the increases in demand.

Over the last few years, it has been observed and projected that AM machine costs would decrease [21]. Since, from this study, it has been observed that the machine costs would have minimal impact on the UFL fixed cost, such reductions in AM machine costs, if any, is not going to affect the hub locations and the study results.

Using the findings from this study, foundries can study their expected demand and find potential AM hubs to work in conjunction with. The results of this study might also influence the foundries in the most demand concentrated states like Pennsylvania, Ohio, Michigan, and California to build shared user AM hubs where the AM hubs would remain dedicated to their respective parent foundries.

6. Conclusions

This study specifically provides a means of addressing the AM need of the existing foundries in the United States. A classical facility location model was used to establish an arrangement where foundries can utilize AM services without having to invest their own capital in equipment and technology. Such integration would also benefit the AM technology with its mass adoption and large scale applications. The model provides optimal location decisions for AM hubs that would 3D print sand molds for nearby foundries. Recent research and surveys show that there are interests among metal foundries to adopt 3DSP since 3DSP has been found to significantly reduce casting lead time while allowing foundries to more efficiently produce increasingly intricate castings. Moreover, such 3DSP hubs, as they become larger and more trafficked, may be able to negotiate better transportation costs.

To summarize, this paper suggests that the increasing demand for 3D sand printing of sand molds and cores in the metalcasting industry can be addressed by establishing 3DSP hubs throughout the U.S. metalcasting network by putting a system in place that would mutually benefit both the AM and metalcasting industries while continuing to improve the U.S. metalcasting supply chain. The prominent findings of this study are:

- In a volatile market, sand and binder costs should be the main driver for such a location analysis.
- Machine costs have minimal impact on the UFL fixed cost and thus on location decisions.
- Transportation costs are affected by AM hub locations since the LTL transportation rate was used in the study.
- LTL transportation mode factors in both the load density and load fragility.

- Transportation costs and UFL fixed costs are the major players in such a logistic analysis.
- For an independent search, 31, 58 and 103 AM hubs are recommended for 5, 10 and 25% demand for 3DSP parts respectively.
- With the evolution of 3DSP demand, 31, 35, 42, 50, 53 and 66 AM hubs are recommended for 5, 8, 10, 15, 20 and 25% demand for 3DSP parts respectively.
- With the increase in demand, the entire production system configuration is optimized when the network gains additional hubs and the existing hubs gain additional capacities.

However, this study does not consider scenarios like time sensitivity of products, accumulation of queues, incorporation of time delay, local and state taxes, and state of AM investment market which can have considerable impact on such location analysis, requiring a dynamic weighted facility location analysis. Moreover, the analysis ignored some local factors like availability of AM raw materials, engineers and policies that might have an impact on the proposed model and the results. Along with the incorporation of these, some future directions for this work may include studying the effect of such evolution on the pricing structure and how the manufacturing decisions change over time, demand time-sensitivity (e.g., aerospace and defense suppliers), accumulation of product queues and their effect, hubs operating at specified utilization rates, a more comprehensive production system model that incorporates time delay.

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A. Appendix

Table 6: Independent Search Results for 5 % Demand

Hub No.	Hub Location	County	Largest city Nearby	Nearest Metropolitan Area
1	Mystic,CT	New London, CT	Warwick , RI	Norwich-New London,CT
2	Kearny,NJ	Hudson, NJ	Jersey City , NJ	New York-Newark-Jersey City,NY-NJ-PA
3	Ingram,PA	Allegheny, PA	Pittsburgh , PA	Pittsburgh,PA
4	Catasauqua,PA	Lehigh, PA	Bethlehem , PA	Allentown-Bethlehem-Easton,PA-NJ
5	Pineville,NC	Mecklenburg, NC	Charlotte , NC	Charlotte-Concord-Gastonia,NC-SC
6	Davie,FL	Broward, FL	Davie , FL	Miami-Fort Lauderdale-Pompano Beach,FL
7	Irondale,AL	Jefferson, AL	Birmingham , AL	Birmingham-Hoover,AL
8	Artesia,MS	Lowndes, MS	Tuscaloosa , AL	Tuscaloosa,AL
9	North Corbin,KY	Laurel, KY	Lexington-Fayette urban , KY	Morristown,TN
10	Henderson,KY	Henderson, KY	Evansville , IN	Evansville,IN-KY
11	Worthington,OH	Delaware, OH	Columbus , OH	Springfield,IL
12	Garfield Heights,OH	Cuyahoga, OH	Cleveland , OH	Cleveland-Elyria,OH
13	Cumberland,IN	Marion, IN	Indianapolis city , IN	Indianapolis-Carmel-Anderson,IN
14	Kendallville,IN	Noble, IN	Fort Wayne , IN	Fort Wayne,IN
15	Southfield,MI	Oakland, MI	Southfield , MI	Detroit-Warren-Dearborn,MI
16	North Muskegor,MI	Muskegon, MI	Grand Rapids , MI	Muskegon,MI
17	Boyne City,MI	Charlevoix, MI	Saginaw , MI	Bay City,MI
18	Cedar Rapids,IA	Linn, IA	Cedar Rapids , IA	Cedar Rapids,IA
19	Franklin,WI	Milwaukee, WI	West Allis , WI	Racine,WI
20	Kaukauna,WI	Outagamie, WI	Appleton , WI	Appleton,WI
21	Lauderdale,MN	Ramsey, MN	Minneapolis , MN	Minneapolis-St. Paul-Bloomington,MN-WI
22	Wood Dale,IL	DuPage, IL	Des Plaines , IL	Chicago-Naperville-Elgin,IL-IN-WI

Table 6 (continued)

23	Freeport,IL	Stephenson, IL	Rockford , IL	Rockford,IL
24	Des Peres,MO	St. Louis city, MO	St. Louis , MO	St. Louis,MO-IL
25	Riverside,MO	Wyandotte, KS	Kansas City , KS	Kansas City,MO-KS
26	Fayetteville,AR	Washington, AR	Fayetteville , AR	Fayetteville-Springdale-Rogers,AR
27	Grand Praire,TX	Tarrant, TX	Grand Prairie , TX	Dallas-Fort Worth-Arlington,TX
28	Hilshire Village,TX	Harris, TX	Houston , TX	Houston-The Woodlands-Sugar Land,TX
29	Vernon,CA	Los Angeles, CA	East Los Angeles, CA	Los Angeles-Long Beach-Anaheim,CA
30	San Leandro,CA	Alameda, CA	San Leandro , CA	San Francisco-Oakland-Berkeley,CA
31	Fairview,OR	Multnomah, OR	Gresham , OR	Portland-Vancouver-Hillsboro,OR-WA

Table 7: Independent Search Results for 10 % Demand

Hub No.	**Hub Location**	**County**	**Largest city Nearby**	**Nearest Metropolitan Area**
1	Mystic,CT	New London, CT	Warwick , RI	Norwich-New London,CT
2	Kearny,NJ	Hudson, NJ	Jersey City , NJ	New York-Newark-Jersey City,NY-NJ-PA
3	Ingram,PA	Allegheny, PA	Pittsburgh , PA	Pittsburgh,PA
4	Sharpsville,PA	Mercer, PA	Youngstown , OH	Youngstown-Warren-Boardman,OH-PA
5	Blossburg,PA	Tioga, PA	Scranton , PA	Williamsport,PA
6	Bath,PA	Northampton, PA	Bethlehem , PA	Allentown-Bethlehem-Easton,PA-NJ
7	Bryn Mawr,PA	Delaware, PA	Philadelphia , PA	Philadelphia-Camden-Wilmington,PA-NJ-DE-MD
8	Sinking Spring,PA	Berks, PA	Reading , PA	Reading,PA
9	Linthicum,MD	Baltimore city, MD	Glen Burnie , MD	Baltimore-Columbia-Towson,MD
10	Pineville,NC	Mecklenburg, NC	Charlotte , NC	Charlotte-Concord-Gastonia,NC-SC
11	Green,OH	Stark, OH	Akron , OH	Canton-Massillon,OH
12	Davie,FL	Broward, FL	Davie , FL	Miami-Fort Lauderdale-Pompano Beach,FL
13	Birmingham, AL	Jefferson, AL	Birmingham , AL	Birmingham-Hoover,AL
14	Hobson City,AL	Calhoun, AL	Birmingham , AL	Anniston-Oxford,AL
15	Lewisburg,TN	Marshall, TN	Franklin , TN	Nashville-Davidson--Murfreesboro--Franklin,TN
16	Artesia,MS	Lowndes, MS	Tuscaloosa , AL	Tuscaloosa,AL
17	North Corbin,KY	Laurel, KY	Lexington-Fayette urban , KY	Morristown,TN
18	Bowling Green,KY	Warren, KY	Bowling Green , KY	Bowling Green,KY
19	Worthington, OH	Delaware, OH	Columbus , OH	Springfield,IL
20	East Cleveland, OH	Cuyahoga, OH	Cleveland , OH	Cleveland-Elyria,OH
21	Sidney,OH	Shelby, OH	Springfield , OH	Lima,OH
22	Cumberland, IN	Marion, IN	Indianapolis city , IN	Indianapolis-Carmel-Anderson,IN
23	Leesburg,IN	Kosciusko, IN	Elkhart , IN	Elkhart-Goshen,IN
24	Auburn,IN	DeKalb, IN	Fort Wayne , IN	Fort Wayne,IN

Table 7 (continued)

25	Madison,IN	Jefferson, IN	Louisville/Jefferson County metro government, KY	Louisville/Jefferson County,KY-IN
26	Evansville,IN	Vanderburgh, IN	Evansville , IN	Evansville,IN-KY
27	Attica,IN	Warren, IN	Lafayette , IN	Lafayette-West Lafayette,IN
28	Southfield,MI	Oakland, MI	Southfield , MI	Detroit-Warren-Dearborn,MI
29	North Muskegon,MI	Muskegon, MI	Grand Rapids , MI	Muskegon,MI
30	East Grand Rapids,MI	Kent, MI	Grand Rapids , MI	Grand Rapids-Kentwood,MI
31	Boyne City,MI	Charlevoix, MI	Saginaw , MI	Bay City,MI
32	Creston,IA	Union, IA	West Des Moines , IA	Des Moines-West Des Moines,IA
33	Cedar Rapids,IA	Linn, IA	Cedar Rapids , IA	Cedar Rapids,IA
34	Fairfield,IA	Jefferson, IA	Iowa City , IA	Iowa City,IA
35	Panorama Park,IA	Rock Island, IL	Davenport , IA	Davenport-Moline-Rock Island,IA-IL
36	Butler,WI	Milwaukee, WI	Milwaukee , WI	Milwaukee-Waukesha,WI
37	Bristol,WI	Kenosha, WI	Kenosha , WI	Racine,WI
38	Kaukauna,WI	Outagamie, WI	Appleton , WI	Appleton,WI
39	Lauderdale, MN	Ramsey, MN	Minneapolis , MN	Minneapolis-St. Paul-Bloomington,MN-WI
40	Le Sueur,MN	Le Sueur, MN	Eden Prairie , MN	Mankato,MN
41	Wood Dale,IL	DuPage, IL	Des Plaines , IL	Chicago-Naperville-Elgin,IL-IN-WI
42	Freeport,IL	Stephenson, IL	Rockford , IL	Rockford,IL
43	Maplewood, MO	St. Louis city, MO	St. Louis , MO	St. Louis,MO-IL
44	Riverside,MO	Wyandotte, KS	Kansas City , KS	Kansas City,MO-KS
45	Fayetteville, AR	Washington, AR	Fayetteville , AR	Fayetteville-Springdale-Rogers,AR
46	Oakhurst,OK	Tulsa, OK	Tulsa , OK	Tulsa,OK
47	Lindale,TX	Smith, TX	Tyler , TX	Tyler,TX
48	Grand Praire,TX	Tarrant, TX	Grand Prairie , TX	Dallas-Fort Worth-Arlington,TX
49	Piney Point Village,TX	Harris, TX	Houston , TX	Houston-The Woodlands-Sugar Land,TX

Table 7 (continued)

50	Fort Bliss,TX	El Paso, TX	El Paso , TX	El Paso,TX
51	Lakeside,CO	Jefferson, CO	Arvada , CO	Denver-Aurora-Lakewood,CO
52	Paradise Valley,AZ	Maricopa, AZ	Phoenix , AZ	Phoenix-Mesa-Chandler,AZ
53	South Gate,CA	Los Angeles, CA	South Gate , CA	Los Angeles-Long Beach-Anaheim,CA
54	Chino,CA	Orange, CA	Chino , CA	Los Angeles-Long Beach-Anaheim,CA
55	Simi Valley,CA	Ventura, CA	Simi Valley , CA	Oxnard-Thousand Oaks-Ventura,CA
56	San Leandro,CA	Alameda, CA	San Leandro , CA	San Francisco-Oakland-Berkeley,CA
57	Happy Valley,OR	Multnomah, OR	Gresham , OR	Portland-Vancouver-Hillsboro,OR-WA
58	Picnic Point,WA	Snohomish, WA	Shoreline , WA	Seattle-Tacoma-Bellevue,WA

