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Acquisition of Additive Manufacturing Capabilities for Expeditionary Operations

November 5, 2022

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Abstract

Additive manufacturing (AM) has the potential to fundamentally change how military expeditionary operations are conducted. By manufacturing spare parts in remote sites, rather than relying on lengthy and extensive supply chains or remaining tethered to an “iron mountain” of logistics support, the expeditionary units have the potential to be more agile, to maintain their readiness at high levels while deployed, and to extend their operational reach.

AM has enjoyed success in a number of specialty fields. Potential benefits for expeditionary units include achieving higher readiness at lower cost, because deployed units can use AM to create replacement parts at or near the point of demand, rather than either relying on carrying large quantities of spare parts or dealing with long lead times for replacements. Another potential benefit is the ability to reduce wastage of the materials used in the three-dimensional (3D) printing process and subsequent posttreatments by only producing what is needed. Finally, if the same compounds can be used to manufacture a variety of parts, AM could help forward-deployed units maintain a high level of readiness while dramatically reducing their logistics footprint.

To realize this potential, program managers have several decisions to make. They must determine how best to acquire AM capabilities, what classes of components are suitable for AM, whether the resulting structural stability and reliability are comparable for components made using AM and current methods, and how differences in reliability may affect the supply chain and readiness levels. If the suitability and reliability are not factored into the decision-making process, then AM may end up being a costly and largely redundant logistics system running in parallel with the current supply chain, rather than being a transformative capability.

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Introduction

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To realize this potential, program managers have several decisions to make. They must determine how best to acquire AM capabilities, what classes of components are suitable for AM, whether the resulting structural stability and reliability are comparable for components made using AM and current methods, and how differences in reliability may affect the supply chain and readiness levels. If the suitability and reliability are not factored into the decision-making process, then AM may end up being a costly and largely redundant logistics system running in parallel with the current supply chain, rather than being a transformative capability.

AM is integrally tied with Department of Defense (DoD) acquisition programs in several ways. First, the capability for AM must be procured. Rather than setting specifications and requirements for parts or component parts, the program managers must set requirements for AM processes that are capable of 3D printing and subsequent finishing operations to produce items that meet the necessary specifications for the parts or component parts. Second, although the flexibility of AM is often touted, the issues of the quality and reliability of the resulting parts are not generally considered—or, these characteristics are considered in isolation, rather than via their effects on the supply chain and operational effectiveness. An implicit assumption in much of the literature is that the resultant parts will be as capable when produced using

AM as they are when produced using standard manufacturing techniques. Third, the current roadmap for employing AM in DoD operations is incremental in nature. For example, the U.S. Army's phases for AM are (i) determining how AM can be used to repair or replace existing parts; (ii) using AM to produce a single part rather than assembling multiple component parts; and (iii) using AM to create parts that do not currently exist (U.S. Army Research, Development, and Engineering Command, 2017). The Navy and Marine Corps have similar guidance (Department of the Navy, 2017; Headquarters Marine Corps [HQMC], 2017).

In this paper, we present a model-based framework for a transformative rather than an incremental approach for incorporating AM technologies within the DoD. We do so by creating simulation models to explore various aspects of networked expeditionary logistics operations—a concept of operations that now may be possible. Because stockpiles of spare parts are no longer the only way of ensuring that the combat logistics element is fully supporting the expeditionary units, we can explore the simulation models' behaviors to gain insight about other alternatives.

In Section 2, we provide a brief summary of relevant research. This includes themes in previous research related to AM in defense and other industries, as well as an overview of logistics concepts for supporting expeditionary operations. In Section 3, we demonstrate how AM can be incorporated into both the iron mountain and iron network logistics simulation models. Our data farming approach uses large-scale designed experiments to provide model-based insights regarding the potential impact of AM. In Section 4, we describe a simulation model that delves into readiness at a more granular level by modeling the use of standard or AM replacement components for a fleet of unmanned vehicles. We then provide illustrative results from a data farming experiment involving this model. We summarize our findings and suggest areas for further research in Section 5.

Background

We begin with a short overview of several key areas that motivate this research. Our discussion is meant to be illustrative, not exhaustive.

Data Farming Approach

Data farming and data mining are different. Lucas et al. (2015) compared and contrasted these metaphors as follows:

> Miners seek valuable nuggets of ore buried in the earth, but have no control over what is out there or how hard it is to extract the nuggets from their surroundings. As they take samples from the earth they gather more information about the underlying geology. Similarly, data miners seek to uncover valuable nuggets of information buried within massive amounts of data. Data-mining techniques use statistical and graphical measures to try to identify interesting correlations or clusters in the data set.
>
> Farmers cultivate the land to maximize their yield. They manipulate the environment to their advantage using irrigation, pest control, crop rotation, fertilizer, and more. Small-scale designed experiments let them determine whether these treatments are effective. Similarly, data farmers manipulate simulation models to their advantage, using large-scale designed experimentation to grow data from their models in a manner that easily lets them extract useful information. … [The output data sets] also contain better data, in the sense that the results can reveal root cause-and-effect relationships between the model input factors and the model responses, in addition to rich graphical and statistical views of these relationships. (p. 297)

The building blocks of data farming are a collaborative approach to rapid scenario prototyping, modeling platform development, design of experiments, high performance computing, and the analysis and visualization of the output—all with the intent of providing decision-makers with timely insights (North Atlantic Treaty Organization [NATO], 2014). Of these, design of experiments is key: it is the only way to break the so-called “curse of dimensionality.” For example, suppose our simulation has 100 inputs (i.e., factors), each factor has two levels (low and high) of interest, and we decide to look at all combinations. A single replication of this experiment would require over 178 millennia on an extremely fast supercomputer (the Summit at Oakridge

National Laboratories), even if each of the 2^{100} (roughly 10^{30}) simulation runs consisted of a single machine instruction! Yet efficient experiment designs enable us to run interesting simulation models with dozens or hundreds of factors on a modern laptop or small computing cluster in a matter of days to hours, taking the study from the realm of the impossible to the realm of the practical.

A data farming approach is useful for the networked logistics study because the simulation models have many potential factors, and the ways in which they affect the system performance are complicated and not (yet) well understood. Running a designed experiment and analyzing the results (both statistically and graphically) provides a quantitative basis for trade-off analysis.

Additive Manufacturing: Previous Research Themes

There has been a rapid escalation of AM research and applications in recent years. It has already demonstrated success in specific industries, where computer-controlled 3D printing using a variety of compounds has opened up new customization possibilities for manufactured parts. For example, the medical field has enjoyed success in customizing polymeric parts, such as right-sizing cardiovascular stents rather than relying on a limited number of sizes. Custom-sized biodegradable stents reduce the risks of complications that arise if an ill-fitting stent moves and ultimately fails, and additional surgery is required to repair or replace the stent (Hodsden, 2016); they can be quite beneficial for infants and children who need temporary assistance while they are growing (Fessenden, 2013). Other successful applications have been reported in areas ranging from sports equipment (Graziosi et al., 2017) to spare parts for air-cooling ducts of the environmental control system for F-18 fighter jets (Khajavi et al., 2014) to 3D-printed jet engines (Sturmer, 2015), and more recently for face shields to reduce COVID-19 transmission (Naval Air Systems Command Public Affairs, 2020).

Previous research related to AM falls into a few general categories. The first is research related to the AM process itself, including the polymeric, metal alloy, or composite materials used in the 3D printing part of the process, along with the posttreatment operations required for the materials to attain their structural capabilities (Frazier, 2014). Posttreatment operations, once the printing process is complete, can include various types of heat treatment to reduce porosity or induce the desired microstructures and properties, such as annealing or hot isostatic pressing.

A second stream of research involves studying the logistics supply chain, contrasting AM versus traditional manufacturing for producing spare parts. This has been accomplished in different ways. Case study approaches have been used as part of an inductive research approach, such as the work by Oettmeier and Hofmann (2016), who conducted and described semistructured interviews for three focal firms, suppliers, and customers for AM devices in the medical industry. They conclude that the effects of AM technology adoption on the supply chain configuration are context specific and depend on several exogenous and supply chain–related factors. Mellor et al. (2014) also used a qualitative case study approach to create a normative structural model of AM implementation, including factors related to the technology and supply chain, as well as other structural and strategic aspects of the organization. See, for example, Silva and Rezende (2013), for further discussion of logistics implications of AM for different industries.

