A METHODOLOGY TO PREDICT THE IMPACT OF ADDITIVE MANUFACTURING ON THE AEROSPACE SUPPLY CHAIN

by

William E. Bihlman

A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

School of Industrial Engineering

West Lafayette, Indiana

May 2020

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. C. Robert Kenley, Co-chair
School of Industrial Engineering

Dr. Gary Cheng, Co-chair
School of Industrial Engineering

Dr. Jitesh Panchal
School of Mechanical Engineering

Dr. William Crossley
School of Aeronautics and Astronautics

Dr. R. Byron Pipes
School of Material Science

Dr. Albert Jones
National Institute of Standards and Technology (NIST)

Approved by:
Dr. Abhijit Deshmukh

To the fastest runner on the block – my mother – to whom much is gratefully owed,

To our eternal Father; and,

In memory of fellow Knight and Boilermaker, Jim Ernst.

ACKNOWLEDGMENTS

I would like to first thank Professor Bob Kenley for his energy, patience, and mentoring since we started collaborating closely in 2018. Secondly, I would like to thank Professor Byron Pipes for providing financial support (and general counsel) for the past three semesters. Professor Gary Cheng was also instrumental in the whole process by encouraging me to apply to Purdue. Thank you. Next, I need to acknowledge and sincerely thank Dr. Al Jones for his unwavering support, including countless weekend phone calls. Professors Bill Crossley and Jitesh Panchal deserve recognition – both made themselves readily available for consultations throughout the research. Also, I thank the INCOSE Foundation and Stevens Institute for the doctoral award and grant. Lastly, I want to express my appreciation to my family and friends for the encouragement along yet another journey.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

ABM	Agent-based model
AC	Advisory Circular
AFRL	US Air Force Research Laboratory
AM	Additive manufacturing
AMS	Aerospace Material Standards (by SAE International)
AS9100	SAE standard quality management system for aerospace manufacturers
ASTM	American Society for Testing and Materials
BOM	Bill of materials
CAD	Computer-aided design software
CFR	Code of Federal Regulations (formerly FAR – Federal Aviation Regulations)
CFRP	Carbon fiber reinforced polymer
CM	Conventional manufacturing (e.g. forging, casting, extrusion)
CNC	Computer numeric controlled (machine)
DED	Directed energy deposition (AM process)
DfA	Design for additive manufacturing
EASA	European Aviation Safety Agency (European counterpart to the FAA)
FAA	United States Federal Aviation Administration
FOSC	First-order supply chain (Excel integer linear program)
GD&T	Geometric dimensioning and tolerancing
HIP	Hot isostatic press
INCOSE	International Council on Systems Engineering
ILP	Integer linear program
IP	Intellectual property
ISO	International Organization for Standardization
KPI	Key performance indicator
LPT	Low pressure turbine (part of the aeroengine hot section)
MBSE	Model-based system engineering
MEI	Matter, energy and information
MRO	Maintenance, repair and overhaul

NDI	Non-destructive inspection
NIST	National Institute for Standards and Technology
OEM	Original equipment manufacturer (e.g. Boeing, Airbus, GE, Roll Royce, P&W)
PBF	Powder bed fusion (AM process that includes DMLS, SLM, SLS, and EBM)
PLM	Product life-cycle management
PP&E	Property, plant and equipment
R&D	Research and development
ROI	Return on investment
SAE	Society of Automotive Engineering International
SCM	Supply chain management
SysML	System modeling language
Tier 1	Level 1 supplier (systems integrator)
Tier 2	Level 2 supplier (sub-system integrator)
Tier 3	Level 3 supplier (build-to-print detailed parts mfg., typically a CNC shop)
Tier 4	Level 4 supplier (metal mills, forgers, foundries)
TRL	Technology readiness level
UML	Unified modeling language
UQ	Uncertainty quantification
V&V	Verification and validation

ABSTRACT

This dissertation provides a novel methodology to assess the impact of additive manufacturing (AM) on the aerospace supply chain. The focus is serialized production of structural parts for the aeroengine. This methodology has three fundamental steps. First, a screening heuristic is used to identify which parts and assemblies would be candidates for AM displacement. Secondly, the production line is characterized and evaluated to understand how these changes in the bill of material might impact plant workflow, and ultimately, part and assembly cost. Finally, the third step employs an integer linear program (ILP) to predict the impact on the supply chain network. The network nodes represent the various companies – and depending upon their tier – each tier has a dedicated function. The output of the ILP is the quantity and connectivity of these nodes between the tiers.

It was determined that additive manufacturing can be used to displace certain conventional manufacturing parts and assemblies as additive manufacturing's technology matures sufficiently. Additive manufacturing is particularly powerful if adopted by the artifact's design authority (usually the original equipment manufacturer – OEM) since it can then print its own parts on demand. Given this sourcing flexibility, these entities can in turn apply pricing pressure on its suppliers. This phenomena increasing has been seen within the industry.

The results of this research should benefit three audiences. The first group is supply chain executives at the various aerospace OEMs. A second group is small and medium enterprises that represent the preponderance of the manufacturing supply base. Owners of these firms would be interested in their vulnerability to displacement due to this new manufacturing paradigm. Finally, due to the powerful nature of this disruptive technology, financial analysts would likely benefit from the conclusions of this research. Some elements of the findings can be applied to areas outside of aerospace.

1. INTRODUCTION

Metal additive manufacturing (AM) has shown great potential to disrupt numerous industries. Perhaps the most illustrious commercial example is provided by General Electric, which created a completely new business unit, GE Additive, in 2016. Much of additive manufacturing's allure is its ability to produce structurally efficient parts, expediently. Aerospace is one of the key target markets given its extensive focus on lightweight designs (Gisario et al. 2019). This novel technology is particularly well suited to create strong, lightweight, optimized parts as reflected by the common notion that for additive manufacturing, "complexity is free" (Lindemann and Koch 2016). According to a GE Aviation spokesman, "the paradigm between the cost of manufacturing and the complexity of a design has been upended. With additive, designs are optimized for performance" (Koenig 2020).

Nevertheless, there are drawbacks as with any burgeoning technology. The principle concern is part quality – there is a lack of consistency of the mechanical properties for final AM parts (Tofail et al. 2018). In light of this uncertainty, most of the published research focuses on the physical build process; accordingly, this constitutes a large majority of the publications (Costabile et al. 2016). Very little effort has been made to investigate the implications downstream, such as that of the requisite production ecosystem (Pollock 2019).

This dissertation investigates the relationship between additive manufacturing and the aerospace supply network. The effort required a broad understanding of the disparate stages of manufacturing, as well as the dynamics of the supplier network itself. A systems approach was employed, comprising a five-step methodology:

1. System decomposition
2. AM part identification
3. Manufacturing workflow characterization
4. Production network prediction
5. Model validation and verification

Each step provides incremental insight to move systematically towards answering the question of additive manufacturing's impact on the supply chain. Steps 2 through 4 are the most critical to the analysis. Each will been studied with increasing level of detail, based upon its relevance to the five proposed research questions introduced in Section 1.2.

This dissertation is organized in the six chapters. This chapter includes the research Motivation, Objectives and Scope. Chapter 2 is entitled Background, and provides additional basis for the research, drawing heavily on the author's 20-plus years of experience in engineering and aviation, as well as over a decade focused on aerospace materials and manufacturing. Chapter 3 introduces the scholarly research gap. It is interesting to note that essentially no research precedence exists to answer the motivating question in the context of serialized production. The Methodology is covered in Chapter 4, and again, is uniquely developed for the problem statement. This chapter includes three subsections that explore the fundamental steps to develop a mathematical model of the supply chain – these steps include part identification, plant workflow, and the network architecture. Chapter 5 contains the Results of the mathematical model, and Chapter 6 closes with Discussion, Conclusions and Recommended Research.

1.1 Motivation

Additive manufacturing, also known as 3D printing, is typically included in the list of technologies that are central to the factory-of-the-future, or more colloquially, Industry 4.0 as rendered in Figure 1 (Renishaw n.d.). All manufacturing industries will likely be disrupted by this novel technology. The digital factory will be highly automated and link AM machines to the digital cloud. This, coupled with advanced analytics such as machine learning, will help to significantly reduce cycle time and improve quality for myriad consumer and industrial products (Mourtzis 2019).

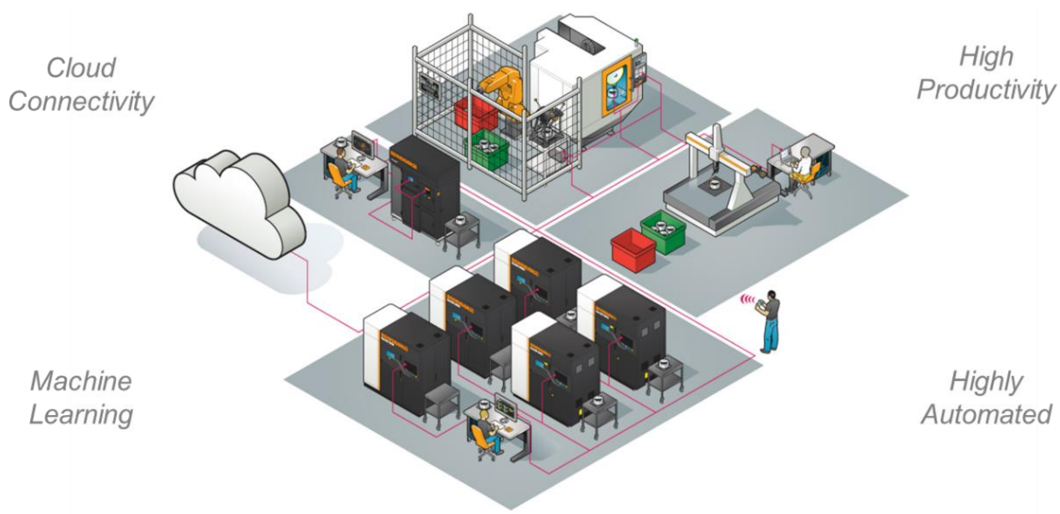


Figure 1: Notional factory-of-the-future with additive and subtractive machines

A fundamental consequence of additive manufacturing is a reduction in the number of parts, and likely suppliers, that are required to build a product. Nevertheless, as stated, only a small percentage of research publications address additive manufacturing's effects on the supply chain. One of the foremost authorities in AM market research, Terry Wohlers, stated that additive manufacturing "has the ability to disrupt the supply chain almost entirely" (Brown 2018, 18). Metal AM research has seemingly focused on characterizing and predicting mechanical properties of the final part. But in order to better understand the diffusion of this technology, it is imperative to comprehend the nature of the AM ecosystem – the supply chain itself.

This research addresses the implications for the aerospace supply chain using a practical approach, combining theory and application. The supplier network is the lifeblood of any complex artifact, and complications can disrupt even the most established companies as evidenced by Boeing's supply chain challenges during its launch of the 787 aircraft (Denning 2013). A literature review suggests that a large portion of the AM supply-chain related research originates in disciplines outside of engineering, such as economics, business, and policy. Given the technical nature of both additive manufacturing and the aerospace design-build-test-certify cycle, it seems fitting that this topic is addressed from an industrial engineering perspective.

This research is multidisciplinary and leverages knowledge from at least four domains: manufacturing (particularly the nuances of additive manufacturing), materials, supply chain, and aerospace product design. The latter category is focused on commercial air transport, and therefore involves the essential role of standards, certification, engineering, production planning, and maintenance over the aircraft's operating lifecycle. A potential fifth domain is optimization, a field of study typical to industrial engineering. In particular, this research utilizes an integer linear program (ILP) for the final supply-chain mathematical model.

Results of this research should benefit at least three audiences. The first group is supply chain executives at the various aerospace original equipment manufacturers (OEMs). A second group is small and medium enterprises that represent the preponderance of the manufacturing supply base. Owners of these firms would be interested in their vulnerability to displacement due to this new manufacturing paradigm. Finally, due to the powerful nature of this disruptive technology, financial analysts would likely benefit from the conclusions of this research. It is worth noting that these conclusions are relatively unique to aerospace, and are not widely generalizable to other industries. This is due to several unique aspects concerning an aircraft's design, production system, and its operation, areas that will be explained in more detail.

This research employs a systematic bottoms-up approach – grounded in certain engineering fundamentals – to help foreshadow the considerable onset of additive manufacturing within commercial aerospace. The methodology developed within provides a needed improvement over the currently available market forecasting regarding this topic. These approaches seem to have overly generalized the subject matter, and have little applicability to commercial aerospace. Indeed, a more technical approach is warranted for an industry that is extremely safety conscious and risk averse to adopting nearly any new technology.

1.2 Objectives

The goal of this research is to develop a methodology to predict the response of the aerospace supply chain to the advent of AM technology. Specifically, the quantity and connectivity of suppliers will be determined. This methodology involves both engineering and business principles and perspectives – indeed, it can be argued that knowledge of both is a requisite for modeling technology adoption in almost any industry. As aerospace OEMs continue to embrace metal additive manufacturing, the question then becomes "*under what conditions will additive manufacturing materially affect the OEM production network*?" This motivating question can be further decomposed into a series of five specific research questions.

Each research question provides a basis to answer, more progressively, the fundamental question concerning the impact to the overall supply chain. These questions are summarized below.

R1. WHICH segments of aerospace are subject to AM disruption, and WHICH metal AM modalities are most likely to prevail?

R2. HOW can the entire production network (i.e. OEM plus the supply chain) be decomposed to capture changes in design and manufacturing methods?

R3. WHAT model can be developed that is sufficiently simple in terms of type and quantity of variables and parameters, yet can adequately predict network behavior?

R4. WHAT is the impact of adopting additive manufacturing according to this model, and HOW sensitive is the network to parameter changes?

R5. WHERE and HOW will evolutionary adjustments in AM technology be manifested throughout the entire network?

In general, it is hypothesized that the small and medium enterprises that participate in the lower tiers of the supply chain (i.e. Tier 3s) are disadvantaged by the onset of additive manufacturing. The simplest explanation is that these detailed-parts manufacturers produce the preponderance of the parts. And as the part count decreases, the demand for their products will also decrease. This situation will be discussed later in the dissertation.

The initial step in answering the research questions is to select the targeted aircraft system or subsystem. The aircraft is a complex machine with multiple interacting subsystems and components. For purposes of this research, the aeroengine (i.e. gas turbine) was chosen. This important simplifying assumption will be justified in Chapter 2. Even with the aeroengine down selected, it is still necessary to define the appropriate level of abstraction for the artifact and its production and/or operating environment. The process to define the research scope is non-trivial.

In order to answer the proposed research questions in the context of the aeroengine, five independent steps were devised. These start upstream with the design of the product, and finish downstream, focused on the impact of the entire production ecosystem. Note that although there are five research steps, they do not correspond directly to the five proposed research questions.

With this in mind, the first fundamental step in a multistep process is to properly scope and subsequently decompose the aeroengine ecosystem. These steps are defined below, and also summarized pictorially in Figure 2.

1. Identify and decompose the targeted system
2. Create a part-screening heuristic to identify candidate AM parts within the system
3. Develop a heuristic to evaluate the impact of new AM parts on plant workflow
4. Establish a mathematical model to synthesize the net effect on the supplier network
5. Provide insight regarding the validity of the model and overall methodology

Figure 2 below illustrates the interconnection between the various elements within the system. Just as importantly, it shows the flow of information – and in this case, parts and dollars – between the various entities. Depending upon the maturity of the chosen research tool or methodology, generally speaking, the final step of validating can be a challenge. In this case, the verification and validations efforts focused on the mathematical model that was developed in Step 4 to predict the production network response.

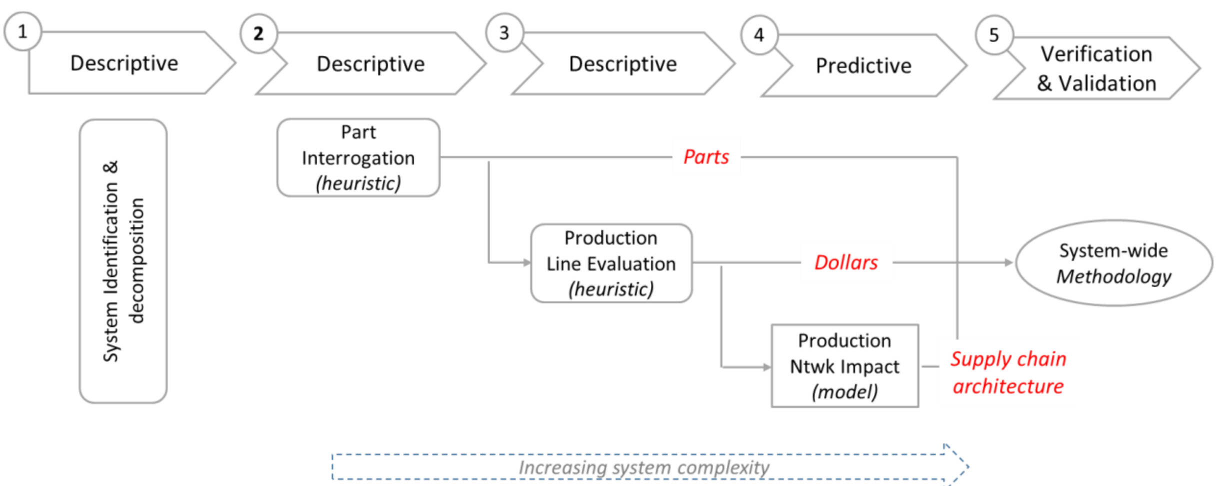


Figure 2: A schematic of the research methodology

1.3 Research Scope

Both the aerospace industry and the AM field are vast domains. Bounding the research scope for such a diverse topic is imperative, and it seems most effectively performed by employing a systems approach. The method used for determining the research scope is motivated by Buede and Millers' decomposition design process as shown in Figure 3 below (Buede and Miller 2016).

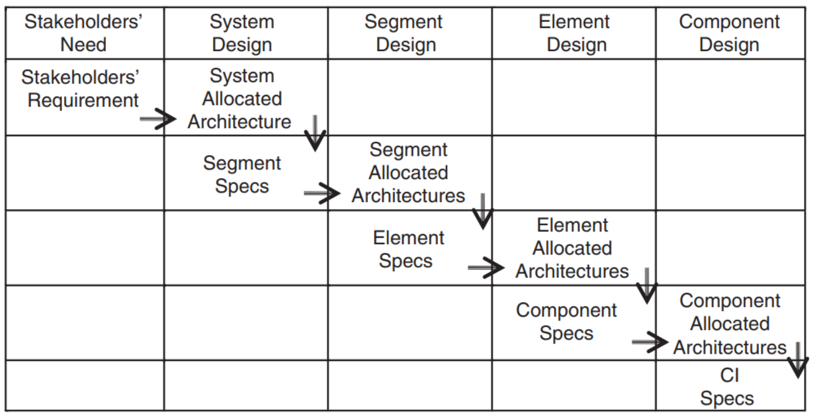


Figure 3: Design decomposition of system architecture and specifications

The process starts by identifying and evaluating the specific customers' or stakeholders' individual requirements. These are the primary inputs that establish the ultimate design objectives for the aircraft, and in turn, the aeroengine. In light of the Buede and Miller's approach, the first perspective considered was that from a more commercial or business standpoint. This methodology served as the basis to derive the engineering-related aspects associated with the actual design of the artifact.

The overarching business objectives for any manufacturing company can be axiomatically stated as better, fast, cheaper. For aerospace, there is an additional imperative, that of *safety* in the form of airworthiness. This criteria alone trumps all other aspects of the design and operation of the aircraft. In general, the design space for the aircraft (and aeroengine) is a tradeoff between cost, weight, and performance, all the while minimizing overall system risk or integrity of the aircraft.

1.3.1 Supply Chain Decomposition

As explained above, Figure 4 offers a decomposition of the entire ecosystem in light of its business characteristics. It is based on N^2 method proposed by Buede and Miller (2016). The schematic highlights the key business considerations at the subsystem level. The process begins in the upper left-hand corner with the end-customer's requirements, in this case the airlines. These criteria then flow downward, sequentially, to the lowest level of abstraction – the basic raw material inputs. Within the hierarchical decomposition, each objective warrants a physical response from the associated subsystem.

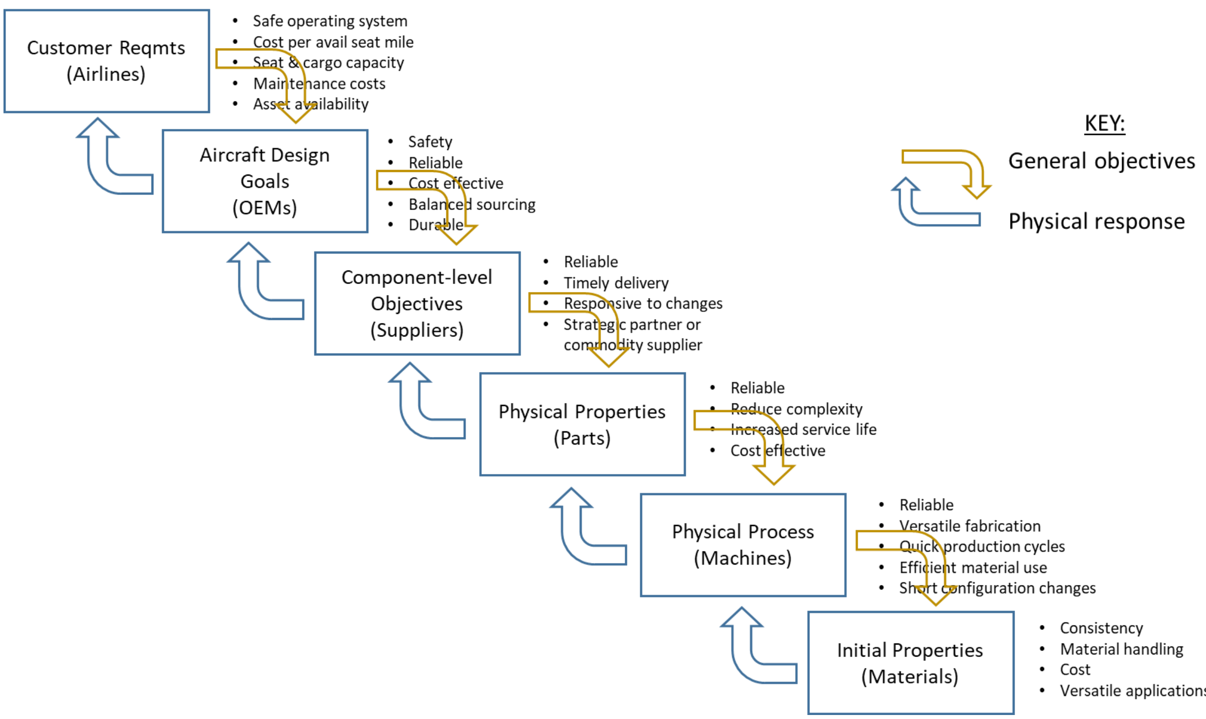


Figure 4: Systems decomposition from the business perspective

Figure 5 below highlights key aspects of Figure 4 but from a different lens. In particular, Figure 5 addresses the engineering elements of the system of interest, with the particular focus of the aircraft OEM. Of course, a similar exercise can performed for the aeroengine OEM, which is arguably its most important supplier. As shown in the figure, the N^2 exercise includes aspects of artifact design, supplier selection, and requirements for the various suppliers throughout the supply chain. This design hierarchy and the nature of the information flow served as important foundation to develop the architecture and behavior of the aeroengine supply chain.

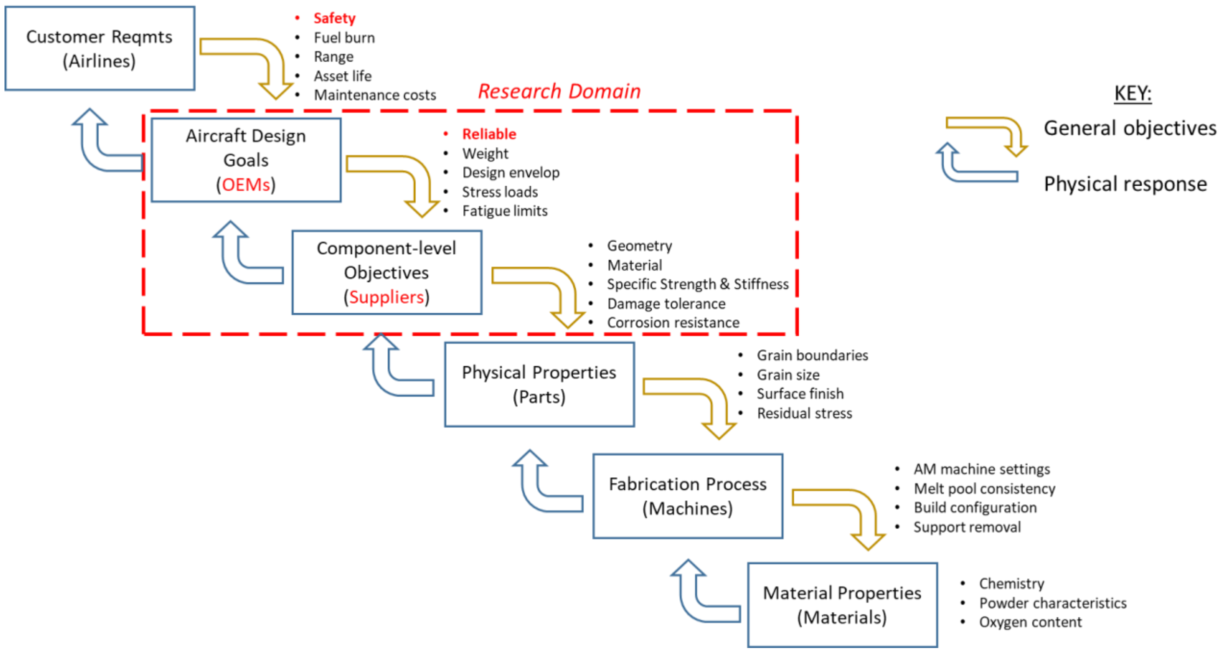


Figure 5: Systems decomposition from the engineering perspective

Another important benefit of the N^2 method was to discern the appropriate level of abstraction for the final supply chain model. Specifically, the final supply chain model will only consider the interaction between the OEM and its immediate suppliers. It does not incorporate additional elements downstream, such as a part's mechanical properties, or any aspects of the machines used in manufacturing parts. This multi-scale, multi-physics type of model will be discussed in Section 4.2. Nonetheless, for the purposes of the supply chain model, this level of detail was deemed superfluous.

Figure 5 was used to develop a much more concise subsystem hierarchy, one that relates the overall production system to the AM build process. The result is Figure 6 on the following page that demonstrates the relationship between the four basic nested subsystems. There were three critical subsystems that are contained within the production systems itself, namely: the (plant) production line, the AM machine, and the build plate (within the AM machine). Therefore, in the context of this research project, the operational definition of the manufacturing ecosystem is that which includes these three key elements.

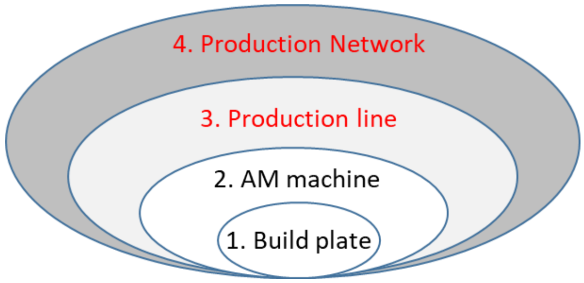


Figure 6: Systems decomposition using nested systems with research focus delineated

In order to characterize the building of an AM part, the most elementary level would be to model the physical melting of the metal. This is influenced by the build plate that serves as the foundation for the part to be "grown" vertically. This process is comprises the interaction of the energy source (usually a laser) with metal powder, which forms the molten metal "melt pool." Note that this melt pool is the genesis for all the material properties for the final AM part. Clearly, the build plate is contained within the AM machine, which, in turn, is part of a larger production line within a given facility. Finally, the entire production network is comprised of a series of these individual production lines. The gray in Figure 6 delineates the two systems of interest for the research scope. In particular, the darker gray highlights the primary focus of the analysis – the aerospace production network.