Table 8: Independent Search Results for 25 % Demand

Hub No.	Hub Location	County	Largest city Nearby	Nearest Metropolitan Area
1	Cumberland Hill,RI	Providence, RI	Pawtucket , RI	Providence-Warwick,RI-MA
2	Hudson,NH	Hillsborough, NH	Nashua , NH	Manchester-Nashua,NH
3	New Britain,CT	Hartford, CT	New Britain , CT	Hartford-East Hartford-Middletown,CT
4	Long Hill,CT	New London, CT	East Hartford , CT	Norwich-New London,CT
5	Kearny,NJ	Hudson, NJ	Jersey City , NJ	New York-Newark-Jersey City,NY-NJ-PA
6	East Syracuse,NY	Onondaga, NY	Syracuse , NY	Syracuse,NY
7	Carnot-Moon,PA	Beaver, PA	Pittsburgh , PA	Pittsburgh,PA
8	Export,PA	Westmoreland, PA	Pittsburgh , PA	Pittsburgh,PA
9	Sharpsville,PA	Mercer, PA	Youngstown , OH	Youngstown-Warren-Boardman,OH-PA
10	McKean,PA	Erie, PA	Erie , PA	Erie,PA
11	Blossburg,PA	Tioga, PA	Scranton , PA	Williamsport,PA
12	Dillsburg,PA	Cumberland, PA	Lancaster , PA	Harrisburg-Carlisle,PA
13	Jamison City,PA	Columbia, PA	Scranton , PA	Bloomsburg-Berwick,PA
14	Bath,PA	Northampton, PA	Bethlehem , PA	Allentown-Bethlehem-Easton,PA-NJ
15	Bryn Mawr,PA	Delaware, PA	Philadelphia , PA	Philadelphia-Camden-Wilmington,PA-NJ-DE-MD
16	Sinking Spring,PA	Berks, PA	Reading , PA	Reading,PA
17	Linthicum,MD	Baltimore city, MD	Glen Burnie , MD	Baltimore-Columbia-Towson,MD
18	Charlotte,NC	Mecklenburg, NC	Charlotte , NC	Charlotte-Concord-Gastonia,NC-SC
19	Blythewood,SC	Richland, SC	Columbia , SC	Sumter,SC
20	Green,OH	Stark, OH	Akron , OH	Canton-Massillon,OH
21	Phenix City,AL	Muscogee, GA	Columbus , GA	Auburn-Opelika,AL
22	Lockhart,FL	Orange, FL	Pine Hills , FL	Orlando-Kissimmee-Sanford,FL
23	Davie,FL	Broward, FL	Davie , FL	Miami-Fort Lauderdale-Pompano Beach,FL
24	Town 'n' Country,FL	Pinellas, FL	Town 'n' Country, FL	Tampa-St. Petersburg-Clearwater,FL
25	Birmingham,AL	Jefferson, AL	Birmingham , AL	Birmingham-Hoover,AL

Table 8 (continued)

26	Hobson City,AL	Calhoun, AL	Birmingham , AL	Anniston-Oxford,AL
27	Mobile,AL	Mobile, AL	Mobile , AL	Mobile,AL
28	Forest Hills,TN	Davidson, TN	Franklin , TN	Nashville-Davidson--Murfreesboro--Franklin,TN
29	Lewisburg,TN	Marshall, TN	Franklin , TN	Nashville-Davidson--Murfreesboro--Franklin,TN
30	Chattanooga,TN	Hamilton, TN	Chattanooga , TN	Chattanooga,TN-GA
31	Artesia,MS	Lowndes, MS	Tuscaloosa , AL	Tuscaloosa,AL
32	North Corbin,KY	Laurel, KY	Lexington-Fayette urban , KY	Morristown,TN
33	Bowling Green,KY	Warren, KY	Bowling Green , KY	Bowling Green,KY
34	Worthington,OH	Delaware, OH	Columbus , OH	Springfield,IL
35	Holland,OH	Lucas, OH	Toledo , OH	Toledo,OH
36	East Cleveland,OH	Cuyahoga, OH	Cleveland , OH	Cleveland-Elyria,OH
37	Woodlawn,OH	Hamilton, OH	Cincinnati , OH	Cincinnati,OH-KY-IN
38	Sidney,OH	Shelby, OH	Springfield , OH	Lima,OH
39	Beavercreek,OH	Greene, OH	Kettering , OH	Dayton-Kettering,OH
40	South Shore,KY	Scioto, OH	Charleston , WV	Columbus,GA-AL
41	Lima,OH	Allen, OH	Springfield , OH	Lima,OH
42	Rushville,IN	Rush, IN	Anderson , IN	Indianapolis-Carmel-Anderson,IN
43	Cumberland,IN	Marion, IN	Indianapolis city , IN	Indianapolis-Carmel-Anderson,IN
44	Bremen,IN	Marshall, IN	South Bend , IN	South Bend-Mishawaka,IN-MI
45	Auburn,IN	DeKalb, IN	Fort Wayne , IN	Fort Wayne,IN
46	Akron,IN	Fulton, IN	Elkhart , IN	Kokomo,IN
47	Madison,IN	Jefferson, IN	Louisville/Jefferson County metro government, KY	Louisville/Jefferson County,KY-IN
48	Evansville,IN	Vanderburgh, IN	Evansville , IN	Evansville,IN-KY
49	Attica,IN	Warren, IN	Lafayette , IN	Lafayette-West Lafayette,IN
50	Southfield,MI	Oakland, MI	Southfield , MI	Detroit-Warren-Dearborn,MI
51	Pigeon,MI	Huron, MI	Saginaw , MI	Bay City,MI
52	Shorewood-Tower Hills-Harbert,MI	Berrien, MI	South Bend , IN	Niles,MI
53	North Muskegon,MI	Muskegon, MI	Grand Rapids , MI	Muskegon,MI

Table 8 (continued)

54	East Grand Rapids,MI	Kent, MI	Grand Rapids , MI	Grand Rapids-Kentwood,MI
55	Boyne City,MI	Charlevoix, MI	Saginaw , MI	Bay City,MI
56	Creston,IA	Union, IA	West Des Moines , IA	Des Moines-West Des Moines,IA
57	Asbury,IA	Dubuque, IA	Dubuque , IA	Dubuque,IA
58	Decorah,IA	Winneshiek, IA	La Crosse , WI	La Crosse-Onalaska,WI-MN
59	Cedar Rapids,IA	Linn, IA	Cedar Rapids , IA	Cedar Rapids,IA
60	Fairfield,IA	Jefferson, IA	Iowa City , IA	Iowa City,IA
61	Eldridge,IA	Scott, IA	Davenport , IA	Davenport-Moline-Rock Island,IA-IL
62	Butler,WI	Milwaukee, WI	Milwaukee , WI	Milwaukee-Waukesha,WI
63	Bristol,WI	Kenosha, WI	Kenosha , WI	Racine,WI
64	Evansville,WI	Rock, WI	Janesville , WI	Janesville-Beloit,WI
65	St. Nazianz,WI	Manitowoc, WI	Appleton , WI	Sheboygan,WI
66	Menasha,WI	Outagamie, WI	Appleton , WI	Appleton,WI
67	Lauderdale,MN	Ramsey, MN	Minneapolis , MN	Minneapolis-St. Paul-Bloomington,MN-WI
68	Hibbing,MN	Itasca, MN	Duluth , MN	Duluth,MN-WI
69	Winona,MN	Winona, MN	La Crosse , WI	La Crosse-Onalaska,WI-MN
70	Le Sueur,MN	Le Sueur, MN	Eden Prairie , MN	Mankato,MN
71	Wood Dale,IL	DuPage, IL	Des Plaines , IL	Chicago-Naperville-Elgin,IL-IN-WI
72	Freeport,IL	Stephenson, IL	Rockford , IL	Rockford,IL
73	West Peoria,IL	Peoria, IL	Peoria , IL	Peoria,IL
74	Sparta,IL	Randolph, IL	St. Louis , MO	Carbondale-Marion,IL
75	Maplewood,MO	St. Louis city, MO	St. Louis , MO	St. Louis,MO-IL
76	Monroe City,MO	Ralls, MO	Columbia , MO	Jefferson City,MO
77	Riverside,MO	Wyandotte, KS	Kansas City , KS	Kansas City,MO-KS
78	Wahoo,NE	Saunders, NE	Lincoln , NE	Lincoln,NE
79	Fayetteville,AR	Washington, AR	Fayetteville , AR	Fayetteville-Springdale-Rogers,AR
80	Oakhurst,OK	Tulsa, OK	Tulsa , OK	Tulsa,OK
81	Tonkawa,OK	Kay, OK	Edmond , OK	Enid,OK
82	Lindale,TX	Smith, TX	Tyler , TX	Tyler,TX

Table 8 (continued)

83	Grand Praire,TX	Tarrant, TX	Grand Prairie , TX	Dallas-Fort Worth-Arlington,TX
84	Eastland,TX	Eastland, TX	Abilene , TX	Abilene,TX
85	Belton,TX	Bell, TX	Temple , TX	Killeen-Temple,TX
86	Houston,TX	Harris, TX	Houston , TX	Houston-The Woodlands-Sugar Land,TX
87	Granjeno,TX	Hidalgo, TX	Pharr , TX	McAllen-Edinburg-Mission,TX
88	Fort Bliss,TX	El, TX	El Paso , TX	El Paso,TX
89	North Washington,CO	Denver, CO	Denver , CO	Denver-Aurora-Lakewood,CO
90	Sandy,UT	Salt Lake, UT	Sandy , UT	Salt Lake City,UT
91	Paradise Valley,AZ	Maricopa, AZ	Phoenix , AZ	Phoenix-Mesa-Chandler,AZ
92	South Gate,CA	Los Angeles, CA	South Gate , CA	Los Angeles-Long Beach-Anaheim,CA
93	Pomona,CA	Orange, CA	Pomona , CA	Los Angeles-Long Beach-Anaheim,CA
94	San Jacinto,CA	Riverside, CA	Hemet , CA	Riverside-San Bernardino-Ontario,CA
95	Simi Valley,CA	Ventura, CA	Simi Valley , CA	Oxnard-Thousand Oaks-Ventura,CA
96	Calwa,CA	Fresno, CA	Fresno , CA	Fresno,CA
97	San Leandro,CA	Alameda, CA	San Leandro , CA	San Francisco-Oakland-Berkeley,CA
98	Happy Valley,OR	Multnomah, OR	Gresham , OR	Portland-Vancouver-Hillsboro,OR-WA
99	Albany,OR	Linn, OR	Albany , OR	Albany-Lebanon,OR
100	Kent,WA	King, WA	Kent , WA	Seattle-Tacoma-Bellevue,WA
101	Bellingham,WA	Whatcom, WA	Bellingham , WA	Bellingham,WA
102	Marysville,WA	Snohomish, WA	Marysville , WA	Mount Vernon-Anacortes,WA
103	Spokane Valley,WA	Spokane, WA	Spokane Valley , WA	Spokane-Spokane Valley,WA

A1: Demand, Transportation Cost and Total Cost of each hub for 5% 3DSP demand

Hub number	City	State	Hub Demand	Transportation Cost	Total Cost
1	Mystic	CT	91,964	$1,554,115.66	$19,742,239.88
2	Kearny	NJ	59,120	$710,871.92	$12,593,499.91
3	Ingram	PA	299,670	$2,856,227.17	$60,920,413.93
4	Catasauqua	PA	253,243	$4,245,852.28	$53,396,835.01
5	Pineville	NC	47,891	$962,995.64	$10,689,844.28
6	Davie	FL	62,107	$1,077,955.45	$13,534,037.26
7	Irondale	AL	158,118	$2,630,950.05	$33,519,530.87
8	Artesia	MS	69,122	$972,898.36	$14,775,742.32
9	North Corbin	KY	44,429	$592,237.94	$9,654,440.75
10	Henderson	KY	207,787	$2,300,638.20	$42,724,832.59
11	Worthington	OH	125,017	$1,987,044.83	$26,520,789.75
12	Garfield Heights	OH	568,724	$5,443,979.53	$115,162,014.17
13	Cumberland	IN	128,187	$2,568,832.29	$27,711,163.96
14	Kendallville	IN	132,213	$2,268,425.31	$28,183,681.34
15	Southfield	MI	177,664	$1,971,560.30	$36,612,644.76
16	North Muskegor	MI	320,353	$3,005,255.45	$65,040,230.73
17	Boyne City	MI	37,753	$295,622.97	$8,076,145.93
18	Cedar Rapids	IA	128,155	$2,112,401.83	$27,248,590.03
19	Franklin	WI	134,601	$1,557,191.31	$27,930,903.23
20	Kaukauna	WI	108,651	$1,347,067.89	$22,738,815.77
21	Lauderdale	MN	121,302	$2,156,542.28	$25,977,069.62
22	Wood Dale	IL	109,620	$1,160,398.88	$22,738,178.47
23	Freeport	IL	138,501	$1,480,549.75	$28,602,996.14
24	Des Peres	MO	68,729	$1,052,349.80	$14,779,744.36
25	Riverside	MO	101,066	$2,137,898.29	$22,073,453.59
26	Fayetteville	AR	182,021	$2,050,035.36	$37,527,590.62
27	Grand Praire	TX	115,984	$2,546,242.53	$25,345,803.21
28	Hilshire Village	TX	44,972	$816,256.67	$9,982,706.36
29	Vernon	CA	194,424	$3,470,807.68	$41,329,530.57
30	San Leandro	CA	45,620	$654,886.10	$9,945,740.89
31	Fairview	OR	195,354	$3,152,178.53	$41,189,445.79