Other research examines the life cycle cost of AM relative to traditional manufacturing techniques. For example, Westerweel et al. (2018) developed an analytic cost model and conducted a full factorial experiment involving seven factors, each at three levels, to gain some managerial insights. They concluded that logistics savings can occur because of the reduced production lead time inherent in AM. They also found that large investments in AM are attractive if there are large numbers of systems with long life cycles, and if the reliability of the AM parts is quite close to that of the parts produced by the original equipment manufacturer (OEM). Still others have looked at the supply chain for the powders used in AM applications, rather than focusing on the supply chain associated with OEM parts (Dawes et al., 2015).

Additive Manufacturing for Military Operations

With regard to military operations, U.S. Army Chief of Staff General M.A. Milley stated, “The convergence of new developments such as ubiquitous information technology and personal communications, proliferation of precision guided weapons, robotics and on-site 3D printing, and rapidly growing urbanization all augur a very different era of warfare” (Barno & Bensahel, 2017, p. 1). AM may be beneficial for legacy systems as well, if the original parts are no longer being manufactured but custom AM parts can be made as needed.

An example of a simulation-based assessment of AM for military operations appears in Moore et al. (2018). They created forecasts of replacement parts for the M109A6 Paladin self-propelled 155mm Howitzer, based on data obtained from the U.S. Army during the initial stage of Operation Iraqi Freedom (OIF). They used these data-driven forecasts as inputs to a simulation model to assess the feasibility of integrating AM into the Army’s supply chain for 48 different combinations of the three factors: the echelon at which the AM is placed, the printing speed, and the available volume of metallic compounds for printing the metal parts. They recommended that “the Army needs to continue experimenting with AM facilities in the field under realistic demand rates and operating environments” (p. 3727) and suggested that AM should most likely start with small items where quality control requirements are not so onerous. Other nations are also intrigued by the prospect of incorporating AM into military logistics support (Ng, 2018).

Some AM approaches are more suitable for harsh and variable environments than others, in part due to their safety requirements. Zelinski (2019) described how metallic 3D printing that involves arc welding metallic compounds deposited by solid wire feed, or by high-velocity cold spray of metal powder, can be relatively safe. In contrast, the safety requirements for setting up and using laser melting systems may prohibit those forms of AM in some operational environments.

Logistics for Expeditionary Operations: Iron Mountain Concept

A graphical representation of an iron mountain logistics approach appears in Figure 1, taken from Sanchez et al. (2019). This logistics concept is based on a scenario from Lynch (2019), who considers expeditionary operations at the Marine Expeditionary Unit (MEU) level. In this graphic (not to scale), we show how the current system often works. The seabase is treated as an essentially unlimited floating warehouse of supplies and fuel. The ultimate goal is meeting the logistics needs of the supported units: in this scenario, two infantry units and a forward arming and refueling point (FARP). Each infantry unit represents a standard Marine Corps infantry rifle company. FARPs do not have a standard size, but the FARP in this scenario is roughly equivalent to the size of an infantry platoon. Most supplies are moved by ship-to-shore connectors from the seabase to a fixed, fortified, onshore position—the so-called “iron mountain”—although jet fuel is typically delivered to the FARP by air assets. The supported units each generate requests for several different types of supply items. Some supplies—such as meals ready to eat (MREs), bottled water, and fuel—are used at rates proportional to the number of personnel in the unit. Ammunition and missile usage are less predictable and depend on the operational tempo. The convoys tend to make regular deliveries over long distances and are comprised of many logistics vehicles (LVs) as well as security vehicles for added protection. The black boxes notionally represent the amounts of supplies at various points in the system. For example, the seabase is typically assumed to have (or have access to) unlimited inventory; the iron mountain has a very large supply on hand; the convoys carry large amounts in each delivery; and the supported units must keep enough on hand for sustainment between convoy arrivals. Of course, this does not capture the full complexity of logistics support in real-world military operations.

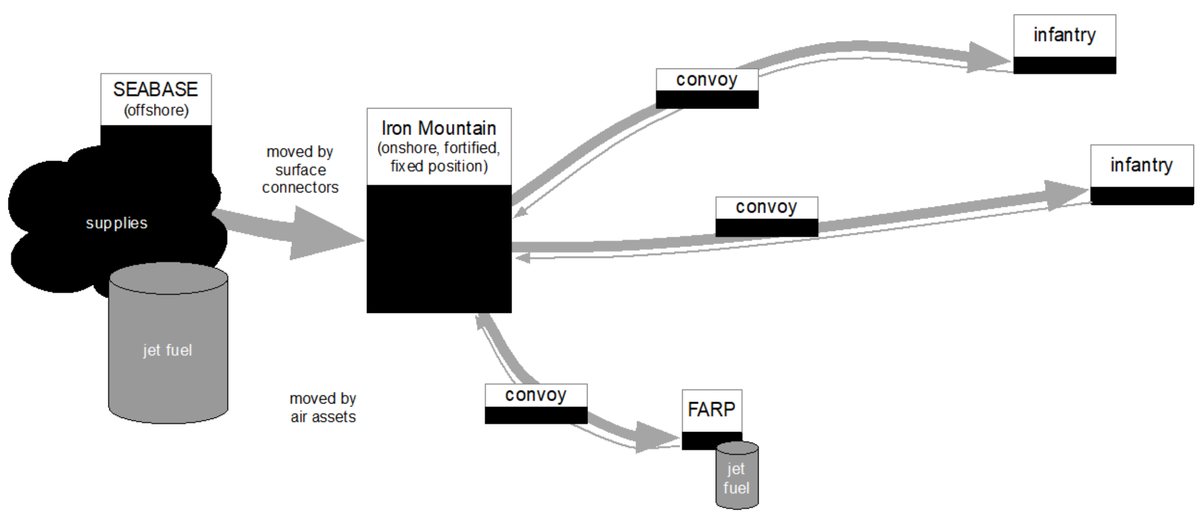

Figure 1. “Iron Mountain” Logistics Supply Movement

The resources contained in these logistics stockpiles are critical to the survival of a military force and directly contribute to their mission success. An adversary capable of destroying these stockpiles or significantly deteriorating the supply distribution process can seriously disrupt or even halt military operations.

As mentioned earlier, plans for near-term use of AM in expeditionary operations focus on AM's potential for repairing or replacing existing parts. By injecting this capability into an existing logistics chain, the primary benefits are those of reducing the storage capacity and lead time for replacement parts without adversely affecting readiness. Parts that can be easily manufactured using AM technologies can range from those used steadily throughout the operations to replacement parts for mission-critical items that are rarely needed. In either situation, it may require less storage volume to ship bulk raw materials (e.g., metallic powders) and manufacture the parts as needed, than to store and access completed parts. Easy access can be particularly problematic in very high-density storage systems such as the hold of a ship (Gue, 2006), or in limited staging areas where containers transferred from ships may await other transportation to their final destinations (Gue & Kang, 2001).

For the logistics system of Figure 1, there are three places where adding AM capability might be beneficial: the seabase, the iron mountain, and the supported units themselves. Each has benefits and drawbacks. The seabase is often considered the most secure, and on larger ships it may be possible to set up dedicated AM facilities (including appropriate posttreatment stations) with access to a ready supply of bulk raw materials. Lead times for 3D printing replacement parts at the seabase may be less than lead times for receiving them from a U.S. or other regional supplier. The iron mountain has similar capabilities, although there may be less control of some environmental characteristics (heat, humidity, dust, vibration) that might affect the AM production schedule or the resulting quality and reliability of the parts. Lead times for 3D-printed parts from the iron mountain might be less than those of 3D-printed parts from the seabase, particularly if small numbers of items are needed. Adding AM capability directly to the supported units has both potential benefits and potential drawbacks. On one hand, it may reduce the lead time for replacement parts even further. On the other hand, it may be the most likely to be adversely impacted by weather conditions, and long posttreatment requirements may either reduce the unit's mobility or result in less reliable replacement parts.