As an aside, it is important to note that the vast majority of the AM research is centered on AM melt-pool characterization. This is indeed the most important, and perhaps the least understood, aspect of AM technology. Its behavior directly influences final part properties, a concept that will be discussed in detail in Section 2.2. The complexity of the thermodynamics process has been difficult consistently and accurately predict. This dissertation, however, makes an important assumption that these concerns will eventually be overcome by scientists and engineers investigating this space. This is represented by an increase in the technology readiness level (TRL), also referred to more casually as "technology maturity" within this document.

1.3.2 Aircraft System Identification

Before studying the effects of the AM build process, it is essential to first select the artifact under investigation. It was previously disclosed that the aeroengine was selected as the targeted aerospace system. This section explains the rationale.

The aircraft can be divided into five primary mechanical systems: aerostructure (fuselage, wing and empennage), hydraulic systems, flight controls, landing gear, and the aeroengine. Apart from the landing gear, it is this author's opinion that each system is effectively subject to AM part substitution. This research will focus only on structural applications of additive manufacturing, thus precluding the hydraulic systems categories.

Between the aerostructure and the aeroengine, the aeroengine shows the most promise for AM part adoption. There are several reasons. The first justification is the extremely high operating temperatures and pressures associated with the aeroengine. Temperatures in this environment easily exceeds the melting point of alloys if not protected, and corresponding pressures make the tolerances between the rotating components extraordinarily tight (Pratt & Whitney 1988). For example, GE's newest engine, the GE9X, reaches an operating temperature of over 2000°F, 500°F above the melting temperature of material (super alloy) itself. Similarly, the pressure ratio is equally as extreme at 60:1, or 60 times standard atmospheric pressure (Norris 2017).

Pressure and temperature are directly proportionally related.[1] And higher pressure in the aeroengine is the result of tighter tolerances between the rotating parts. Since the 1960s, there has been increasing emphasis on geometric dimensioning and tolerancing (GD&T) with the advent of high-precision computer-numeric controlled (CNC) machining. This tolerances for aerospace can exceed ±0.005 inches. Moreover, materials that are heat resistant, such as nickel and cobalt super alloys, and to a lesser extent titanium, are extremely difficult to machine. The simplest explanation is that they have extremely low thermal conductivity and do not dissipate heat well, which is a critical consideration while machining metals. Additive manufacturing's ability to produce "ultra-near-net" shapes helps to significantly minimize machining (Richter and Walther 2017). These near-net shapes are defined as geometries that are extremely close to that of the final part, and thus require minimal machining.

In addition to machining difficulty and high tolerances, part size is another critical factor. Aeroengine parts are considerably smaller than aerostructure parts. This is salient since the AM build chamber is relatively small, and on average, less than one meter cubed (Molitch-Hou 2017). As a consequence, the parts and components of the aeroengine are much better candidates for AM adoptions.

[1] Recall from basic chemistry the ideal gas law: $PV = nRT$, where P is pressure and T is temperature.

One last consideration regarding the adoption of AM technology is production rate. It is worth noting that additive manufacturing was initially developed in the 1980s for rapid prototyping. In this context, for relatively small production runs and for unique, complex parts, the technology was considered sufficiently fast. In fact, in many cases, additive manufacturing is the only method that can produce a given part – *this is a key concept that underpins this dissertation research*. In contrast, serialized production typically relies on relatively high-rate manufacturing; for these reasons, additive manufacturing is often deemed too slow (Nazir and Jeng 2019). One popular example is the automotive industry that may produce thousands of units a day at a given factory. It is generally accepted that this industry is not a good candidate for this technology.

A large portion of automotive parts are produced in a matter of minutes, given the high level of daily throughput. Metal AM parts, alternatively, usually require several hours if not days to be produced. Therefore, production rate is an important consideration. Figure 7 below compares various characteristics for the aircraft, aeroengine and automotive industry. Furthermore, Wildemann and Hojak (2017) provide a fairly comprehensive summary of the implication of product design and supply chains for both aerospace and automotive. Ultimately, these various attributes inform the appropriate AM strategy for each end market.

Units Produced:	3500	10,000	60,000,000
Product Size:	100 - 200 ft	5 - 10 ft (dia)	5 x 15 ft
Part Count:	2,500,000	30,000	25,000
Quality Drivers:	Product integrity	Product integrity	Production integrity
Key Challenge:	Size	Tolerance	Production Rate
Supplier Base:	Duopoly	Oligopoly	Globally competitive

Figure 7: Summary of the key features for aircraft vs aeroengine vs automobile

1.3.3 AM System Identification

The previous two sections identified the production system and artifact under consideration. Next, it is important to consider the specific AM technology or "modality" that should be the focus of this research. Since 2010, there has been a proliferation of modalities that align to various companies entering into the AM market (Wohlers 2016). It is interested that, in many cases, these technologies seem to vary in name only. The ASTM F42 committee has helped to minimize the confusion by classified additive manufacturing into seven process categories or basic ontologies. Of these seven, three modalities are dedicated to the metal melting process as summarized in Figure 8 (www.astm.org).

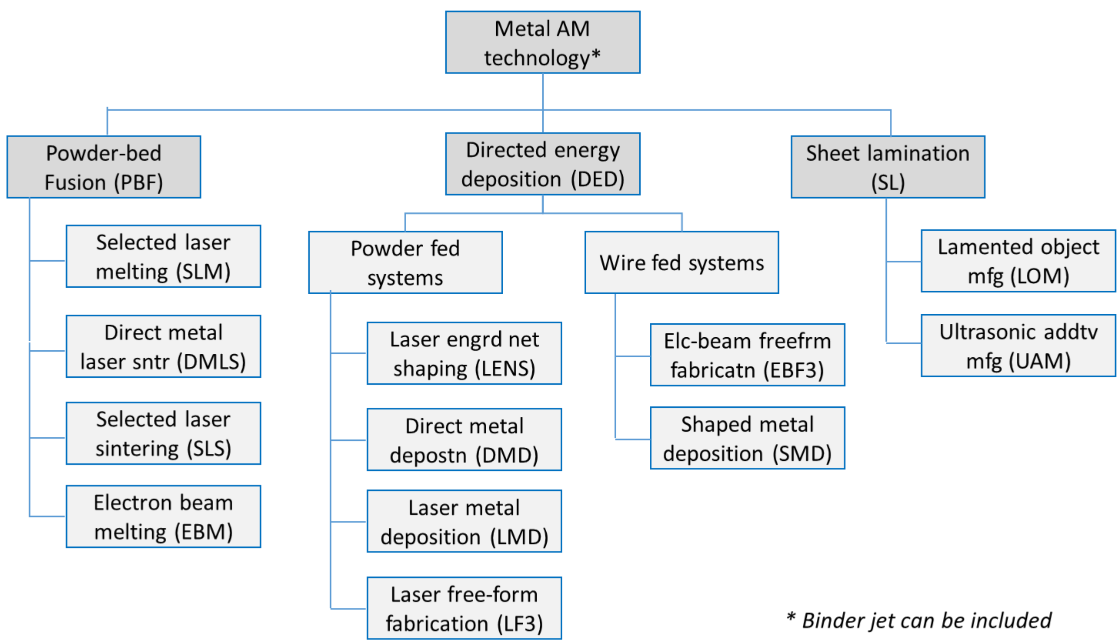
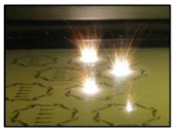


Figure 8: ASTM's classification of metal AM modalities

Powder-bed fusion (PBF) and directed-energy deposition (DED) are the most common modalities used in aerospace (Bihlman 2016). The fundamental difference between the two technologies is form of the metal substrate and the rate of metal deposition. The details of these two modalities are outlined in Figure 9 on the following page (Bihlman 2016).

Powder-bed Fusion (PBF)



Grows layers via melting* powder, developed in 1980s at the University of Texas as selected laser sintering

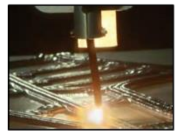
Advantages: near net, complex geometry

Disadvantages: limited size, small batches, source material control

Common materials: TI 6-4, IN 718, CoCr

Target market: engine castings

*Wire Directed-energy Deposition (DED)***



Melting wire – similar to welding – to create molten pool to build linear layers

Advantages: high deposition, economical

Disadvantages: more machining required, residual stresses, voids/occlusions

Common materials: TI 6-4, 17-4 PH

Target market: airframe forgings

* for metals, process *melts* not fuses or sinters
** powder DED is less common

Figure 9: The two most common AM modalities for aerospace structural parts

With its ability to produce fine features and offer a smooth surface finish, PBF has become popular for aeroengine parts and components. Moreover, laser PBF is the most ubiquitous metal AM modality, likely representing some two-thirds of the total metal AM systems (Bihlman 2016). In addition to aerospace, another major end market is biomedical, with a growing number of applications in prosthetics and medical devices (Debroy et al. 2019; Sing et al. 2016). This becomes an important factor when considering the GE case study in Section 2.2, as GE participates extensively (and profitably) in both aerospace and medical.

1.3.4 Target System Summary

To summarize, the research initially considered the entire aircraft production ecosystem. There were three steps involved to make the dissertation analysis more tractable. First, the scope was limited to the production network, specifically targeting the relationship between the OEM and its immediate suppliers. Secondly, the aeroengine was selected as the specific aircraft system to be evaluated. And thirdly, of the seven AM modalities, metal PBF was chosen as the process to be targeted. The following section provides more details regarding the aerospace production system and metal additive manufacturing.

2. BACKGROUND

Additive manufacturing technology is nascent. Even with a single modality such as the ubiquitous laser PBF, there is no broad consensus on the technology readiness level (TRL) (Diegel, Nordin, and Motte 2019). Relatively speaking, the TRL for this process is still fairly low (Debroy et al. 2019), and aerospace is exceedingly risk averse with regards to the safety of its passengers. This clearly creates some tension for adoption.

In general, new technology adoption in aviation is notoriously slow. One exception may be during a war-time environment, where circumspection gives way to the national imperative of military readiness (Johnson 1985). Nevertheless, a cautious prudence usually governs commercial aerospace in its development and operation since it involves passengers. The debacle in 2019 with the Boeing 737 MAX aircraft serves as a sobering reminder of the potential perils of a major engineering modification (Gates et al. 2019). This 100-year old organization has been shuttered by engineering mishap, and some argue, hubris regarding design and development. Quality and safety will always be imperatives for aviation (Herzner 2017).

The purpose of this chapter is to provide an overview of the aerospace design and manufacturing process. It also explores the nuances specific to additive manufacturing. The chapter offers information relevant to both business and engineering. This will help provide some of the necessary background to address the proposed research questions.

2.1 Aerospace Manufacturing

Since the 1980s, aerospace supply chains have become increasingly complex in size, dispersion, and interdependence as both aircraft and aeroengine OEMs have moved to less vertically integrated business models (Michaels 2018). It has been stated that the aerospace supply chain is “the most complex and the longest compared to the other industries” (Singamneni et al. 2019, 1). This complexity stems from the OEMs desire to reduce labor costs, mitigate product-development risk (including design, development and production), and in some cases, provide access to capital and technology. In the context of military aircraft, an additional consideration could be country offset and future aircraft sales (Michaels 2018).

Large-scale industrial-product manufacturing is inherently complex. Industries such as automotive and aerospace inevitably involve: a) global operations; b) enormous capital investments in property, plant and equipment (PP&E); c) a sizeable labor force; d) a vast number of parts and complex assemblies; and, e) an immense supplier network. Commercial aerospace is further complicated by at least two additional considerations, namely the size of the parts, and quality standards that are predicted upon its safety imperative.

Quality and safety are the two greatest issues that drives design and development for aerospace. Perhaps no other industry, save nuclear power, receives more attention and scrutiny from the government, media and general public (Tang, Goetschalckx, and McGinnis 2013; Ghadge, Dani, and Kalawsky 2010). Indeed, the importance for safety in all phases of the aircraft product life-cycle (design, production, operation and maintenance), and the inherent liability of the OEM can be underscored by the Boeing 737 MAX crisis, previously mentioned (Gates et al. 2019).

The commercial-aerospace supply chain is often depicted as a hierarchy or tiered system as shown in Figure 10 below. The OEM resides at the top of this pyramid-like structure, and each subsequent tier manufactures a less sophisticated artifact (i.e. parts or components). Nominally, information, either in the form of specific detailed designs or artifact specifications, is passed down to the lower tiers. In exchange, artifacts flow upwards.

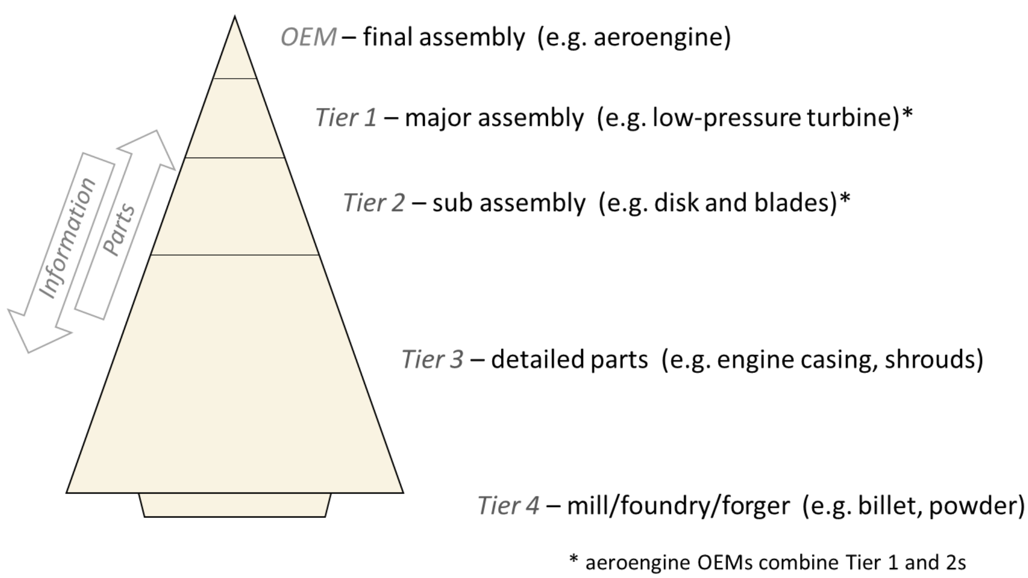


Figure 10: Hierarchy and nomenclature for an aerospace production network

The area of each tier in the figure corresponds to the quantity of suppliers at that level. The aeroengine supply chain has between three to four thousand suppliers. This compares to some 13 thousand for Boeing, for example. The majority of the suppliers for each product are considered to be Tier 3s (Michaels 2018).

There has been a consolidation of aerospace OEMs since the 1960s. In addition to OEMs becoming less vertically integrated, they have increasingly delegated their engineering design authority to their supply chain partners. This will be discussed in further detail since it has important implications regarding the commercial long-term viability of the firm. With the exception of Tier 4s, the entities are typically smaller (and organizationally less sophisticated) towards the bottom of the pyramid (Michaels 2018).

2.1.1 Aircraft and Systems

Both the aircraft and the aeroengine are complex machines. A typical widebody aircraft has between 2.3 to 4 million parts, while the aeroengine has 10 to 30 thousand parts. This requires a sophisticated manufacturing and production-planning system. OEMs have increasingly engaged their supply chains as strategic partners, increasing their responsibility for the design-build-test of parts and components. This is perhaps best illustrated by the development and product launch of the Boeing 787 aircraft that entered service in 2009 (Bihlman 2015); although, other examples include Brazil’s Embraer 170/190, Candida’s Bombardier C-Series, France and Germany’s Airbus A350, Japan’s Mitsubishi SpaceJet, and China’s COMAC 919 aircraft. No OEM seems to be immune to this phenomenon.

In conjunction with the “letting” of large work packages, these aircraft OEMs have fundamentally shifted their design authority to their supply base. The previous approach was known as “build-to-print,” where the OEM clearly controls the design and intellectual property (IP). The approach now is known as “build-to-spec” work packages, where the engineering is more limited to the basic specifications of the design of the component or subsystem. Both the engineering burden and, to a certain extent, the liability, have shifted away from the OEM. This has important implications regarding product testing, certification and overall product quality and liability (Michaels 2018).

In addition to operational safety, fuel efficiency is another important imperative for aircraft and aeroengine development. This can be loosely translated into two basic design objectives – durable but lightweight structures. These two performance imperatives must be optimized relative to cost for the initial development through production of the aircraft (i.e. airframe) and aeroengine. These concepts were translated into a slightly more technical language, and presented below graphically in Figure 11 below (Bihlman 2016).

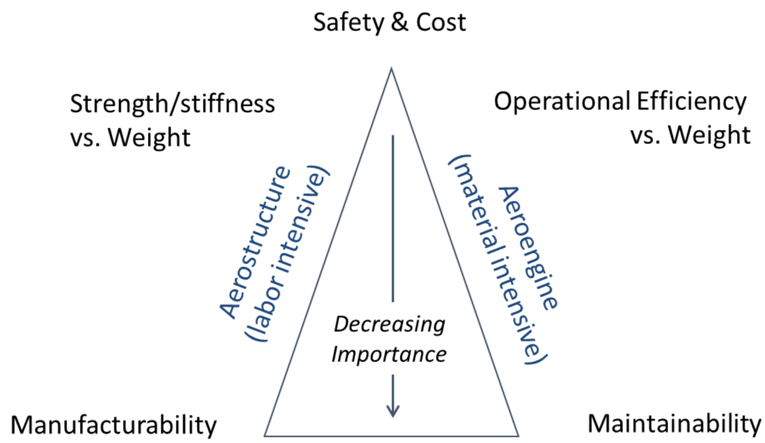


Figure 11: Aerospace design priority hierarchy

Exceptionally high-quality standards are enforced by the Federal Aviation Administration (FAA), mandating strict guidelines codified in the Code of Federal Regulations (CFRs). Furthermore, when the FAA certifies an aircraft, for example, it substantiates two elements in the process. The first item is the aircraft Type Design (i.e. 14 CFR Part 25), and second item is the aircraft Production System (i.e. 14 CFR Part 21).[2] Both design and production system need to be conformed to the original engineering. This ensures that the design is properly engineered and deemed safe, and the production process is accurate, controlled, and stable over an extended period of time. Finally, both Type Design and Production System certificates are the ultimate responsibility of the OEM.

[2] It is important to note the FAA only certifies three artifacts – the propeller, aeroengine, and aircraft; thus, parts themselves are not certified (with the exception of how the term is used within the U.S. military). This is widely misunderstood, and its confusion has had an effect on the qualification path for commercial aerospace AM parts.

2.1.2 Regulation and Standards

The FAA also regulates the lower-tier suppliers, usually indirectly, since part quality is often industry governed. A majority of the quality standards are provided by industry trade associations, such as SAE International, the American Society for Testing and Materials (ASTM) International, and the International Organization for Standardization (ISO). These are transnational non-profit organizations that provide an important service for the aerospace industry. Nearly all US manufacturing suppliers, for instance, possess an AS9100 certification issued by SAE International to show production conformity. In fact, the OEM often requires this certificate as prerequisite before a supplier can even bid on a work package.

Global technical standards are a critical instrument for disseminating technology. In theory, this applies to all industries, regardless of government regulation. The FAA, and its European counterpart, the European Aviation Safety Agency (EASA), rely heavily on these organizations to provide an industry consensus. This form of self-governance, in a sense, assists the regulatory authorities since their financial resources and expertise has dimensioned considerably since the 1970s.

The role of technical standards cannot be over emphasized for emerging technologies. There is a certain sentiment that AM standards are the pathway to mass adoption (*Aerospace Manufacturing and Design* 2019). In fact, the adoption of standards was critical to the adoption of carbon-fiber composites for primary structures in commercial aviation with the advent of the Boeing 787 in 2004 (Tomblin, Tauriello, and Doyle 2002). The parallels to additive manufacturing are noteworthy. SAE and ASTM are both working on standards following the National Center for Advanced Materials Performance (NCAMP) business model. NCMAP is part of the National Institute for Aviation Research at Wichita State University, and it maintains the design allowables database for carbon fiber reinforced polymer (CFRP) (NASA n.d.).

Both additive manufacturing and CFRP have been associated with a relatively new material category called “process-intensive” materials (MMPDS 2018). The justification is that each process is highly anisotropic and its mechanical properties are directly determined by the manufacturing method. The advantage of process-intensive materials is that the material can be added where needed to optimize a part’s strength; the disadvantage is that many variables must be understood and controlled during the manufacturing of the part. These potential manufacturing complications create uncertainty in the mechanical properties of the final part.

Aerospace standards can help delineate important criteria for both raw materials and the manufacturing of these process-intensive materials. A concerted effort is underway by various agencies for AM standards globally – the oldest and most widely known for additive manufacturing is the F42 Committee by ASTM, which was initiated in the United States in 2009 (Koch 2017).

2.2 Additive Manufacturing Overview

The concept of additive manufacturing can be traced back to the mid-1980s. In its most primitive form, it is simply adding material, layer by layer, to make a three-dimensional part. The term, however, was not formalized until 2009. The appellation stemmed from the creation of the ASTM F42 committee, which, at the time, was in need of a name for its subcommittee. Various titles were discussed. Interestingly, the term "3D printing" was one of the earliest consideration, but it was readily discarded since it specifically refers to a technology that was invented by MIT professors in 1993 (Bourell 2016).

The MIT 3D printing modality is now colloquially referred to as binder jet. MIT commercialized binder jet by creating the company, Z Corp. This company was eventually acquired by 3D Systems (Diegel, Nordin, and Motte 2019). 3D Systems has since become one of the most important companies in the industrialization of metal additive manufacturing.

The term "additive manufacturing" was eventually adopted by the ASTM committee, and within a few years, the ISO Technical Committee TC261 also embraced the appellation. This helped to facilitate its acceptance internationally. This term is now widely used in the United States as technical parlance, whereas 3D printing is used more readily by the media and general public (Bourell 2016). At the same time, it is important to distinguish that the term 3D printing is most commonly used in Europe, even when describing the industrial printing process. This is based upon the author's personal experience presenting at numerous global AM conferences.

There were three critical milestones for the industrialization of metal additive manufacturing for its eventual use as structural parts. The first was its initial development and commercial launch of the concept itself. This occurred in 1984 by Chuck Hall of California. He invented stereolithography (SLA), a technique that uses ultraviolet lasers to cure a photopolymer resin. This technology was facilitated in a large part by the invention of solid-state lasers around that same time period. In the process, Hall created the STL computer-aided design (CAD) file format – the *de facto* standard for digital slicing and AM tool path. In 1986, he was granted a patent, and established his company, 3D Systems Corporation. Meanwhile, other important work was being conducted at MIT and University of Texas (Horvath 2014).

A second important development involves selected laser sintering (SLS). This AM technology has become the most ubiquitous amongst metal systems – and nearly synonymous with PBF – although the original process was developed using polymers. The modality was briefly introduced and will be explained in more detail. The basic premise involves using an energy source to sinter/fuse/melt a powder substrate in sequential vertical layers. SLS was first commercialized by Carl Deckard while at the University of Texas. He co-founded the Desk Top Manufacturing (DTM) Corporation for rapid prototyping based upon his patent that was awarded in 1990. DTM was subsequently acquired by 3D Systems in 2001 (Bourell 2016).

The third important development for metal additive manufacturing is centered on Greg Morris from Ohio. Morris founded his company Morris Technologies Inc. (MTI) in 1994 in Cincinnati, home to GE Aviation. Initially, MTI only had one software license and a SLS printer. After a visit to Germany in 2003, he was introduced to the concept of printing metal parts. He immediately realized its potential. Morris is cited as being the first to introduce metal sintering machines to the United States (“The Minds behind GE Additive: Greg Morris” 2018).

In 2005, Morris started experimenting with printing cobalt chrome (CoCr). Previous metals proved prone to cracking and porosity. Initially, SLS CoCr parts were used to make high-pressure turbine blades for limited used on test engines. These blades were only needed for a few hundred hours, and SLS parts were much quicker to produce than an investment casting (*Aviationweek.Com* 2015).

Morris then doubled the number of his German EOS metal printers from two to four, and started to focus almost exclusively on metal printing. His operation grew steadily, reaching 20 metal machines by 2012. That same year, GE Aviation acquired MTI. In addition to the turbine blades, the two companies had been collaborating extensively on printing a portion of LEAP aeroengine fuel nozzle using CoCr (“The Minds behind GE Additive: Greg Morris” 2018). It is this author’s opinion that this event became the catalyst for the explosion of popularity for additive manufacturing, enthusiasm exhibited by both institutional investors and the media at large (e.g. Mann 2016).

That following year, 2013, was unprecedented. The investment community displayed an "extraordinary appetite for AM-related companies and technology" (Wohlers 2016, 26). What in hindsight became understood as irrational exuberance, infected manufacturing corporations, too. As a result, many companies engaged in fairly aggressive acquisitions, some eventually proved to be fateful (Wohlers 2016). The following chronicles just a few key events.

In 2013, the first mutual fund dedicated to additive manufacturing, Printing Fund LLC, was launched. There were a number of important initial public offerings (IPOs), such as Voxeljet, Materialise, and SLM Solutions. Moreover, a series of critical acquisitions by Renishaw, 3D Systems and Stratasys were announced. This paralleled a wave of new products and AM machine launches. GE announced it would print its fuel nozzles – the world's first flight-critical AM production part. It also hosted a crowd-sourced competition with an attractive financial award for a design-for-additive AM solution (Wohlers 2016).

In the second half of 2013, a California startup raised over $1 million in just three weeks to design and build a new AM machine. NASA test-fired a newly designed and printed injector nozzle. It also teamed with California's Made-in-Space corporation to develop a printer for the International Space Station. Finally, one of the global leaders in CNC machine tools, DMG Mori, announced it would build a hybrid additive-subtractive metal machine (Wohlers 2016).

But then the market was jolted by a major correction. Arguably the world's most prominent AM company, 3D Systems, was in dire financial condition. Its stock price had risen remarkably from $10 in December 2011 to $133 by January 2014, only to fall precipitously to just under $7 by January 2017. As of March 2020, 3D Systems stock price remains around this same price. This bomb-and-bust cycle is depicted below in Figure 12 (yahoofinance.com).

Figure 12: 3D Systems historical stock price on the NYSE

Nevertheless, 3D Systems' is still the world's largest AM corporation. The company has a market capitalization of $1.3 billion, followed closely by US-based Statasys at $1 billion – the leader in polymers – and Germany's EOS at $915 million.

The ramifications of 3D Systems stock volatility can be felt hitherto throughout the AM industry. In the end, the adoption of additive manufacturing needs to be grounded in both engineering fundamentals and justified by a profitable business case. The next two sections explore these two important concepts.

2.2.1 Engineering Case Study

Difficult-to-machine alloys are excellent candidates for additive manufacturing (Koenig 2020). These "hard alloys" such as titanium and super alloy are critical to aerospace. Titanium alloy is popular due to its high specific strength and specific stiffness and high corrosion resistance; it is used extensively in the both the aerostructure and aeroengine. High-nickel and cobalt alloys, known categorically as "super alloys," are popular for similar reasons but they can also maintain their shape and mechanical properties at extreme temperatures exceeding 1500°F. In particular, they are not overly susceptible to the phenomenon known as creep. As such, super alloys have become the mainstay of the aeroengine "hot section" – the aft section of the engine that includes the combustor and the turbine (see Figure 13 for details (www.geaviation.com)).