A2: Demand, Transportation Cost and Total Cost of each hub for 10% 3DSP demand

Hub number	City	State	Hub demand	Transport cost	Total Cost
1	Mystic	CT	183,479	$3,093,175.52	$38,850,642.28
2	Kearny	NJ	115,567	$1,361,279.57	$24,080,783.25
3	Ingram	PA	568,536	$4,968,037.79	$114,649,979.60
4	Sharpsville	PA	77,865	$1,232,304.86	$16,713,657.94
5	Blossburg	PA	102,608	$1,808,345.75	$22,039,939.15
6	Bath	PA	230,620	$1,918,290.10	$46,726,036.90
7	Bryn Mawr	PA	51,487	$491,720.92	$10,908,941.15
8	Sinking Spring	PA	81,539	$1,045,101.93	$17,231,801.29
9	Linthicum	MD	59,660	$619,423.52	$12,605,722.45
10	Pineville	NC	93,774	$1,866,318.01	$20,401,931.81
11	Green	OH	67,646	$653,554.65	$14,173,031.41
12	Davie	FL	124,214	$2,155,910.89	$26,535,493.31
13	Birmingham	AL	168,820	$1,520,097.52	$34,463,282.56
14	Hobson City	AL	81,040	$1,443,340.51	$17,534,240.25
15	Lewisburg	TN	107,604	$1,941,463.23	$23,132,204.69
16	Artesia	MS	126,007	$1,622,430.80	$26,346,239.09
17	North Corbin	KY	85,985	$1,116,161.23	$18,156,417.89
18	Bowling Green	KY	51,031	$607,968.10	$10,937,643.98
19	Worthington	OH	180,571	$2,386,284.62	$37,585,464.24
20	East Cleveland	OH	1,009,990	$8,084,817.50	$202,518,510.87
21	Sidney	OH	98,036	$1,584,869.28	$20,938,715.48
22	Cumberland	IN	95,197	$1,396,252.65	$20,205,058.55
23	Leesburg	IN	152,831	$2,315,991.37	$32,189,557.02
24	Auburn	IN	120,724	$1,307,603.70	$25,017,164.75
25	Madison	IN	83,582	$1,093,776.99	$17,672,698.02
26	Evansville	IN	336,909	$2,656,001.15	$67,869,450.28
27	Attica	IN	67,488	$787,288.16	$14,276,431.57
28	Southfield	MI	350,923	$3,841,188.33	$71,745,090.03
29	North Muskegon	MI	572,378	$4,465,631.87	$114,885,173.13
30	East Grand Rapids	MI	73,158	$701,261.86	$15,278,950.02
31	Boyne City	MI	75,506	$591,245.94	$15,619,710.65
32	Creston	IA	75,318	$1,376,816.97	$16,369,188.84
33	Cedar Rapids	IA	142,069	$1,585,969.18	$29,393,411.63
34	Fairfield	IA	65,131	$822,449.05	$13,859,088.06
35	Panorama Park	IA	88,969	$1,076,507.39	$18,689,641.92
36	Butler	WI	221,528	$2,075,253.70	$45,137,489.24
37	Bristol	WI	60,873	$783,826.10	$13,003,000.64

A2 (continued)

38	Kaukauna	WI	209,561	$2,517,712.65	$43,282,485.23
39	Lauderdale	MN	181,969	$2,841,382.78	$38,308,954.91
40	Le Sueur	MN	59,293	$856,439.86	$12,772,280.94
41	Wood Dale	IL	191,414	$1,705,938.54	$38,986,791.99
42	Freeport	IL	246,709	$2,224,483.05	$50,121,047.55
43	Maplewood	MO	116,858	$1,592,172.57	$24,559,526.56
44	Riverside	MO	98,206	$917,927.05	$20,304,410.40
45	Fayetteville	AR	306,553	$2,610,426.78	$61,996,033.90
46	Oakhurst	OK	76,117	$1,454,039.57	$16,599,806.02
47	Lindale	TX	59,136	$904,907.61	$12,790,607.34
48	Grand Praire	TX	142,208	$2,401,819.39	$30,235,947.51
49	Piney Point Village	TX	85,627	$1,521,725.71	$18,493,252.39
50	Fort Bliss	TX	20,358	$195,279.65	$4,636,254.84
51	Lakeside	CO	55,729	$1,416,929.30	$12,648,542.27
52	Paradise Valley	AZ	28,735	$284,469.87	$6,333,688.33
53	South Gate	CA	138,952	$1,153,144.12	$28,362,174.94
54	Chino	CA	112,327	$1,547,791.55	$23,645,269.67
55	Simi Valley	CA	90,228	$854,274.19	$18,709,115.57
56	San Leandro	CA	90,984	$1,300,547.14	$19,300,527.82
57	Happy Valley	OR	283,638	$3,051,793.66	$58,038,105.75
58	Picnic Point	WA	101,450	$1,970,013.98	$21,979,290.83

A3: Demand, Transportation Cost and Total Cost of each hub for 25% 3DSP demand

Hub number	City	State	Hub Demand	Transportation Cost	Total Cost including OC
1	Cumberland Hill	RI	83,787	$1,102,399.23	$17,720,676.82
2	Hudson	NH	82,720	$923,920.25	$17,337,351.77
3	New Britain	CT	98,265	$1,033,336.07	$20,431,146.43
4	Long Hill	CT	196,068	$1,520,410.19	$39,694,753.45
5	Kearny	NJ	281,622	$3,215,503.96	$57,814,777.92
6	East Syracuse	NY	71,775	$1,186,814.16	$15,498,989.55
7	Carnot-Moon	PA	1,309,695	$10,414,781.47	$262,386,799.81
8	Export	PA	117,570	$1,345,587.52	$24,449,633.55
9	Sharpsville	PA	132,483	$1,663,476.41	$27,630,567.91
10	McKean	PA	85,052	$1,231,605.80	$18,092,742.13
11	Blossburg	PA	109,366	$946,152.37	$22,475,168.23
12	Dillsburg	PA	51,909	$534,574.92	$11,032,812.06
13	Jamison City	PA	68,843	$710,898.01	$14,460,178.66
14	Bath	PA	563,272	$4,500,530.56	$113,171,872.80
15	Bryn Mawr	PA	128,717	$1,229,302.30	$26,473,385.07
16	Sinking Spring	PA	167,114	$1,782,387.86	$34,398,049.55
17	Linthicum	MD	133,096	$1,184,903.28	$27,269,680.48
18	Charlotte	NC	137,696	$2,328,998.55	$29,296,898.46
19	Blythewood	SC	104,804	$1,481,434.50	$22,134,623.01
20	Green	OH	166,156	$1,566,891.80	$33,998,633.59
21	Phenix City	AL	88,429	$1,557,985.89	$19,067,449.49
22	Lockhart	FL	64,452	$902,961.12	$13,809,243.54
23	Davie	FL	209,658	$2,416,098.19	$43,199,493.14
24	Town 'n' Country	FL	41,550	$379,125.96	$8,888,609.13
25	Birmingham	AL	415,677	$3,626,476.68	$83,962,058.51
26	Hobson City	AL	101,471	$997,613.45	$21,010,921.94
27	Mobile	AL	48,077	$732,320.06	$10,494,877.58
28	Forest Hills	TN	95,492	$1,354,756.44	$20,220,197.38
29	Lewisburg	TN	120,672	$1,415,193.74	$25,114,771.66
30	Chattanooga	TN	98,580	$1,363,071.93	$20,821,357.00
31	Artesia	MS	271,295	$2,804,999.90	$55,421,663.35
32	North Corbin	KY	178,000	$1,867,272.38	$36,572,863.19
33	Bowling Green	KY	120,048	$1,349,345.66	$24,929,126.07
34	Worthington	OH	339,858	$3,303,303.34	$69,082,910.93
35	Holland	OH	93,288	$1,326,982.08	$19,769,292.05
36	East Cleveland	OH	2,524,974	$20,212,043.74	$505,497,213.39
37	Woodlawn	OH	49,462	$410,025.13	$10,438,479.38

A3 (continued)

38	Sidney	OH	82,631	$746,322.01	$17,142,667.02
39	Beavercreek	OH	85,649	$813,444.29	$17,789,194.59
40	South Shore	KY	80,638	$837,777.39	$16,851,499.88
41	Lima	OH	94,058	$869,622.68	$19,459,759.71
42	Rushville	IN	123,421	$1,259,230.85	$25,486,570.59
43	Cumberland	IN	145,885	$1,805,226.58	$30,345,276.92
44	Bremen	IN	119,739	$1,138,585.09	$24,659,042.69
45	Auburn	IN	265,830	$2,452,631.89	$54,020,107.15
46	Akron	IN	170,327	$1,658,924.95	$34,891,428.67
47	Madison	IN	166,049	$1,765,370.19	$34,176,569.77
48	Evansville	IN	840,649	$6,598,599.87	$168,521,666.18
49	Attica	IN	154,489	$1,623,631.63	$31,815,505.43
50	Southfield	MI	724,009	$6,002,047.31	$145,532,193.17
51	Pigeon	MI	98,184	$1,119,387.66	$20,501,647.38
52	Shorewood-Tower Hills-Harbert	MI	72,664	$810,994.44	$15,293,842.89
53	North Muskegon	MI	1,430,945	$11,164,079.68	$286,414,061.02
54	East Grand Rapids	MI	177,356	$1,625,819.72	$36,207,773.35
55	Boyne City	MI	188,765	$1,478,114.84	$38,250,404.80
56	Creston	IA	95,598	$950,737.62	$19,836,528.78
57	Asbury	IA	43,282	$380,661.03	$9,222,659.10
58	Decorah	IA	40,758	$357,341.52	$8,714,773.99
59	Cedar Rapids	IA	281,095	$2,225,912.89	$56,724,011.70
60	Fairfield	IA	116,378	$945,022.72	$23,820,224.78
61	Eldridge	IA	167,049	$1,404,636.71	$34,007,819.50
62	Butler	WI	506,113	$4,143,673.29	$101,841,447.80
63	Bristol	WI	115,159	$1,115,946.70	$23,757,121.24
64	Evansville	WI	86,139	$1,214,261.75	$18,284,083.82
65	St. Nazianz	WI	186,895	$1,934,622.50	$38,347,903.87
66	Menasha	WI	336,018	$3,235,379.82	$68,277,771.92
67	Lauderdale	MN	303,097	$3,012,596.41	$61,734,709.59
68	Hibbing	MN	78,125	$1,512,821.52	$17,044,090.23
69	Winona	MN	103,170	$1,486,460.67	$21,825,948.62
70	Le Sueur	MN	143,565	$2,010,488.26	$30,105,137.58
71	Wood Dale	IL	477,490	$4,240,764.62	$96,443,404.00
72	Freeport	IL	582,267	$4,819,286.95	$117,137,350.07
73	West Peoria	IL	64,325	$802,361.07	$13,684,261.62
74	Sparta	IL	95,697	$880,083.18	$19,784,880.68

A3 (continued)

75	Maplewood	MO	198,020	$1,822,250.83	$40,371,345.30
76	Monroe City	MO	48,802	$559,481.49	$10,461,226.83
77	Riverside	MO	243,332	$2,241,131.75	$49,489,368.98
78	Wahoo	NE	97,294	$1,511,569.81	$20,722,964.48
79	Fayetteville	AR	766,381	$6,526,066.95	$154,190,924.96
80	Oakhurst	OK	120,839	$1,952,098.16	$25,683,737.28
81	Tonkawa	OK	69,453	$1,096,397.89	$14,962,788.29
82	Lindale	TX	147,713	$2,259,289.59	$31,150,285.22
83	Grand Praire	TX	244,173	$3,159,073.95	$50,568,769.05
84	Eastland	TX	70,882	$784,644.88	$14,925,379.28
85	Belton	TX	85,572	$1,646,938.89	$18,607,906.49
86	Houston	TX	132,892	$1,350,000.01	$27,395,612.63
87	Granjeno	TX	36,306	$281,307.65	$7,784,030.92
88	Fort Bliss	TX	50,498	$475,684.04	$10,703,032.88
89	North Washington	CO	78,374	$1,286,405.79	$16,865,478.32
90	Sandy	UT	62,028	$1,021,480.71	$13,462,395.85
91	Paradise Valley	AZ	71,520	$700,783.80	$14,964,003.47
92	South Gate	CA	342,511	$2,783,155.66	$69,072,094.68
93	Pomona	CA	178,427	$1,493,771.85	$36,281,339.49
94	San Jacinto	CA	107,257	$1,458,326.63	$22,582,449.93
95	Simi Valley	CA	224,712	$2,112,965.35	$45,786,475.40
96	Calwa	CA	48,842	$400,549.05	$10,309,973.72
97	San Leandro	CA	179,475	$1,926,951.72	$36,915,717.75
98	Happy Valley	OR	602,443	$4,782,517.72	$120,974,033.89
99	Albany	OR	86,722	$1,362,768.79	$18,544,517.07
100	Kent	WA	69,712	$579,619.56	$14,495,733.61
101	Bellingham	WA	46,194	$359,180.29	$9,760,233.45
102	Marysville	WA	81,428	$883,630.74	$17,049,019.96
103	Spokane Valley	WA	75,460	$1,537,947.67	$16,557,581.15

CHAPTER

4

PROTOCOL DESIGN AND IMPLEMENTATION OF A PUBLIC LOGISTICS NETWORK

1 Introduction

The trucking industry plays an integral part of the U.S. economy, hauling 72.5% of all freight transported in 2019, and generating $791.7 billions in revenues in 2019, which represented 80.4% of the nation's freight transportation bill (American Trucking Association, 2020). One of the major challenges this industry faces is the under-utilization of truck capacity (MAI, 2018). With transportation costs increasing every year, medium to large transportation companies are losing money on underutilized trucks since these, besides being depreciating assets, have to be registered and maintained irrespective of what value they generate. Due to decentralized nature of the organizations, underutilized trucks are mostly prevalent in the inbound side (Augsburger, 2016). Survey results have shown that 15% – 25% of the time these trucks travel empty and 36% of the time with partially empty loads, meaning, trucks are filled to full capacity on an average only 40% of the time (Vecna Robotics, 2019). Companies have struggled for years to find ways to effectively optimize truck load. Besides reducing business costs associated with labor and fuel, maximizing freight capacity can also reduce the emission levels — just half of the underutilized truck capacity is responsible for freight emissions of over 100 million tons per year (Vecna Robotics, 2019).