Logistics for Expeditionary Operations: Iron Network Concept

Headquarters Marine Corps (HQMC) recently published the Marine Corps Operating Concept (MOC), which states the Marine Corps must "[redesign] our logistics to support distributable forces across a dynamic and fully contested battlespace—because iron mountains of supply and lakes of liquid fuel are liabilities and not supportive of maneuver warfare" (HQMC, 2016, p. 9).

During the wars in Iraq and Afghanistan, the insurgent forces were incapable of conducting an attack on the scale required to destroy a large base containing massive quantities of supplies. Attacks such as those on Camp Bastion and Camp Shorabak caused damage and some casualties (to Afghan troops), but did not pose a serious threat for the viability of the entire bases and their operations (Shah et al., 2019; Snow, 2019). As the United States has transitioned to preparing for a conflict with a near-peer adversary, this is no longer true: an iron mountain is a very enticing target. Logistics sustainability is considered "both a critical requirement and critical vulnerability" (HQMC, 2020, p. 5) as the concepts of Distributed Maritime Operations (DMO), Littoral Operations in a Contested Environment (LOCE), and Expeditionary Advance Base Operations (EABO), continue to shape the evolving vision of how the Navy and Marine Corps will fight in the future.

Even in situations where enemy actions are not a concern, iron mountains can still be liabilities. The 2010 fire in the Supply Management Unit lot in Camp Leatherneck, Afghanistan is one such example: although the fire was eventually contained with no casualties, most of the inventory was destroyed—including construction materials, medical supplies, and repair parts (Pelczar, 2010). In this way, a networked logistics structure may add resilience.

Consequently, a new method of providing logistics support to expeditionary forces is needed. Lynch (2019) created a simulation model intended to help analysts explore the function of a networked logistics force. A simplified graphical representation (not to scale) appears in Figure 2. Instead of consolidating and distributing supplies from a large, stationary iron mountain, the supplies are redistributed to smaller logistics support nodes that occasionally move around the battlefield. There are three types of units that require support from these logistics nodes: infantry units and a FARP as in Figure 1, as well as a shore-based missile unit. The shore-based missile unit is based on a platoon from the Army High Mobility Artillery Rock System (HIMARS) Battalion, because providing shore-based missile support is “a relatively new concept for the Marine Corps” (Lynch, 2019, p. 13).

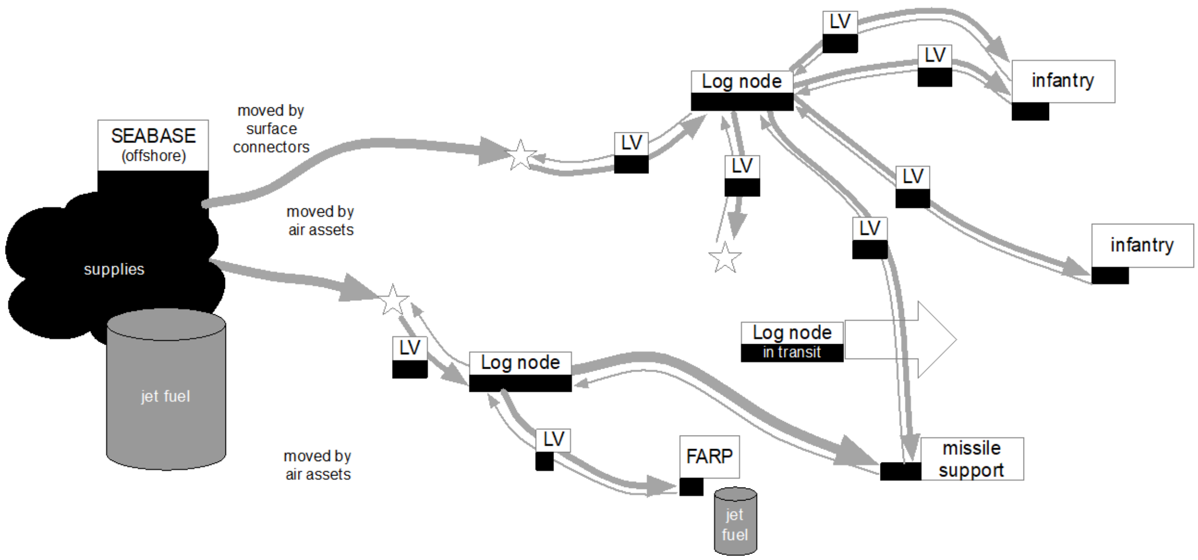

Figure 2. “Iron Network” Logistics Supply Movement

The supported units each generate requests for several different types of supply items as before. Ammunition and missile requests are randomly generated, providing an implicit rather than explicit representation of their use during combat operations. The supplies are loaded on LVs for delivery. For the current model instantiation, each LV can be considered a truck that carries supplies on pallets. As before, black boxes represent inventory locations, with moderate amounts at the logistics nodes and smaller amounts in transit on LVs and at the support units.

The networked logistics of Figure 2 is clearly more complex than that of Figure 1, as can be seen by the larger number of potential routes taken by LVs. The networked logistics structure is highly dynamic, as the locations of the supported units, logistics nodes, and rendezvous points are all changing over time. Ideally, this dynamic structure will enhance the maneuverability of the forward units and make the force less vulnerable to attacks by a near-peer adversary. There are other differences as well. The black boxes that represent the amounts of supplies at various locations in the network tend to be much smaller than those in Figure 1. This has the potential to increase the agility and extend the operational reach of the supported units. However, care must be taken to ensure they are mission capable despite their decreased logistical footprint. Conversely, the units may not achieve their requisite readiness levels if the iron network is unable to provide required logistics support in a timely manner, if too much time is consumed by maneuvering, or if enhanced maneuverability does not lead to reduced vulnerability of the forward units. In Table 1, we provide a brief comparison of the iron mountain and networked expeditionary logistics structures.

Table 1. Comparison of Iron Mountain and Iron Network Logistics Concepts

Element	Assumptions: Iron Mountain Logistics	Assumptions: Iron Network Logistics
Seabase	Offshore, invulnerable, infinite capacity	Offshore, invulnerable, infinite capacity
Supported units	Two infantry, one FARP	Two infantry, one FARP, one shore-based missile support
Onshore logistics element	Iron mountain: immobile, heavily fortified, very large capacity, regularly resupplied from seabase	Logistics nodes: mobile, self-sufficient, use their own LVs to change logistics node locations in a single trip, resupply from fixed or ad hoc rendezvous points
Seabase -> onshore	Large deliveries to fixed location at fairly regular intervals	Smaller deliveries to LVs at both fixed and ad hoc rendezvous points
Convoys	Large, heavily armed, long and regular trips to supported units	Single LVs travel faster, make frequent short trips to supported units, travel along less predictable transit routes

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Simulation Models for Investigating Additive Manufacturing Capabilities

In this section, we describe the simulation models used to explore how AM might influence expeditionary logistics, as well as the data farming approach used to generate quantifiable and useful insights from these models. All have limitations—no single model can characterize all possible future operations where AM might be employed. However, for their respective use cases, they readily can be explored to reveal interesting behaviors. The insights can either be quantitative or qualitative. For example, one use of a logistics model could be to predict the request turnaround times for a system of interest—a quantitative result. Alternatively, the analyst might seek to find out which factors have the greatest impact on turnaround time, either separately or jointly. Even if the quantitative outputs from the model are not useful for prediction, they may focus efforts on improving the system and indicate whether, say, an improvement in one of the important inputs has a diminishing or increasing rate of return.

All models are written in the Ruby programming language. This is free cross-platform software available for download from https://www.ruby-lang.org. Our simulation models also make use of several Ruby gems, including the SimpleKit and datafarming gems (Sanchez, 2018, 2021), which facilitate discrete-event modeling and data farming experimentation, respectively. These are available for download at https://www.rubygems.org for ease of installation and upgrades. The simulation models are maintained on a restricted git repository but available on request.

Iron Mountain with Additive Manufacturing

Initially developed by Lynch (2019), this model was extended to incorporate AM features. A graphical representation (not to scale) appears in Figure 3, where boxes have been added to indicate AM capabilities. The majority of AM would take place at fixed locations, such as the seabase and the iron mountain. In these locations, AM may reduce the total storage volume by keeping common stores of bulk raw materials instead of separate stockpiles of spare parts for groups of items amenable to AM composed of the same materials. AM capability at forward units is more limited. It may be further constrained by environmental conditions, safety concerns, and operational tempo.