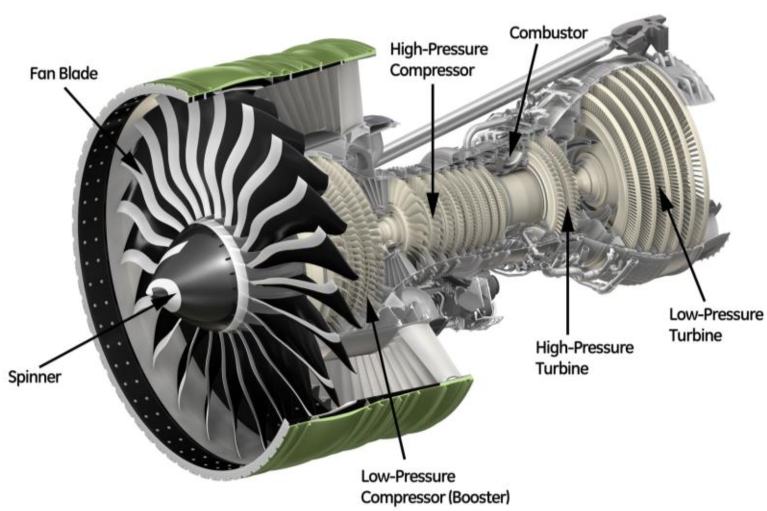


Figure 13: Cutaway of the GE90 aeroengine showing the core and key sections

Nevertheless, both titanium and super alloy are difficult to machine due to a phenomenon known as “work hardening.” This is a process that increases the strength of the metal because it has been plastically deformed. Work hardening results from a metal’s high chemical reactivity, low elastic modulus, and poor thermal conductivity (Rahman, Wong, and Zareena 2003). During machining, the extreme temperatures generated undermine the tool life, adding considerably to both time and cost of producing a part. These metals and associated parts are ideal candidates for additive manufacturing. This point can hardly be overstated.

For aerospace, as posited in Chapter 1, the ultimate goal of additive manufacturing is to “lightweight” a part. Accordingly, the principal fabrication advantage of the additive manufacturing is the ability to optimize part topology during the design phase. Topology optimization creates highly optimized shapes that are considered lightweight, yet tough enough to meet the specified engineering requirements.

There are two popular design approaches. The first is now known as “organic” shapes, and the second involves hollowed forms with a complex internal lattice. Note that a third concept is emerging, parts with a sponge-like core. Each of these concepts leverage the notion of optimization by adding material parsimoniously, and only where it is needed. For structural parts, this means adding material along the part’s load path and, in particular, where the stress concentrations are the greatest.

In addition to organic shapes and internal lattice structures, another unique design advantage is the ability to consolidate parts. This is central to the AM business and will be explored in the following section. Figure 14 illustrates each of these AM design-and-build concepts. It is important to realize that in each of these three scenarios, these parts simply cannot be produced via a conventional machining (CM) process.

* GE LEAP fuel nozzle tip

Figure 14: Three types of designs enabled by additive manufacturing to lightweight parts

In general, additive manufacturing can be classified by material form and power source, as depicted in Figure 15 (Bihlman 2017). This figure also summarizes the key benefits and concerns for the technology as a whole. The previous section introduced the various manufacturing classifications or “modalities” (see Figure 8 for details), and discussed the characteristics of BPF and DED systems. A more detailed comparison between the three metal modalities is provided by Dutta and Froes (2017).

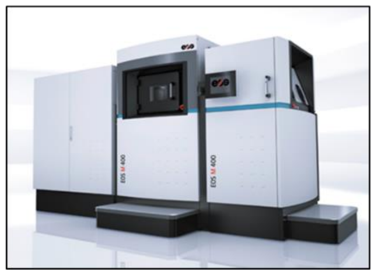


Figure 15: Overview of AM classifications, benefits and aerospace applications

As outlined in the figure above, there are several attractive benefits for targeted parts. The advantages basically apply to various AM modalities (i.e. energy and material combination). Similarly, the two concerns identified are relevant for both powder and wires systems; however, the powder systems are much more susceptible to issues with grain microstructure (Herzog et al. 2016).

Wire DED process

Wire-feed DED is analogous to welding and is used to produce basic "net shapes." As a consequence, these artifacts need to be machined. The main targets for this modality are titanium closed-die (CD) forgings used within the aerostructure (Bihlman 2016).[3] As detailed in Figure 9, the principle advantage of DED is high deposition rates as compared to PBF. The DED process is much more expedient than the conventional forging process, which involves molten metal first to be casted, then open-die forged into a billet, followed by CD forged over a series "knock down" or blocker-die steps. This CD forge shape still has to be extensively machined.

The objective of wire-feed DED is to reduce the intermediate steps from billet to final CD forged shape. This process can take 12 months or longer. Minimizing these steps is critical during the development of new parts as investments in tooling by OEMs and Tier 1s can be in the hundreds of millions of dollars (Sprock, McGinnis, and Bock 2018).

There are only two major AM machine suppliers in the relatively small market for wire-feed DED: Chicago-based Sciaky and Norway's Norisk Titanium. The latter began moving aggressively into aerospace via a strategic partnership with Spirit Aerosystems to provide parts for the Boeing 787 (Siebenmark 2018). Arconic has also developed a similar technology, marketed as Ampliforge (Brooks 2015).

PBF Process

Powder-bed fusion (PBF) is the most ubiquitous metal AM modality – it has become practically synonymous with metal additive manufacturing, as discussed. Given this modality's popularity, it has attracted the attention of a large number of companies that have developed AM machines. As a result, PBF has a number of acronyms, each of which are associated with commercial entity, yet the technologies are basically similar.

PBF involves a relatively small build chamber, less than one meter cubed for even the largest machine (Molitch-Hou 2017). At the bottom of the chamber is a metal build plate that is eventually covered with a thin layer of metal powder. A power source (usually a laser) then

[3] Note there is also a blown-powder DED process, hence the distinction 'wire-feed'; powder DED seems more common in space applications, such as rocket nozzles being research at NASA Marshall (Bihlman 2016).

melts the metal particles in the pattern matching that of the desired part geometry. Perhaps it is important to note an important technical misnomer. At the inception of PBF in the 1980s, powder was original fused (or sintered); however, current PBF machines actually melt the material, but the appellation remains.

The part is digitally decomposed into thousands of successive horizontal thin layers. After the first layer is melted, the build plate then drops imperceptibly, and a mechanical spreader adds another thin layer of powder. The melt-drop-add-melt sequence then repeats until the part is completed. As a result, the metal part is effectively "grown" in the vertical or z-direction, usually requiring thousands of layers.

One can imagine the repetitiveness of the process by simply understanding its small scale. The powder itself is a fraction of thickness of a human hair. For laser systems, the powders used in aerospace typically average 40µ in diameter (Uhlmann, Kersting, and Borsoi 2015). Powder for electron-beam (E-beam) systems is about twice that diameter mainly due to the prodigious amount of energy delivered by the E-beam (Bihlman 2016). Figure 16 illustrates the PBF build process.

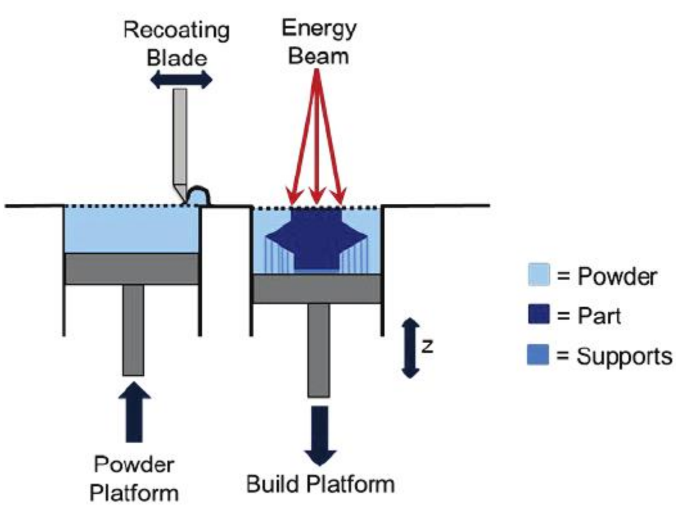


Figure 16: Schematic of the PBF process illustrating powder, part and physical supports

Given the versatility and relative affordability of PBF, it has become the most widely contested commercial market. There are a dozen known competitors globally, the largest of which include EOS, Concept Laser, 3D Systems, Renishaw, SLM, Additive Industries, TRUMPF, and Aurora Labs, with still more that seem to be entering this crowed space.

In general, most of the machine builders located in Europe. The powder, in contrast, is mainly created in the United States. Most powders are gas atomized and its chemistry and particle geometry are tightly controlled (Uhlmann, Kersting, and Borsoi 2015), so much so that few companies in the world can produce aerospace-grade powders, particularly for Ti 6-4. The United States also has the largest end-application markets for additive manufacturing, namely aerospace and medical.

2.2.2 Business Case Study

General Electric (GE) has invested heavily in additive manufacturing, and is often considered a leader in AM adoption as posited in Section 2.2. This century-old company was the first corporation to fly a safety-critical AM part on a certified product. The CFM LEAP fuel nozzle, as previous explained, has received considerable media attention since its introduction in 2014. In 2018, the company announced that it had printed its 30,000th fuel nozzle at its Auburn, Alabama facility. This is a dedicated 300,000-square-foot plant that contains 40 metal AM printers and over 200 employees (B. Jackson 2018).[4]

In 2017, GE acquired two leading AM companies, Arcam and Concept Laser, for $1.4 billion. Arcam was widely considered the market leader in E-beam PBF, and Concept Laser was top contender in laser PBF. GE then established a separate division – GE Additive, based in Munich, Germany – that is vertically integrated. This division sells machines, powder, services and will soon offer parts to the customers globally, in addition to the support it offers its parent, GE Aviation (Davies 2018).

There are a few other noteworthy GE-related developments. Within the past few years, GE Aviation has been developing a new aeroengine, under the auspice of its European counterpart. Walter Engine is a Czech Republic-based company that was acquired by GE in 2008 (www.geaviation.com). The aeroengine is called the Catalyst as shown in Figure 17.

[4] It is the author's opinion that GE made this strategic investment in additive manufacturing to vertically integrate, as it lacked assets in castings and die forgings, unlike its competitors Roll-Royce and Pratt & Whitney, respectively; a second factor is GE's exposure to medical, as biomedical and dental are major AM end markets.

It is a 1500-shaft horsepower turboprop that will compete directly with the P&W PT6A that has dominated the market for decades. The Catalyst is 35% printed. According to GE, 855 parts have been replaced by a dozen, mostly affecting structural castings.[5] This process has reduced weight and fuel burn, although perhaps more profoundly given the business model of aeroengines, it will likely reduce the product lifecycle management (PLM) related costs. Furthermore, and very germane to this dissertation, nearly a dozen suppliers have been eliminated (Brown 2018).

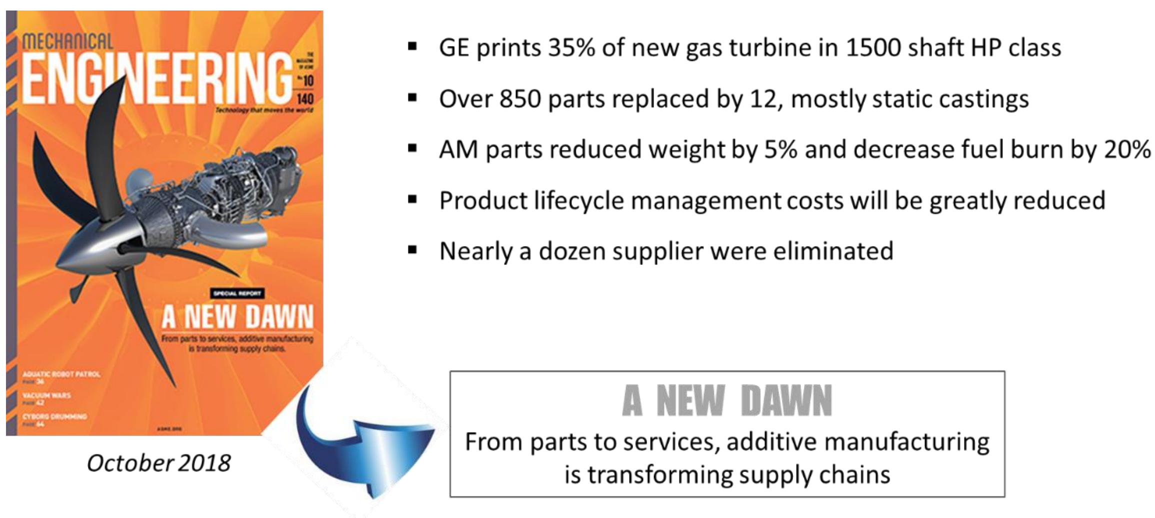


Figure 17: ASME magazine cover that featured the GE Catalysis engine

Next, there is the example of the mid-frame assembly that is also under development at GE Aviation. At an AM conference in October 2019, a GE General Manager shared a slide the underscored the impact of additive manufacturing beyond just product design. The slide is reproduced in Figure 18 on the following page. As shown in the slide, additive manufacturing is transforming the entire production ecosystem. Consequently, GE suppliers have been fundamentally impacted – both now and in the foreseeable future – by this new approach involving a digital manufacturing ecosystem.

The CEO of GE Aviation, David Joyce, summarized the organization’s position as, “additive fits GE’s business model to lead in technologies that leverage systems integration,

[5] For more information regarding trade-offs between AM and structural castings, see Kang and Ma (2017).

material science, services, and digital productivity" ("GE Offers $1.4B to Acquire Arcam, SLM Solutions Group" 2016). This ties seamlessly into the digital thread and digital twin concepts.

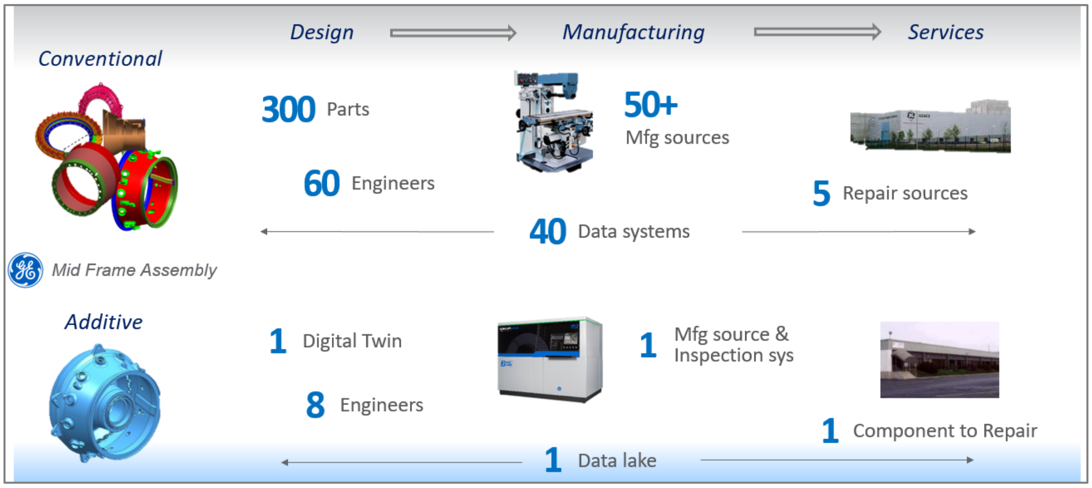


Figure 18: A GE slide showing the impact of additive manufacturing on an assembly

Finally, GE successfully printed one of the most flight-critical parts within the aeroengine – the low-pressure turbine (LPT) blade (Arnold 2019). These are flight-critical rotating parts that have historically been investment casted using a sophisticated material technology known as single crystal or simply SX. SX involves either lost-wax or spin casting. These are both long-standing casting processes readily used in aeroengine parts manufacturing. As a result, these super alloy SX castings have complex internal-cooling channels that prevent the part from melting as they endure the extreme conditions of the hot gas path.

The GE division responsible for printing the LPT blades is the Italian firm, Avio It was acquired by GE in 2013, and historically, Avio was best known for its aeroengine gearboxes. Avio is using a 3000-watt Arcam system to print the LPT blades using titanium aluminide (TiAl) (Kellner 2018), a material that shows great promise to create aeroengine parts.

TiAl has been used in the LPT since the 1980s. Nonetheless, it is well-known for being "light, expensive, brittle and hard to cast" (Herzner 2017) and extremely difficult to machine, according to Fred Herzner, the engineer who oversaw the introduction of the material during his tenure at GE. TiAl has a "very high contraction ratio and can become fragile and prone to cracks as it cools – E-beam printer solves these problems" (Kellner 2018). Avio will use these printed blades on the new GE9X engine that powers the Boeing 777X, as illustrated below in Figure 19 (www.geaviation.com). This is transformational.

Figure 19: AM printed TiAl LPT blades for the GE9X

2.2.3 AM Value Proposition

GE Aviation was able to leverage additive manufacturing to consolidate parts, as well as print LPT blades in lieu of using investment casting. Both of these applications are highly disruptive to business. In particular, SX investment castings can be produced by only a few foundries in the world. The financial operating margins, consequently, amongst this elite group of suppliers are extremely high. *In lies the true AM value proposition – its ability to displace well-entrenched suppliers*. Obviously this has very profound strategic implications for manufacturing companies throughout the supply chain.

In terms of the mobility industry, aerospace often considers itself unique due to the emphasis on product safety and the long-design life of the aircraft. Most aircraft have service lives that approach 30 years. As a result, aerospace designers need to account for fatigue, creep, and corrosion over this extended period, greatly complicating the initial design effort. Furthermore, it was explained that aeroengine components are subjected to extreme operating temperatures, in addition to caustics gases, and exceptional centrifugal forces. For instance, the force on each aeroengine fan blade at takeoff is nearly 200,000 lbs. (Michaels 2018).

As stated, additive manufacturing is particularly attractive for aerospace applications because it can be used to lightweight structural parts (Laureijs et al. 2016). As with any new technology, additive manufacturing was first used in less safety critical applications. Early applications include tooling and part prototyping for design verification, as depicted in Figure 15. The current challenge is to implement additive manufacturing for serialized production parts. This requires control over the entire build process, and the ability to safely and effectively scale the operation (e.g. see Kumar and Nair (2017)).

Part Consolidation

Part consolidation was introduced as a fundamental design and manufacturing advantage for additive manufacturing. Figure 20 shows a cost curve for a conventional manufacturing (CM) process versus that of additive manufacturing (Debroy et al. 2019). The marginal cost for the CM process fall precipitously due to the amortization of the initial non-recurring fixed costs. This is the cost of the tooling required to build parts, and in this case, it would be a reusable casting mold. The total cost of tooling includes the initial engineering effort (often referred to as NRE – non-recurring engineering), as well as the manufacturing of the tool itself. Since conventional manufacturing require tooling, whereas additive manufacturing does not, the AM business case must consider the total number of parts to be produced in order to ascertain the break-even threshold. For more information regarding fixed versus variable costs in manufacturing, see Frazier (2014).

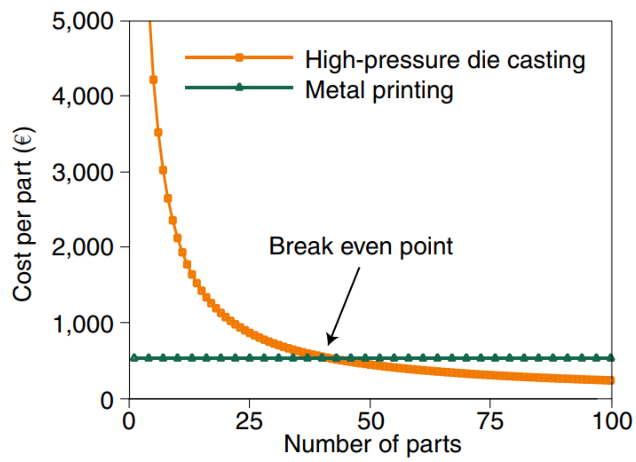


Figure 20: Cost comparison for an aerospace part using a CM vs AM process

From Figure 20, it is axiomatic that for small production runs, additive manufacturing is more economical than conventional manufacturing. In this case, AM parts would be cost effective for quantities less than the break-even point of roughly 40 parts. This explains why additive manufacturing is attractive for prototyping. It is further explains why additive manufacturing has been heavily research for its use in maintenance, repair and overhaul (MRO) of older, legacy aircraft. This is especially true for military MRO due to part obsolescence (Yusuf, Cutler, and Gao 2019; Singamneni et al. 2019).

In addition to the number of parts produced, a second critical consideration is part complexity. This directly impacts the cost of a part. Figure 21 below demonstrates that for simple parts, additive manufacturing is likely not cost effective (Debroy et al. 2019). This make intuitive sense given that simple parts are usually optimized to be built using conventional manufacturing. This figure is also consistent with "complexity-is-free" concept that was introduced in the opening of the dissertation (Lindemann and Koch 2016).

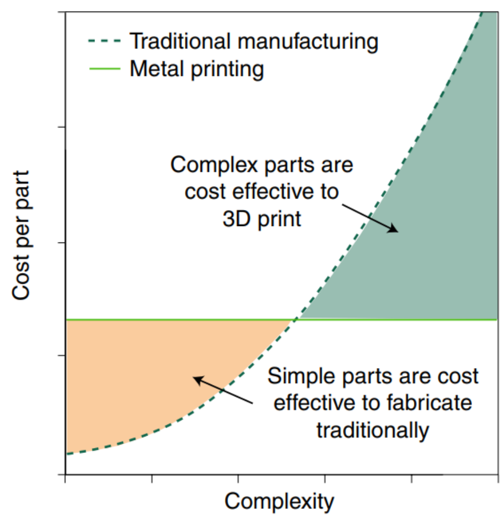


Figure 21: Part cost as a function of part complexity for CM vs AM processes

The ability to characterize the level of part complexity is a profound topic itself. There has been ongoing research that endeavors to quantify geometry and feature complexity for mechanical designs (Summers and Shah 2010). There are additional complications that arise from printing parts. Additional supports are needed to physically support the part as it is being built, as well as the need to dissipate heat in order to control the part's grain structure. Given some of these AM specific challenges, a rubric has been created that helps to quantify part complexity that also accounts for the physical-build process (Booth, Alperovich, and Reid 2017). This only focuses on single parts, however.

As introduced in the previous section, much of additive manufacturing's lure is to be able to consolidate parts as exemplified by the GE fuel nozzle. On average, the more parts involved, the more complex the assembly. Part consolidation is an important benefit of using additive manufacturing, so much so that it would be considered imperative for low-production runs to be considered cost effective. Consolidated AM parts are designed and optimized in a process known as "design for additive" or DfA. In general, this single AM part would have the same functionality as a CM cluster of parts or an assembly.

This concept is introduced notionally in Figure 22 below. The shift in the blue CM curve represents the additional cost associated with more parts and the need for physical assembly, which often includes manual labor in aerospace. Again, this is an essential consideration for the AM business case – designs that include AM parts will likely have fewer parts and less labor. Nevertheless, it is important to realize that a direct comparison between AM and CM parts is often difficult if not impossible. DfA AM parts will have fundamentally different geometry from the "corresponding" CM parts or assemblies. These unique approaches to design were introduced previously in this section.

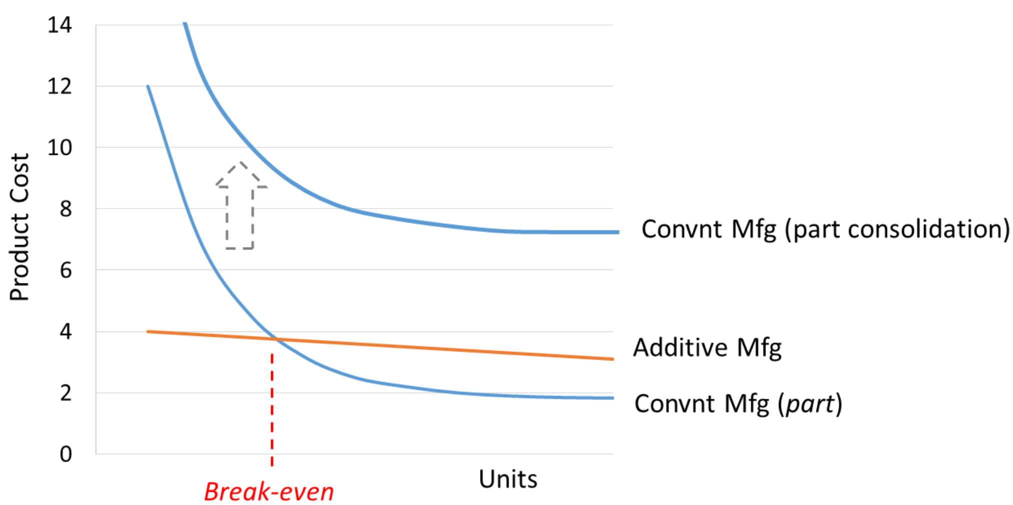


Figure 22: Notional cost curve for CM vs AM parts

One point to consider involving actual fixed cost. Forging press or casters are large, expensive pieces of equipment and are costly to maintain. Most often, unfortunately, internal company politics obfuscate the ability to objectively evaluate the actual costs associated with legacy production regimens for companies considering an AM alternative. Legacy processes and divisions involved in forging, casting, and extrusion inevitably feel threatened. As a result, a CM versus AM direct cost comparison undoubtedly suffers.

The initial set-up or fixed costs associated with tooling is not the only consideration when developing the AM business case. Another important consideration is the time required to develop and manufacture the tooling. Naturally, this directly impacts the available of the first parts for production. Molds and dies require lengthy development times that are often measured in months. For these reasons – number of parts produced, complexity of part, accurate fixed cost, premium for timely parts – make it very difficult to ascertain in advance the return on investment (ROI) for AM part substitution (e.g. see Fera et al. (2018)). Much of the business case is still managed iteratively as the technology and general knowhow evolves.

Material Efficiency

A final consideration for the AM value proposition concerns the efficiency of material use. Generally speaking, aerospace materials are expensive, and the CM process are considered inefficient. The aerospace vernacular for efficiency of material use is known as the buy-to-fly ratio. This is the amount of material purchased versus the amount of material that ends up in the aircraft. Average buy-to-fly ratios are around 7:1 for commercial aircraft (Michaels 2018). This implies that seven pounds of metal are required for every one pound of finished metal on the aircraft. This waste accumulates throughout the metal working process, from the initial melting and pouring of the ingot, to the metal that is machined away as scrap (Koenig 2020).

Roughly speaking, all AM modalities are considered more material efficient than conventional manufacturing; however, PBF is perhaps the most material efficient as it produces high "near-net" shapes that require minimal final machining (see Section 1.3.2 for details). And even though Ti 6-4 powder is expensive at $150 per pound, for example, the percentage of raw material cost for a final part is relatively low. Typically material costs for PBF parts are on the order of 5 to 10% of the total cost (Dutta and Froes 2017; Beck 2020).

2.2.4 Current Process Maturity

There are two fundamental challenges that have slowed the industrialization of PBF: *microstructure quality* and *process repeatability*. Both directly impact the part's final mechanical properties, and both can be *traced to the behavior of the AM melt pool* (Herzog et al. 2016). Controlled and precise mechanical properties are required to provide a safe and satisfactory design. The microstructure (or grain structure) is dictated by the crystallization of the metal, which, in turn, is determined by the rate of cooling of the molten material.

Heat transfer depends upon a number of factors, some of which can be controlled, such as the geometry of the part and build-plate packing density. Other factors have proven to be more difficult to understand. Note that the technology adoption for additive manufacturing will be discussed in more detail in relation its technical maturity. Nevertheless, as stated in the introduction of this chapter, this is no industry consensus for the levels associated with metal additive manufacturing.