New developments in transportation collaboration networking, like Lanehub (Johnson, 2016) (sharing real–time information with partners or sharing truck with another shipper as an opportunity to consolidate and co–ship) seem to have massive potential towards alleviating the under utilization issue. Unlike transportation management systems (TMS) such as Keubix, companies using such collaboration networks do not require high investments for building resources or developing infrastructure. However, the collaboration is contingent upon getting another shipment with matching lanes, satisfying the shippers' constraints, setting up a mutually agreeable revenue or cost sharing arrangement (Johnson, 2016). Sometimes maintaining the associated synergies may turn out to be difficult and hence, scheduling becomes more time–intensive and painstaking. This platform also allows two shippers to collaborate and jointly procure a carrier — of course after agreeing on a price with the carrier (Johnson, 2016). The platform provides a going rate of services and consequently, the price setting is more influenced by the displayed rate rather than the shipper's willingness to pay. Hence, the collaboration is largely dependent upon finding the right contract. Moreover, on the traditional demand side, US parcel shippers are becoming increasingly frustrated with more price hikes, with UPS and FedEx implementing additional surcharges around May 2020 (The load star, 2020). Further, FedEx, in its announcement of 2021 rate schedule, declared that there would be an average of 4.9% increase for the domestic transport rates once again (O'Brien, 2020).

In this work, we propose and extend a public logistics network (PLN) and its protocols as discussed by Kay (2004) as an alternative to private logistics network for ground transport, and analyze the implementation of a PLN on a small network. We envision PLN to be operating analogous to packet transmission through Internet — a package sent from a public distribution center (DC) would get routed through a sequence of DCs over a network and get delivered to its destination. Here, the DCs would function like routers in the internet. The PLN design focuses on three independent entities: DCs, packages and trucks. The DCs are basically a platform used for holding the packages for pickup and dropoff, and for facilitating the transaction between the package and the trucks. A key aspect of our proposal is that, rather than being price takers, the packages bid for transportation services. The packages, upon arriving at a DC, bid for services of the trucks to reach to their destination, and pay each DC a fraction of the accepted bid and a per-unit time cost of waiting at the DC, akin to a holding cost in a typical inventory setting. These bids can be accessed and seen by all the involved agents. Trucks see these packages, their associated requirements and bids, and then decide which, if any, package to accept in order to maximize their profit. Each package's bid and truck's decision making would be managed by its own software agent who would interact via protocols for services established by each DC or the network as a whole. In PLN, unlike a private logistics network, since the entities of the network are independent, no single firm can provide centralized control of the entire network and hence, the coordination among the entities is more difficult. The aim of such a decentralized coordination mechanism is to allow the packages and the trucks to exploit the dynamics of the system, and to maximize their value from transport and profit, respectively.

The agent-based bidding is similar to a name–your–own–price (NYOP) system, rather than a auction setting. NYOP is a participative pricing strategy where the buyer (package, in our context) places a bid and the seller (trucks) either accepts or rejects. We refer the interested readers to Fay (2004) and Wagner & Pacheco (2020) for a thorough treatment of this stream of literature. Here, we allow the packages to bid/rebid every time a new package arrives and such a mechanism will facilitate an environment similar to real–time bidding where the agents can use past data and trends to optimize their bid. As the companies start using PLN repeatedly, the agents become non-myopic and try to learn to exploit the system, leveraging the available data. Motivated by the increasing use of data analytics in businesses, and studies stressing the importance and potential of using data and machine learning in order to effectively bid — be it on supply side or demand side — in electricity markets (Wang & Yu, 2019; Pinto et al., 2016; Zhou et al., 2017; Kamyab et al., 2015), display advertising (Ren et al., 2017; Nuara et al., 2020), revenue maximizing auctions (Nedelec et al., 2019) and even in procurement auctions (Kim & Jung, 2019), we expect the agents to actively and heavily leverage data to bid. We refer these packages as "smart packages". Moreover, we envision each of the software agents — both trucks' and packages' — to have necessary computational capability to determine their optimal decisions by taking system information such as past acceptance history, package requirements, past package history and so on into consideration.

In this chapter, we first extend several necessary protocols as proposed by Kay (2004) which, we believe, would enable efficient coordination and performance of a PLN in the bigger picture, that is, for a large network. However, since the coordination of the operation of such a PLN is very complex and there is no prior work on which each of the pieces can be analyzed, we conduct a limited study — yet an interesting one — on a small network (with 3 DCs) to perform a feasibility analysis and gain insights on different trade-offs among the entities. It is important to note that, this small network is not representative of a country wide trucking network, but rather resembles a segment of a geographically limited network, more specifically a localized distribution network.

Our analysis emphasizes the behavior of smart packages in a localized segment of a network consisting of 3 DCs. This, in future, can be extended as a part of a larger network by solving for each of its subsets first — we illustrate an example (for $N = 4$) and provide further discussions in Section 6. We further evaluate the performance of the smart packages against a clairvoyant policy — an optimal policy based on perfect knowledge of the present and future state of the system.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. In Section 3, from the perspective of a generalized setting (large networks), we discuss our model, a representative scenario and potential concerns towards efficient implementation of a PLN, and design several protocols that help alleviate them. This section would really help the readers understand the bigger picture — what we are envisioning. However, from the next portion, in order to perform a feasibility study and derive necessary insights, we consider a localized segment of network consisting of 3 DCs and start analyzing the behavior of packages, trucks and the coordination among all the entities involved. In Section 4, we discuss the assumptions and the behavior of a smart package. Section 5 illustrates the proposed approaches and assesses the performance of the approaches against a clairvoyant policy. In Section 6, we discuss the limitations of our study and provide future directions and lastly, Section 7 presents our discussion and concluding remarks.

2 Literature Review

In this work, we propose and extend several protocols of a PLN to facilitate effective system operations and associated coordinations. Previously, only Xiang et al. (2007) and Xiang et al. (2008) have studied aspects of a PLN. They considered the DCs as platforms responsible for supply-demand matching and studied only the DC data infrastructure and DC queuing aspect of a PLN. However, we analyze the coordination of all the involved entities of a PLN for a small network and particularly focus on the packages while positioning DCs as platforms used for merely holding the packages left for pickup and dropoff. Here, the matching of supply and demand is driven by the decision making (preferences and optimization problem) of the packages and the trucks and in that way, every entity has incentive to participate and would strive to extract maximum benefit from the system. Hence, our mechanism design and setup is completely different. In this regard, the stream of collaborative logistics (CL) probably comes close to our setting and conversely, PLN helps addressing various existing issues in collaborative logistics.

CL refers to the practice where companies work together to maximize their supply chain efficiencies through collaborative transportation (Cruijssen et al., 2007; Lv et al., 2017), collaborative consolidation centres (Reaidy et al., 2015) and collaborative procurement (Schotanus et al., 2010). However, as discussed in Section1, implementing such collaboration has proved to be difficult (Nyaga et al., 2010). Along with having matching requirements, satisfying associated constraints and pricing, lack of trust among the collaborating companies — usually competing firms — has been identified as a major barrier to the implementation of such collaborative network (Pomponi et al., 2015; Baalsrud Hauge et al., 2014; Daudi et al., 2016). In our proposed PLN system, the packages compete against each other to get into a truck and hence, do not need to form trust or match shipping requirements (or constraints) with their competing packages. Hence, they do not need to consider anything other than their own requirements (a more detailed discussion of the package protocols are provided in Section 3).

Since we are allowing the packages to bid in a name–your–own–price (NYOP) setting, we discuss our bidding practices in the context of NYOP mechanism. NYOP is a participative pricing strategy where the buyer (package,in our context) places a bid and the seller (trucks) either accepts or rejects. Devising an optimal NYOP structure has been an interest to several researchers (Hann & Terwiesch, 2003; Fay, 2004; Terwiesch et al., 2005; Cai et al., 2009; Chen, 2012). Many researchers have investigated whether to allow buyers to bid once, or multiple times based on the effect such practices have on the buyer's (and/or company's) profit. Fay (2009) suggested allowing single bidding will enable the seller to gain strategic benefit against a observant, competing seller with a pricing strategy, and single bidding can be enforced by charging a bidding fee (Bernhardt & Spann, 2010). However, enforcing a single–bid rule does not improve seller's profit — even if the buyer is willing to increase its bid, a sale might not occur, resulting in potential lost revenue for sellers (Fay, 2004; Spann et al., 2004; Karahan & Abbas, 2012). Allowing buyers to rebid can provide benefits to both buyer and seller (Gupta & Abbas, 2008; Cai et al., 2009). Hence, in our PLN, every time a new package arrives, the existing packages are notified of the characteristics of the new package, and we allow the packages to submit their bid again. This would allow the packages to compete against each other and adjust their bids. However, to prevent the packages any unfair advantage, we impose a cost that the package has to pay to the DC for the amount of time it spends in it. Since the packages are software–agent controlled, this trade–off would incentivize them to exploit the system dynamics and past data to submit a bid that maximizes its surplus (i.e., willingness to pay – bid) while maximizing its probability of acceptance.

We study the packages' decision making problem in the context of a standard multi–armed bandit (MAB), where the packages try to estimate the truck's acceptance behavior through exploring the system by trying several bid levels, observing the outcomes and then exploiting the information to bid. We are not making any methodological contribution to the MAB literature — our smart bidding technique reassembles a simplified MAB structure. We refer the interested readers to see Gittins et al. (2011) and Bubeck & Cesa-Bianchi (2012).

To summarize, we extend the associated protocols of a PLN proposed by Kay (2004) to facilitate effective coordination among the agents in a generalized context. We then implement a PLN for a small network to perform a feasibility analysis, and further analyze the coordination among each of the entities involved, primarily focusing on the packages. We provide insights, discuss about the implications and provide future directions towards effectively implementing a PLN together in a larger context.

3 Model

In this section, we discuss our vision of how a PLN should work on a generalized setting (large network). The PLN design consists of three independent entities: DCs, packages and trucks. Here, DCs are platforms used for holding the packages left for pickup and dropoff, and for facilitating the transaction between the package and the trucks. Packages arrive at a DC at a rate λ and bid for services of the trucks to reach to its destination, and pay each DC a fraction of the accepted bid and a per-unit time cost of waiting at the DC, akin to a holding cost in a typical inventory setting. These bids can be accessed and seen by all the involved entities. Every time a new package arrives, other packages present at the DC receive the necessary notifications (weight requirement, space requirement, destination requirement and so on) regarding the new package and are allowed to change/resubmit their bids. Trucks see these packages, their associated requirements and bids, and then decide which, if any, package to accept in order to maximize their profit. We provide, briefly, a high–level illustration of the functionality of a PLN in the Section 3.1.

3.1 Representative scenario

Referring to Figure 1, suppose package *A* needs to travel from DC 1 to DC 4 and has decided to take a route of DC 1 to DC 3 and then to DC 4 (a part of packages' decision making). Since the package is controlled by its software agent, such a routing decision would imply that directly traveling from DC 1 to DC 4 proved to be more expensive and/or more time consuming, depending on the objective. So, once it reaches to DC 3, it will be unloaded, sorted and then again loaded into a shipment going to DC 4 — usually on a different truck. In order to visualize this system more vividly, consider the trucks in the network are moving from point–to–point among the adjacent DCs and the packages, travelling through a sequence of DCs, finally reaching their destinations.

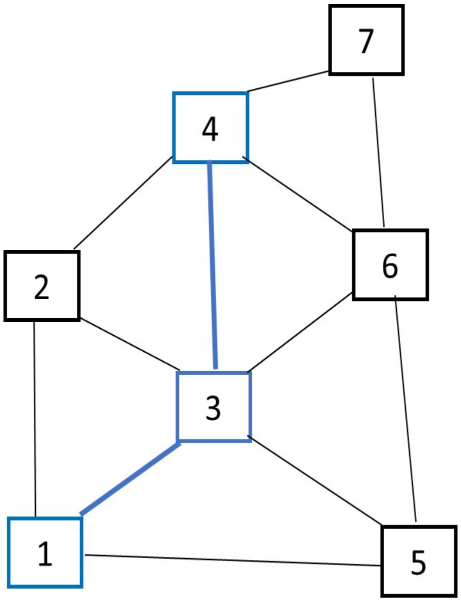

Figure 1: Transport of a package

On the truck side, the accepted packages from a DC form a load for that truck and the sum of bids of all the accepted packages is the load bid for that truck. Here, packages compete with each other to join a load. As shown in Figure 1, the adjacency relationship between DCs represents the existence of an established lane, and thereby defining the topology of the network. It is important to note that new direct lanes — say, from DC 1 to DC 4 for package *A* — may well be established and/or utilized should the software agent of the truck find it optimal. This might result when a package with same destination (DC 4, in this case) bids high and/or has a short due date.