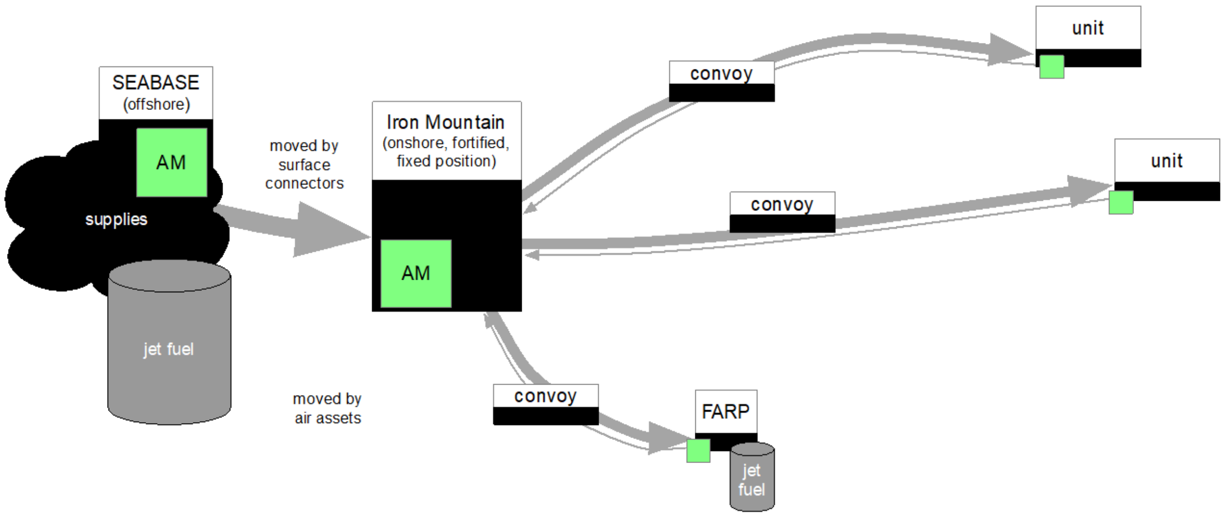


Figure 3. Potential Placement of Additive Manufacturing Capabilities for Iron Mountain Logistics Concept

AM may reduce lead times and costs for some parts. Neither the seabase nor the original manufacturer may have spare parts available for highly specialized items or those that rarely need replacement. However, if the time required for local AM production is long, then it may not be beneficial. Finally, indirect—but extremely important—aspects of AM are the quality and reliability of the AM parts. Their quality and reliability may be comparable to, higher than, or lower than the quality and reliability of original parts. Lower quality may mean the units are less mission-capable, while higher quality enhances their effectiveness. Lower reliability means that parts will fail and need replacement more often, increasing the overall shipping volume and putting additional demands on the logistics system. Higher reliability means that parts will fail and need replacement less often, tending to reduce the logistics demands. What is less certain is the overall impact of any wastage of raw materials during the AM process. This affects the volume and weight of raw materials transported to and kept at the forward locations.

Iron Network with Additive Manufacturing

Lynch (2019) implemented the networked logistics simulation model using the Ruby programming language. Each run of the simulation represents 180 days of operation, beginning from a time where all supplies have arrived at the seabase and each logistics node and supported unit has the supplies they need to begin operations. Logistics nodes and supported units all use supplies over time; the logistics nodes are handled as internal requests that require no transportation when the node has the requested supplies on hand. Each logistic node will move its location after filling a specified number of requests. An LV at a stationary logistics node will begin moving to a requesting unit as soon as either the LV is nearly full (e.g., seven or more of eight pallet spaces filled), or the request has been waiting a sufficiently long time. Logistics nodes place requests for resupply to the seabase whenever their inventories drop below specified levels but can also receive direct shipments by air if needed.

A few other modeling choices deserve mention. LVs can encounter breakdowns or enemy attacks at random times during transit. If an LV suffers a maintenance breakdown, that delays the delivery process by a relatively short amount of time (hours to days). If an enemy attack occurs, there is some probability that the LV wards it off and continues on after a short delay. There is also some probability that the attack succeeds and the LV and its inventory are all destroyed. In the latter situation, new requests are automatically generated for all destroyed items.

Another key assumption is that inventory levels are visible to all players in the simulation. This is essential because in the situation where one logistics element cannot provide support requested by a unit, it must then pass that request to another logistics node. Trust in the logistics structure is also critical in practice (Spangenberg, 2017). Without that trust, each unit has incentives to hoard items or make larger requests than necessary, which may keep the logistics footprint large or reduce the agility of the force. For further details of this networked logistics simulation model, see Lynch (2019).

There are several places where AM capabilities might be added to the iron network: at the seabase, at the logistics nodes, or at the supported units (Figure 4). The same basic benefits and drawbacks apply. Stationary units (such as the seabase) can be heavily protected, and AM may reduce storage and lead time requirements. Still, the mobility of the logistics nodes and the use of single LVs rather than large convoys may affect the way AM is implemented, or vice versa. If AM is added at logistics nodes, then those nodes must wait to change locations until all post-printing treatments are complete. Both the duration of AM operations and timing of logistics node moves are decisions that must be made.

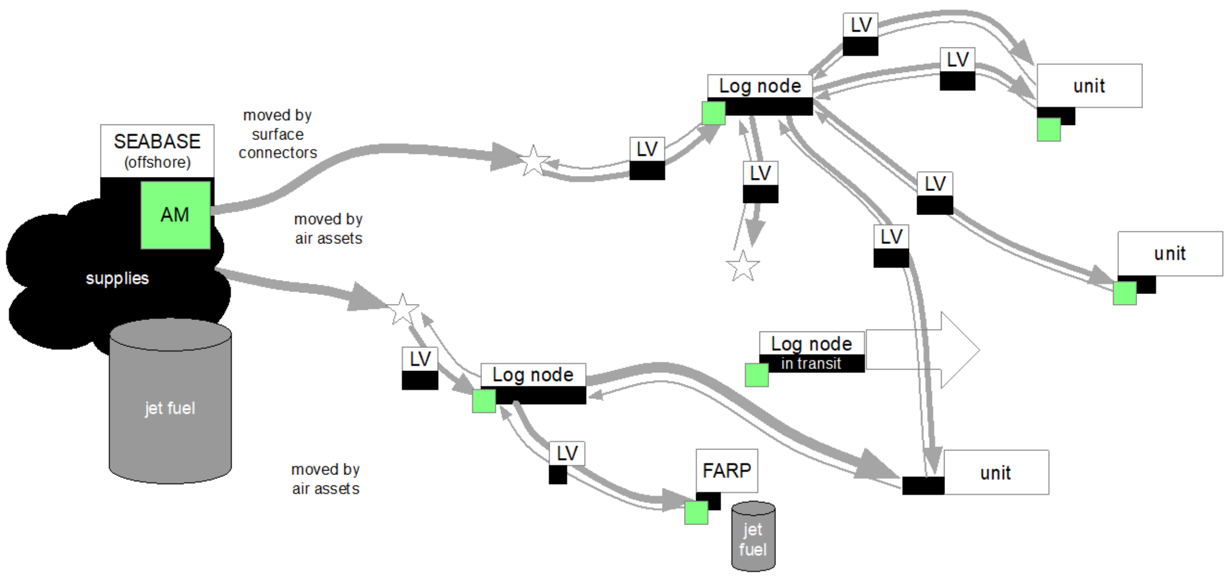


Figure 4. Potential Placements of Additive Manufacturing Capabilities for Iron Network Logistics Concept

Data Farming Results

The output from a data farming experiment allows the analyst to make use of a wide variety of statistical and visualization tools, also known as simulation analytics. In this section we illustrate a few of these analytic products. For a detailed exploration of the baseline iron mountain and iron network models (without AM), we refer the reader to Lynch (2019). A limited set of examples appears in Sanchez et al. (2019).