Part Microstructure

Research has demonstrated the effects of part build height and rate of cooling. In particular, the metal build plate is an important factor. This large mass serves as a powerful heat sink; therefore, as the energy source moves further away from the plate during the build process, the part cools at a slower rate. This can create anomalies in the microstructure or grain of the material – such irregularities in the columnar grain are shown in Figure 23 on the following page (Herzog et al. 2016).

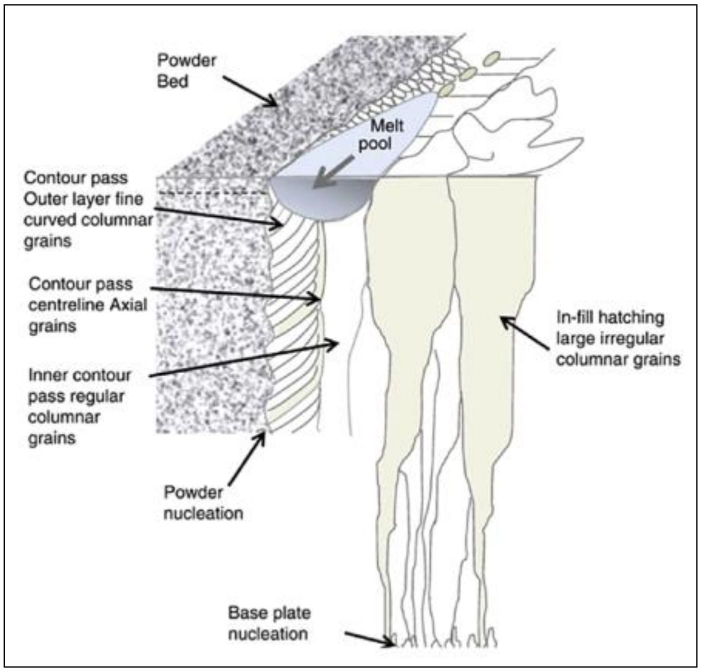


Figure 23: Schematic of variation of microstructure as a function of part height

A second physical phenomenon that affects grain structure is the melting and remelting of the various layers. As the energy source strikes the surface of powder, it melts these particles in addition to remelting a number of solid metal layers below the surface (Pollock 2019). This causes variations in the crystal morphology, which change as a function of the part's height. An example of the different grain patterns is provided by Herzog et al. (2016) in Figure 24.

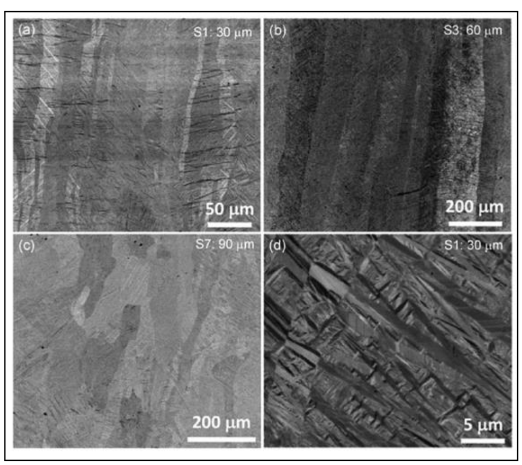


Figure 24: Grain boundaries of PBF part as a function of build height

Both of these factors create a high degree of anisotropy in the final part. The asymmetry of the mechanical properties vary spatially. This can be highly problematic if uncontrolled or unpredictable since it makes ascertaining material's physical properties (such as yield and fatigue) difficult.[6]

Process Repeatability

The issue of process repeatability with metal AM systems was brought squarely into the public's attention by a series of controlled experiments led by NIST from 2012 to 2015. There were eight different organizations that engaged in this "round-robin" study. The study focused on the mechanical properties of CoCr AM specimens build by five "nominally identical" laser-based PBF machines. The stated goal was to "develop a manufacturing plan and generate seed data for design allowable material properties" (Moylan, Brown, and Slotwinski 2020, 1012). The manufacturing plan included (2020, 1012):

- part geometry, location in the build volume, and orientation,
- machine requirements including suggested maintenance and calibrations,
- raw material requirements and material handling,
- building platform requirements,
- machine setup, laser exposure settings, and laser path strategy,
- in process monitoring,
- part removal, and
- post-processing of the part

Figure 25 on the following page demonstrates a considerable variation in stress of the final parts, particularly for laser systems (Moylan, Brown, and Slotwinski 2020). This scatter of 10 to 15% for the stress plots is disconcerting for aerospace designers in particular.

[6] Controlled anisotropy can be used in design optimization to maximize material strength, perhaps best illustrated via carbon-fiber composites – in components, the fibers are oriented in the direction of the maximum tensile load.

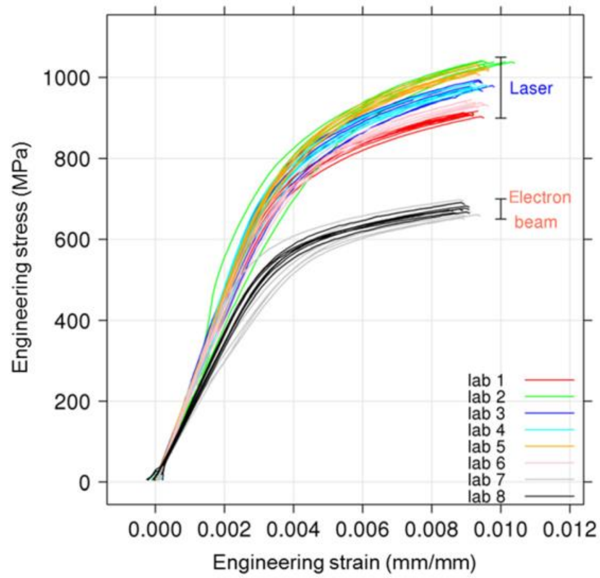


Figure 25: Stress-strain curves for the NIST BPF round-robin tests

Other important material properties were also tested. This includes ultimate tensile stress, yield strength, elongation, and material modulus. Figure 26 below includes all eight laboratories in a slightly different scenario (Moylan, Brown, and Slotwinski 2020). The blue entries were all from the same type of machine. The red entries are from three different machine manufacturers. Again, these results raise a number of questions about the technology readiness of metal AM systems for production-type environments.

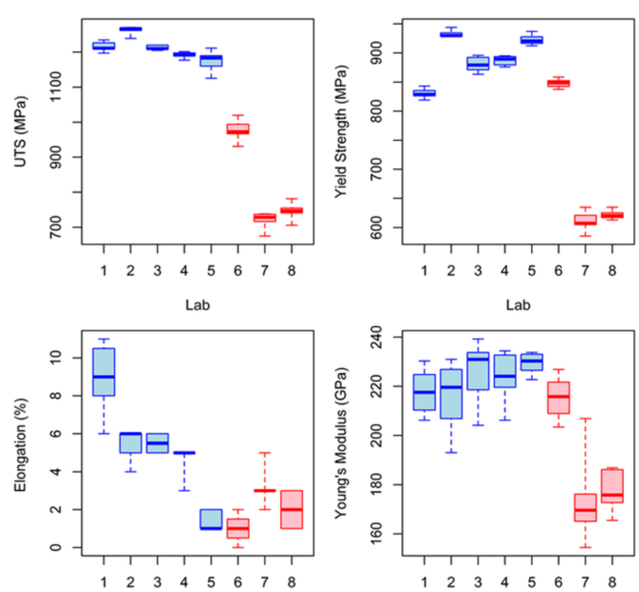


Figure 26: Additional material properties tested during the NIST BPF round-robin

Process Parameters

There are other challenges in PBF that affect build quality and process repeatability. A typical machine has well over 100 parameters that can be adjusted, not to mention the notion that PBF parts often vary from machine to machine for any given manufacturer. This is capture by the saying that "every AM machine is a foundry." In fact, there has been an ongoing debate within the SAE Aerospace Material Standards (AMS) AM standards committee about the extent of qualification. This work is still in progress.

Pal et al. (2016) discuss the impact of machine process parameters on a part's mechanical properties. Some of the key parameters along with typical values for a laser PBF system are summarized in Table 1 (Pal et al. 2016).

Table 1: Sample PBF machine process parameters that affect final part properties

Process parameters	Value
Laser powder, P	Varied from 150 W to 195 W
Scan speed, v	Varied from 700 mm/s to 900 mm/s
Scan type	Hatching
Layer thickness, H	40 μm
Trace Width (Laser Beam Diameter, D_{lb})	0.1 mm
Overlap of traces, OL	30%
Hatch distance, $h = D_{lb} - OL \times D_{lb}$	70 μm
Beam compensation, B_o	0.050 mm
Pre-Heating	40°C

A second article that discusses the impact of build conditions on material properties is Kok et al. (2018). It provides an excellent summary of the effects of various AM machine settings, such as energy source, preheat temperature, beam diameter, deposition rate and layer thickness. Grain morphology is creatively evaluated using inverse pole figure (IPF) coloring, producing illuminated crystal-orientation maps. This article underscores the importance of build parameters, and their difficult to control.

DebRoy et al. (2018) provides perhaps the most comprehensive analysis of the variation of mechanical properties between various metal AM modalities. Included are both PBF and DED systems. Their analysis covers the theoretical foundations of heat and mass transfer for those interested in a deeper mathematical understanding. By contrast, a simpler treatment of the same topic is offered by Yang et al. (2017).

Machine parameters are certainly critical, but there are other important factors. There are at least four other areas that need to be considered and controlled, this includes Material, Labor, Post-processing, and Inspection. Each area has a series of items that need to be monitored. This entire ecosystem is captured in the following Figure 27 (Bihlman 2017).

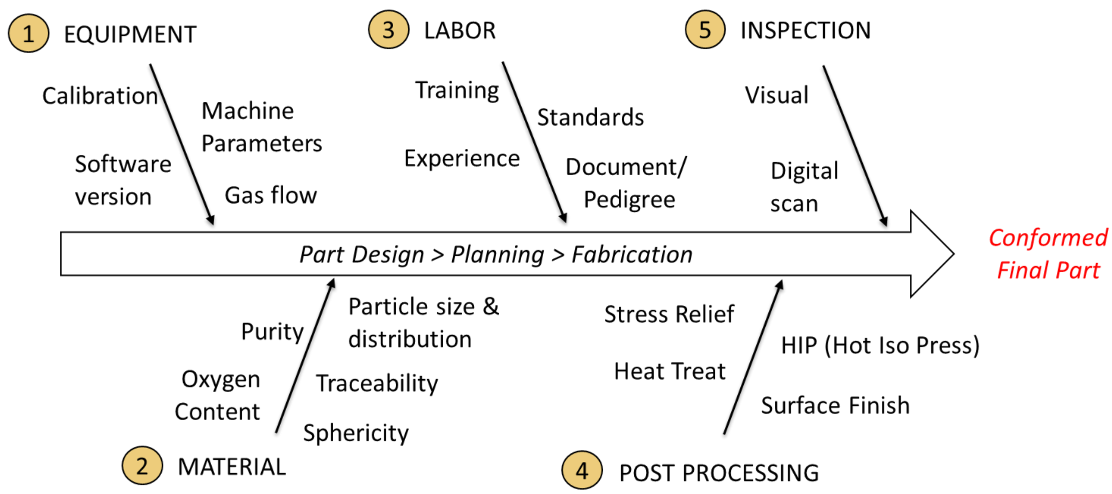


Figure 27: Critical process control parameters for PBF systems

Process Monitoring

The inability to accurately model the melting process, in conjunction with inadequate *in-situ* process monitoring, have also impeded technology commercialization. The complex thermodynamics process makes it extremely difficult to predict part integrity. Additionally, ongoing research has attempted to classify defects – such as voids and occlusions – to determine potential impact on final-part mechanical properties (Seifi et al. 2016).

In general, there are parallels between AM parts and castings when compared to forgings or extrusions. The similarity between the two processes involves the ability to create more complex geometries than a forging or an extrusion. Nonetheless, the grain structure of a casting is fundamentally different from that of additive manufacturing. It has yet to be proved that PBF and investment castings are analogous in terms of failure modes, for example. This type of uncertainty is unacceptable for commercial aerospace.

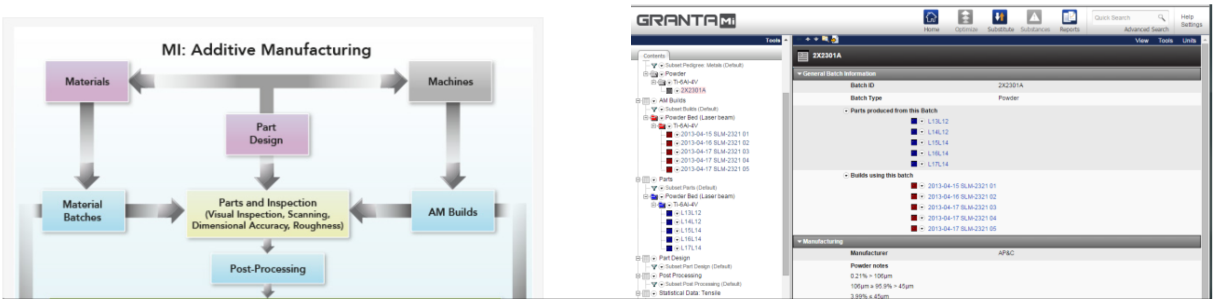
One method to mitigate risk and bound uncertainty is to implement tight process control parameters for the factors identified above in Figure 27. To the extent possible, a Pareto analysis can be performed to identify key input variables. Moreover, with the advent of machine learning, uncertainty quantification (UQ) has become a particular popular field of study. This corresponds to the availability of more sophisticated mathematical models, increased amounts of field data, and greater computational power.

Part Pedigree

Overall, thorough and accurate documentation was determined to be one of the most important controllable parameters for aerospace confirmed parts. With the gigabits of data involve in the total AM build process, proper recordkeeping is even more challenging. The common parlance is now known as part pedigree, and is fundamental to promoting the notion of the increasingly important digital thread (West and Blackburn 2017; Kim et al. 2015).

It is worth noting that the National Institute for Standards and Technology (NIST) is playing an important role in developing AM-specific data requirements via its Measurement Science for Additive Manufacturing (MSAM) program (Witherell 2017). Assuredly, other programs are underway throughout Europe, as well. And harmonization between ASTM and ISO will help to drive convergence and expedite adoption of standards at the global level ("The ASTM International/ISO Partner Agreement" 2011).

One example of a commercial entity offering a solution to the challenge of documenting the part pedigree is Granta Design. On the following page, Figure 28 illustrates a software solution offered by Granta Design to tracking and identifying specific AM parts. This is critical for aerospace parts given the rigor required by the FAA and EASE for critical flight hardware. Nevertheless, as of 2020, there are no formal requirements by either organization regarding the type and extent of data storage for AM parts. Granta's software joins a fairly competitive pool of global suppliers, including two leaders in the digital thread domain: France's Dassault Systemes and Germany's Siemens Corporation.



Layout Headings - Granta AM Schema v1.01

Machines	Materials	Part Design	Material Batches	Builds	Parts
General Information	General Information	General Information	Project Information	Project Information	Project Information
Calibration	General Properties	Original Design	General Batch Information	General Information	Part Information
Machine Specifications	Composition overview	Re-Design	Manufacturing	Build Information	Part Specifications
Material	Bulk Mechanical Properties	Dimensions	Material Quality	General Build Parameters	Samples
Machine Properties	Bulk Thermal Properties	General Material Properties	Particle Properties and Size Distribution	Build Atmosphere	Visual Inspection
Build Environment	Bulk Electrical Properties	Processing	Interstitial contamination	Material Used	Accuracy Testing
Laser Properties	Biological	Static Tensile Properties	Flowability	Support	NDT Testing
Electron Beam Properties	Chemical	High-cycle fatigue properties	Wire Properties	Filament Information	Post Processing
	Eco	Fracture Toughness	Chemical Analysis and Composition	Substrate	Heat Treatment
	Cost	Fatigue Crack Growth		Quality of Welding Consumables	HIP
	Safety and Handling	Surface Roughness Requested		Build Alarms	Machining
	General Information	Other Requested Properties		Themes Used	Laser Polishing
	Requirements	Final Part Details		Powder Build Parameters	Other Post Processing

Figure 28: Sample software to manage part pedigree for AM process

Raw Material

Finally, there are a few concerns about the AM raw materials that should be addressed. Metal powder is just as critical to the part's final properties as machine parameters and post processing, and its characterization is quite elaborate (Slotwinski et al. 2014). Without exception, all metal powder and wire currently used in aerospace applications were not developed for the AM process. The certification path is costly, and in order to help reduce risk of mechanical failure, OEMs prefer to use existing materials.

There are some exception. Most OEMs do not want custom alloys as part of their certified product if the mill supplying the metal is not willing to license it to other mill producers. Without this agreement, OEMs would be forced into a sole source contracts with proprietary metals, which is risky from a long-term sourcing strategy. Perhaps one of the more illustrious recent examples is ATI's struggle to fully commercialize its Inconel 718-plus. Its initial adoption was slow because of ATI insistence on sole sourcing the material, according to one of its former marketing executives.

To minimize sourcing risk, OEMs prefer to utilize commoditized materials. Titanium grade 5 (i.e. Ti-6Al-4V or simply Ti 6-4) being among the most common alloy and is used extensively in both the aerostructure and aeroengine (Uhlmann, Kersting, and Borsoi 2015). For this same reason, the most ubiquitous AM metal powder is Ti 6-4, although it was not initially developed and optimized for powder applications. This has created limitation. A similar story is seen with the popularity of nickel super alloys, namely IN 718 and IN 625, and stainless steel, principally PH 17-4 (Koenig 2020; SAE International 2018). These metals were developed for forging and wrought products, and not powder-made parts.

The chemical composition of a powder may change when melted via laser or E-beam. In particular, some of the chemical compound may be altered, affecting the part's material properties. One such example is the disproportionate vaporization rate of aluminum versus titanium in TiAl. Additionally, alloys such as titanium and aluminum in powder form are highly reactive with oxygen. Thus, these powders are melted in an inert environment – usually an argon-filled chamber for PBF. Many believe that additive manufacturing will improve markedly with the onset of custom-designed alloys. This is another important area of research.

Lastly, a comment about the Materials Genome Project. This is research being conducted by the Integrated Computational Materials Engineering (ICME) consortium. ICME will likely help develop powders specifically designed and optimized for additive manufacturing. Work within the last decade from this emerging discipline has accelerated materials development by using a holistic system's approach. This has been facilitated in large part by more accessible supercomputing. ICME modeling involves complex mathematical formalisms, and incorporates multi-physics, multi-scale characterizations. Rolls-Royce is a founding member of the consortium. Aerospace high-temperature materials – including both metals and ceramics – have been identified as one of the priorities of the organization (Cedoz et al. 2014; Martukanitz et al. 2014).

2.2.5 Testing and Evaluation

The FAA mandates that the likelihood of critical part failure is substantiated to a probability of failure of one in a billion. Structural assemblies need to conform to what is called A- or B-basis allowables, depending upon system criticality to the aircraft's airworthiness. The specifics are not important beyond the fact that A-basis is more stringent and is applied to the aircraft's most critical systems and components. In particular, A-basis requires at least 99% of the test population to exceed a minimum specified value. This is in contrast to B-basis that has a 90% threshold (Rice et al. 2003). These design requirements are codified in 14 CFR §25.613.

This rubric determines the extent of the structural redundancy in order to maintain safety margins (Gorelik 2017). Thus, A-basis allowables require greater structural redundancy to prevent a catastrophic failure. Figure 29 below illustrates a typical design margin (or margin of safety) for engineering-related parts. Since lightweighting is essential, aircraft tend to have the lowest margin of safety of nearly any other industry. Aircraft margin of safety is typically between 1.5 to 2:1, whereas automobiles is typically twice that figure (Bihlman 2016).

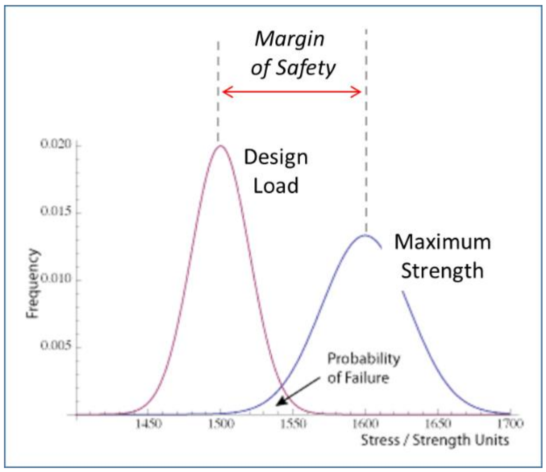


Figure 29: Notional design margin-of-safety for structural parts

The FAA does have a precedence for addressing material characteristic variation as influenced by manufacturing process. Casting provides the easiest comparison in the form of a "casting factor." The margin of safety for a casting can be either 1.0, 1.25 or 1.5 as prescribed by 14 CFR §25.621. The choice of casting factor depends upon three criteria – the level of criticality of the part, the extent of material testing conducted, and the amount and type of inspection performed. Hence, investing in more extensive testing and inspecting can potentially lower the casting factor, and thus, the weight of the final part.

A second important factor is "the fidelity of applicable NDI (non-destructive inspections)" techniques commonly used to interrogate castings (Gorelik 2017, 172). Consequently, the FAA is using a similar approach to determine protocol for AM part substantiation. Current policy involves point design, supported by testing on a part-by-part basis. Each candidate must petition the individual design as directed by an FAA Issue Paper (Werner 2017; FAA 2020). It is understood, nevertheless, that the FAA is drafting a more comprehensive policy Advisory Circular (AC). This will provide more clarity to companies interested in pursuing AM parts. Some initial considerations for the qualification path for AM within commercial aerospace were discussed in Seifi et al. (2017).

It is important to note that both the raw material and manufacturing process require formal FAA conformity. Logically, uncertainty from either item can be compensated by simply increasing the design margin; this, in turn, increases part weight and ultimately the aircraft operating cost. Final part design often judiciously balances stress mitigation, damage tolerance, operating life, and weight. These design trade-offs need to be considered in light of the total system design objectives, as constrained by the program budget and schedule.

2.2.6 Challenges for Mass Adoption

The previous two sections addressed the main concerns for AM adoption, issue that surround microstructure, process monitoring and repeatability, and final part inspection. This section discusses some aspects regarding adoption based upon historical precedence. First, there are a two cautionary tales provided. Both underscore the mercurial nature of a burgeoning technology in terms of perceived risk. This section then concludes with observations regarding the important role of governmental policy in managing technology diffusion.

Worldview is essential. In his 1962 book, *The Structure of Scientific Revolutions,* Kuhn first introduces the world of science to the concept of paradigm shift (Kuhn 2012). He explains that changes of worldview are often gradual, or at least slower than history often acknowledges. There are many facets that influence this rate of adoption, and how well received this new concept is within a given society. Perhaps most important is the individual who originated of the idea. Indeed, a perceived "outsider" will likely have a difficult time establishing credibility due to an initial bias or mindset of the establishment. This alone can completely stifle change.

The first cautionary tale is in regards to incorporating computers within machine tools. This is a story of the collision of two fundamentally different cultures. As Olexa explains, the advent of computer numeric controlled (CNC) machining in the early 1960s was confounded, in part, by the fact that the individuals who were selling the idea "didn't really know manufacturing – they were computer people" (Olexa 2001, 43)

This is a striking analogy in light of today's challenges of adopting additive manufacturing. The market leaders for AM machines are not the traditional manufacturers of

CNC tools, such as DMG Mori, Mazak, Makino, Mitsui Seiki or Okuma. Mostly Japanese corporations that have likely flourished in connecting with the automotive industry. The incumbents, naturally, will not likely cannibalize their own products. In most situations, famed Harvard Business School professor Clay Christensen argues that true disruption rarely originates from within an organization.

For AM, a majority of the companies started with an expertise in lasers. Example include EOS (Electro-Optical Systems), SLM, 3D Systems, Concept Laser, and RPM Innovations. It is this author's opinion that many traditional members of the aerospace supply chain, including the OEMs themselves, consider these companies as industry outsiders, or at least initially – perhaps for good reason. They lack the decades of experience building qualified flight hardware. The entrance of traditional CNC companies into additive manufacturing, such as DMG Mori, Mitsui Seiki, or more recently, the machine-tool maker Sandvik, will only help accelerate support for overall AM adoption in aerospace. Their market entry serves as a harbinger to the disruptive potential of additive manufacturing.

The second cautionary tale is specifically related to aerospace. It also involves powder metallurgy (PM), and a prediction for its market penetration. The events unfolded in the 1970s. In general, PM parts have better mechanical properties due to its small, uniform grain structure. According to FAA Chief Scientist for Fatigue and Damage Tolerance, Michael Gorelik, the early development of super alloy PM carried great expectation. This was to significantly increase the performance of forged disks in the aeroengine hot section (Gorelik 2017).

As early as 1971, it was predicted that "in 5 years, 20 to 25% of the weight of advanced engines would be PM super alloys" (2017, 170). Today that value is still less than 15%. What happened? An F-18 fighter jet crashed in 1980. Impurities associated with PM in the LPT disk were deemed the cause (Gorelik 2017). The lesson learned from these events is that any catastrophic high-profile failure could mortally wound the accent of additive manufacturing within aerospace.

Lastly, it is worth observing what the role of government regarding AM technology diffusion (Schniederjans 2017). As with most public policy, this is not without some controversy. The government has a role in the diffusion of nearly any technology; however, their role is considerably more salient within industries that are heavily regulate, with the goal of protecting the general public. Examples of such industries include commercial air transportation, pharmaceuticals, and nuclear power generation.

Some would argue that governments should not interfere with market forces by actively picking winners and losers. Nevertheless, the United States, China, Singapore and the European Union have proactively committed hundreds of millions of dollars to develop and to actively promote their AM industries. In many cases, it is viewed as an opportunity to revitalize domestic manufacturing and decrease foreign dependency for strategic industrial goods. And, in some cases, it even became an issue of national pride. The result is a tension among global policymakers (Roca 2017).

Government sponsored topics range from somewhat controversial issues to less contentious – for example, environmental safety to workforce development (Simpson, Williams, and Hripko 2017). The extent of a government's willingness to subsidize technology diffusion will remain a topic for debate for the foreseeable future. At any rate, its involvement will not be without meaningful consequences to the technology's diffusion.

2.3 Supply Chain Implications

The previous two sections introduced two essential concepts. First, the notion that the commercial-aerospace supply chain can be modeled as a well-structured hierarchy was presented. Secondly, it was argued that commercial aerospace is extremely risk averse, and would be slow to adopt additive manufacturing given its current list of technical limitations (as outlined in Section 2.2.4). For the purposes of modeling the supply chain, these challenges are addressed simply by the categorical assumption of proper "technology maturity" at some point in the future. This is a key assumption that will be discussed in Chapter 4, Methodology.

The scope of this dissertation was delimited in Figure 6 as the production network and the individual production line. In order to measure and ultimately to predict the behavior of this network, however, it is imperative to develop the relevant metrics. Since the model is limited to these two higher levels of abstraction, performance metrics will likely be in terms of economic factors. Nevertheless, the exact metrics and corresponding model still needs to be devised. The following chapter investigates various methodologies that might be a suitable framework to develop such an economic model.

3. LITERATURE REVIEW

There has been a significant increase of AM publications since 2010. Nevertheless, most publications ignore the implication for the broader supply chain. This general trend in publications is summarized by Costabile et al. (2016) in Figure 30, which is consistent with Singamneni et al. (2019), in addition to the author's personal experience.