Note that, while presenting the representative scenario, we do not specifically discuss all aspects of the package and truck decision-making process, treating them as non–strategic. However, in order to derive maximum benefit, sometimes, each of them might want to exploit the system to gain unfair advantages, disrupting the system coordination and imposing potential concerns towards the effective implementation of a PLN.

Concerns regarding Trucks:

- Reneging: Trucks, after accepting a load, might renege and keep switching between load bids — newly formed load bids and the reneged load bid — in order to maximize its profit.
- Delaying: After accepting a load, trucks having surplus capacity might want to wait in the DC to fill its capacity.
- Collusion: Trucks, might also want to collude with other trucks so that its surplus capacity is filled.

Concerns regarding packages:

- Delaying: Packages might want to wait in the DC for a load bid to form, bid very low, and join it.
- Exploiting free rides: Packages might wait for "free rides" (getting into trucks who are merely passing through the DC with free capacity, having accepted a load bid in another distant DC — see the illustration in 3.2.2.2)
- Colluding: Packages colluding with each other and bidding.
- Withdrawing: Packages withdrawing from an already accepted load and joining a forming load to maximize its value.

These issues have adverse effects on the system dynamics, affecting the efficiency of a PLN (discussed in Section 3.2). In order to address these concerns, and also, to provide a effective operating platform to each of the agents, we summarize some protocols as proposed by Kay (2004)) and design some additional protocols and mechanisms for trucks and packages in the following section.

3.2 Protocol Design

When a sender/company needs to send a package to its destination, the sender goes to the nearest DC with the following information: destination, weight requirement, space requirement, due date and a penalty cost to be paid by the delivery truck if the the due date is violated. The package submits its bid (penalty cost can be considered as a fraction of the bid). The truck, seeing the bids and the available packages, selects a load bid that maximizes its profit. Considering these characteristics the packages and trucks, in this section, we design the protocols the packages and trucks should follow in order to achieve effective coordination of the associated operation. We start by discussing the package protocols first where we summarize and simplify the protocols proposed by Kay (2004), and additionally design the package bidding protocol.

3.2.1 Package Protocol

Here, we discuss the agent–based bidding of the packages. To reiterate, packages arrive at the DC with the following information: dues dates, destination, space requirement, weight requirement and penalty cost for late delivery. Every time a new package arrives, having received the necessary notification, all the packages are allowed to change their bids. In this section, we first discuss some implications of smart bidding and then formulate some rules, constituting the package protocol, in order to address the issues discuss in Section 3.1.

3.2.1.1 Package bidding

Each agent solves a joint optimization problem in order to minimize its regret and maximize its probability of getting accepted. This involves using the available data extensively to submit a minimal bid while maximizing its probability of acceptance estimated using a data driven approach. The agent's decision does not need to be one–dimensional — its bid will be a function of route it takes. That is, it can either decide on bidding for directly to its destination, hence bidding for one lane (i.e., myopic approach), or it can travel through a series of DCs, hence placing bids on multiple lanes (i.e., non-myopic approach). For example, referring to Figure 2, suppose a package, say package *B*, needing transport from DC 1 to DC 2, may decide to take a route from DC 1 to DC 3 and then to DC 2. The agents, having access to all the data and being non-myopic, may find it optimal to take that route. This will happen when package B can join an already formed load with a low bid and submitting a comparatively higher bid at DC 4. Hence, the agent can submit bids on a different set of lanes, with its bid to its direct destination being superadditive. Again, for this, the agent can use the available data and data-driven approaches to place bids to be strategically myopic (placing bid on a single lane) and non-myopic (placing bids on multiple lanes). For the rest of the paper, we refer this bidding strategy as "smart bidding". Once the bids are placed, loads are formed based on a truck's capacity. We discuss this in detail in Section 5.2. The next three package protocols (i.e., load formation, withdrawal and rebidding, and allocation of bids) are inspired and are basically summarized version of what Kay (2004) proposed.

3.2.1.2 Load formation

Loads are formed from the agent-based decision in trucks (to be discussed in Section 3.2.2.1). Simply, for several packages with same capacity requirement, destination requirement and no due time requirement, the loads are formed in the decreasing order of the available bids to the truck's capacity — any newly arrived package with higher bids may readily get its place on the load bid before any truck accepts it (if other packages do not refresh their bids). Since the packages are allowed to rebid once a new package arrives with new information, the package agents compete with each other to get onto the load. A package can also withdraw itself from an already formed load bid, but not without a consequence.

3.2.1.3 Withdrawal and Rebidding

If a package withdraws from a load, it is still charged the amount of its bid. Withdrawal of a smart package, say for *B*, makes sense if it withdraws from a load going to DC 3 and join another load to DC 4 and still be benefiting. However, any package that was dropped from a forming load — due to the arrival of new packages with higher bids — can submit a new bid (once the new package arrives) without any charge but has to pay the DC for staying in it until it gets accepted, which the package agent tries to minimize since any payment other than its bid is adding to its regret.

3.2.1.4 Allocation of Load bid

Once the truck accepts a load bid, the truck's portion of the load bid does not change, even if it has surplus capacity. So, if a package with same destination requirements wants join that load, its bid is then redistributed to other packages in the load in proportion to their bid amounts. Such redistribution is also applicable when a new package substitutes a package in the load bid with same space and destination requirement but a higher bid, due to withdrawal. Such allocation of load bid will incentivize the package to bid early and, at the same time, discourage a truck from waiting at the DC after it has accepted a load bid. Further, the trucks also cannot wait to accept a load (imposing some time restrictions) as the opportunity to accept the load bid will move to the next available truck.

3.2.2 Truck Protocol

In this section, we design and propose the truck protocols. Here, we first discuss the potential function of the agent based truck decision support system. We, then, formulate rules constituting the truck protocol that help to mitigate the issues discussed in Section 3.

3.2.2.1 Load bid design

Once packages arrive at a DC with their specific set of requirements, priority is given to the trucks for accepting or rejecting packages in increasing order of their distance from the said DC. Each truck's software agent decides which packages to accept, and thereby which route to take, based on the available sets of packages. The decision making involves maximizing the profit it can derive from an available set of packages, I, where the profit function consists of the earnings gained from bids of the packages, operating cost as a function of truck's routing, and the associated penalty cost. In order to do so, it needs to solve a combination of three problems: the knapsack ($O(nb)$) (where b is the capacity of the truck), cumulative vehicle routing (NP–hard), and vehicle routing with due date constraints (NP–hard). Table 1 provides a comprehensive summary of notation used for designing the load bid of a truck. Based on the introduced notations, the software agent sets the package selection decisions (i.e., x_{ij}) so as to

$$\text{Maximize} \quad \sum_{i=1}^{I}\sum_{j=1}^{J} b_{ij}x_{ij} - c\sum_{k=1}^{K}\sum_{j=1}^{J} d_{kj}y_{kj} - \sum_{i=1}^{I}\sum_{j=1}^{J} p_{ij}z_{ij}$$

$$\text{subject to} \quad x_{ij} = \sum_{k\in K} y_{kj}, \quad \forall i \in I, \quad \forall j \in J \tag{1}$$

$$\sum_{j\in J} y_{kj} \leq 1, \quad \forall k \in K \tag{2}$$

$$\sum_{j\in J} y_{1j} = 1 \tag{3}$$

$$\sum_{k\in K/\{1\}} y_{kj} = \sum_{k\in K/\{1\}} y_{jk}, \quad \forall j \in J \tag{4}$$

$$\sum_{i\in I}\sum_{j\in J} s_{ij}x_{ij} \leq S \tag{5}$$

$$\sum_{i\in I}\sum_{j\in J} w_{ij}x_{ij} \leq W \tag{6}$$

$$t_{ij} = \frac{1}{v}\left[y_{1j}d_{1j} + \sum_{p \in J\setminus\{j\}} y_{1p}d_{1p} + \sum_{m \in J\setminus\{1,j\}}\sum y_{mm}d_{mm} + \sum_{m \in J\setminus\{1,j\}} y_{mj}d_{mj} \right], \quad \forall i \in I, \quad \forall j \in J \tag{7}$$

$$t_{ij} \leq q_{ij} + M(1-\delta_{ij}), \quad \forall i \in I, \quad \forall j \in J \tag{8}$$

$$t_{ij} \geq q_{ij} - M\delta_{ij}, \quad \forall i \in I, \quad \forall j \in J \tag{9}$$

$$-M(1-\delta_{ij}) \leq z_{ij} \leq M(1-\delta_{ij}), \quad \forall i \in I, \quad \forall j \in J \tag{10}$$

$$t_{ij} - q_{ij} - M\delta_{ij} \leq z_{ij} \leq t_{ij} - q_{ij} + M\delta_{ij}, \quad \forall i \in I, \quad \forall j \in J \tag{11}$$

$$x_{ij} \in \{0,1\}, \quad \forall i \in I, \quad \forall j \in J$$

$$y_{kj} \in \{0,1\}, \quad \forall k \in K, \quad \forall j \in J$$

$$\delta_{ij} \in \{0,1\}, \quad \forall i \in I, \quad \forall j \in J$$

$$z_{ij} \geq 0, \quad \forall i \in I, \quad \forall j \in J$$

Table 1: Truck's load bid design notations

Sets:	
I	Set of available packages, $I = \{i\}, i = 1,2,....\lvert I\rvert$
J	Set of destination DCs for the available packages, $J = \{j\}, j = 1,2,....\lvert J\rvert$
K	Set of origin and intermediate DCs, $K = \{k\}, k = 1,2,....\lvert I\rvert$, (for origin DC, k=1).
Parameters:	
b_{ij}	Bid for i-th part arrival to j-th adjacent destination.
p_{ij}	Penalty for i-th part arrival to j-th adjacent destination.
q_{ij}	Due time requirement for i-th part arrival to j-th adjacent destination.
s_{ij}	Space requirement for i-th part arrival to j-th adjacent destination.
w_{ij}	Weight requirement for i-th part arrival to j-th adjacent destination.
c	Per unit mile operating cost.
S	Available space capacity of truck.
W	Available weight capacity of truck.
v	Average speed of a truck.
d_{kj}	Distance from i-th part arrival to j-th adjacent destination.
Decision	variables:
t_{ij}	cumulative distance travelled for i-th part arrival to j-th destination $\longrightarrow$ derived from the output of the decision variables.
x_{ij}	binary variable indicating selection of i-th part arrival to j-th destination, $\in (0,1)$
y_{kj}	binary variable indicating selection of k-th origin to j-th destination, $\in (0,1)$
δ_{ij}	binary variable indicating violation of due date for i-th part to j-th destination, $\in (0,1)$
z_{ij}	amount of time by which i-th part to j-th destination has violated its due date $\in (0,1)$

The agent wishes to select the set of packages that maximizes its profit where the profit function consists of the sum of the bids of the selected packages, operating cost as a function of truck's routing and the associated penalty cost for, if any, delayed delivery. Here, constraint (1) indicates the linking or mapping of the selected package with its destination, constraint (2) ensures that each destination is visited at most once, (3) indicates initialization at $k = 1$ (i.e., starting at current DC), (4) eliminates any sub–tours (not requiring the vehicle to end at originating DC), constraints (5) and (6) indicates space and weight limitations, constraint (7) is the estimation of t_{ij} based on the route, constraints (8) and (9) whether a package inclusion might incur a penalty (if delivered later than due date), and constraints (10) and (11) determines the amount of time by which, if any, a package delivery is delayed (if $\delta_{ij} = 0, z_{ij} = 0$ and if $\delta_{ij} = 1, z_{ij} = t_{ij} - q_{ij}$). Here, note that, determination of t_{ij} itself is $O(n^2)$. Moreover, the truck's decision making problem is a combination of 3 NP–hard problems.

3.2.2.2 Dwell point and Dynamic priority

Apart from the package selection decisions, the software agents of trucks, in the long run, will be dynamically setting the dwell point locations and establishing its priority for DCs in order to exploit the dynamics of a PLN. An optimal dwell point location for a truck can be defined as the location in the network, staying where it can quickly respond to a DC, especially when other DCs have been idle (i.e., no or very few incoming package) for some time. Using data and machine learning techniques, the agent can learn its optimal dwell point location based on its locality, past package arrival history and other truck's location in the network. The dwell point location may well be also a function of time of the day (and even month and year). This approach is inspired by different Uber driver's strategy to set their dwell point near airports before busy flight schedule times.

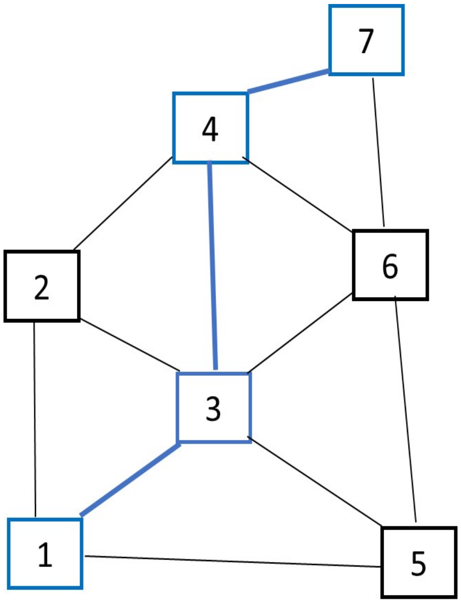

Figure 2: Intended path from DC 1 to DC 7

On the flip side, trucks accepting a high, lucrative bid at a distant DC (DC 7) might accept low bids at the intermediate DCs (DCs 1, 3 and 4) in order to maximize its earning (see figure 2). As a result, packages with very low bids may get accepted: as if it gets a "free ride". Since all the data is publicly available, these situation can be exploited by the package agents.