Lynch (2019) found the iron network far superior to the iron mountain for distributed expeditionary operations, provided there is visibility of inventory levels throughout the area of operations. Resource tracking must be effective because requests go to different entities (different logistics nodes or the seabase) based on their current supply levels, delivery capabilities, and locations. In his experiments, a total of 39 vehicles were needed for the iron network, while 50 vehicles (five convoys of 10 vehicles each) were required to obtain similar delivery performance for the iron mountain. Note that higher numbers of vehicles also mean there are higher numbers of personnel required to drive and maintain these vehicles, and consequently higher sustainment logistics requirements for food, water, ammunition, and other expendable items. Because our interest is in supporting expeditionary operations, we present results from experiments involving the AM-enhanced iron network model.

Iron Network with Additive Manufacturing

In Table 2, we list the factors we chose to vary for our AM-enhanced iron network model, along with brief descriptions. The first set of factors characterize the logistics network. These include some decision factors, such as the number of LVs assigned to each node or the maximum time (after the initial item is loaded) that a partially loaded vehicle will wait before departing. The probabilities associated with unscheduled breakdowns (maintenance events), enemy attacks, and kills are not controllable; but in this experiment we assume that enemy actions are rare but that maintenance events are not uncommon.

The four factors that characterize AM capabilities merit more detailed descriptions.

- *Proportion AM-plus-other*: First, we assume that a portion of the logistic requirements considered “ammunition” in the original code specification actually represents a mix of other parts, some of which could be produced using AM. For example, Moore et al. (2018) suggested that metal replacement parts for communications equipment might be suitable. Treating this as a proportion keeps the average logistics requirements the same for ease of comparison.

- *Proportion AM*: The proportion of the AM-plus-other demand that can be produced using AM techniques.

- *Reliability multiplier*: The relative reliability of the AM parts, compared to the original spare parts. In our experiment, this ranges from AM parts being half as reliable to twice as reliable as the original spare parts.

- *Self-supply adjustment*: This adjusts the distribution for the time between requests based on demand that can be satisfied or partially satisfied by local AM. If the adjustment is positive, it means that extra raw materials are required for AM parts and the unit must be resupplied more often. For example, some raw materials may be rendered unusable during the AM process. If the adjustment is negative, it means the unit is more self-sufficient and does not need resupply as often.

For example, in the initial model, the time between demands for ammunition at a logistics node is a random variable with a mean of 3 days based on the user-specified factors provided for the minimum, maximum, and mode of a triangular distribution. In the new model, suppose that *Proportion AM-plus-other* multiplier is 0.4 and the *Proportion AM* multiplier is 0.25. Then the average interarrival time between ammunition demands is $3/(1 - 0.4) = 5$ days, that for AM parts is $3/(0.25 \times (1 - 0.4)) = 20$ days, and that for other (non-ammunition, non-AM) parts is $3/((1 - 0.25) \times (1 - 0.4)) = 6.67$ days.

Table 2. Factors, Factor Descriptions, and Ranges for the Iron Network With AM Model

Factor	Description	Minimum Value	Maximum Value	Decimal Places
Logistics factors				
Number of LVs	Number of vehicles per logistics node	8	20	0
Time between requests (days) Minimum Maximum Mode proportion	Parameters associated with the days of resupply kept at logistics nodes; random times are generated from a triangular distribution	 0.5 2.5 0.25	 1.5 3.5 0.75	 4 4 4
Onload time (days) Mean Distribution shape	Mean time (days) to load an LV, random times are generated from a gamma distribution	 0.25 8	 0.65 10	 4 0
Offload time (days) Mean Distribution shape	Mean time (days) to offload an LV, random times are generated from a gamma distribution	 0.1 8	 0.5 12	 4 0
External resupply time	Wait time for logistics node resupply (days)	2	10	0
Maximum wait time	Maximum time LVs wait before departing (days) if they do not have a full load	0.5	3.0	1
Maintenance event probability	Probability of an unscheduled maintenance issue for an LV	0.05	0.25	4
Other factors				
Enemy attack probability	Probability of an enemy attack	0.01	0.1	4
Enemy kill probability	Probability of an attack destroying the LV	0.01	0.03	4
Additive manufacturing factors				
Proportion AM-plus-other	Proportion of the "ammunition" category that are for AM parts or other items	0.2	0.6	4
Proportion AM	Proportion of AM-plus items that can be produced using AM	0.1	0.5	4
Reliability multiplier	Relative reliability of AM parts compared to original spares	0.5	2.0	4
Self-supply adjustment	If positive, the proportion of AM materials that are lost or discarded during the AM process. If negative, reduces the demand requirements.	−0.2	0.2	4

In all, our experiment involves 17 factors: 11 factors related to the logistics network, two factors related to the enemy behavior, and four factors related to the AM.

The design we use in our first data farming experiment is a nearly orthogonal Latin hypercube (NOLH) with 129 factor combinations (Cioppa & Lucas, 2007), so each continuous-valued factor can be explored at up to 129 different levels. Each factor combination is called a design point. Integer-valued factors may have fewer levels due to rounding. For comparison purposes, a brute-force approach to studying even just 13 factors at 129 levels each would require over 2.7 octillion design points! For our second experiment, we use a crossed design based on separate NOLHs for AM and non-AM factors for a total of 17 × 65 = 1,105 design points. We remark that both experiments will yield similar results. The first experiment is more efficient in terms of the computation time required, but the second is advantageous for certain graphical analyses. Since the model is stochastic, multiple replications are needed. We chose to conduct 100 replications. This required 160 minutes and 25 hours of total CPU time, respectively, on a single multicore laptop. The actual time was less because runs were conducted in parallel.

A variety of statistical and visualization techniques are possible. We illustrate a few here and in Section 4.3, but refer the reader to Morgan et al. (2017), Sanchez (2018, 2020), or Sanchez et al. (2020), or for other examples.

Consider the request turnaround time. The output from each simulation run includes the average computed over all orders that have been delivered. (The number of pending requests when the simulation halts is also provided, along with the average time they have been waiting.) The results of the first experiment show that while the AM factors have statistically significant effects on many of the performance measures, these effects are small. When the four AM factors are the only potential predictors, a partition tree with eight splits accounts for only 0.305 of the data summarized over design points. It is significant (p value < 0.0001), and the relative column contributions are shown in Figure 5.

Column Contributions

Term	Number of Splits	SS	Portion
p_AM+other	3	1.2889	0.4476
p_AM	3	0.9791	0.3400
reli_mult	1	0.3105	0.1078
selfsuff_mult	1	0.3008	0.1045

Figure 5. Column Contributions From Partition Tree of Mean(Average Request Turnaround) for Additive Manufacturing Factors From Iron Network Logistics Model, Experiment 1

The partition tree is one type of a metamodel that can be fit to the output of a data farming experiment. Regression is another type of metamodeling. We remark that the term “metamodel” is used in the simulation community because the simulation model is itself a model of reality.

A regression metamodel for the mean(average request turnaround) is summarized in Figure 6. Here, seven of the 11 logistics factors appear, with the maximum wait time before departing with a less-than-full load, and the means of the offload and onload process have the highest impact. The maximum wait time also has a small quadratic effect and a small interaction with the mode (hence the mean) of the logistics node demand distribution. A long maximum wait time has a larger detrimental effect if the logistics node demand is high. The graph of the actual versus the predicted responses in Figure 7 shows that the metamodel fits quite well. The metamodel is statistically significant (p value < 0.0001) and fits the data well ($R^2 = 0.98$).