In light of Figure 30 below, an independent search was performed to verify the continued trend of the accelerated increase in AM research and the dearth of supply chain literature beyond 2015. Purdue's Engineering Village was used to query both Compendex and Inspec databases and to conduct a search for 2018 articles using the delimiter [{additive manufacturing} OR {3D print*}] – the total number of article was 5358, including 3437 journals. For comparison, a similar search with Google Scholar yielded over 50,000 results. The figures dropped precipitously when adding the additional constraint [... AND {supply chain}]. The net result is a paltry 24 articles, or roughly 0.5% of the total for that year. Furthermore, when adding the character string either aerospace or aviation or aircraft, the number then drops to only 5 articles for all of 2018.

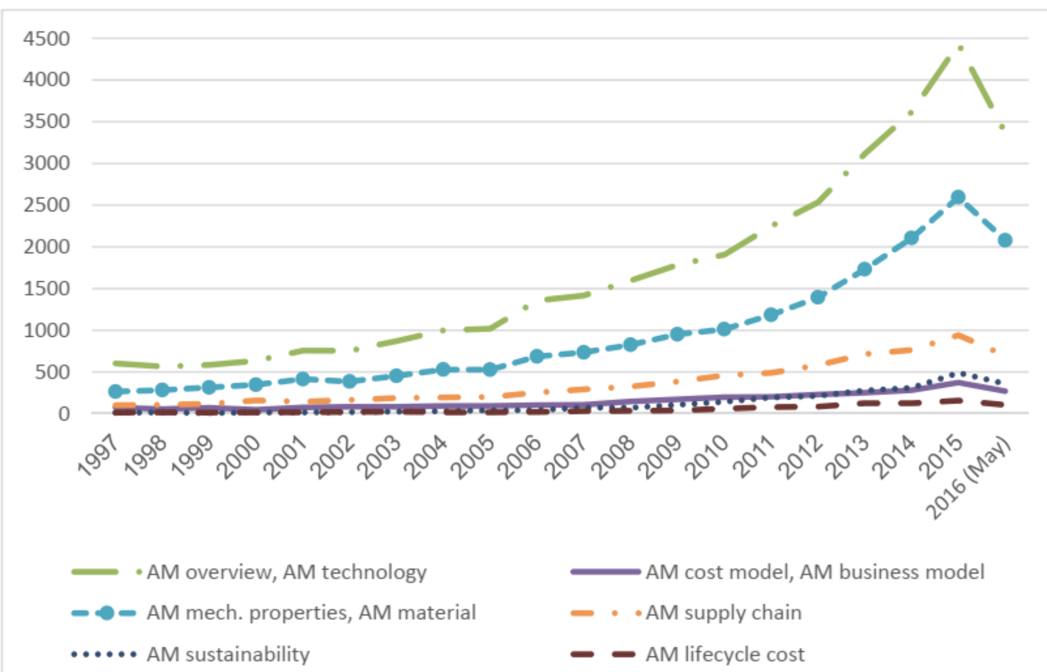


Figure 30: Various AM-related publications from 1997 to 2015

Generally speaking, the various supply chain articles target low-rate production scenarios. This concept was introduced in Chapter 2, including the additive manufacturing's appeal for military aircraft maintenance, repair and overhaul (MRO). The use of additive manufacturing to produce military spares of obsolete parts creates a compelling business case; in fact, this scenario dates back to as early as 2003 for the McDonnell-Douglas/Boeing F-18 jet fighter (Engler-Modic 2018).

According to US Air Force Reacher Laboratory (AFRL), the average age of its fleet is 27 years. It is easy to imagine many of these parts are no longer stocked, and the tooling for spares is likely unavailable. In fact, a recent presentation from a chief engineer from Boeing St Louis revealed that his foray into additive manufacturing resulted from a casting for a military aircraft that had a two-year lead time (Wegge 2019). For both commercial and military aircraft, the opportunity cost of aircraft-on-the-ground (AOG) situations can be prohibitive (Togwe, Tanju, and Eveleigh 2018).

There are a number of other articles reviewed that address the AM business case (e.g. Oettmeier and Hofmann 2017; Niaki and Nonino 2017). These were deemed too generic to be applied to critical aerospace parts, however. An adequate critique of AM adoption requires proper understanding of the intersection between cost and design, a notion introduced in Section 2.2.3. Thus, approaches such as Lindemann and Koch (2016) and Busachi et al. (2018) provide some insight regarding methods. In the context of the business case, Stevenson et al. (2017) astutely considers the argument of part consolidation, in addition to Singamneni et al. (2019). This is truly central to the AM business case. At the same time, none of these resources provided a methodology that seemed suitable for serialized production of commercial aerospace parts.

For serialized production, it has been argued, it nearly impossible to justify additive manufacturing without invoking complex geometry. This requires a certain working-level knowledge of mechanical design. Various design approaches were reviewed initially, such as the role of modularity Baldwin and Clark (2000), and the notion of the conceptual design space (McManus, Hastings, and Warmkessel 2008). Articles that specifically addressed design complexity were also studied, including Williams, Panchal, and Rosen (2003) and Booth et al. (2016), as well as the well-known experts in this field, Summers and Shah (2010). In the end, most researchers seemed to specialize in the engineering design or manufacturing. Their methodologies were too narrowly focused to be applicable to this research.

On the other hand, articles that addressed AM's impact on the supply chain from purely an economic standpoint were deemed of little value (e.g. Scott and Harrison 2016; Feldmann and Pumpe 2017; Barz, Buer, and Haasis 2016). Most use a methodology comprised of transportation or inventory cost optimization, a standard practice in operations research. This seems reasonable for commodities and consumer goods, but insufficient for aerospace production. Recall the emphasis on both artifact design and production.

Other industries were also consider concerning some type of technology adoption-prediction methodology. For example, automotive uses additive manufacturing, and there are many similarities to aerospace, but it uses additive manufacturing primary for tooling and rapid prototyping (Leal et al. 2017; Bahnini et al. 2018). Thus, that would not serve as a wise comparator. In general, automotive's volumes are too high to consideration additive manufacturing for serialized production, a concept posited in Chapter 2.

Next, biomedical was used as a possible benchmark since it second largest AM market behind aerospace (Debroy et al. 2019). Moreover, like commercial aerospace, biomedical is heavily government regulated. This proved to not be a meaningful comparison, either. The biomedical community does in fact use Ti 6-4 extensively; although, there are appreciable differences in part size and end-use application (Sing et al. 2016), making synergies between markets tenuous at best. Recall that creep and fatigue are the primary failure modes in aerospace, due to the extreme temperatures and forces. This places exceptional emphasis on the quality of the microstructure and, in particular, size and quantify of the grain boundaries. Alas, additive manufacturing's application in aerospace is truly unique.

In conclusion, there is no known research that adequately addresses the intersection of the supply chain with that of serialized parts production for aerospace. Without a reasonable precedence, it is therefore necessary to create a methodology to predict the impact of additive manufacturing on the aerospace supply chain. The following section explores potential paths.

3.1 Methods Review

Careful consideration of the research topic over a four-year period has led to the conclusion that – in order to properly model this problem – techniques from multiple domains will be required. The solution would need to be multistep and multidisciplinary, involving at least four domains: engineering design, manufacturing, systems engineering, and supply chain.

The following Table 2 summarizes some of the common attributes associated with these domains; meanwhile, a few other related areas were explored. Interestingly, although all involve systems thinking in some capacity, each has somewhat of a unique approach and associated method for addressing a given system as a result of the field's own heritage.

Table 2: Summary of research broadly related to the topic of interest

Domain	Type	Typical Discipline	Research Genesis	Popular Research Focus	Key Researchers
Manufacturing	Field	IE, ME	mid 1800s	Automation, digital enterprise, precision machining, sustainability	Dickerson, Yamazaki, Koren
Additive Manufacturing	Field	ME, MSE, AE, Physics	1990s	Melt pool and build analysis, process repeatability, microstructure	Bueth, King, Simpson
Supply Chain Management	Field	Mgmt, IE	1930s	Last mile, inventory, in-bound logistics, digital thread	Chopra, Shapiro, Simchi-Levi
Operations Research	Field	IE, Mgmt, Stats, CS	1940s	Queuing, critical path, throughput optimization	Nelson, Nocedal, Shanbhag
Systems Engineering	Field	IE, EE, Mgmt, Life Sci	1940s	Production lifecycle mgmt, config mgmt, simulation, model standards	Buede, Miller, Schindel
Network Theory	Method	Math, CS, IE, CE, Soc Sci	1950s	Neural nets, Internet, power grids, transportation	Newman, Faloutsos, Renyi
System of Systems	Field	AE, IE, CE	1980s	Fault mgmt, transportation, space exploration, warfare	DeLaurentis, Luzeaux, Lane
Agent-based Modeling	Method	Info Sci, Soc Sci, IE, AE	1980s	Supply chain, distributed computer, biological evolution, portfolio mgmt	Railsback, Fagiolo, Carley

There are a few things to note about this table. Most importantly, it is not a comprehensive summary of all the areas that were explored during this research endeavor. For example, the well-known system engineering V-model was not included, but is presented later in this document. The purpose of the table is to provide readers with insight regarding the research journey; in particular, it includes topics that were pondered initially in the process of selecting the final research methodology.

Secondly, the table is organized chronologically by topic. This is an estimated timeframe for the origin of the stated field (or research method). In other words, it is the period when the field had become more formally recognized as a research discipline. The third consideration is that the three indented topics are subcategories of the topic which they proceed. And finally, the fourth point is that only a few topics warranted further investigation, and are subsequently presented herein. More precisely, the areas discussed in the following sections include: supply chain, systems engineering, networks, and operations research (in the form of integer linear programs).

The literature review was vast, starting with a general search of scholarly methods loosely associated with networks, systems, and manufacturing supply chains. Consequently, it varied not only in end application and breadth of topic, but also by level of abstraction and mathematical rigor. The unifying theme was systems and mathematical modeling. Topics ranged from traditional domains of various forms of network optimization to product lifecycle management (PLM) and systems engineering – to even more philosophical contemplations – including that of ontology and notions of genre.

The works of various eminent scholars were reviewed, including: Bonabeau, Deming, Jackson, Maier, Newman, and Simon, and von Bertalanffy to name a few. The following summarizes the most salient sources. In general, the section begins rather broadly, but finishes more focused, closer aligned with the research topic at hand.

3.1.1 Supply Chain Management

Supply chain management was the first area targeted for the literature review. As mentioned, there is very little published research that involves additive manufacturing in this field. It stands to reason as the AM science itself is still evolving; thus, the idea of eventual scaling the operation for its wide-spread industrialization is secondary at best.

The discipline of supply chain management (SCM) is rooted in the 1950s. According to Huan et al. (2004), there was a dramatic increase in research publications since the 1990s. There are three basic categories of study: operational, design, and strategic.

Operational SCM focuses on the daily operations of the facility, either the plant or the distribution center. The primary focus is inventory management and distribution. The second area, design, involves studying the physical location and the objectives of the supply chain itself. And the final area, strategic, includes the various decisions made by business managers that require fundamental knowledge of the dynamics of the supply chain. This includes topics such as strategic sourcing, resilience, etc. (Huan, Sheoran, and Wang 2004).

Each area has its own domain of mathematical models and approaches. Notwithstanding, none of these seem to offer an adequate methodology to model the strategic implications for additive manufacturing, as contemplated by this dissertation. One of the preeminent text books on SCM is by Chopra and Meindl (Costantino et al. 2012). As an aside, Professor Sunil Chopra from Northwestern University was contacted for this research – his comments will be addressed later in the Chapter 6. Due to the lack of precedence for a reasonable SCM methodology, it was decided that a much broader approach was required.

3.1.2 Systems Thinking

The exact definition of what constitutes a system has been long since debated. According to International Council on Systems Engineering (INCOSE), the most basic definition of a system is an interacting combination of elements, viewed in relation to function (Buede and Miller 2016). Systems thinking is a process of viewing various phenomena in the context of a broader system.

The foundations of systems thinking can be traced back to the ancient Greeks. Indeed, Aristotle used this notion to illuminate the fundamental nature of the ethereal – the body and soul – as well as the more immediate and practical – the relationship between the individual and the State. He posited, for example, the soul gives the body its purpose and, by extension, its fundamental identity. This general concept is known as *telos*, an entity's ultimate purpose or goal. Furthermore, parts (of the body, organism, system, etc.) can only achieve their purpose through this entity – for instance, an eye can see only when connected to the body (M. C. Jackson 2007). Systems and philosophy, akin to science in general, are inextricably linked.

Most believe it was von Bertalanffy's seminal article in 1950 that formally established systems thinking as an intellectual movement (M. C. Jackson 2007). In his *The Theory of Open Systems in Physics and Biology*, von Bertalanffy provides first principles for the distinction between closed and open systems. In particular, he elucidates key elements of an open system, namely that of *feedback*, *regulation*, and *equifinality*. Each of these are required for a system to avoid chaos and disorder.

It is suspected that Bogdanov's *Tektology*, published in Russia in the 1920s, and Wiener's work on cybernetics[7] during in the United States in the 1940s, served as foundations for Bertalanffy's research. This culminated in his publication in 1968 called *General Systems Theory* (M. C. Jackson 2007).

Another pivotal figure in systems thinking, particularly in light of industrial engineering, is W. Edwards Deming. With a PhD in physics, he was most known for his work in applied statistics, and its application to industrial manufacturing quality. In fact, he is attributed as the person who helped Japan recover from WWII by systematizing efficiency and quality metrics (Aguayo 1991).

His book *Out of the Crisis* in 1982 established his worldview, known as System of Profound Knowledge. Deming outlined four fundamental areas of understanding that need to be mastered to properly study a given phenomenon, specifically knowledge of: the system, variation, psychology, and epistemology (Deming 1986). There is strong evidence that Deming was heavily influenced by the profound philosopher C.I. Lewis, founder of conceptual pragmatism (Cunningham 1994).

3.1.3 Ontology

One of the fundamental precepts of systems thinking is the idea of morphology. It pertains to the study of structure and form. Problems (or systems) can be decomposed into basic variables or fundamental elements. These parameters can be arranged to form a series of logical permutations, known as a morphological box (Hall 1969). Thus, each combination of these elements defines a potential solution to the problem being studied. According to Hall, effective systems engineering entails at least three dimensions.

First, the element of time is considered, delineated by major milestones. The second dimension is that of a problem-solving procedure – this traces the progressive logic required to solve a particular problem. The final dimension is that of body of facts or models that constitute a particular discipline. The extent of mathematical formalism can be yet another interpretation of this dimension (Hall 1969). More recently, this construct has been applied to areas of mechanical design (Buede and Miller 2016).

[7] Originally, this was defined as the science of control and communication, and included both man and machine, rooted in negative feedback – it later evolved into control theory (M. C. Jackson 2007).

A similar concept to morphology, yet on a more elemental level, is that of ontology. Or more simply, classification. This is considered one of the most fundamental branches of metaphysics. It endeavors to identify the most basic features of reality. Therefore, it is unlike other disciples of science that address only entities within their purview (Guizzardi 2005). Developing this taxonomy is arguably the most fundamental step before pursuing more complicated analyses of structures, organizations, phenomena, etc.

Ontology helps delineate borders and identify thresholds between states or taxonomies. This, in turn, enables one to ascertain the question at the heart of philosophy – as illuminated originally by Socrates – what matters and why? In a word, essence. Or in a deceptively simple and seemingly jocular example – what makes a bird a bird?

In his PhD dissertation, Guizzardi uses this method of deconstruction to build a schema that eventually results in a modeling language. This is especially noteworthy in systems since this Unified Foundational Ontology (UFO) is the predecessor to Unified Modeling Language (UML). The later has become the basis for metamodeling in systems engineering. More precisely, System Modeling Language (SysML) is the *de facto* modeling language in system engineering, and is an extension of UML.

An understanding of the logic underpinning UFO – given the parallels – would help users of SysML. The relationship between model-concept-language-specifications is presented in Figure 31 (Guizzardi 2005). This has become a familiar construct to anyone comfortable with modeling in SysML.

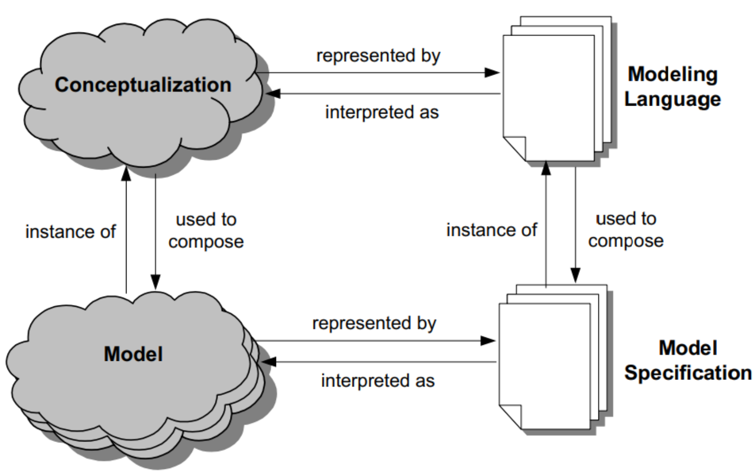


Figure 31: Ontological relationship for four basic elements for the UFO language

This work is should be viewed in light of Morris' contribution to elements and relationships, published in the 1930s. Specifically, he proposed that any language requires three essential components: semantics, syntax, and pragmatics (Morris 1938). Semantics is the meaning of the word or label (i.e. its significance). Syntax is the relationship between these entities. And pragmatics is the relation of these entities to its interpretation, or its *deixis*. In other words, vocabulary that needs to be considered in proper context to provide an accurate interpretation.

Ultimately, ontology can be used to establish theories of causality and change. Questions regarding classification, evolution, essence, whole versus part can be addressed more systematically (Guizzardi 2005). The following figures provided examples of relationship classification – the first for genealogy (Figure 32 by Guizzardi (2005)), and the second for manufacturing in the figure on the following page (Figure 33 by Farid (2007)). In each case, the decision logic is mapped in detail.

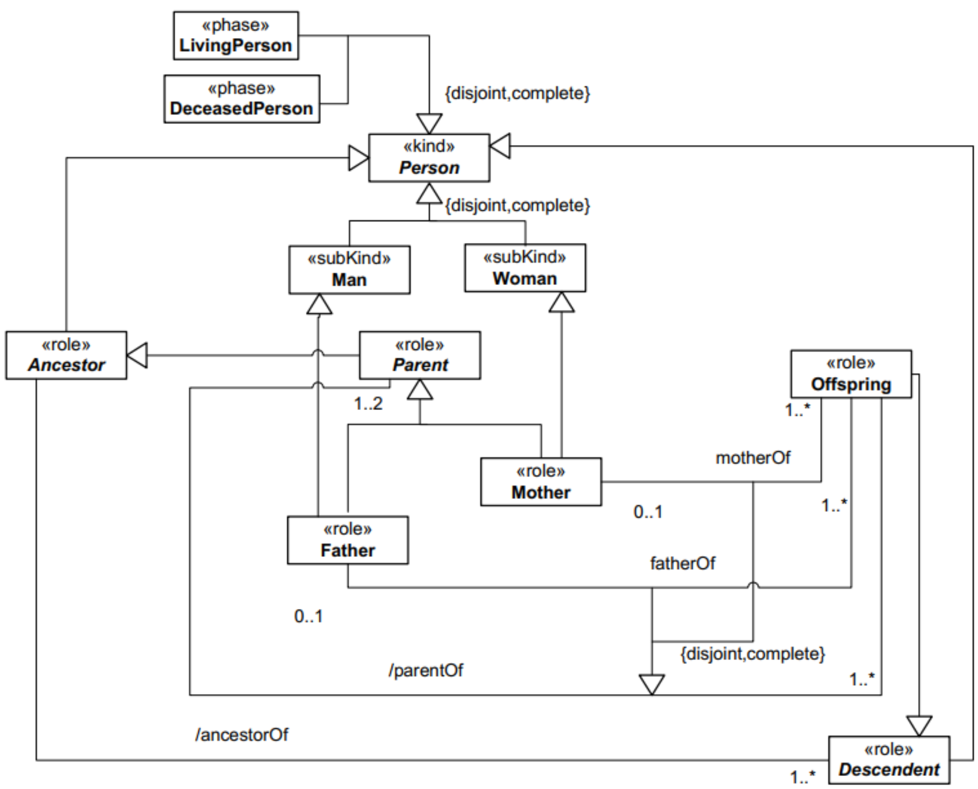


Figure 32: A sample ontology for a generic genealogy

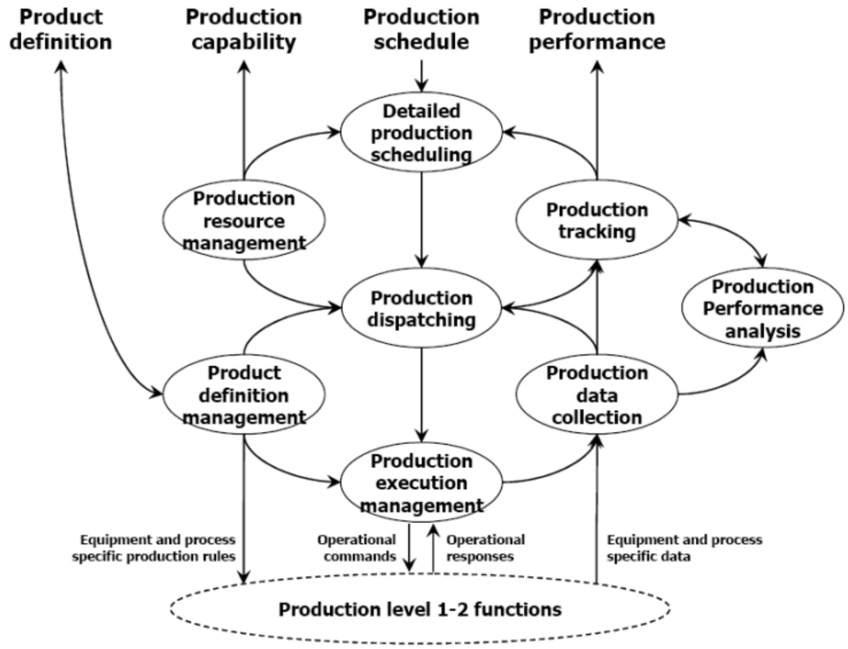


Figure 33: A possible ontology for manufacturing per ISA-S95 (based on Purdue ERAM)

Another major contributor to the concept of ontology, through more obliquely, is Britain's Peter Checkland. He admonishes that all scientific knowledge is simply provisional. Nonetheless, the experimental method that generates that provisional knowledge is now taken as a given due to the success of science which created that worldview. This scientific method is predicated on three general principles: reductionism, repeatability, and refutation (Checkland and Holwell 1998).[8] Note the entire scientific evaluation starts with a fundamental reduction or deconstruction of the problem statement.

This concept was first proposed by Rene Descartes in the 1600s, who was best known for his profoundly philosophical statement "*cogito, ergo sum*," or roughly, "I think, therefore I am." Descartes believed that you could ascertain a system's behavior by systematically understanding the behavior of its individual components. Clearly, this ignores the effects of emergent behavior or the complex coupling between the system's various components (Jones et al. 2008).

One can apply these concepts of reductionism, syntax, morphology, etc. quite broadly. For instance, effective classification and codification could greatly enhance efficiency in

[8] The *scientific method* initiated the Age of Enlightenment, starting early 17th Century. Founding fathers include Bacon, Descartes, and Galileo. It culminated with Newton, and was mostly centered on Britain's Royal Society.

manufacturing (Girdhar 2001). These concepts could also facilitate develop and risk mitigation as one progresses through, say, the technology-readiness levels (TRL) for new industrial products. An effective approach would help one to better understand system complexity and, ideally, the thresholds of the various elements and links involved. Helping to quantify risk, this could contribute to better control over such critical development items such as cost, schedule and manufacturability (El-Khoury and Kenley 2014; Simon 1996).

3.1.4 Network Optimization

The origins of graph theory are curious. According to Biggs et al., the genesis of the discipline were "humble, even frivolous" (1986, 1). It started with a puzzle, essentially, and soon capture the imagination of celebrated mathematicians. The original problem was that of the Konigsberg Bridge in 1736 of the then nation-state of Prussia. The idea was to connect two islands to the city by seven bridges. The problem was solved by Swiss polymath Leonhard Euler, ultimately leading to this now widely popular branch of mathematics (Biggs, Norman, E. Keith Lloyd 1986).

Graph theory is used to model pairwise relationships between objects. In computer science, network theory is a subset of graph theory. In some situations, there is a converging of the science of network theory with that of model-based systems engineering (MBSE) – a topic that is discussed in detail in the following section. For the most part, however, these two disciplines remain fairly culturally and technically distinct.

In their book *Heterogeneous Graph Theory for Smart Cities*, Schoonenberg et al. (2019) combine techniques from MBSE with that of the network science community. The authors state this is "assumed as an entry point to multi-functional graph theory as a whole" (2019, 3). The origin of hetero-functional graphs, although, actually stem from automated mass-customized production systems literature.

Much of this motivated by the fact that consistently changing structure and behavior of the network, and the need for reconfigurable production facilities (Schoonenberg, Khayal, and Farid 2019; Farid 2007). The heterogeneous graph theory book elaborates upon the implementation of SysML modeling to allocate functions for a four-node smart city network. This network consists of transportation, electricity, and water infrastructure. Service feasibly matrices and petri nets were then employed to model the operand dynamics of the system (Schoonenberg, Khayal, and Farid 2019).

The intersection of optimization and networks can be viewed in light on the facility location problem, now standard in operations research. One example is the work by Nobil et al. (2018). They considered a multi-period, three-echelon supply chain with the objective of maximizing both the net present value (NPV) and the fill rate. The decision variables include the plant location, the supply and distribution patterns, and funding source. The solution involved both a Pareto-based non-dominated sorting genetic algorithm, and a multi-objective biogeography-based optimization algorithm.

The authors explain the discrete facility location problem was pioneered in the 1950s by Balinski. A very common problem formulation is capacity-constrained version of the facility location problem (known colloquially as CFLP), which limits supply. Their contribution was to develop a model that replaced direct cost with NPV (Nobil, Jalali, and Niaki 2018). Earlier work of convex piecewise-linear programming (CPLP) was performed by (Sridharan 1995). He utilizes branch-and-bound and Lagrangian relaxation via a mixed integer program. This category of problems are generalized as the bin-packing problem.

The book *Supply Chain Science* was reviewed in light of system-wide optimization. Pertinent to this research was the issue of supply chain goal or overarching objective. Each network will contain a series of stock-points that meter the ebb and flow of products or services. But how does a network determine efficiency and effectiveness – is this only based upon flowrate and cost? The author provides an approach. Hopp suggests that one starts with cost, then one needs to “trade this with one of the four following characteristics, namely: quality, speed, service and flexibility” (Hopp 2011, 3).

3.1.5 Systems Engineering

The term systems engineering originates from military research activities at Bell Telephone Laboratories during the 1940s. A taskforce was devised to improve communications with the air warning service. One of the earliest and most-notable examples of a successful systems engineer project was the intercontinental ballistic missile (ICBM) during that same period (Buede and Miller 2016).

Those who have experience in manufacturing probably realize that it is significantly easier and less expensive to anticipate problems during the initial design phase. This includes both the artifact, as well as the production system. According to Buede and Miller (2016), there is a strong case for concurrent engineering and the value of systems engineering. They elaborate:

> ... about 80% of the cost of the system is committed by the end of design and integration, while only about 20% of the actual cost for the system has been spent. Obviously, mistakes made in the frontend of the system life-cycle can have substantially negative impacts on the total cost of the system and its success with the users and bill payers (2016, 8).

The solution is an interdisciplinary and highly collaborative approach. Interestingly, he explains the process of integration receives less attention than design. In fact, the latter is typically seen as the *yang* (stronger, active side), whereas the former (i.e. integration) is the *yin* (weaker, passive side) (Buede and Miller 2016).