3.2.2.3 Reneging

Besides proposing few decision mechanisms for the trucks, we also impose some rules which would help in addressing the issues discussed in Section 3.1. Reneging will have adverse effect on the dynamics of the trucks' decision making and might result into trucks colluding. It will also impact the packages' decision making — incurring additional waiting time cost to the packages. A potential solution would be to a high cost to the trucks for reneging, which would demotivate the trucks to renege.

With these restrictions, along with some other discussed in Section 3.2.1.4 (as a consequence of package protocol rule), we establish the protocols for trucks. Having established the protocols and implications of smart bidding behavior previously, we implement a PLN configuration for a small network and study the behavior of the packages in the next section.

4 Experimental Setup

As evident by the discussion in Section 3, the coordination of the operation of such a PLN is very complex and there is no prior work on which each of the pieces can be analyzed. Hence, it is imperative to highlight and reiterate that, starting this section, we study only a segment of a network (consisting of 3 DCs) to analyze the coordination of all entities involved, especially the package side of things in a concise, yet insightful manner and gain insights on different trade-offs among the entities involved.

Following are some assumptions, relaxing some protocols, which will help us to analyze PLN on a small scale and yet, allow us to derive insights:

- Ground transport of packages among N DCs.
- Trucks' trip operating cost or minimum threshold for acceptance = per unit mile operating cost times the distance travelled.
- Trucks do not have a weight restriction.
- Reneging for trucks and withdrawal for packages not allowed.
- Trucks get to accept or reject loads based on the closest distance to a DC. If a load is rejected by a truck, the next closest truck gets to accept or reject.
- Packages do not have to pay the DC for waiting.
- Packages are of unit capacity.
- Packages do not have a due date and hence, no associated penalty.

- Packages are allowed to resubmit their bids every time a new package arrives.
- Packages controlled by software agents are called smart packages.

With these assumptions, we can analyze the following scenario. A company recurrently using a bidding based logistics service, decides to employ smart bidding agents to bid for the service. We consider two different bidding environments, design the bidding mechanisms for smart agents in each and analyze their impact:

- all dumb packages: bidding a random fraction of its valuation (a random variable), having no sense of system dynamics.
- all honest packages: bidding their valuation (a random variable), focusing solely on maximizing the probability of getting service.

Intuitively, on average, such dumb packages would generate larger savings (valuation – bid) while waiting longer in the system whereas the honest packages would wait for a shorter time while bidding its valuation (i.e., savings = 0). As discussed in Section 3.2.1.1, each package agent solves a joint optimization problem in order to minimize its regret and maximize its probability of getting accepted. In this way, the smart packages would try to generate savings (bid < valuation) while waiting in the system for a shorter time. However, at the time of bidding, a truck's preferred load bid and its size is not known to the package, since it does not know which truck with what capacity is going to accept but it can access the information regarding the nearest available truck.

4.1 Smart Bidding

Here, the smart packages do not have any information on the trucks' operating cost. They use the widely known Multi–Armed Bandit (MAB) mechanism. In a standard multi-armed bandit problem, given a set of options (arms), the decision maker needs to choose a single arm at each turn, observe its rewards and update its belief (history). Based on its belief and state of the system, it keeps on choosing an arm and updating its belief in order to minimize its regret. Here, the smart packages try to submit a bid in the hope of joining a load and observe whether the truck accepts it or not as a part of the load bid. Of course, since the truck accepts a load bid rather than a single bid, the choice of bidding for the smart packages is dependent on the bid levels of the available packages. The idea here is for the smart packages to come up with a bidding policy to minimize their regret and, over time, to converge to the actual operating costs of trucks, enabling it to bid optimally.

Let $s \in R^+$ be the minimum that a truck is willing to accept as a load bid, i.e., its operating cost. Here, this s is unknown to the packages and the smart packages try to bid by estimating it.

Given an arm $c_i \in R^+$ — corresponding to a specific operating cost, we define μ as the probability that the truck will accept a load bid as a function of c_i,

$$\mu(c_i) = Pr(s \leq c_i) \quad \left(= \int_0^{c_i} S(x)dx, \quad \text{when } s \text{ is a random variable with pdf } S \right)$$

Here, since s is the minimum threshold, $c_i < c_j \iff \mu(c_i) < \mu(c_j)$. Once the smart package, with willingness to pay v, arrives at DC n and observes an ordered set of bids of packages present, β, capacity of the nearest truck, K, and considers a finite set of ordered arms (operating costs), $C = \{c_1, c_2, \ldots, c_N\}$ with $c_i \leq c_j$ iff $i \leq j$, and let $P = \{p_1, p_2, \ldots, p_N\}$ be the corresponding bid levels it registers, where,

$$p_i(\beta, K) = c_i - \sum_{j=1}^{min(K-1,|\beta|)} \beta_j$$

The smart packages, in each instance, have a reward function, $r_i = (v - p_i)\mu(c_i)$, which they want to maximize — instead of minimizing the regret ($p_i - \gamma$), where γ is the bid of a clairvoyant. However, s and as a result, μ_i is unknown. So, given a history of accepted load bids and outcomes of previously played arms, the smart package chooses to play an arm c_i in order to learn and exploit the operating cost of trucks. Every time it plays an arm, it observes the outcome and updates its belief, helping it to choose an arm next time. For the sake of simplicity of analysis, we consider s to be deterministic for a lane where the randomness of s can be investigated in future having smart agents estimating for certain percentiles or performing some predictive analysis. Hence, after observing trucks decision, $\mu(c_i)$ becomes a binary output $(0, 1)$ of whether the truck has rejected or accepted the load bid of c_i.

If B_t denotes the load bid formed at time t, we consider $H_t = \{B_{t'} \quad | \quad \mu(B_{t'}) = 1, \quad t' < t\}$ as the history of accepted load bids till time t and $h_t = \{B_{t'} \quad | \quad p_i \in B_{t'}, \quad \mu(B_{t'}) = 0, \quad t' < t\}$ as the history of rejected load bids when an arm is played — when a smart package has participated. Apart from observing β, the smart packages also need to predict the bids of newly arrived packages (i.e., the bids of the packages not yet submitted) and then play for c_i. Once the bids are submitted and based on the outcome, H_t, h_t and β are updated. We initiate the c_i by $\gamma * \min(H_t)$ and from then on, we select the c_i as $\gamma * (\min(H_t) + \max(h_t))$. For this study, we have chosen $\gamma = 0.5$. This selection process is $O(logn)$ and is motivated by the use of binary search in several selection algorithms (Kumari & Singh, 2014).

5 Computational Experiment

In this section, we discuss the implementation of a PLN outlined in Section 4 with $N = 3$ with DCs at Morrisville, Durham and Chapel Hill where the package arrivals are exponentially distributed with $\lambda_1 = 3$, $\lambda_2 = 2$ and $\lambda_3 = 4$, respectively. We assume the package weights to be uniformly distributed with $m \sim U(20,\ 100)$, and their valuations,v, to be function of m such that $v = 0.5 * m + \xi$ where $\xi \sim U(-10,\ 10)$. To respond to these packages, we consider there are K = 100 trucks available in the area (or registered with the system) whose capacities are uniformly distributed between 1 and 5. We initialize the truck locations randomly and from then on, keep a track of the trucks and their accepted packages. We consider per-mile cost for trucks as \$6 per mile and average truck speed as 4 miles per hour to be scalable with other problem parameters. We observe the system till $T = 1200$ hours where smart packages are considered to arrive every 100 hour.

Consider packages arriving at DC n at time t and requesting to be delivered at destination $d \in N/n$, and we denote the set of such packages as a_t^{nd}. The package observes P_t^d — the set of packages waiting at time t (sorted by decreasing bids) to be accepted by a truck to deliver it to destination d — and bids as per its practice (honest $\rightarrow$ bid = valuation, dumb $\rightarrow$ bid = rand*valuation, smart $\rightarrow$ bid = smart bid), while other packages are notified about the arrival of the new package and are also allowed to update their bids. Once the packages submit their bids, trucks evaluate whether to accept any set of packages based on the profit it might derive. Truck's profit estimation, S, is a function of its capacity K, operating cost for travelling to DC d, $o(d)$, and P_t^d. Here, d with multiple destinations suggest that $o(d)$ is the operating cost for travelling along the shortest route. The trucks' decision–making involves selecting the set of packages that maximizes their profits, Ω (i.e, the load bid, B_t^n), and as long as they derive positive profit margins, they accept the load bid. Based on the outcome, the history (i.e, H_t^n and h_t^n) and P_t^d are updated.

Table 2: Notations

Parameters:	
N	Set of DCs, $N = \{n\}, n = 1,2,3.$
d	Destination of packages, $d \in N/n$.
a_t^{nd}	Package arriving at DC n with destination d at time t.
P_t^d	Set of package still waiting at time t (sorted by decreasing bids) to be accepted by a truck to deliver it to destination d.
b_i^d	Submitted bid of the package i in P_t^d, where $i = 1,2,..\lvert P_t^d \rvert$
ρ_j^d	Set of first j packages of P_t^d
H_t^n	History of accepted load bids till time t at DC n, where $H_t^n = \{B_{t'}^n \quad \mid \quad \mu(B_{t'}) = 1, \quad t' < t\}$
h_t^n	History of rejected load bids till time t at DC n when the load had a smart package, where $h_t = \{B_{t'} \quad \mid \quad s(B_{t'}) = 1, \quad \mu(B_{t'}) = 0, \quad t' < t\}$
ε	Minimum bid amount for smart packages.
k_t^n	Average capacity of the trucks accepting packages at n till time t.
${}^u\Psi_t^n$	u-th percentile of bids of all packages at n till time t.
η	Fraction by which to shade bid. (assume $\eta = 0.5$)
Decision variables:	
$o(d)$	Operating cost of the truck to reach destination d.
S	Profit of the truck
Ω	Set of selected packages
B_t^n	Load bid formed at time t in DC n.
$s(B_t^n)$	Binary variable indicating the presence of a smart package in B_t^n
p_t	Submitted smart bid at time t.

For smart packages, their decision making involves predicting the bids of the newly arriving packages. Once new packages comes in and all the other packages are notified with the associated information, the smart package leverages this data as well as the past package data to forecast the bid levels of the new packages, and submit its bid accordingly. This can be done using any machine learning algorithm and in this work, we resort to linear regression in order to avoid additional complexity and yet, provide the underlying insights. The smart packages also need to predict the minimum acceptable threshold of the truck, s, ($o(d)$ in this case) in order to bid, which they do by using the technique discussed in Section 4.1. The smart packages, for their decision-making, leverages the past system history — that includes the history of past packages, trucks and the outcome of a load bid. Having analyzed and estimated the requisite parameters, the smart packages bid as a function of its immediate destination. Table 2 provides a comprehensive summary of notation.

In the subsequent sections, we study sample implementations of the decision making of the trucks and the smart packages, and design several algorithms which help us defining the behavior of the trucks and the packages.

5.1 Implementation of Truck's decision making

Suppose a truck, with space capacity K, is considering whether to transport any packages from DC1 ($n = 1$) and if so, which packages to accept. Since $n = 1$, $d = \{2, 3\}$ (and let $d_1, d_2 ..., d_{|d|}$ denote the elements of d). With the assumptions laid out in Section 4, the decision making problem in Section 3.2.2.1 can be solved using Algorithm 1.

Algorithm 1 Truck's decision making for $N = 3$

```
Step 1:
if $|P_t^{d_1}| \geq K$ then
    $S_2 = \sum_{i=1}^{K} b_i^{d_1} - o(d_1)$
    $\Omega(S_2) = \{\rho_K^{d_1}\}$
else
    $S_{21} = \sum_{i=1}^{|P_t^2|} b_i^{d_1} - o(d_1)$
    $\Omega(S_{21}) = \{P_t^{d_1}\}$
    $S'_{21} = \sum_{i=1}^{|P_t^{d_1}|} b_i^{d_1} + \sum_{i=1}^{K-|P_t^{d_1}|} b_i^{d_2} - o(d_1, d_2)$
    $\Omega(S'_{21}) = \{P_t^{d_1}, \rho_{K-|P_t^2|}^{d_2}\}$
    $S_2 = max(S_{21}, S'_{21})$
    $\Omega(S_2) = \underset{S_2}{argmax}\{\Omega(S_{21}), \Omega(S'_{21})\}$
end if
Step 2:
Repeat Step 1 for $P_t^{d_2}$, and obtain $S_3$ and $\Omega(S_3)$.
Step 3:
$S \leftarrow \max(S_2, S_3)$
$\Omega \leftarrow \underset{S}{argmax}\{\Omega(S_2), \Omega(S_3)\}$
Step 4:
if $S > 0$ then
    Accept service for $\Omega$.
else
    Reject service for all packages.
end if
$H_{t+1}, h_{t+1}, P_{t+1}^{d_1}, P_{t+1}^{d_2} \leftarrow$ update$(S, \Omega)$
```

To summarize:

- Step 1: Truck calculates its profit for a load bid for one lane. If it has additional capacity, it checks whether carrying packages of an additional destination provide higher profit.
- Step 2: Repeat Step 1 for each lane.
- Step 3: Finds the optimal set of packages, Ω.
- Step 4: Accepts Ω iff it derives positive profit.