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
max_wait	0.1947	0.0054	36.00	<.0001*
offload_mean	1.2585	0.0354	35.56	<.0001*
onload_mean	1.1564	0.0351	32.94	<.0001*
log_mode	0.176	0.0107	16.43	<.0001*
resupply_time	0.0268	0.0017	15.96	<.0001*
maint	0.6072	0.0651	9.33	<.0001*
(max_wait-1.75039)*(max_wait-1.75039)	-0.057	0.0087	-6.59	<.0001*
n_LV	0.0034	0.0007	5.21	<.0001*
(log_mode-2.00001)*(max_wait-1.75039)	0.0482	0.0152	3.17	0.0020*
Leaf Number[7]	0.0228	0.0082	2.80	0.0060*
Leaf Number[8]	0.0455	0.0188	2.42	0.0171*
(resupply_time-6.03101)*(resupply_time-6.03101)	-0.002	0.0008	-2.21	0.0294*
(onload_mean-0.45001)*(max_wait-1.75039)	-0.095	0.0435	-2.18	0.0317*
Leaf Number[4]	-0.032	0.0172	-1.85	0.0667
Leaf Number[6]	-0.019	0.0124	-1.57	0.1203
Leaf Number[1]	-0.018	0.0162	-1.13	0.2626
Leaf Number[2]	0.0021	0.0087	0.24	0.8129
Leaf Number[5]	0.0021	0.0118	0.18	0.8569
Leaf Number[3]	0.0012	0.015	0.08	0.9354

Figure 6. Factor Effects for Regression Metamodel of Mean(Average Request Turnaround), Experiment 1

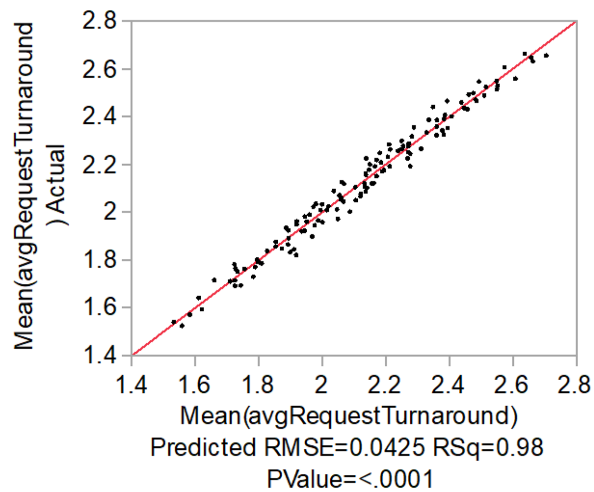


Figure 7. Actual Versus Predicted Plot for Regression Metamodel of Mean(Average Request Turnaround), Experiment 1

Figures 8, 9, and 10 are based on the crossed design we used in Experiment 2. Here, we have separate (but largely overlapping) lines for each of the 17 AM design points. On average, the turnaround time is between 1.6 and 2.8 days (Figure 8). The standard deviations are fairly low except for a few design points (Figure 9). By using a squared error loss and summarizing the results appropriately (Figure 10), we can see that the results are stable across all AM design points with a few exceptions (Design Points 16 and 37). This reinforces the earlier insight that most of the difference in the logistics system performance is due to the logistics factors rather than the AM factors.

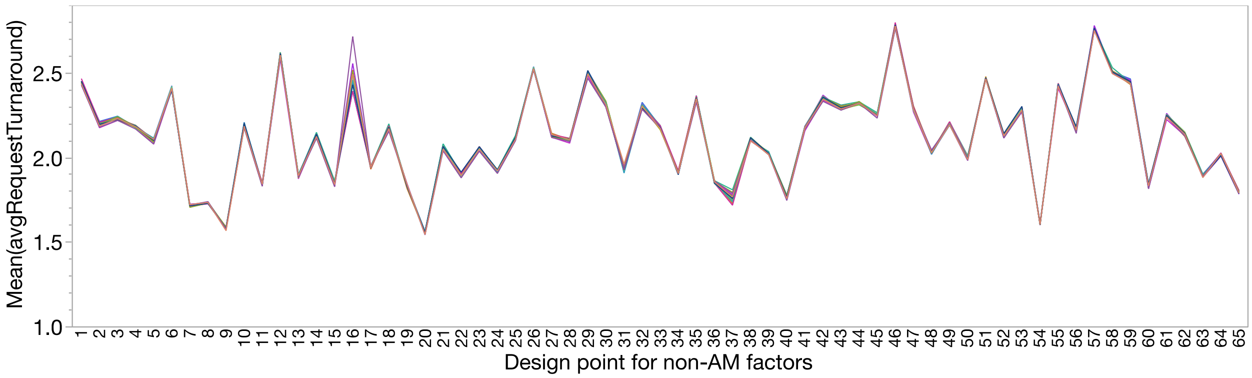


Figure 8. Mean(Average Request Turnaround) Versus Non-AM Factor Design Points, Experiment 2

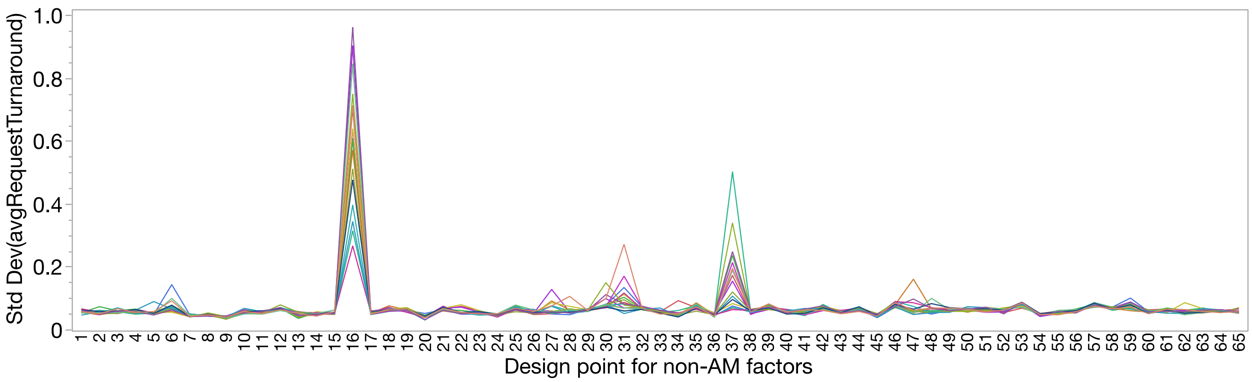


Figure 9. Standard Deviation(Average Request Turnaround) Versus Non-AM Factor Design Points, Experiment 2

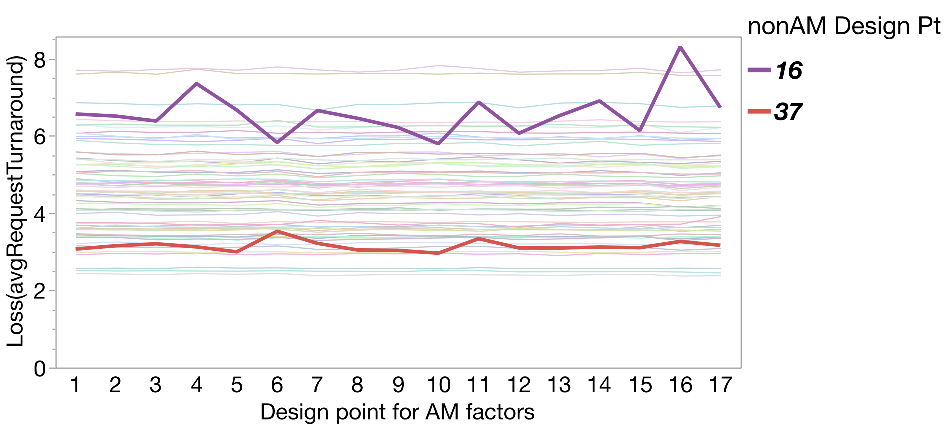


Figure 10. Loss(Average Request Turnaround) Versus Non-AM Factor Design Points, Experiment 2

Many other measures of effectiveness are available. Some are closely related to others, some are not. A closer look at the other performance measures (not shown) indicates that they, too, are affected only in a small way by the addition of AM capabilities. This indicates that the iron network is robust to the way replacement parts are pushed through the logistics system. In other words, the presence of AM is not necessary for an effective network logistics support concept—but it is also not detrimental to such a system. This means that the distributed logistics concepts could continue to be developed and vetted without a concern that everything being learned will become irrelevant if AM at remote or mobile locations becomes widely available.

We use notional data, and there are several other underlying assumptions that we make, so we caution the reader that our results are illustrative only. A more detailed assessment of the breadth and demand for items that could be produced using AM would be needed before setting policies. Nonetheless, the bottom line shows that it appears possible to include AM in a distributed logistics iron network.

Operational Availability Model with Additive Manufacturing

Once we established that incorporating AM does not break an iron network, we decided to take a closer look at the relationship between AM and readiness. We built a new model of operational availability for a fleet of vehicles. Suppose the unit starts out with a complete fleet of unmanned aerial logistics vehicles (ULVs): all operational, with no backlog for maintenance. These could be the aerial assets used to deliver parts from the seabase to the logistics nodes in Figures 2 or 4. Rather than using these vehicles to deliver AM parts, we consider how AM might be used to help maintain readiness for this fleet. Further suppose that recent results from field experiments indicate that the primary cause of breakdowns is due to wear and tear on a particular part. Due to advances in AM, a replacement part can be produced and swapped in with much less effort if identified early. In other words, taking care of this during scheduled maintenance may prevent more breakdowns.