There are several other important systems concepts that Buede and Miller illuminates in his text, such as IDEF0, stakeholder analysis, normative models, uncertainty, and measure of effectiveness (MOE). One concept that deserves special attention is his relations map between entities, called an influence diagram (see Figure 34 below for details (Buede and Miller 2016)). This can be a particularly useful tool – mapping the requirement to the fundamental objective, using the individual components of the systems.

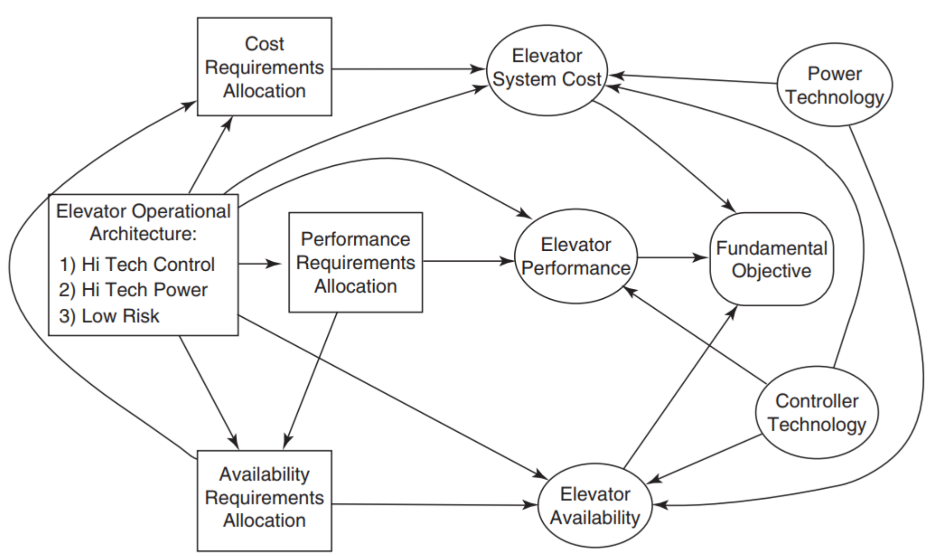


Figure 34: Sample influence diagram for allocation of system requirements

Model Based Systems Engineering

Buede and Miller (2016) introduce other concepts that are powerful when contemplating system design. For example, he argues that there are four fundamental categories of requirements, specifically: input/output, technology and system-wide, trade-off, and test. He also elaborates on the characteristics of SysML, an “interconnected set of visual modeling diagrams” (2016, 66).

The value of CORE, a commercial system engineering software product by Vitech Corporation, is explained by Buede. This software implements a data modeling technique called entity-relationship diagrams. CORE includes classes (e.g. requirements, functions, and items), examples of those classes, and relationships between classes. Staring at the highest level of abstraction and with the basic system requirements, these models progress layer-by-layer to define how the system should satisfy its objective. This requires increasingly more mathematics and physical detail (Buede and Miller 2016).

Model-based system engineering (MBSE) is a concept that had been widely discussed for decades, yet was finally formalized in 2006 by INCOSE. The objective is to support design, analysis and evaluation of products, in light of the specified program requirements (Haskins 2014). This fundamental model ideally is to aid operation of the asset throughout the entire life-cycle, including design, production and sustainment. This is illustrated in Figure 35 on the following page (Steiner 2014).

Intuitive, this is a principle concern for owners of capital-intensive assets with long-product lives, such as aircraft. One important aspect is configuration management. In particular, organizations need the ability to archive and easily retrieve current and accurate information throughout the product life-cycle. This provides the basis for the digital twin and is sometimes referred to as the “single source of truth.”

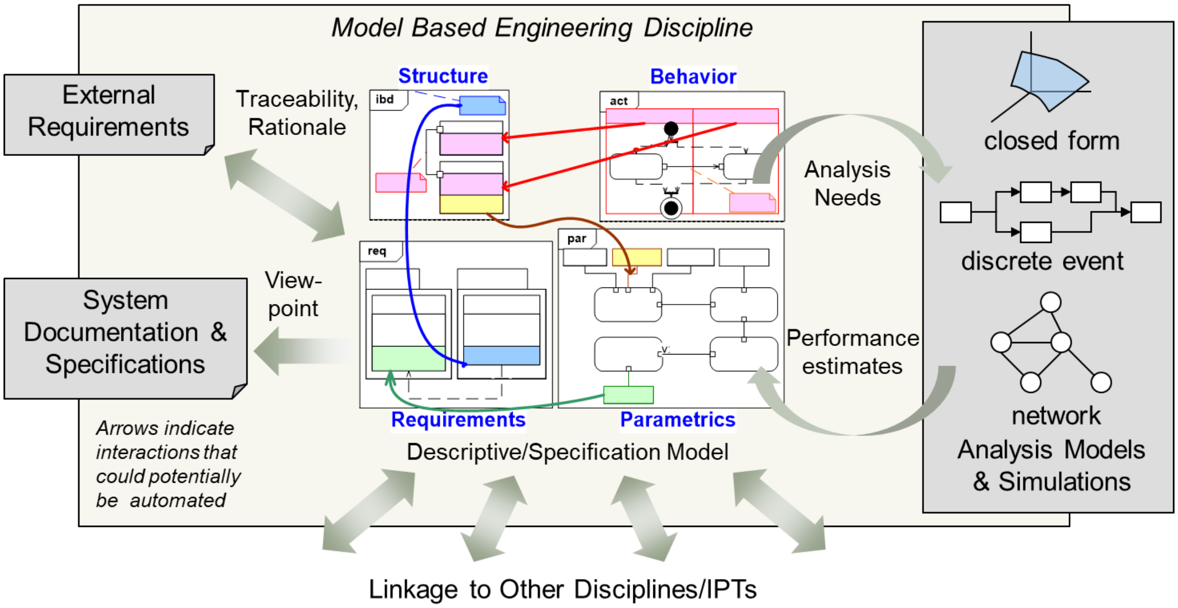


Figure 35: Schematic of the MBSE metamodel showing various entities and relationships

The essence of MBSE was to transition from paper-based designs to electronic models. This is analogous to mechanical design migrating from two-dimensional paper blueprints to three-dimensional computer-aided design (CAD) models in the 1960s. Readers interested in detailed account of the history of CAD can refer to Wesiberg (2008).

The schema is based upon what is commonly known as RFLP core for Requirements-Functional-Logical-Physical (Kleiner and Kramer 2013). Thus, with math as a universal language, important design issues can be assessed across heterogeneous levels for a given hierarchy, independent of source (Chadzynski, Brown, and Willemsen 2018). This proved revolutionary.

The complete evolution of MBSE is a rich history, combining computer science, engineering and management. Perhaps the most important milestone was the development of Unified Modeling Language (UML) in 1997. With the support of INCOSE, UML was modified to create an open-source systems-engineering-specific software known as Systems Modeling Language or SysML (Haskins 2014). As previous stated, this has become the MBSE standard.

MBSE has also been used for optimal allocation of resources. One such example includes hardware versus software trade-off. McKean et al. (2019) explains that computer systems provide a more "heterogeneous combination of processing resources" (2019, 172). The main attributes to be optimized are performance, energy, and heat dissipated. These characteristics were viewed in light of three operating different types of operating conditions, and optimized using a cost function. By varying the coefficients, this function could be manipulated to optimize overall system performance (McKean, Moreland, and Doskey 2019).

More recently, MBSE has been applied to production environment to simulate complex, heterogeneous logistical systems. This becomes increasingly necessary as OEMs continue to outsource product, engaging with disparate global strategic partners. In fact, a major focus of a current INCOSE-lead effort is to provide standard libraries for resource, process, behavior and control models (Sprock, McGinnis, and Bock 2018; Mas et al. 2018). Companies such as Boeing and Rolls-Royce are also actively engaged in this type of modeling and simulation effort. The goal is to significantly reduce time and money associated with new product development.

IDEF0 Functional Model

In the 1970s, the US Air Force Research Laboratories (AFRL) at Wright Patterson developed a modeling paradigm needed to describe manufacturing while leveraging computer technology (AFRL 1981). The result was IDEF0 (integrated computer-aided manufacturing DEFinition for Function Modeling). This provided the standard syntax and semantics required to effectively communicate complex processes. Graphical representations of various functions or activities were used in a structured format.

One of the most notable features is the block diagrams, defining specific uses of inputs, outputs, controls and mechanisms or resources (AFRL 1981). By strict convention, these functions originate from left, right, top and bottom, respectively. It is important to note these are non-executable descriptive models. This is one of the limitations of IDEF0 – it cannot be used for prescriptive modeling to simulate the dynamic behavior of system.[9]

Most system modeling uses IDEF0 in a similar fashion for functional-flow block diagram, colloquially known as FFBD (Buede and Miller 2016). There is one important distinction. FFBD is used to illustrate the functional flow of a product. In contrast, IDEF0 shows data flow, system control, and functional flow of across the life-cycle of an asset or system.

[9] For more information regarding descriptive vs predictive vs prescriptive models, see Hindle and Vidgen (2018).

In most cases, the applications of IDEF0 and FFBD are for traditional industrial system design. There is at least one example of a recent novel application of IDEF0 that focuses on the product development cycle that helps illustrate the schema's versatility (O'Donnell and Duffy 2002). Primarily due to a long and complex product development cycle, there are considerable challenges with defining and accurately measuring design quality.

There has been ongoing work addressing system efficiency and effectiveness, although most performance-related articles do not define performance itself. Generally, models involve the performance of design (i.e. the artifact) and not the work-steps in the development process.

As a result, O'Donnell and Duffy (2002) posit a new model, E^2. This provides a unique combination of both efficiency and effectiveness. The primary approach is to structure the systems as a black box, in the form of an IDEF0 model. Efficiency, he argues, is a function of the input, output and resources of the model. Whereas system effectiveness is predicated by the relationship between model output and goal(s).

A key challenge is quantifying the change in knowledge related to these parameters. Another challenge identified is the formulation of key performance indicators (KPIs) – these are often subject to an output of an activity, not its goal. The solution is to combine these variables in an expanded, yet coherent model (see Figure 36 below by O'Donnell and Duffy (2002)). With the key elements of a formalism sufficiently characterized, the author argues, system performance can be analyzed and subsequently improved (O'Donnell and Duffy 2002).

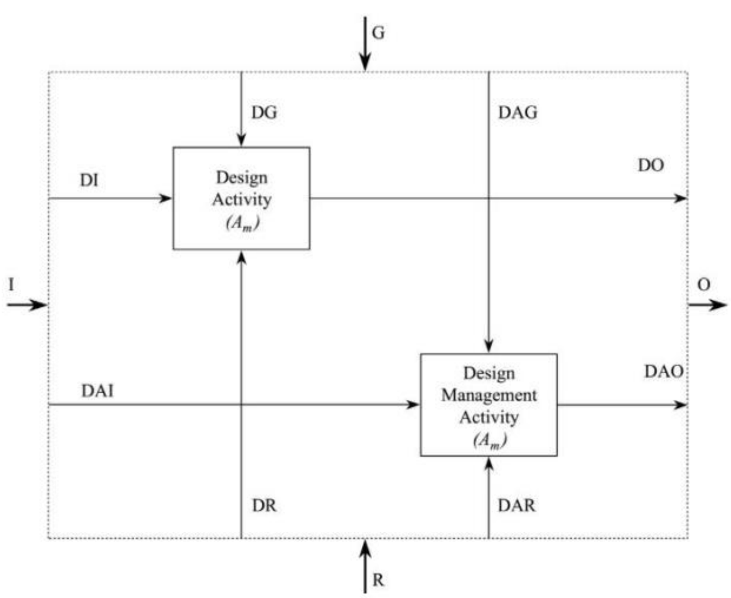


Figure 36: IDEF0 for the design and management process for a given activity

3.1.6 System of Systems

Systems of systems (SoS) is a special type of system. The term was first introduced in 1989 in association with the Strategic Defense Initiative to "describe an engineered technology system" (Gorod, Sauser, and Boardman 2008, 486). There is no standard definition. However, the notion is that it contains (sub)systems that are heterogeneous, interdependent and form a complex, multifunctional system when combined. The system has an objective or goal. Optimization of its elements, though, does not necessarily optimize the overall system performance (Gorod, Sauser, and Boardman 2008).

There are two basic types of networks that help classify SoS: small world and scale free. In a small-world network, the majority of nodes are not directly connected. Nevertheless, every node can be reached via a small number of steps. In scale-free networks, edges follow a power-law distribution; thus, some nodes function as hubs. As a result, these networks are much more vulnerable to a focused attack (Newman 2002). Clearly, implication of this type of network span from military operations to airline routing and the internet.

One of the earliest publishers and one of the most influential researchers on the subject, Maier was able to distinguish monolithic systems from SoS (Gorod, Sauser, and Boardman 2008). In particular, Maier provided a series of distinguishing characteristics for SoS based upon five features. These features include: managerial and operational independence, evolutionary nature, emergent behaviors, and a geographic breath (Maier 1998). Each characteristic adds layers of complexity, confounding the ability of the components to exchange information (Tamaskar, Neema, and Delaurentis 2014). According to DeLaurentis et al., there are three fundamental representations or taxonomies: a) dynamic systems, decision-making and control, and interaction modes (DeLaurentis, Crossley, and Mane 2011).

DeLaurentis built on this concept by including an additional three dimensions. Acknowledging that emergent behavior was essential to understanding, the author further emphasized the characteristics of networks, heterogeneity, and trans-dominion. The last, and perhaps the most involved, requires working-level knowledge across the distinctive disciplines of engineering, economy, policy, and operation (DeLaurentis 2005). This has been organized into a simple but effective heuristic entitled ROPE (DeLaurentis and Callaway 2004). This methodology can be a powerful mechanism to dissect complex operations.

The supply chain can be treated at a SoS (Mastrocinque et al. 2014). Its ability to self-organize can be interpreted in terms of its operational and managerial independence. These characteristics are writ large given the overall market structure. The properties of each, nonetheless, are heavily dependent upon the individual company culture. In general, the supply chain should be able to maintain independence and evolve to remain competitive. This includes the adoption of new technology, thereby also benefiting its customer base in the process (Mastrocinque et al. 2014).

3.1.7 Agent-based Models

System of systems are notorious for their complexity and often capricious emergent behavior. For aerospace, this becomes even more intractable as manufacturers increasingly turn towards commercial-of-the-shelf (COTS) components to help minimize asset cost (Tamaskar, Neema, and Delaurentis 2014). Proper integration is challenging. Within the past two decades, agent-based models (ABM) have received the attention of researchers. Increasingly, this has become an attractive modeling of for SoS since they can: a) potentially capture emergent behavior, b) properly replicate a complex system, and c) provide architectural flexibility (Bonabeau 2002).

In Mour et al. (2014), Forester's system dynamics model from the 1950s was compared to ABM. There is a notable difference – system dynamics employs a top-down solution using continuous feedback. Basically, the model is centrally controlled. In contrast, ABM contains discrete entities that operate independently, yet can be influenced by their environment. This results in a bottom-up approach (Mour et al. 2014).

The result is system-wide behavior due to a collective dynamic "micro" behavior of the agents. Due to this "socialized" element, interesting patterns in the system often emerge. In general, agents are effective for identifying stochastically stable states as each can be initiated as an individual state vector (Axtell 2000).

A second related article explores ABM though in the context of MBSE. Kenley et al. (2015) combine UML Activity Diagrams for executable generic agents. ABM is used to both define and evaluate the architecture of the system. Specifically, the model would automatically generating communication links between missile command posts based upon emergent conditions of the agents. Nodes represented functions and were connect by links that signified tracking, typing, targeting, and killing. Platform autonomy was varied from centralized control to fully autonomous (Kenley et al. 2015).

Nodes were enabled as agents, and initialized with objectives and desires. Each also has initial knowledge, beliefs, and information (including the physical properties and energetic state of its platform). Agents can transfer the three fundamental elements – *matter*, *energy* and *information* – to its environment. Their interaction with each other or with the environment itself has the potential to modify their objectives and desires.

The agents used a fairly common learning cycle codified as update-decide-act. Designers of system architecture strived to balance flexibility with workload, in terms of managing communication agents. This problem was managed by creating two agent classes – an intra-agent and inter-agent. In the end, SysML was combined with the agents that could also specify concurrent, asynchronous complex interactions of the missile network as defined by the authors (Kenley et al. 2015).

3.1.8 Integer Linear Programs

In operations research, an integer linear program (ILP) is a common tool. In particular, it is used extensively for production planning and scheduling. ILP is a mathematical optimization program that searches for feasible solutions based upon an objective function and a series of constraints. Both conditioning elements are linear as the name implies (Bixby 2012).

Its trajectory as a research tool is well established. Linear programming was developed in 1947 by George Dantzig, who created the simplex algorithm for military operations – both the military operation and the algorithm itself were treated as highly confidential at the time (Bixby 2012). Given the versatility of the methodology, there are myriad applications of ILPs for manufacturing and production planning to queuing. The following summarizes just a few key articles since 1999 that may be relevant to this dissertation research.

A heavily cited article by Beamon (1999) entitle “Measuring supply chain performance” identified that supply chain models predominately use two different types of metrics: cost, or a combination of cost and customer responsiveness. ILPs can be formulated as single or multi-objective problems. Thus, an ILP could be effectively constructed to identify the minimum cost sourcing option within a multi-tiered supply chain.

Wu et al. (2000) provide an early example of implementing an LP for single supplier selection during a manufacturing production process. This work was conducted in the context of an agile manufacturing framework. A similar research effort used ILPs to help determine an optimal supply chain configuration of the partner network for the logistics of integrated e-supply chains (Dotoli et al. 2005). A continuation of the work was performed by Costantino et al. that formulated a multi-criteria objective problem, and solved it by using an ILP with the objective of "providing a set of the possible alternative solutions to the decision maker" (Costantino et al. 2012, 452).

More recently, Kaur et al. (2019) devised an ILP to solve a complex joint outsourcing and offshoring decision model. They use a multi-criteria decision-making based model in conjunction with fuzzy logic to capture the uncertainty in the firm's preferences towards suppliers. Finally, one article seemed very closely related to the proposed research questions concerning the implication for strategy and the supply chain architecture.

Ziegler et al. (2019) explore the application of a mixed ILP to support strategic production network design for industrial artifacts. The company researched coincidentally is TRUMPF, a diversified German manufacturer that is also a well-known manufacturer of PBF machines. The specific application focuses on the effects of product reallocation throughout its vast global production network. The deployment of AM technology within their production network was not considered.

3.2 Methods Summary

Since there is no apparent research precedence, the literature review was deliberately broad. The research problem was generated based upon practical experience and had been contemplated since 2015. Nevertheless, the theoretical foundation for a reasonable solution that could also be easily validated was lacking.

The literature review started with general considerations for systems thinking. The Background section provided a fairly extensive introduction to the relevant issues concerning additive manufacturing and aerospace manufacturing at large. The literature review section was thus dedicated to discovering a method in the realm of either networks or systems engineering since method versatility was deemed important. As such, the methods review touch upon aspects such as network optimization, tools within systems engineering, and the construct of systems of systems.

Based upon a preliminary literature review, the original research approach was predicated upon the use of ABM in the context of a SoS architecture. The ABM problem formulation yielded results that were considered unsatisfactory. Consequently, an ILP was chosen as an alternative due to the rich precedence of research related to production and supply chain systems.

4. METHODOLOGY

The Objectives section introduced the five research questions, each formulated to address the rather unique topic regarding the impact of additive manufacturing on the aerospace supply chain for serialized-part production. The research questions were:

R1. WHICH segments of aerospace are subject to AM disruption, and WHICH metal AM modalities are most likely to prevail?

R2. HOW can the entire production network (i.e. OEM plus supply chain) be decomposed to capture changes in design and manufacturing methods?

R3. WHAT model can be developed that is sufficiently simple in terms of type and quantity of variables and parameters, yet can adequately predict network behavior?

R4. WHAT is the impact of adopting additive manufacturing according to this model, and HOW sensitive is the network to variable changes?

R5. WHERE and HOW will changes in AM technology be manifested throughout the entire network?

Naturally, the process of discovery for a complex system involves numerous levels of abstraction. A fundamental initial step was to clarify the system's operation concept as prescribed by Buede and Miller in *The Engineering Design of Systems* (2016). This, in turn, lead to a series of more targeted questions that was used to develop the final multistep methodology. The entire process is presented in the following two sections.

4.1 System Interrogation

Buede and Miller (2016) provides a simple construct to guide system design and development. It consists of four elementary categories, beginning with the operational concept or the overarching objective of the system. It is interesting to note its parallels to Aristotle's principle of *telos* described in the previous chapter. The authors explain that the operational concept provides both an initial description of the system and its stated mission requirements. Buede and Miller further posits that there should be a set of scenarios that prescribe the system's behavior in light of its interaction with other systems. Using the system's operational concept, designers should then identify both the functional and physical architecture of the network. Note this method presupposes the design of a new system, and not necessarily the modification of an existing one; yet, in both cases, these concepts should still apply.

This distinction between the two architectural elements is made manifest in the system design by specifying the functional allocation to the physical architecture. Perhaps one of the easiest examples to conceptualize involves computers. The versatility of software allows functionality to be separated from dedicated hardware in comparison to say a manufacturing plant with fixed production lines. The general concepts are relayed graphically below in Figure 37 (Buede and Miller 2016).

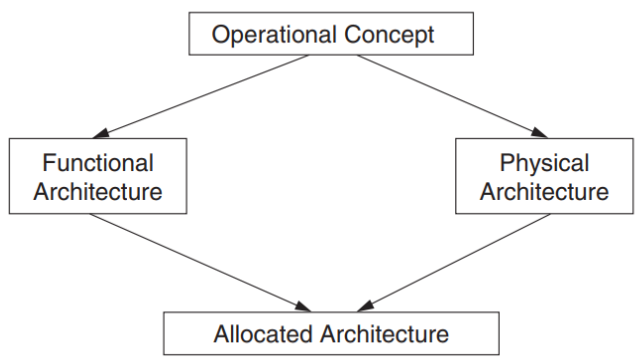


Figure 37: Methodology for developing and engineering a complex system

The operational concept for a supply chain is a network that produces quality parts, reliably. It must furthermore be cost effective, resilient, and reasonably expedient. Each of these concepts, of course, is subject to further detailed qualification. To help minimize ambiguity and to move towards a more scientifically objective statement, numerical data are required.

For developing the operational concept for the stated research problem, the system was subdivided into a physical architecture that is comprised three entities or subsystems. The first subsystem is the initial design process that creates the bill of materials (BOM). The BOM codifies design choices and ultimately determines which parts will be produced via conventional manufacturing versus additive manufacturing. The second subsystem involves the plant workflow. Clearly, the choice of manufacturing process will impact the process workflow, such as the number and extent of the work steps. The third and final subsystem includes the supply chain itself. Each supplier is part of a broader network that contribute to the production of the final artifact by either machining or installing parts. The flow of these parts and the associated information are key aspects to the modeling the overall production network. These distinctions help to facilitate a system-wide interrogation, and is delineated in Figure 38.

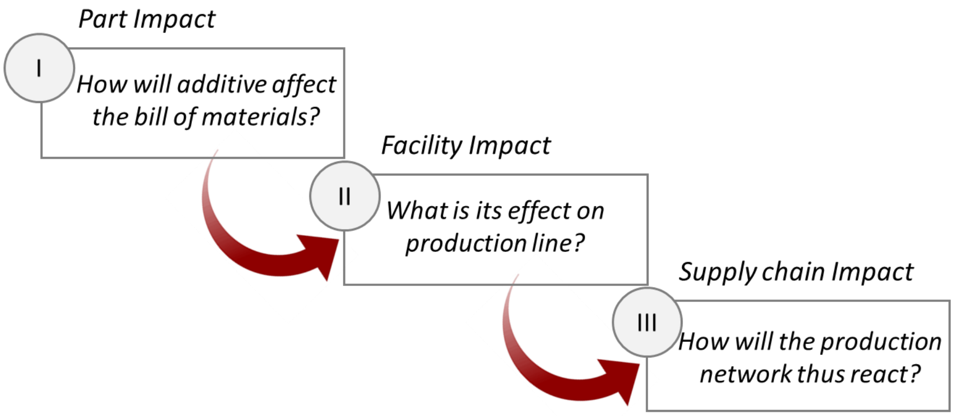


Figure 38: Three questions to progressively decompose the manufacturing system

This process of system decomposition requires a fairly thorough understanding of the entire manufacturing ecosystem. Recall that the basic architecture of the aerospace supply chain was introduced in Section 2.1 as Figure 10. This hierarchy will be used as the basis for the system architecture. The following section explores the implication of each of these three questions in light of this architecture.

4.2 Production Network Abstraction

The three questions recently proposed can be answered by systematically dissecting the entire production network. Figure 39 on the next page outlines the elements associated with each level identified, aiding in a more systems-engineering evaluation.

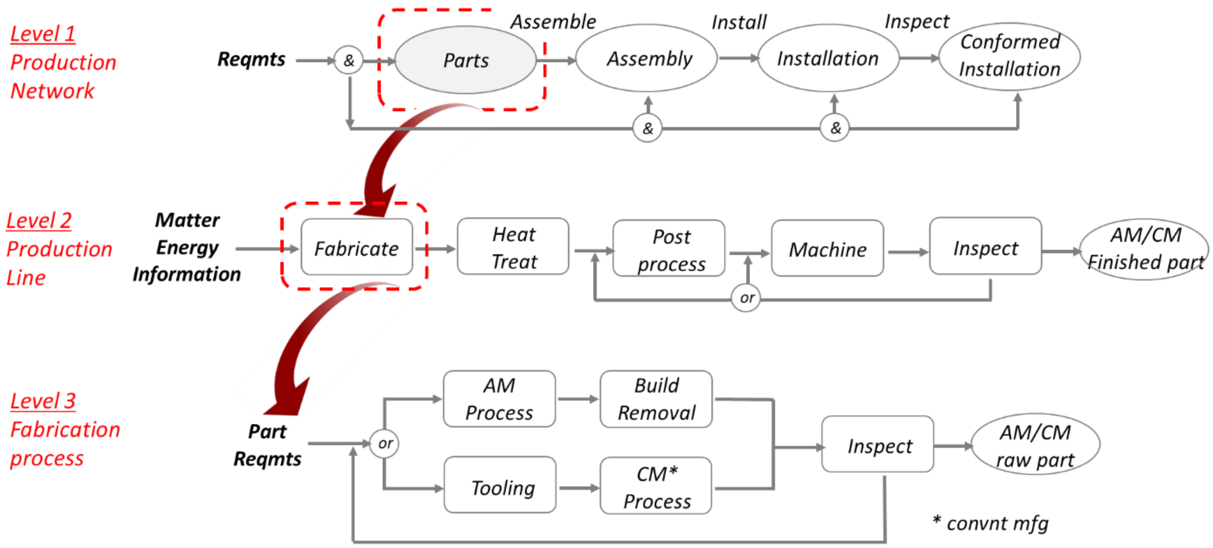


Figure 39: Three levels of the production network ecosystem

Recall that the detailed parts manufacturers or Tier 3s was targeted, as it will likely be the most impacted by additive manufacturing. The simplest explanation pertains to the part consolidation advantage of the design for additive (DfA) approach, introduced in Chapter 2. Fewer parts equals few suppliers. There are additional reasons why Tier 3s will be disproportionately affected by additive manufacturing; however, this will be discussed later in the document.

The three questions from Figure 39 above were reformulated in terms of a simple, more quantifiable construct. Figure 40 on the following page outlines the Methods, Tools and expected Outputs associated with each of the three questions. The level of detail of the methodology was determined by its impact upon the final answer, which in this case, is the architecture of the aeroengine production network.