5.2 Implementation of Smart bidding

Suppose a smart package, with valuation v^s, arrives at DC 1 (i.e., $n = 1$) with $d = 3$. It can try three different avenues to exploit the state of the system:

- Myopic approach: join load forming for $d = 3$ and smart bid accordingly.
- Non-myopic approach: Check whether it can gain more by first travelling to an adjacent DC (DC 2) and then to its intended DC (DC3) based on, of course, the existing state of the system.
- Opportunistic approach: Check if it can exploit high load bid for adjacent lane (i.e., $d = 2$) and smart bid to cover the predicted cost of trucks for travelling DC 2 and DC 3.

To elucidate the approaches, let us consider the following example:

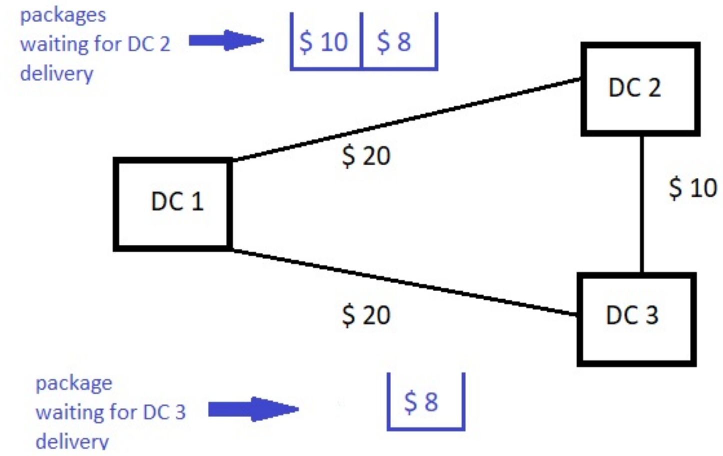

Figure 3: Sample instance for smart bidding approach

Consider a smart package (with $n = 1$ and $d = 3$) arrives at time t and sees two packages in P_t^2 with bids \$10 and \$8 and one package in P_t^3 with bid \$8. Figure 3 illustrates the scenario where the arc values represent the predicted operating cost of trucks for travelling that route. Notice that, the current load bids for individual lanes are not enough for a truck (with say, $K > 3$) to accept where the maximum it can earn is \$26 incurring a minimum cost of \$30. The myopic approach for the smart package would be to bid slightly above \$12 to make the new P_t^3 attractive to the truck whereas under non-myopic approach it would bid over \$2 (say \$2.1) to reach DC 2 and then bid again there using myopic approach for DC 3 (total bid being \$2.1 + predicted bid from DC 2 to DC 3). However, under the opportunistic approach, the smart package bidding slightly above \$4 will make the entire load bid (P_t^2 and P_t^3) attractive to the truck. So, the smart packages, at any time, would use all these approaches to exploit most from the system.

5.2.1 Myopic approach

Here the smart package competes with packages with same destination requirement and tries to join a load forming for that destination (i.e., $d' = 3$). Algorithm 2 shows the myopic approach which can be summarized as follows:

- Step 1: Smart package predicts the bid of the newly arrived package.

- Step 2: In order to predict and exploit the incoming truck's acceptance threshold, it sets bounds based on historical data — upper bound (based on H_t) and a lower bound (based on h_t) — and selects an arm or option (c_t) to explore.

- Step 3: Based on the trucks capacity and the information regarding the available packages, the smart packages bid by predicting the truck's acceptance threshold in an O(logn) manner over several explorations.

Algorithm 2 Myopic approach for smart packages

```
Step 1:
if $a_t^{1d'} \neq \phi$ then
    $P_t^{d'} \leftarrow$ predict and update$(a_t^{1d'}, P_t^{d'})$
end if
Step 2:
$G_3 = \{H_t^n | d = d'\}$
$g_3 = \{h_t^n | d = d'\}$
$UB_M = \min(G_3)$
if $g_3 = \phi$ then
    $LB_M = \gamma * UB$
else
    $LB_M = \max(g_3)$
end if
$c_t = \gamma * (UB_M + LB_M)$
Step 3:
if $|P_t^{d'}| < K$ then
    $b'_t = \max(c_t - \sum_{i=1}^{|P_t^{d'}|} b_i^{d'}, \varepsilon)$
    if $b'_t < v^s$ then
        $b_t^M = b'_t$
    else
        $b_t^M = \eta v^s$
    end if
else
    $b'_t = \max(c_t - \sum_{i=1}^{K-1} b_i^{d'}, \varepsilon)$
    if $b'_t > b_K^{d'}$ and $b'_t < v^s$ then
        $b_t^M = b'_t$
    else
        $b_t^M = \min(b_K^{d'} - \varepsilon, \eta v^s)$
    end if
end if
```

5.2.2 Non-myopic approach

Here, we discuss and analyze the package agent's smart bidding problem, where the agent is non-myopic, trying best to exploit the current state of the system and thereby, bidding and optimizing its bid for all possible/available set of lanes — direct delivery as well as delivery through a sequence of DCs. This approach basically exploits the case when it can get virtually a free ride to an adjacent DC (DC 2 in this case) and there it can bid again using a myopic approach directly for its destination. Let $\delta = N/\{n, d'\}$. Prior to that, the smart package needs to evaluate whether it is worth taking a detour. Algorithm 3 shows the non-myopic approach which can be summarized as follows:

- Step 1: Smart package predicts the bid of the newly arrived package.

- Step 2: To join a load bid for an adjacent DC for virtually free, and to ensure and evaluate its future bids at a sure-shot level, it sets the trucks acceptance threshold (c_t) as the historically accepted minimum amount (based on H_t).

- Step 3: Based on the trucks capacity and the information regarding the available packages, pays the difference of the threshold and sum of available bids. It also calculates its future bid in a pessimistic manner, considering trucks acceptance threshold as the historically accepted minimum amount, and estimating for average package bids and average truck capacity levels. It goes ahead with the estimation iff the total bid (present + projected) does not violate its valuation.

Algorithm 3 Non-myopic approach for smart packages

```
**Step 1:**
**if** $a_t^{1\delta} \neq \phi$ **then**
    $P_t^{\delta} \leftarrow$ **predict and update**$(a_t^{1\delta}, P_t^{\delta})$
**end if**
**Step 2:**
$G_2 = \{H_t^n | d = \delta\}$
$c_t = min(G_2)$
**Step 3:**
**if** $|P_t^{\delta}| < K$ **then**
    $b_t' = \max(c_t - \sum_{i \in P_t^{\delta}} b_t^{\delta}, \varepsilon)$
    $G_3' = \{H_t^2 | d = d'\}$
    $UB_N = \min(G_3')$
    $\theta_2 = {}^{u}\Psi_t^{\delta} * (k_t^{\delta} - 1)$
    $b_t'' = \max(UB_3 - \theta_2, \varepsilon)$
    $b_t^{N\prime} = b_t' + b_t''$
    **if** $b_t^{N\prime} < v^s$ **then**
        $b_t^N = b_t^{N\prime}$
    **else**
        $b_t^N = Inf$
    **end if**
**else**
    $b_t^N = Inf$
**end if**
```

5.2.3 Opportunistic Approach

Sometimes the myopic approach and non-myopic approach may not be attractive, for example, due to few available packages in the load forming for the same destination. In these cases, the smart packages might want to resort to opportunistic approach. The opportunistic approach exploits the case when none of the load bids is individually attractive for the trucks but some arbitration of them might be. Algorithm 4 shows the opportunistic approach which can be summarized as follows:

- Step 1: Smart package predicts the bid of the newly arrived package.

- Step 2: To be a sure shot, it sets the trucks acceptance threshold as the historically accepted minimum amount.

- Step 3: Based on the trucks capacity and the information regarding the available packages, pays the difference of the threshold and sum of available bids iff it does not violate its valuation.

Algorithm 4 Opportunistic approach for smart packages

```
Step 1:
if $a_t^{1d'} \neq \phi$ then
    $P_t^{d'} \leftarrow$ predict and update$(a_t^{1d'}, P_t^{d'})$
end if
if $a_t^{1\delta} \neq \phi$ then
    $P_t^{\delta} \leftarrow$ predict and update$(a_t^{1\delta}, P_t^{\delta})$
end if
Step 2:
$G_{23} = \{H_t^n | d = N/\{n\}\}$
$c_t = min(G_{23})$
Step 3:
if $|P_t^{d'}| < K$ and $|P_t^{\delta}| < K$ then
    $Z = \max(\sum_{i \in P_t^{d'}} b_i^{d'} + \sum_{i=1}^{K-|P_t^{d'}|} b_i^{\delta}, \sum_{i \in P_t^{\delta}} b_i^{\delta} + \sum_{i=1}^{K-|P_t^{\delta}|} b_i^{d'})$
    $b_t' = \max(c_t - Z, \varepsilon)$
    if $b_t' < v^s$ then
        $b_t^O = b_t'$
    else
        $b_t^O = Inf$
    end if
else
    $b_t^O = Inf$
end if
```

5.2.4 Smart Bidding

The smart bidding process combines all three approaches — myopic, non-myopic, opportunistic — and selects the best outcome. Finally, Algorithm 5 depicts the smart bidding approach.

Algorithm 5 Smart Bidding

```
Step 1:
Solve Algorithm 2 and obtain $b_t^M$
Solve Algorithm 3 and obtain $b_t^N$ and $b_t'$
Solve Algorithm 4 and obtain $b_t^O$
Step 2:
$p_t' = \min(b_t^M, b_t^N, b_t^O)$
Step 3:
if $p_t' = b_t^N$ then
    $p_t = b_t'$
else
    $p_t = p_t'$
end if
Step 3:
$P_t^2 \leftarrow$ update$(p_t, P_t^2)$
$P_t^3 \leftarrow$ update$(p_t, P_t^3)$
```

5.3 Clairvoyant Policy

The myopic and opportunistic approaches largely depend on predicting the bids of newly arrived bids and the truck's operating cost, and the non-myopic approach additionally depends on the future package arrivals and their bids at an adjacent DC. A Clairvoyant policy, in this case, refers to the optimal set of decisions for the smart packages if they had the perfect knowledge about the trucks operating costs as well as the future events like package arrivals and their bids. To design the clairvoyant policy, we recreate the scenarios for each smart package from the moment they arrived in the system providing them information regarding all future events, enabling them to choose the most cost effective option. In terms of time restriction, to maintain a good data structure, we allowed the smart packages to select any alternative within 50 time periods of reaching any starting or intermediate DCs. The outcome of the clairvoyant policy is then considered as the optimum and compared against the smart bidding mechanism. Hence, to evaluate the performance of the smart bidding algorithm, we consider the following performance metrics:

$\Re_W$ = ratio of average waiting time under the clairvoyant policy to that under smart bidding where $\Re_W < 1$ would indicate that, on average, average waiting time under smart bidding is higher than that under clairvoyant policy. Here, $\Re_W^S$ and $\Re_W^D$ would denote the performance evaluation under the honest package and the dumb package scenario, respectively.
$\Re_S$ = ratio of total spent under the clairvoyant policy to that under smart bidding. Since $0 < \Re_S < 1$, the higher the value, the closer the smart bidding is to the clairvoyant policy. Here, $\Re_W^S$ and $\Re_W^D$ would denote the said ratio under honest package and dumb package scenario, respectively.

5.4 Results

In addition to evaluating the performance of smart bidding against a clairvoyant policy, we also compare the performance of the smart packages against that of other packages (honest and dumb) and we evaluate them using the following performance metrics:
W_S^+ = average waiting time for smart packages - average waiting time for honest packages.
S_S^+ = average savings for smart packages - average savings for honest packages.
W_D^+ = average waiting time for smart packages - average waiting time for dumb packages.
S_D^+ = average savings for smart packages - average savings for dumb packages.

The bid levels of dumb packages, on average, are comparatively low since they pay a random fraction of their valuation. Hence, their savings are larger when they are accepted by any truck. However, in doing so, the dumb packages, with low bid levels, struggle to form an attractive load bid within a short time and hence, end up waiting in the system for longer period of time. This implies that the dumb packages are only worried about generating savings and have little interest in when they are actually delivered. On the other hand, the bid levels of honest packages, generally, are higher as they bid their valuation. In doing so, they do not generate any savings. However, on average, they can form attractive load bids pretty fast. This implies that the honest packages are only interested to get service as soon as possible. It is almost like paying a premium (i.e. its valuation: the maximum it can spend) for an expedited service. We introduce the smart packages in each of these scenarios and observe how the smart packages behave with respect to the other packages. We further evaluate the performance of smart bidding against a clairvoyant policy both in terms of amount spent and waiting time.

From Table 3, upon performing several Monte Carlo simulations, we see that smart packages, in contrast to dumb packages, spend a bit higher while waiting considerably lesser time in the system in order to get their requisite services. Moreover, the smart packages almost always resort to the clairvoyant policy. Dumb packages, on average, generate higher savings solely due to the nature of their bidding which sometimes results in their never getting accepted by any trucks. For these simulation runs, we have observed that, on average, 12% of the dumb packages are never served by the system, that is, they are left stranded. On the other hand, honest packages packages are served almost 98.4% of the time. From Table 5, we see that, on average, in contrast to honest packages, the smart packages are considerably saving on their bids while spending a bit longer in the system. Moreover, the smart packages, on average, reaches 93% of the clairvoyant policy in terms of its spend while spending lesser time in the system than the clairvoyant policy ($\Re_W > 1$). Hence, we can evidently conclude that the smart bidding mechanism derives the benefit of both honest and dumb packages.