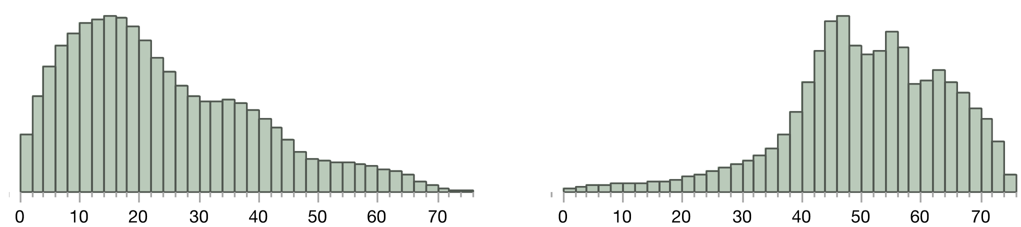
Now suppose that on any given day, the seabase needs at least 42 of these ULVs operational to meet mission readiness requirements. Any day where at least 42 are operational is considered a good day; any day where this mark is not met is considered a bad day. The factors (and other inputs) for this model appear in Table 3, along with brief descriptions and the factor ranges used in our experiment.

Table 3. Inputs, Descriptions, and Ranges for the Operational Availability With AM Model

Factor	Description	Minimum Value	Maximum Value	Decimal Places
Logistics factors				
Maximum vehicles available	Size of the fleet of ULVs	42	75	0
Number of maintenance personnel	Number of personnel available for maintaining and repairing fleet vehicles	2	20	0
Reliability Regular parts	Rate at which unscheduled breakdowns occur if no scheduled maintenance event intervenes	0.01	0.02	6
Maintenance cycle (days)	Length of time between scheduled maintenance events (in calendar days)	30	120	0
Mean repair time Regular parts	Average repair time for unscheduled event, random times are drawn from an exponential distribution with this mean	4	40	0
AM factors				
Reliability multiplier for AM parts	Multiplier of the Reliability (Regular parts) factor: 0.5 means AM parts break down half as often as Regular, 2.0 means AM break down twice as often	0.5	2.0	6
Repair time multiplier for AM parts	Multiplier of the Mean repair time (Regular parts) factor: 0.25 means AM parts are repaired four times as fast, on average. Random times are drawn from a shifted exponential with this mean.	0.0625	0.25	6
Other inputs		Value		
Number of days to run	Length of time	365		
Headers and columns for inputs and days?	If "yes" the output is a separate line for each day with the number of operational vehicles, if "no" there is summary output for the average number available	y		

To data farm this model, we used two stacks of an NOLH with 129 design points to obtain 258 design points for each alternative (regular or AM repair parts) and made 25 replications. This resulted in 12,850 runs corresponding to 12,850 simulated years of operation and nearly 4.7 million rows of output. For each run, we calculated the number of days (out of 365) for which the fleet had at least 42 operational ULVs. The readiness goal is for the unit to be mission capable for at least 347 days (95%) during a year.

Overall, the results are quite different depending on the part type used. Figure 11 shows histograms of the number of vehicles available at the beginning of each day for all runs involving regular and AM parts, respectively. (Note that these data are neither independent nor identically distributed, since they arise from different design points and the availabilities are correlated over days within each run.) For regular parts, only 13% of the days were mission capable with 42 or more ULVs available. With AM, 79% of the days met this threshold.



(a) Regular (b) Additive manufacturing

Figure 11. Histograms of Daily ULV availability for Operational Availability Experiment With (a) Regular Spare Parts and (b) Additive Manufacturing

For assessing how well the seabase meets its readiness goals, we need to know the number of days in each year where ULV availability is at least 42. If this is 347 or more (95%), we will say the seabase meets its readiness goal. The differences between regular and AM spare parts are again stark, as Figure 12 shows. Only 6% of the years met the annual readiness goal for regular parts, while 64% did so when AM was used.

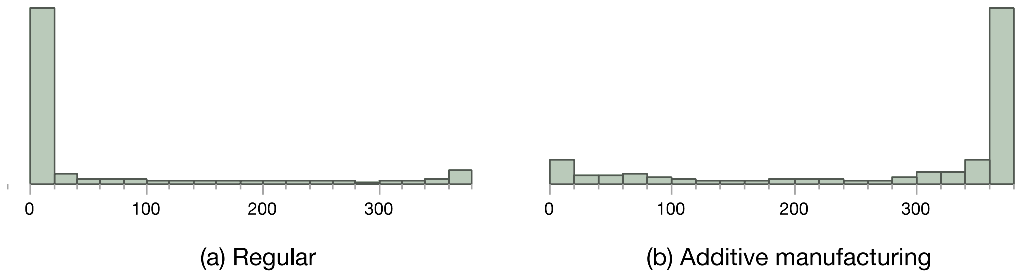


Figure 12. Histograms of Days Per Year With at Least 42 ULVs Available for Operational Availability Experiment With (a) Regular Spare Parts and (b) Additive Manufacturing

We construct metamodels of the annual readiness (i.e., metamodels of the probability of sufficient ULVs available for 347 or more days per year) using partition trees involving the summarized data. Figures 13 and 14 (best viewed in color) show the results for regular and AM parts, respectively. Each leaf on a tree provides the count (number of design points), along with the average and standard deviation of the readiness for points within that leaf. We circle leaves to highlight those with high readiness (at least 0.90) in dark green, moderate readiness (0.75–0.94) in light green, partial readiness (0.50–0.74) in yellow, or very low readiness (less than 0.10) in red. Any leaf with readiness between 0.11 and 0.49 is not distinguished in any way.

We first discuss the tree for regular parts in Figure 13. It achieves $R^2 = 0.805$ with four splits. The only good leaf is on the bottom right and corresponds to an average repair time less than 11 hours, 11 or more maintainers, a fleet size of 56 or more, and a breakdown rate less than 0.0171 (one breakdown per 58.5 days per vehicle, on average). Note that 11 hours is fairly fast given that the potential average repair times range from 4 to 40 hours. Extremely poor results occur for three of the four other leaves.

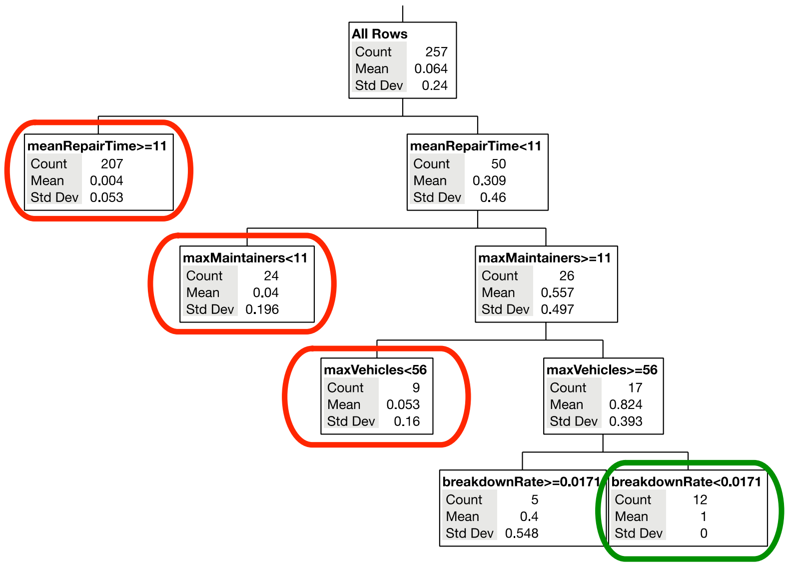


Figure 13. Partition Tree of Mean(Readiness) for Operational Availability Experiment With Regular Spare Parts

The metamodel for AM parts in Figure 14 merits more discussion. It achieves $R^2 = 0.805$ with seven splits. The only leaf with very good performance is on the bottom right and corresponds to an average repair time less than 5.686 hours, seven or more maintainers, and a fleet size of 49 or more. Note that the average repair time constraint is not very restrictive. Its values range from 0.32 to 9.38 hours and are obtained by multiplying the mean repair time input (ranging from 4.0 to 40 hours) by the repair time multiplier (ranging from 0.0625 to 0.25). We fit other metamodels treating these as separate factors, but this simpler representation explained the data better and is easier to interpret. Fewer maintainers and a smaller fleet size are required to achieve very high performance when using AM parts than when using regular parts. The tree in Figure 14 has some very bad leaves, but also indicates there are mitigation efforts that could be undertaken if the resources required to operate in the best leaf are prohibitive. For example, on the left of the tree we see that if the fleet size is less than 47, we can still achieve a moderate readiness (0.79) if the repair time when using AM parts is quite rapid. The second branch indicates that with a sufficiently large fleet size, adding more maintainers can partially mitigate the negative effects due to relatively long repair times. The third branch indicates that with a sufficiently large fleet size and relatively short repair times, a very low breakdown rate can partially mitigate the deleterious effects of having fewer than seven maintainers.