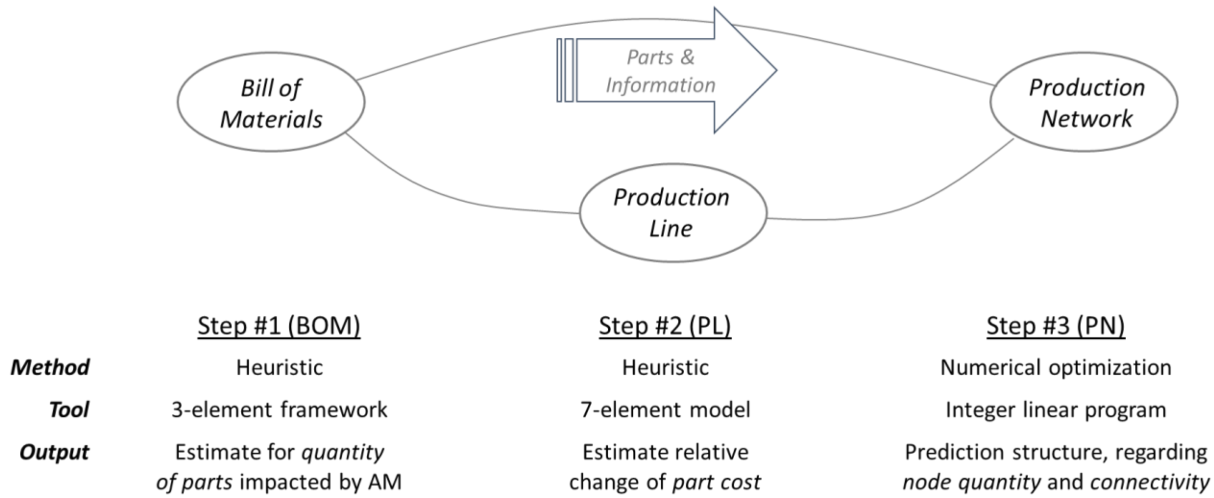


Figure 40: Steps to quantify the production network impact

The specifics of each step are elaborated in the following sections. These three steps serve as the fundamental basis of the final, overarching methodology. Thus, in conjunction with an initial system Identification and Decomposition step (as described in Section 1.3), and a final Verification and Validation step, the methodology takes the form as delineated in Figure 41.

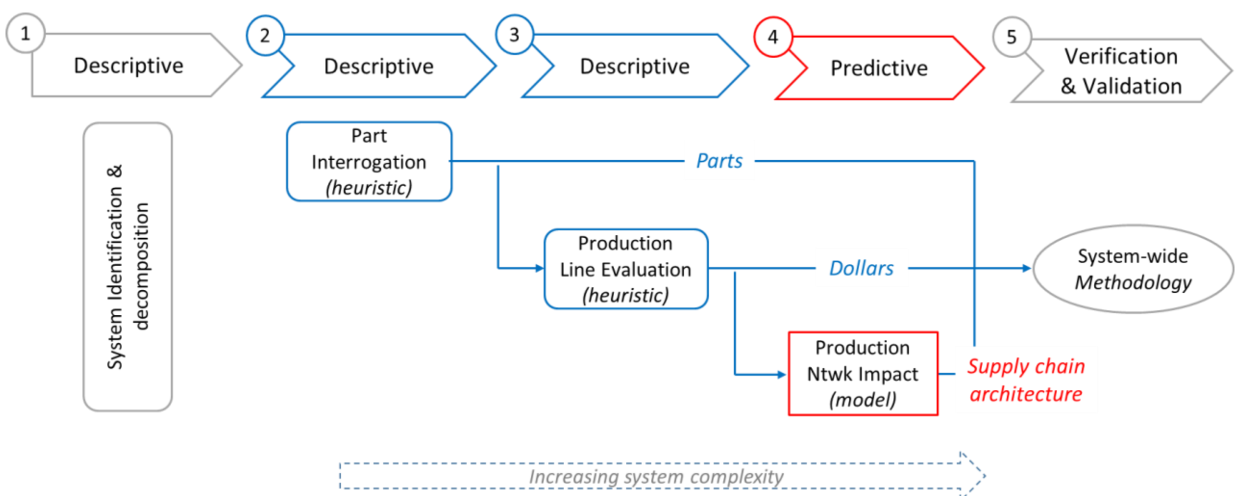


Figure 41: The aerospace supply chain research methodology

The methodology contains two important descriptive heuristic steps based upon the author's extensive work experience, in addition to information gathered during this research. The two upstream abstractions provide necessary input for the predictive model, denoted as

Step 4. It is reasonable to assume that each heuristic provides a sufficient bases for the inputs to the predictive production network model. These are estimates in lieu of actual figures (i.e. exact number of parts or total dollars) since these data are not publically available. Moreover, a sensitivity analysis was conducted to provide adequate coverage for a range values for both the number of parts and their associated costs.

4.2.1 System Decomposition

The process of system identification and its subsequent decomposition is as important as specifying the system's operational concept. And the proper level of abstraction is a critical concept that requires astute judgement and perhaps some amount of iteration. A combination of system identification and subsystem decomposition was used to produce Figure 42 below. This figure also patently delineates the research focus in gray (recall this figure was introduced earlier as Figure 6). This helps to underscore the relationship between the various subsystems and to establish the priority for research.

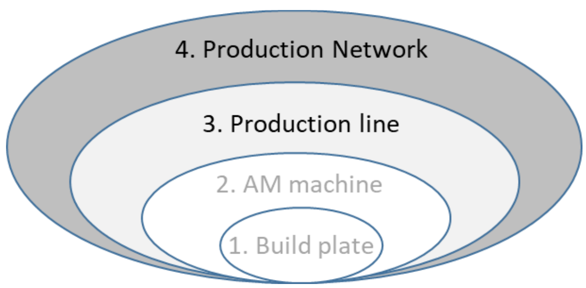


Figure 42: The nested systems with delineated research focus

The most sophisticated model would ideally link the behavior of the melt pool with the performance and characterization of the AM machine. This then would be mathematically fused to the various activities within the production line, and finally that of the broader production network. As explained, most of the additive manufacturing research does in fact attempt to correlate melt pool properties – such as geometry, cooling rate and resulting crystalline structure – to final part mechanical properties.

In general, this approach is known as a multi-scale, multi-physics modeling and is grounded in scientific first principles. Some of the most advanced applied research is being conducted at Lawrence Livermore Laboratories by Dr. Wayne King and his colleagues (see for example Francois et al. 2017). This requires expert knowledge of thermodynamics, heat and mass transfer, and lasers, and perhaps coupled with proficiency in fracture mechanics and other disciplines within mechanical engineering. Given the scope of this research, this level of modeling was obviously considered extraneous.

4.2.2 Part Identification

Once the system-level-of-abstraction has been properly defined, the next step is to identify the specific parts affected. This is essential because the level of AM impact is inextricably linked to the extent of the parts affected – but will 5% of the aeroengine BOM be affected or 55%? The answer to this question is critical to gauge impact on the downstream supply base.

Intuitively, there is a symbiotic relationship between the part designer (i.e. the OEM) and the part manufacturer (i.e. the supply chain). There is some overlap in capabilities. The OEM does manufactures parts, and a portion of the supply chain does in fact engineer and design parts. This research will assume that these activities are distinctively separate. This helps during the assessment of which parts will most likely be impacted by additive manufacturing.

There is another very important consideration. The level of additive manufacturing adoption is predicated upon the level of technology maturity, also known as technology readiness level (TRL). Recall, this concept had been discussed on a few previous occasions. The general tendency of technology adoption follows the well-known S-curve and is related to a product's lifecycle. It is difficult to ascertain the threshold when there is sufficient confidence to mass produce a new product. This results from a highly dynamic collaboration between the key internal stakeholders, namely engineering, marketing, finance, and manufacturing concerning the product's long-term viability. New product development is an ongoing field of research within strategic marketing and can span from consumer end-markets with short lifecycles, such as mobile phones, to heavy industrial products, such as automobiles and aircraft.

Determining which parts are candidates for additive manufacturing is not a trivial exercise. As discussed in Section 2.2, the challenge of identifying candidate parts requires the engineer to think in terms of design complexity and part consolidation. This is the crux of the AM business case. It was previously explained that mechanical design complexity is an extensive topic. For the purposes of this research, a few simplifying assumptions have been made to facilitate the analysis.

Chapter 2 justified the selection of the aeroengine as the most susceptible aerospace mechanical system to be disrupted by additive manufacturing. This results from the difficulty of machining hard alloys, the high tolerances, and the complex shapes for turbine components. Another consideration is the high cost of the aeroengine materials. These factors place considerable emphasis on a manufacturing concept known as near-net shape. For instance, investment castings are considered near net, whereas closed-die forgings are not; accordingly, latter requires extensive machining. Additive manufacturing produces highly near-net shapes and is thus an attractive option.

On the other hand, the aeroengine is arguably the most important mechanical system, and its safe operation are of paramount importance. In order to implement additive manufacturing, the first step is to decide which aeroengine components are considered non-flight critical. For the purposes of this investigation, non-flight critical parts are classified as both non-rotating and non-fracture critical. These may be primary load-path parts, however, depending upon the redundancy of the design. Recall the discussion regarding design allowables (i.e. A versus B-basis) based upon part criticality.

There are two additional steps that are required to down-select AM parts. The second step is to determine if these candidate parts meet three selection criteria. The third step is to determine that if there were an AM part substitution, would this still result in a safe design. Both of these considerations will be explained in more detail in the following sections. These three steps are summarized in the following Figure 43 as a series of sequential binary decisions.

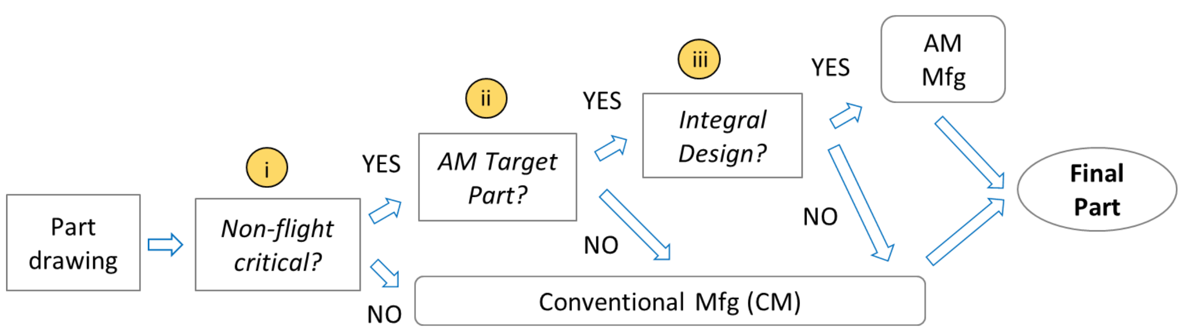


Figure 43: Decision sequence to identify AM part candidates

Non-flight Critical Parts

Four steps were used to ascertain the level of flight criticality. First, the basic part families of the aeroengine were identified – there were seven total, specifically:

1. Fan
2. Compressor
3. Combustor
4. Turbine
5. Nozzle
6. Shaft
7. Casing

Next, the static components were selected, resulting in three sections, namely the combustor, casing and nozzle. The third step was to evaluate these in the context of the manufacturing process. In general, forgings and sheet are not preferred product forms for AM parts. Forgings are particularly strong, critical parts, and sheet is easier to fabricate by a traditional (rolling) process. The final result would be castings and combination of bar and extrusion within the aforementioned turbine sections. This process is replicated in Figure 44.

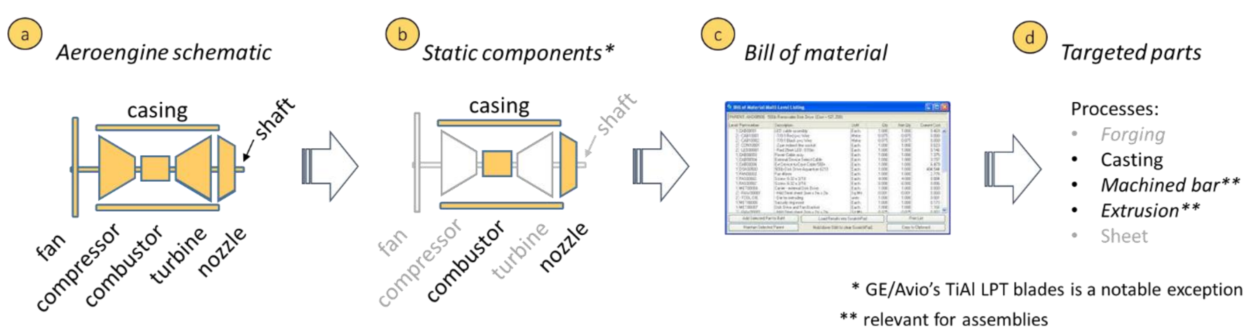


Figure 44: The intermediate steps to identify AM parts candidacy for the aeroengine

AM Candidate Parts

It is important to understand the role of the PBF machine for part selection. Size is a critical factor. Powder bed systems are relatively small – the largest build chamber is only 1 m^3 (for the GE ATLAS machine).[10] The machines continue to evolve in both in terms of size and number of lasers. This increases the range of parts that can be built, as well as the number of parts that can be built at any given time. Low production throughput PBF systems is a common criticism (Debroy et al. 2019). Multiple small parts can be built concurrently on the same build plate or, with E-beam systems, can be stacked vertically (Bahnini et al. 2018).

Economics is the other key consideration. The breakeven for part production – where the cost at which additive manufacturing and conventional manufacturing intersect – is not easily understood for most parts due the role of part consolidation, and the general fledgling nature of the technology itself. What is known is that the AM marginal cost curve is relatively flat as depicted in Figure 22, and the CM cost curve shifts upwards with increasing complexity. Conversely, the cost curve for additive manufacturing remains relatively unchanged with changes in design complexity (Lindemann and Koch 2016).

For the purposes of this research, it is sufficient to conclude that AM parts are more attractive when two conditions are met: they are considered "complex" and produced in relatively "low volume" (e.g. von Tell 2017). Again, these are qualified terms – each would have to be studied in detail relative to the CM parts they are intended to replace. These three characteristics are summarized graphically in Figure 45 below.

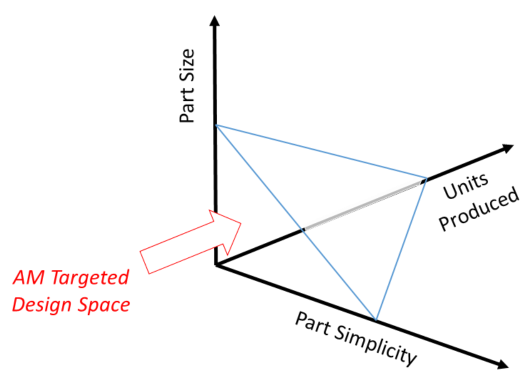


Figure 45: The AM design space as a function of three variables

[10] As a side note, it is the author's opinion that part size (in addition to the need for customization) is an important reason why biomedical is more amenable to additive manufacturing in comparison to aerospace.

An Integral Design

The final step is slightly more ambiguous. Engineering needs to make a final determination that the entire design is effectively integral and safe upon incorporating the new AM part(s). Since the geometry and grain structure of an AM part are different, its failure modes will be different from the failure modes of a CM part. This is true for individual CM replacement parts or when AM is used to consolidate multiple CM parts. Regardless, the process of replacing CM parts with AM always needs to be viewed holistically from the perspective of the final installation. The actual substantiation criteria for AM parts is still be developed in conjunction with the FAA and EASA.[11] As such, it seems that much of the acceptance criteria is still a matter of engineering discretion.

It is interesting to note that most AM designs are created by a machine learning algorithm known as generative design. As such, the mechanical failure modes are not intuitive in terms of the fundamental principles of structural design and analysis. In time this will become less important as the technology matures, given the corresponding increase in the confidence of the AM build process, the ability to inspect parts, and the improvement in algorithms themselves.

4.2.3 Production Line

For certain parts, it was explained that the overall AM process is more efficient in terms of both time and materials (see Section 2.2 for details). Figure 39 introduced the basic notion of layers within the production network. Levels 2 and 3 can be combined into a more intuitive, physical representation of the production line. This allows pairwise step-by-step comparison between the CM and AM process. The schematic comparing these two is shown on the following page as Figure 46.

[11] The FAA accepted substantiation process begins with testing coupons, then parts, followed by whole components, and then entire aircraft sections, if necessary; see appendix for details for a hierarchy schematic.

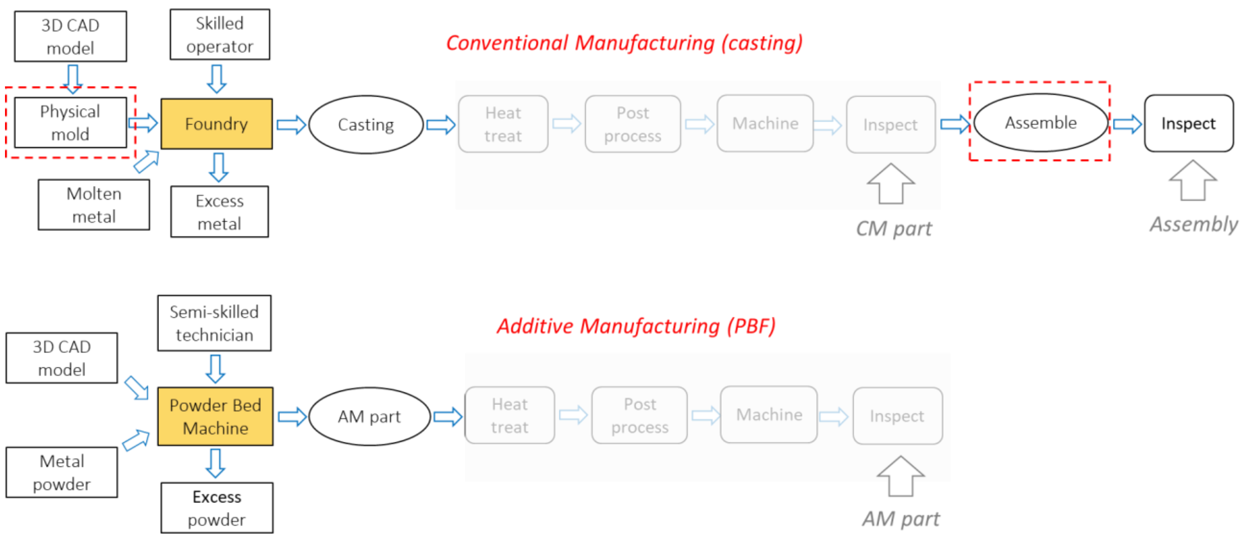


Figure 46: Production line schematic for CM vs AM parts

Upon initial inspection, there appears only a subtle difference between the CM and AM process – in particular, the CM process often requires an additional final assembly step. There is an important upstream difference, too. Conventional manufacturing requires tooling. This often involves a fairly extensive engineering and tool-building process; and in the case of an investment casting, this would result in an expensive steel or ceramic mold. The total number of tools required depends upon the number of parts to be produced – tools also have a design life that can vary considerably.

Process Resource Utilization

Armed with the process map from Figure 46, the analyst may begin to discretely compare resource utilization. Matter, energy and information (MEI) are standard resource metrics used within the systems and industrial engineering communities. Businesses typically focus on the high-order variables – and usually tracked at the program level by accounting – of cost and schedule. Clearly, there is a relationship between the two approaches; moreover, it can be argued that in principle, everything can be converted into units of currency.

The business case for additive manufacturing must ultimately be considered cost effective, either initially or over the life of the asset. The latter is becoming increasingly popular. Both airline operators and the military are turning towards the metric of total cost of ownership when considering their purchasing decision. OEMS such as Boeing, Rolls-Royce, and Pratt & Whitney have modified their business models accordingly to offer performance based or "power-by-the-hour" contracts (Thurber 2010; "Pratt & Whitney to Focus on Powered-by-Hour Business Model" 2015).

This has important implications for aircraft maintenance, repair and overhaul (MRO) spare parts, given their attractive profits for parts manufacturers (Richter and Walther 2017). The primary benefit would be to reduce the inventory for spares by being able to produce the part expediently on demand. In a continuous manufacturing scenario as with serialized production, the time savings for additive manufacturing is much less important. This conclusion is essential when constructing the final mathematical model.

Cost Analysis Case Study

Data from an Indianapolis-based AM company was used to compare the CM versus AM cost structure, consistent with process maps outlined on the previous page in Figure 46. Chris Beck is founder of Innovative 3D Manufacturing, and he generously shared data from an aerospace project conducted in 2019. The part, called the augmenter, in contained within the middle section of a jet engine afterburner. The engine is under development as part of a domestic hypersonic aircraft startup. When finished, the augmenter was approximately 10 inches in diameter, made of Inconel 718, and weighted roughly 17 pounds. Figure 47 on the next page shows the part being printed on the Renishaw AM 400 laser PBF machine. The photo on the right demonstrated the part still partially buried under the raw metal super alloy powder.

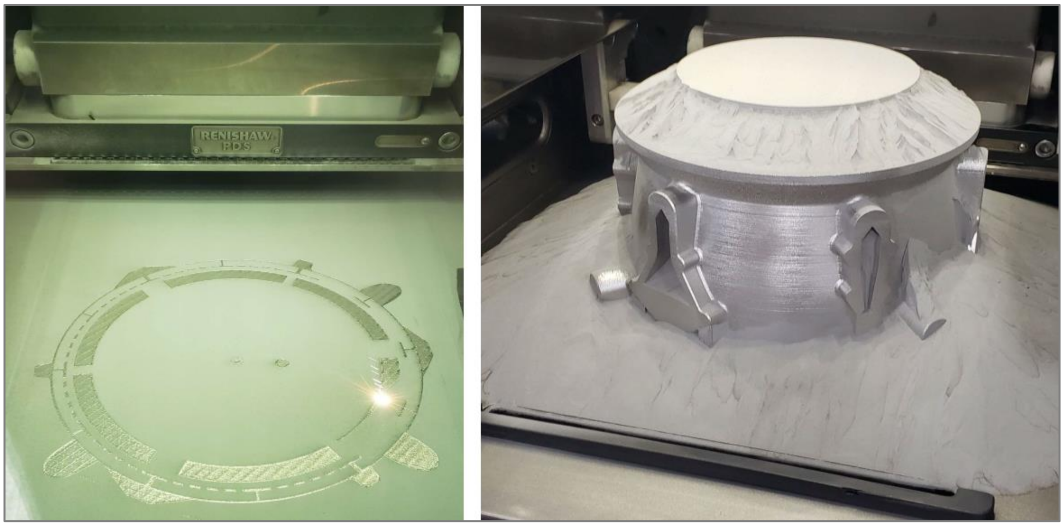


Figure 47: Printing the augmenter casing using laser PBF

The part took 125 hours to print, using 60 µm layers with a final part tolerance of ±0.010 to 0.020 inches. The initial build preparation required roughly two days in order to modify the build layout to make it suitable for printing. The total time required to finish and post process the part was four weeks.

The finished part is considered complex due to the hollow chambers and variation of wall thicknesses as illustrated in Figure 48 on the next page. In fact, it is difficult to predict just how many CM parts – in the form of an assembly – would have been required to build a similar part. For an assembly, each CM part would have to be joined with either fasteners or welding, and each process has its own limitations concerning the part life and associated maintenance regime (if this were an actual production part for an aeroengine).

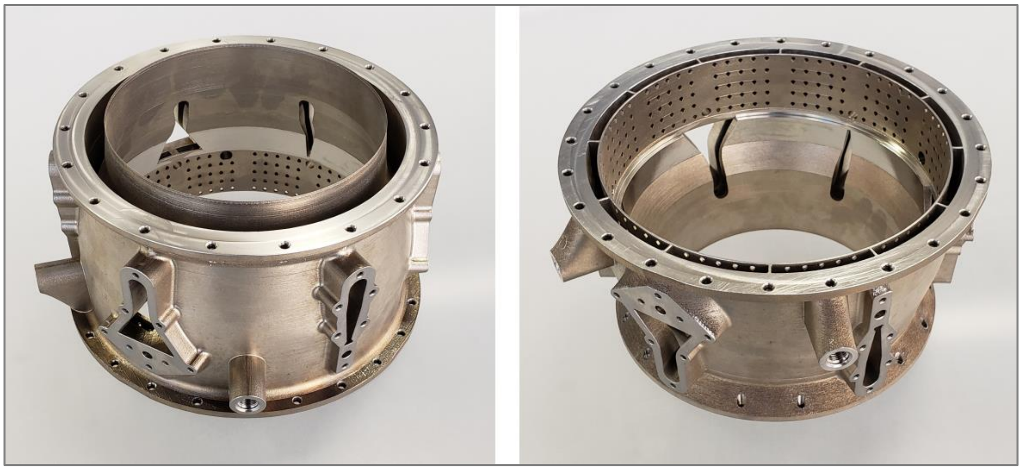


Figure 48: Finished augmenter casing printed as a single part

The augmenter was custom designed to allow for extensive instrumentation during engine testing. Figure 49 below shows the augmenter installed and fully instrumented within the jet engine afterburner on the test stand at Purdue's Zucrow Lab, the nation's largest university-owned propulsion laboratory.

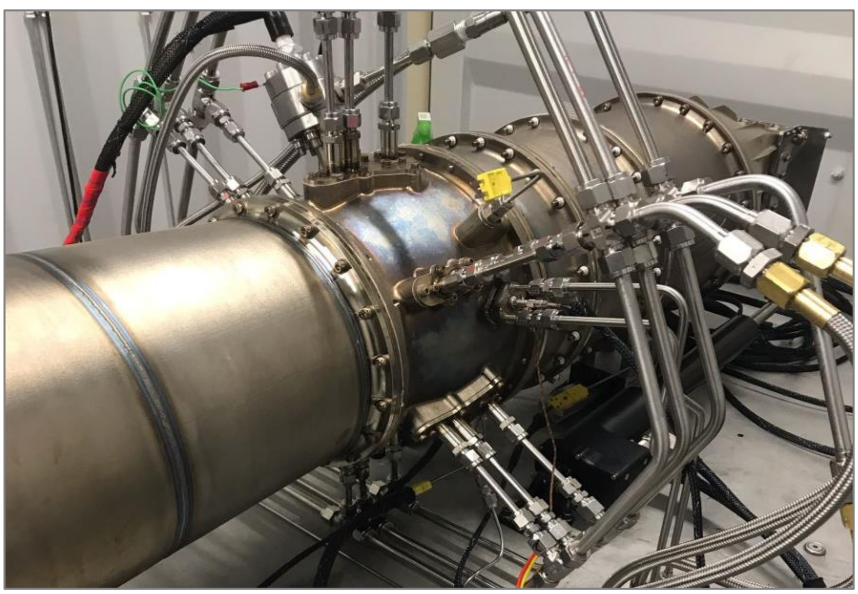


Figure 49: Jet engine afterburner with the instrumented augmenter on the test stand

The augmenter served a fundamental role for the testing and development of the hypersonic jet engine. It was used for extensive proof-of-concept bench testing in the configuration shown below in Figure 50. According to Beck, the program was a success. The original quote was only for two pieces, he elaborated, but his company ultimately made 30 parts by the end of the project over a short eight-week period.