Moreover, the tendency of the smart packages to aim for the nearest truck and to exploit the bidding information of other packages while submitting their bids allow them to get into loads as soon as possible, spending as little time as possible in the DC. This provides more attractive load bids for the trucks which results in quicker acceptance of the load. On average, we observed that the load bids containing a smart package are accepted more quickly than the ones which did not. This resulted in an increase in the throughput of the DCs and as a result, the network obtained a more active participation of the trucks. However, smart packages, in doing so, sometimes replace some packages which would otherwise be in the load. These packages are usually of low bid levels which then have to wait a little longer for a suitable load bid to form. This does not seem to be problematic for dumb packages because, by definition, they are only worried about spending less. But, some honest packages with low valuations are more impacted by the additional waiting times since their only objective to get the service as soon as possible by paying as much as it can. However, due to the presence of smart packages in a load, the other packages in the load (mostly medium to high valuation packages) seem to get an expedited service.

Table 3: Performance Evaluation in dumb package environment for $N = 3$

Performance Metrics	Interpretation	Values
W_D^+	average waiting time relative to dumb packages	-12.53
S_D^+	average savings relative to dumb packages	-4.13
$\Re_W^D$	fraction of clairvoyant waiting attained in dumb scenario	1.02
$\Re_S^D$	fraction of clairvoyant spending attained in dumb scenario	0.99

Table 4: Performance Evaluation in honest package environment for $N = 3$

Performance Metrics	Interpretation	Values
W_S^+	average waiting time relative to honest packages	1.03
S_S^+	average savings relative to honest packages	16.03
$\Re_W^S$	fraction of clairvoyant waiting attained in honest scenario	1.09
$\Re_S^S$	fraction of clairvoyant spending attained in honest scenario	0.93

$\Re_W > 1$ also implies that (i) some smart packages, having selected the myopic, non-myopic or opportunistic approach, could generate more savings if it waited longer in the system, and (ii) some smart packages, which had selected myopic approach, could have done better if it had selected a non-myopic approach instead.

However, few observations had $\Re_W < 1$ which means some smart packages, having selected a non-myopic approach, would have generated more savings if it had selected a myopic approach after waiting some time.

6 Limitations, Extensions and Future directions

In the chapter, we studied the behavior of trucks and packages, and analyzed the coordination of all the entities involved in a PLN for a small network by relaxing some protocols. We specifically emphasized on modeling and analyzing the decision making for smart packages in a small network. The way the decision making of smart packages is studied, they can operate in the same way for $N > 3$ as they do for $N = 3$. For smart packages, the idea here is to first exploit the adjacency relationship among the DCs while bidding and all the subsequent nodes (look ahead in the network) can be estimated using non-myopic approach. Usually, in a network of DCs, the adjacency relationship a DC has is around $3-5$ (M. Kay, personal communication, January, 2021). So, here we illustrate a representative scenario with $N = 4$ and discuss how the packages can use the same smart bidding approach as discussed in Section 5.2.

In addition to the setup discussed in Section 5, we assume another DC at Leesville, NC (DC4). Now, the packages arrivals are considered exponentially distributed with $\lambda_1 = 3$, $\lambda_2 = 4$, $\lambda_3 = 3$, and $\lambda_3 = 4$, respectively. To merely focus on the smart bidding behavior, we assume the starting point for the smart packages to be DC 1 and the desired destination, however, can be any of DC2, DC3 and DC4, with adjacency relationship present among them. Accordingly, we observe the system till $T = 600$ hours. As mentioned previously, since the decision making for smart packages depend on the history and past outcomes of trucks decision making, we first redesign the trucks' decision making algorithm first for $N = 4$. Table 5 provides the performance evaluation of smart bidding technique against honest packages and clairvoyant policy. The results demonstrate that smart bidding mechanism provide similar performance and insights as that of Section 5.3.

Table 5: Performance Evaluation for $N = 4$

Performance Metrics	Interpretation	Values
W_S^+	average relative waiting time	1.76
S_S^+	average relative savings	20.96
$\Re_W$	fraction of clairvoyant waiting attained	1.02
$\Re_S$	fraction of clairvoyant spending attained	0.91

While all these work well with $N = 3, 4$ or even a handful of them having adjacent relationship, a larger network consisting of many DCs — some disjointed and some having adjacency relationship– needs to examined. We have several ideas that would help address several issues associated with a larger network. As a start, we wish to solve the full-scaled version of truck's decision making problem as outlined in Section 3.2.2.1 — a combination of 3 NP–hard problems — using techniques from large neighborhood search (Ribeiro & Laporte, 2012; Ropke & Pisinger, 2006; Pisinger & Ropke, 2010) and monkey formation problem (Mucherino & Seref, 2007). This would allow the trucks to be non-myopic and opportunistic as well, by optimizing over its dwell point locations and dynamic priority. As of now, since the smart packages optimize its bids by using historical data consisting of package history and past outcomes of trucks decision making, the trucks' behavior, system dynamics and smart package behavior are tied together. Solving the full-scaled version of truck's decision making problem would help studying the implementation of a PLN over a larger network.

For a larger network topology (for example: a state–wide trucking network), smart packages can determine their route among the adjacent DCs, first, using this approach, and then determine its future route along the subsequent DCs using strictly the non-myopic approach to begin with. As it starts travelling through the network, it will update its belief and bidding behavior in the same manner. Additionally, for a distant destination requirement (over several DCs), the smart package will identify the shortest route and determine bounds — a narrower stream of DCs it can, at maximum, route through. This would allow the smart packages to broadly analyze just a few adjacent DCs each time.

In this work, we have also ignored scenarios where smart packages are also competing with other smart packages. As discussed previously, the smart packages, in order to estimate its bid, requires performing two predictions: (i) the bids of other packages, and (ii) the acceptance threshold of a truck. Hence, in an environment with competing smart packages, we envision the agents to use a variety of machine learning techniques to perform the predictions and use variants or extensions of Algorithms 2, 3, 4, as a result, 5 to bid and compete against each other.

7 Discussion and Conclusion

In this work, we propose and analyze a PLN, providing a potential solution to the under utilization issues in transportation industry as well as addressing the shipping price concerns on the demand side. We proposed several protocols which would provide an efficient operating platform to each of the agents, alleviating potential issues resulting from any of the entity taking unfair advantage of the system. Since the coordination required in the operation of a PLN is very complex and there has been no prior framework on which each of the pieces can be studied, we studied a snippet of a network ($N = 3$ and $N = 4$) to analyze the demand side, especially the package bidding behavior, in a concise and insightful manner. We studied a smart bidding mechanism where the smart package uses the system information to make predictions regarding the bids of other packages and truck's preference, and uses a simplified MAB approach to submit a bid in order to generate higher savings while increasing its chances of getting accepted. It is important to note that, due to the nature of DCs offering packages to trucks sequentially and each package competing with each other to get into a load, our design is free from any deadlocks occurring.

We studied the smart bidding behavior under two scenarios: (i) dumb package scenario, and (ii) smart package scenario. We also compared the performance of the smart bidding mechanism with a clairvoyant policy. Under the dumb packages scenario, we observed that smart packages save less while spending considerably lesser time in the system. Moreover, the smart packages almost always resort to the clairvoyant policy. On the other hand, on average, in contrast to honest packages, the smart packages are considerably saving on their bids while spending a bit longer in the system. Moreover, the smart packages almost reaches 93% of the clairvoyant policy in terms of its spend while spending much lesser time in the system than the clairvoyant policy. Hence, we can evidently say that the smart bidding mechanism can derive the benefits of both honest and smart packages, and believe the smart packages will demonstrate similar performance in a heterogeneous scenario.

Moreover, the smart packages, exploiting the bidding information of other packages and aiming for the nearest truck while bidding, get into a load as soon as possible, spending as little time as possible in the DC. This practice provides more attractive load bids to the trucks which results in quicker acceptance of the load. We observed that the load bids containing a smart packages are accepted more quickly than the ones which did not. However, smart packages, in doing so, sometimes replaces some packages — which would otherwise be in the load. These packages are usually of low bid levels which then have to wait a little longer for a suitable load bid to form. This does not seem to be problematic for dumb packages because, by definition, they are only worried about spending less. But, some honest packages with low valuations are more impacted by the additional waiting times since their only objective to get the service as soon as possible by paying as much as they can. However, due to the presence of smart packages in a load, the other packages in the load (mostly medium to high valuation packages) seem to get a expedited service.

We believe this mechanism would be useful in scenarios where several smart packages are competing against each other as discussed in Section 6. In order to study a full-scale implementation of a PLN and consequently a scaled version of the smart bidding, the full-scaled implementation of truck's decision making problem (see Section 3.2.2.1) would be vital, which we wish to address in future following the discussions and suggestions made in Section 6.

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CHAPTER

5

CONCLUSION

In this dissertation, we analyze and optimize the performance of an existing supply chain and its logistics operations, incorporating and proposing the introduction of new technologies. We compartmentalize this dissertation into three parts as discussed in Chapter 1. In each part, we propose the incorporation of new technology or a mechanism and discuss our approach in optimizing the performance measures.

In the first part, we analyze the role of AM both as a recourse as well as a dedicated source in a TM network setting. We consider the problem of a firm that is evaluating whether to incorporate AM capabilities into its supply network. We modeled the firm's problem as a three-stage stochastic optimization problem, where in stage 1 the firm decides on locations (if any) for new AM facilities, stage 2 involves decision making regarding the production quantities at each EF under the new configuration, and stage 3 addresses the problem of allocating realized demand to each production mode. In this context, we derive an optimal allocation rule, effectively allowing us to reduce the three-stage optimization problem to a two-stage optimization problem. We study when AM creates the most value. We structurally characterize, for the case of uniformly distributed customer locations, how the value is created in different settings, and numerically confirm our structural insights. Specifically, our results suggest that AM creates most value as a recourse when backorder costs and/or holding costs are high whereas it creates the most value as a dedicated source when holding costs are low, transportation costs are high, and/or when the difference in the production costs between AM and traditional manufacturing is low.

In the second part, we provide a means for addressing the AM need of the existing foundries in the United States. A classical facility location model was used to establish an arrangement where foundries can utilize AM services without having to invest their own capital in equipment and technology. Such integration would also benefit the AM technology with its mass adoption and large-scale applications. With the increased 3DSP demand, the findings of this work will help (1) existing AM organizations seeking to locate new sites or an investor looking to establish an AM service providing facility and (2) foundries that can capitalize on the benefits of AM by working in conjunction with such AM organizations. Further, this work might also influence the existing AM organizations, having excess capacity, to approach nearby foundries as potential customers in order to obtain such a 3DSP arrangement. The results from this study provide insights into such a network, and the findings demonstrate a means of studying the appropriate location candidates and associated costs. However, this study does not consider scenarios like time sensitivity of products, accumulation of queues, incorporation of time delay, local and state taxes, and state of AM investment market which can have considerable impact on such location analysis, requiring a dynamic weighted facility location analysis.

In the third part, we propose and analyze a PLN, providing a potential solution to the under utilization issues in transportation industry as well as addressing the shipping price concerns on the demand side. We proposed several protocols which would provide an efficient operating platform to each of the agents, alleviating potential issues resulting from any of the entity taking unfair advantage of the system. Since the coordination required in the operation of a PLN is very complex and there has been no prior framework on which each of the pieces can be studied, we studied a snippet of a network ($N = 3$ and $N = 4$) to analyze the demand side, especially the package bidding behaviour, in a concise and insightful manner. We studied a smart bidding mechanism where the smart package uses the system information to make predictions regarding the bids of other packages and truck's preference, and uses a simplified MAB approach to submit a bid in order to generate higher savings while increasing its chances of getting accepted. We studied the smart bidding behaviour under two scenarios: (i) dumb package scenario, and (ii) smart package scenario. We also compared the performance of the smart bidding mechanism with a clairvoyant policy. Under dumb packages scenario, we observed that smart packages save lower while spending considerably lesser time in the system. Moreover, the smart packages almost always resort to the clairvoyant policy. On the other hand, we notice that, on average, in contrast to strategic packages, the smart packages are considerably saving on their bids while spending a bit longer in the system. Moreover, the smart packages almost reaches 93% of the clairvoyant policy in terms of its spend while spending lesser time in the system than the clairvoyant policy. Hence, we can evidently say that the smart bidding mechanism can derive the benefits of both strategic and smart packages, and believe the smart packages will demonstrate similar performance in a heterogeneous scenario. While all these work well with $N = 3, 4$ or even a handful of them having adjacent relationship, a larger network consisting of many DCs — some disjointed and some having adjacency relationship — needs to examined. We have some ideas that would help address several issues associated with a larger network. As a start, the full-scaled version of truck's decision making problem — a combination of 3 NP–hard problems — needs to be solved which would allow the trucks to be non-myopic and opportunistic by optimizing over its dwell point locations and dynamic priority. Moreover, for a larger network topology, smart packages can determine its route among the adjacent DCs, first, using smart bidding mechanism, and then determine its future route along the subsequent DCs using strictly the non-myopic approach to begin with. Additionally, for a distant destination requirement (over several DCs), the smart package can identify the shortest route and determine bounds — a narrower stream of DCs it can, at maximum, route through. This would allow the smart packages to broadly analyze just a few adjacent DCs each time.