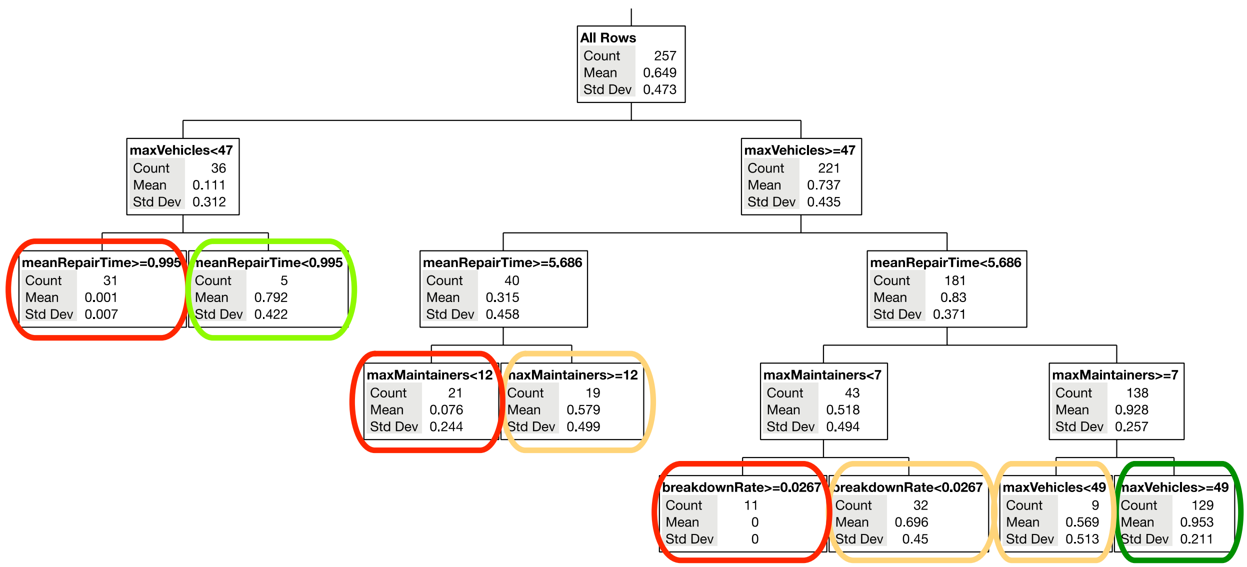


Figure 14. Partition Tree of Mean(Readiness) for Operational Availability Experiment With Additive Manufacturing

It is also interesting to note that one of the factors (maximum cycle time in days) did not show up in either of these two partition tree models. For this experiment, the timing of scheduled maintenance is not important over the range we investigated (30 days to 120 days).

Cost and Capabilities

Legal issues regarding AM parts are a very important topic. They fall into several categories that may be viewed or prioritized differently by different stakeholders. An ongoing concern is that of intellectual property rights. As Lein (2015, p. 7) stated, "A majority of military systems for which AM might provide spare parts are patented by their original manufacturers, and ignoring these protections would expose DoD organizations to the potential risk of litigation, while also jeopardizing relationships with key industry partners."

- *Cost*: As more industries turn to AM in the private sector, the question may not be "Should AM parts be used" as much as "Where and by whom should AM parts be produced?" All else being equal, vendors might not be amenable to providing AM templates versus finished parts without some sort of a guaranteed profit or licensing arrangement. Long-term contracts that are currently in place may need to be renegotiated.

- *Quality*: Many parts supplied to the DoD are required to use statistical quality control or other forms of quality assurance to make certain they meet specifications. Failure to do so may adversely impact the mission. If AM is used in a high operational tempo expeditionary environment, there may be external pressures to create AM parts as quickly as possible. Care must be taken to avoid rushing the AM setup, manufacturing, and posttreatment processes to avoid producing low-quality parts that might compromise the mission. Conversely, if operational guidelines have not accounted for sufficient lead times for AM parts, then the mission may be delayed, increasing the risk of failure.
- *Liability*: Liability and quality are tightly coupled. If a faulty replacement part could compromise a mission, then the original manufacturer might be averse to allowing other entities (including the DoD) to manufacture the item unless these entities assumed liability for any adverse consequences. For certain classes of parts, the DoD might prefer arrangements where external manufacturers are accountable for the suitability of AM items, particularly if the costs of training or specialty equipment are high.

In these and other situations, a model-based data farming approach may help inform decision makers about cost versus capability trade-offs related to AM. Some of these trade-offs could be addressed using the models in Sections 4.1 and 4.2 by careful choice of factor ranges. A few examples follow.

- For the iron network model, lead time distributions could reflect the times required to produce different classes of AM parts. If most AM parts are expendable and quality is of lesser concern (as recommended by Moore et al. [2018]), then the production times are likely to be short and consistent. Alternatively, lead times could be longer if AM is used for parts with lengthy posttreatment processes, or highly variable if it may take several attempts to produce a part of sufficient quality. If AM is used sparingly for mission-critical items, lead times could incorporate the transport time from potential manufacturing locations (i.e., original manufacturer, seabase, logistics node) when exploring alternatives.
- For the operational availability model, experiments could be conducted to help set suitable reliability guidelines or compare the costs of using AM parts from different suppliers with different reliability profiles. Suppose that A and B represent two different suppliers, or replacement parts for the same item but made with different polymers, or replacement parts producing using two distinct AM methods. If A is both more reliable and faster than B for the same cost, it is clearly preferred. However, eventually there are diminishing returns to mission

effectiveness if we improve reliability or decrease the production time. Identifying "knees in the curve" may help program managers set appropriate reliability goals. Comparing both costs and readiness might help the DoD and its industry partners develop mutually agreeable contracts for AM parts.

In other circumstances, higher-fidelity models may be more suitable for a more detailed treatment and examination of how the quality, reliability, and time required to produce AM parts influence networked expeditionary logistics. For example, if AM parts are produced in batches rather than individually, there are issues related to the batch size and inventory control for these items—particularly for mobile units that could face the decision of locally manufacturing parts, reordering parts from a logistics node, or reordering raw materials for local production. Fortunately, the data farming approach is very efficient even for models with dozens or hundreds of factors. Expertise about various properties and characteristics of different materials used in AM (e.g., polymeric materials, composite materials, and metal or alloy composition powders), as well as posttreatments required for the parts to achieve their final structural and physical characteristics, may guide the simulation model factors related to quality, reliability, and lead times required for manufactured parts.

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Concluding Thoughts

Our interest is in investigating the impact of AM on military logistics and life-cycle costs for Marine Corps expeditionary operations. We view AM as a potential transformative capability, but to realize its full potential for expeditionary operations, the Marine Corps logistics concept of operations must change. Our work provides a template for augmenting the acquisition decision process by using simulation analytics—specifically, a data farming approach. Many characteristics of an AM-capable expeditionary operational unit can be explicitly studied as factors within large-scale simulation experiments. Consequently, we can identify which sources of data (e.g., demand patterns, reliability, quality, printing and processing time, lead time) or their interrelationships are the key drivers of readiness and performance. This may help program managers set initial requirements, determine what should be monitored most closely as AM programs are rolled out, or assist in estimating the potential benefits as new AM compounds or processes become available over time.

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