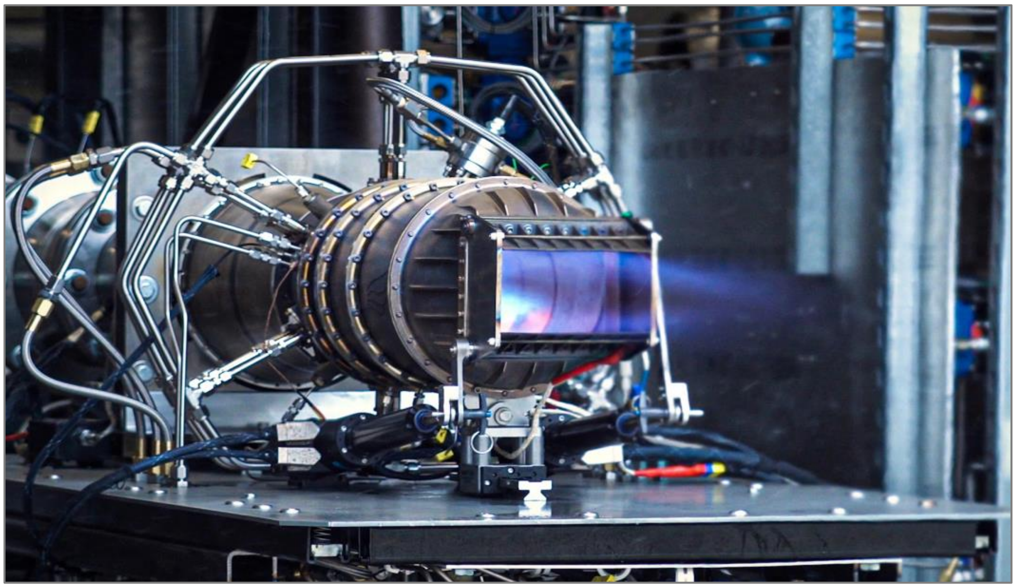


Figure 50: Hypersonic rocket engine being fired on the test stand

The total cost of the printed casing was $23,550, excluding the hot isostatic press (HIP) and computed tomography (CT) scan. These are processes that are considered standard for production aerospace parts. HIP increases the density of part, although in this case, the augmenter was assessed as 99.6% dense, and per Beck, HIP was not required by the customer. Taking these two costs into consideration with estimates provided by Beck, the total part cost would be roughly $30,000.

Beck explained that the material cost per part is less than 5% of the initial $23,000 figure. This is due to the efficiency of the printing process with the nickel super alloy powder at roughly $50 per pound. Figure 51 on the following page illustrates that almost half of the cost of the part is related to the printing process and machine preparation. The second largest expense is machining at nearly 20% of the total.

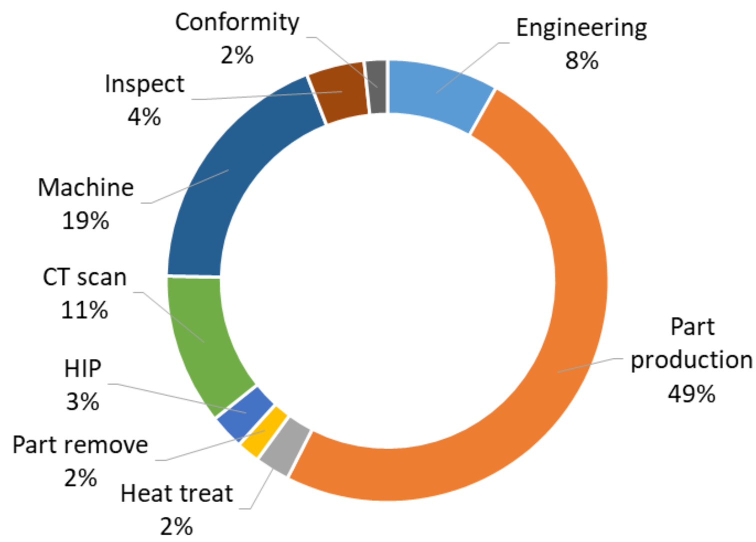


Figure 51: Cost breakdown of the AM augmenter casing

The next step was an attempt to compare this AM part to a CM equivalent; in this case, the complexity of the part would warrant an investment casting for the casing, in addition to other CM parts required to build an assembly that would include the combustion liner, etc. No meaningful data, however, were found to enable a comparison. Initially, costs estimates were made for the investment casting portion that included adjustments for an increased number of units produced. Recall the concept of amortization for tooling and non-recurring engineering. In the end, it was decided that fictitious CM assembly cost model constructed on a part-level basis is senseless as it would involve a large number of broad assumptions, many of which would be difficult to justify.

The best illustration for a cost comparison was a series of notional costs for the main elements of the manufacturing process. One the following page, Figure 52 shows that upstream investment in manufacturing engineering and tool fabrication would be significant and by far the largest initial cost drivers for a CM assembly. Furthermore, there could be a considerable downstream cost for final assembly. This would be part of the variable cost as it is directly related to the number of parts on the BOM and the number (and difficulty) of work steps involved in assembling those parts. According to Beck, the equivalent CM assembly could require a dozen or so parts.

Moreover there is the additional challenge of fastening or welding these parts to the investment casted casing. Again, these are estimates and are based upon the author's experience.

It is important to note that the magnitude of these three cost drives for conventional manufacturing are heavily dependent upon the complexity of the assembly and the number of assemblies to be produced. This subject will be addressed in more detail in Chapter 6.

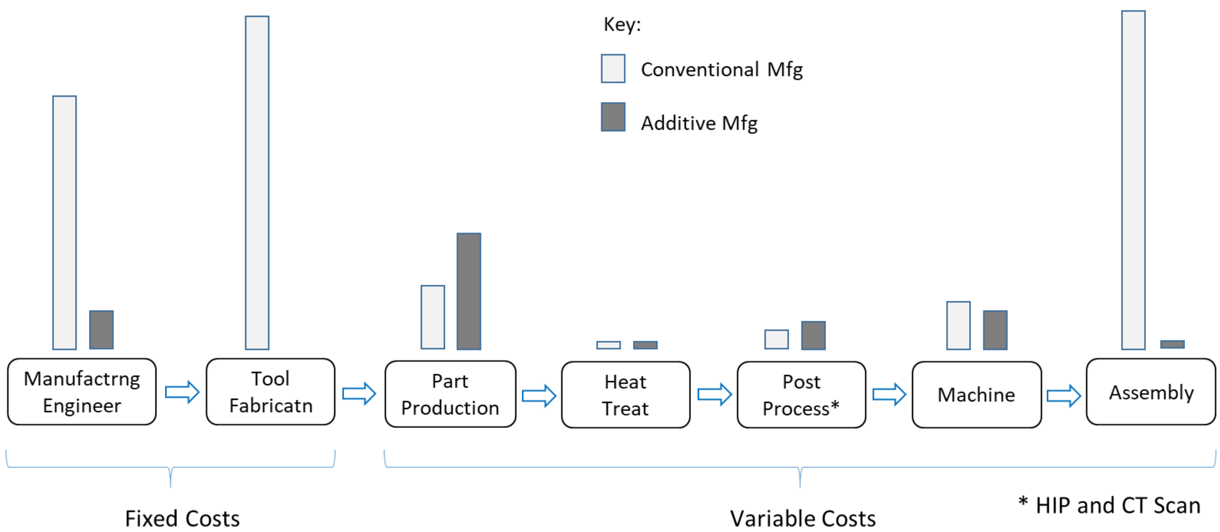


Figure 52: Notional cost comparison of a CM assembly with a similar AM part

It is important to consider a few of the limitations of this case study. First, it is fatuous to believe that a single AM part can be easily compared to a CM assembly. This point was discussed – additive manufacturing is an entirely new paradigm, greatly confounding direct references to a conventional process. An assembly, by definition, will require multiple parts and work steps, and would likely involve outside suppliers for fabrication and special processing. Thus, an assembly requires a more complicated BOM and associated work instructions for labors to assemble the various parts. It is possible that the assembly process can be automated, yet with the relatively low volumes in aerospace, this is unlikely. Furthermore, involving human labor invariable introduces the likelihood of "quality escapes" in the final product.

A second important element of building an assembly is the time required. Since assemblies are comprised of multiple parts, in many cases, multiple tools are needed. This could add inordinately to the design and engineering process. Quite often multiple suppliers are involved since each may have its own dedicated area of manufacturing competency. Adding outside suppliers adds both time and execution risk. In general, CM assemblies take months to develop and qualify suppliers, engineer and build the tooling, produce the various parts, and to assemble the final assembly. As evidenced in this case – a situation that is consistent with the AM business case discussed in Section 2.2.2 – an entire AM part can be completed in just a few weeks, and in some cases, only a few days.

The third limitation is that the actuals provided by Beck are representative of a small manufacturer with only two AM machines and supporting computer numeric controlled (CNC) equipment. His facility has no special processing equipment. As a result, his overhead is understandably low. Nevertheless, this situation is adequate for creating prototype parts; however, it would not suffice for serialized production.

Fourthly, the costs and processes were generated for only a small number of AM parts. A conformed formal production process would involve a number of changes, adding complexity to the manufacturing process and time and cost to the final product. Generalizations from one-off scenarios can be dangerously misleading. Beck cautions that in a production environment scenario, there is a need for dedicated project management in order to track the routing of the part during outside process steps. This would add materially to the final part cost.

Nevertheless, Figure 52 on the pervious page provides a first-order approximation for the purposes of this dissertation. It is apparent that the cost difference between conventional manufacturing and additive manufacturing may be considerable and is highly variable. The figure offers an important reference point for the supply chain model introduced in the following section. With this construct, a more informed aeroengine network architecture can be contemplated.

4.2.4 Network Architecture

The last modeling step is to characterize the behavior of the supplier network. The operational definition will be the aeroengine OEM plus its supply chain. The network is structured like a pyramid, a concept that was introduced in Figure 10. This can be characterized as depicted in Figure 53 on the next page in anticipation of modeling the interaction between the various levels and the nodes. Each node represents an individual corporation.

For aeroengines, the Tier 1 and 2 are basically combined since OEMs such as GE, Pratt & Whitney and Rolls-Royce have much smaller supply chains in comparison to Boeing or Airbus. This concept was discussed in Section 2.1. In both cases, this upper portion of the supply chain focuses on assembly, whereas Tier 3s are dedicated primarily to detailed parts fabrication (Michaels 2018).

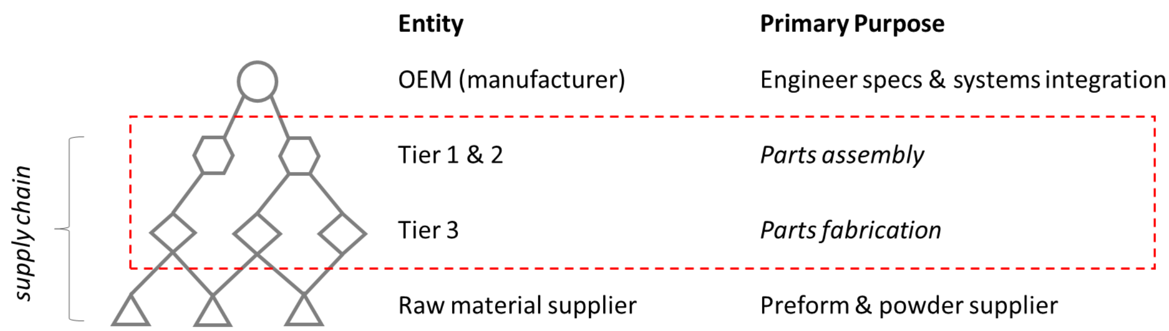


Figure 53: A simplified representation of the aeroengine production network

Key Model Assumptions

Four important assumptions were made in the process of developing the aeroengine production network. First, the purpose of each tier is considered singular in nature – this concept was previously discussed. This implies that the primary purpose listed above in Figure 53 is the sole function of the companies within that tier. Generally speaking, this is a reasonable approximation to the business focus of each tier. The second assumption is a bit more liberal.

Since Tier 3s are dedicated to fabricating parts, for purposes of this model, it was deemed that only Tier 3s can implement additive manufacturing. The justification was that additive manufacturing is simply another method to fabricate a part. On the other hand, additive manufacturing does require a fairly sizable investment in and deep understanding of the digital ecosystem. This would disadvantage many of the Tier 3s, which are basically smaller companies with less resources than their Tier 1s or 2s counterparts. This is a topic that will be discussed in the Conclusion section.

Many Tier 3s may lack the financial wherewithal to develop an extensive and a sustainable AM ecosystem. And the barrier to entry for aerospace is particularly high given its emphasis on quality and safety. These resource constraints have profound implication regarding the make-buy strategy for OEMs. At least one aerospace company, GE, has made a major investment to develop additive manufacturing as a core competency. In practice, all levels of the production network have invested to varying degree in additive manufacturing.

The third assumptions is more easily justified, and is based upon the preceding two concepts. It was assumed that the entire dynamic of the AM impact can be captured by the interaction between the Tier 1-2 and Tier 3s. The two layers become the exclusive focus of the mathematical supply chain model.

The fourth assumption is perhaps most critical – the entire mathematical model is based upon economics. In particular, it operates on the grounds that acquisition cost is the only factor for down-selecting AM parts suppliers. Clearly, this is not entirely true. At any rate, the Discussion section will explore this limitation in more detail.

The last assumption, number five, is that the supply chain is assumed perfectly efficient. This implies that there are no problems with material availability, delays, communication, quality, etc. that can normally plague a real supply chain. Time is considered only implicitly. Recall that a major advantage of additive manufacturing is the rapidity in which one can produce parts from initial concept due to the lack of need for tooling. This will be addressed in more detail in Chapter 6.

Predicated upon these five assumptions, a series of scenarios were developed for the mathematical supply chain model. Each scenario is based upon an increasing level of AM technology maturity. An integer linear program (ILP) was formulated to analyze the change in behavior for each of the four scenarios. In each case, the goal was to minimize the total cost for an assembly, or the price that the Tier 1-2 would pay. Figure 54 provides a simple graphic of each case in order of increasing technology maturation.

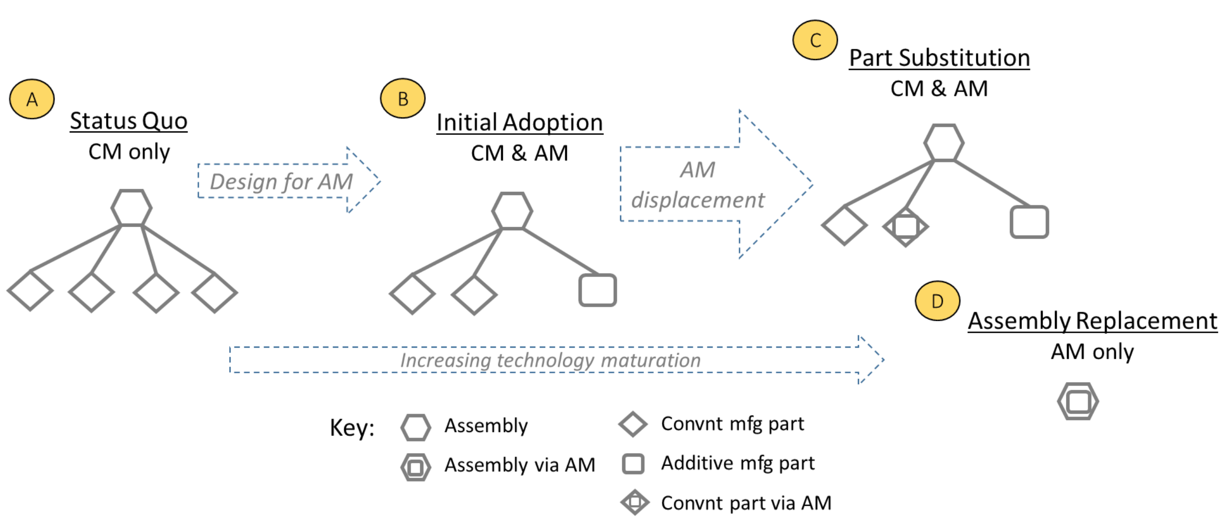


Figure 54: Four scenarios for AM part sourcing with increasing technology maturity

AM Scenario Analysis

Case A is the baseline scenario. It accepts that all parts will be produced via conventional manufacturing. The second case, B, considers AM-specific parts as called out by the BOM. These would be a single AM part that was designed specifically for additive to replace multiple CM parts or assemblies. Case B effectively reflects the current level of technology as of the year 2020. Unfortunately, there are only a few success stories of AM parts that have been approved and are being flown. The most notable example is the GE/Safran CFM LEAP fuel nozzle introduced in Section 2.2.

The third scenario, Case C, assumes that there is sufficient confidence in AM technology by the FAA and EASA to allow AM parts to substitute for CM parts. This is quite fanciful. It implies that AM parts will be mechanically equivalent to parts that were originally design and fabricated using CM technology. Granted, this will not happen for some time, but it will eventually happen. Again, much of this depends upon the attitude and the confidence of the certifying authorities which will slowly improve with each successful use case.

Replacing the entire assembly at the Tier 1-2 level with additive manufacturing is the fourth and final scenario. In Case D, no supplier (i.e. Tier 3s) bidding is necessary. It simply requires a direct cost comparison between the anticipated cost of the AM consolidate part versus the total cost of the original CM assembly. This case is highly unlikely because replacing an entire assembly could fundamentally alter the failure modes of the entire aeroengine. The Discussion section will explore this concept further.

Integer Linear Program

The first three scenarios were modeled using an ILP. A creatively simple model was developed using only four entities – three were conventional manufacturing and one was additive manufacturing. Each entity was considered to be an individual firm. This model is called the *First-order Supply Chain* model or FOSC, a term that will be used for the remainder of this dissertation.

The FOSC model includes the variable cost for conventional manufacturing and additive manufacturing, yet only the fixed cost for conventional manufacturing. The lack of tooling significantly reduces the non-recurring costs for additive manufacturing, as presented graphically in Figure 22. Both capacity and demand were specified for CM parts, and if included within the BOM (as seen by the Tier 1-2), the AM parts. The decision variables were the number of units produced by each facility. A binary condition was used as part of the site-selection criteria. The objective function was to minimize the total cost of the assembly, or the price that the Tier 1-2 would pay.

The FOSC model was first developed using Excel and then coded in Python in order to validate the initial results. The Excel version of the model is reproduced in Figure 55 below that captures the parameters, decision variables and constraints. Excel has additional functionality as part of its Solver Add-in that was used to codify the binary and integer cells. The Python code as based upon the PuLP solver library. A copy of the code is provided in the appendix.

Parameters	CM			AM
Facility:	**A**	**B**	**C**	**D**
Variable cost ($)	va	vb	vc	vd
Fixed cost ($)	fa	fb	fc	--
Capacity (prt)	ca	cb	cc	cd
Demand (prt)		dc		da

Decision variables	A	B	C	D	
Units produced	xa	xb	xc	xd	*<< integer*
(used?)	ya	yb	yc	yd	*<< binary*

Resource allocation					Used		Constraint	Limit	Type
As	1				-	<=	ca	0	Capty
Bs		1			-	<=	cb	0	Capty
Cs			1		-	<=	cc	0	Capty
Ds				1	-	<=	cd	0	Capty
A+B+C+D	xa	xb	xc	xd	-	=	dc+da		Dmd
Ds				xd	-	>=	da		Dmd

Cost multiplier					Total Cost
Var ($)	va	vb	vc	vd	-
Fxd ($)	fa	fb	fc	--	

Figure 55: The First-order Supply Chain (FOSC) Excel ILP model

The mathematical formulation followed a fairly standard fixed-cost ILP facilities problem. There was one nuance. The program had to allow AM parts to substitute for CM parts; consequently, the AM hard constraint had to be relaxed. This was rather trivial using Excel, but required a bit more ingenuity when translating into Python code. The math script is summarized below with the objective function, constraints, and description of the variables.

$$\min_{x_i^c, x^a} \left[\sum_{i \in \{1,2,3\}} \left(v_i^c x_i^c + I_{\{x_i^c > 0\}} f_i^c \right) + v^a x^a \right]$$

subject to

$$x_i^a \leq c_i^c, \forall\, i \in \{1,2,3\}, \tag{1}$$

$$x^a \in [c^a, td], \tag{2}$$

$$\sum_{i \in \{1,2,3\}} x_i^a \leq td^c, \tag{3}$$

$$td = td^a + td^c. \tag{4}$$

where: x_i^c = *units produced by CM*
x^a = *units produced by AM*
v_i^c = *variable cost coefficient by CM*
v^a = *variable cost coefficient by AM*
f = *fixed cost coefficient for CM*
I = *binary conditional operator for CM*
c^c = *production capacity for CM*
c^a = *production capacity for AM*
td^c = *total demand for AM*
td^a = *total demand for AM*

4.2.5 Verification & Validation

In order for a system to be deemed acceptable, it must ultimately be qualified. In this case the system to be qualified is the FOSC model. Qualification is the act of verifying and validating both the design and behavior of the system and its various components. These must be accepted or proven conformal per the system’s stakeholders according to Buede and Miller (2016). Consequently, the verification and validation, or colloquially stated, V&V, is a fundamental systems engineering process at the end of design-build-test cycle. This spans from individual components to an entire system. It is more than just testing the artifact or the system, however. Validation is the process of ascertaining that the system designed and built is the *correct system*, as initially specified by the stakeholder requirements. In contrast, verification is corroborating that the individual elements and the entire system itself have been *built correctly* (Buede and Miller 2016).

These concepts, nevertheless, quite often cause confusion mainly due to semantic difference between the various disciples involved in system's architecture. ISO 24765 provides a series of definitions for both terms. A majority of these ISO Standards are based upon previous work within the software design community in its effort to conform models. The software industry naturally has a rich history of building and then qualifying digital models.

According to ISO, validation is the "confirmation, through the provision of objective evidence, that the requirements for a specific intended use or application have been fulfilled" ("International Standard ISO/IEC/IEEE 24765" 2017, 9:499). It further states that this is to ensure the systems is able to accomplish its intended purpose or goal; or, even more simply, to "solve the right problem" (499). Thus, there is an outward facing objective or external component to the model validation process. This sentiment is capture in yet another definition, which further clarifies "the assurance that a product, service, or system meets the needs of the customer and other identified stakeholders. It often involves acceptance and suitability with external customers" (499).

Verification is much easier to conceptualize. The formal definition according to the same ISO standard is "confirmation, through the provision of objective evidence, that specified requirements have been fulfilled" ("International Standard ISO/IEC/IEEE 24765" 2017, 9:503). It further expounds that this is often deemed an internal process. It is probable that the contrast between validation as an external process and verification as in internal process traces back to concept of external and internal validity of experiments for social settings by Campbell (1957).

For systems engineers, the V&V process is most commonly articulated in terms of the V-model. This iconic model was introduced in the late 1990s by Mooz and Forsberg. It includes a series of cascading requirements, starting with the initial stakeholder needs. The system is design top-down and from left to right. The individual components are then integrated from the bottom-up while referencing the individual subsystems as devised during the system's design phase. The last step is to obtain stakeholder satisfaction.

The entire process is illustrated in Figure 56 on the next page, along with the fundamental attributes of each intermediate stage (Scheithauer and Forsberg 2013). This particular figure represents the "Assurance V" and has implication for quality in the form of continuous process. The authors of the paper explain that this continual improvement was first introduced by Toyota quality expert, Taiichi Ohno. In particular, this process emphasizes that “any systems engineering work product should have passed quality checks before it is released to serve as a point of reference for downstream engineering activities” (Scheithauer and Forsberg 2013, 510). For purposes of this dissertation, the V-model will not be implement; nonetheless, it principles are fundamental to the understanding of the role of V&V for FOSC model, as well as systems engineering, in general.

Figure 56: The system engineering V-model applied to quality assurance

Model Validation

There is no known precedence for the V&V of the FOSC model as presented herein. An agile architecture framework proposed by INCOSE Fellow Rick Dove in the 1990s was initially considered. This is an approach to create a flexible and resilient architecture for an enterprise system. Agile principles have since become widely popular for developing enterprise-related software, yet this implementation is somewhat orthogonal to the original framework for agile system architecture (Dove 2012). The exact definition of agile varies. According to Dove, in its most basic form in the context of system architecture, it is the “ability of a system to thrive in an uncertain and unpredictably evolving environment” (Dove and Labarge 2014, 863).

The agile model includes four metrics for a given system: timely, affordable, predictable, and comprehensive. Moreover, agile enterprise systems have effective “situational responses” under conditions with varying degrees of uncertainty for different combinations of known and unknown variables. Dove further prescribes three fundamental principles to ensure agile designs for a given system, namely that of reusable, reconfigurable, and scalable. This is known casually as the RRS model (Dove and Labarge 2014).

The RRS is a heuristic that encapsulates the essence of an agile system. But how does this relate to the model developed for this dissertation or the motivating question? The AM process does exhibit reusable, reconfigurable, and scalable characteristics. In fact, recall that the primary advantage of additive manufacturing is its inherent flexibility, both in terms of designing and building parts. Notwithstanding, it is not the AM process itself that is being scrutinized, but the FOSC model. After further consideration, the agile model was deemed more appropriate to judge the fitness of an enterprise, but not for an analytical model. Moreover, these three attributes alone do not constitute a comprehensive rubric to meaningfully validate the model. Another method was required.

Next, the NASA Standard for Modeling and Simulation (Handbook 7009) was evaluated. This, too, was not chosen because its principle basis was more aligned with modeling and simulation, and subsequent testing of physical artifacts. For example, the Standard addresses the process of reconciling a finite element model (FEM) with an actual physical test specimen, often referred to as the real world system or RWS (Steele 2013).

This is understandable as it is consistent with NASA's rich history of designing and building launch vehicles and satellites. NASA employs the multi-scale, multi-physics mathematical models that were introduced earlier, that are based upon first principles of mechanics, such as the stress-strain behavior of a material. For this reason, the NASA Standard was also considered inadequate to validate the FOSC model.

The third validation tool considered was the widely-known Supply Chain Operations Reference (SCOR) model. This diagnostic tool was originally developed in the mid-1990s by a the management consultant firm PRTM (White 2018). The framework is now a part of APICS and the Association for Supply Chain Management, and is considered by many as the *de facto* standard for supply chain model interrogation (www.apics.org).

The original SCOR model considers four distinct processes, including: source, make, deliver and plan (Huan, Sheoran, and Wang 2004). Hence, this provides a basic outline for a generic manufacturing process. Each of the four categories is further subdivided into three to five subtopics. In turn, these subtopics are broken down further into themes. For example, under the “make” category, there is the subtopic “make-to-order.” This then is subdivided into seven additional topics, specifically: (1) schedule production activities, (2) issue sourced product, (3) produce and test, (4) package, (5) stage final product, (6) release finished product, and (7) waste disposal (APICS Supply Chain Council 2017).

It is evident from this example that even with this level of granularity, it is not an appropriate framework to validate the FOSC model. More specifically, it does not capture the essential elements needed to predict the supply chain’s behavior. Finally, the detailed classification still lacks a corresponding numerical rubric needed to evaluate the fitness of the FOSC model.

One final comment regarding the SCOR model. The FOSC model only considers two of the four categories that are covered by the SCOR model. Only the “make” step of the manufacturing process operation and a portion of the “source” step (depending upon how sourcing is defined) is addressed in the FOSC model. This model only allocates parts from the various Tier 3 suppliers to the Tier 1-2 for assembly based upon the BOM. Secondly, the FOSC model assumes that all raw material required would be instantaneously available to each of the Tier 3 suppliers. This assumption was discussed earlier in the document.

In contrast, the source steps with the SCOR model is much more involved. For instance, for the “make-to-order product” category there are five steps that are considered: (1) schedule product deliveries, (2) receive product, (3) verify product, (4) transfer product, and (5) authorize supplier payment. The steps are predominately logistics and are beyond the scope of the FOSC model. In the end, the SCOR model was deemed inappropriate as well.

The fourth and final methodology considered for validating the FOSC model was devised by Manufacturing Enterprise Solutions Association (MESA) International. This non-profit consists of a global set of manufacturers and information system providers. Its primary focus is to help facilitate the use of technology within these businesses. Similar to Dove’s agile model, the organization promotes practices that are considered flexible and agile for its member companies. MESA constructed a series of manufacturing and production metrics that are organized into an operational framework as seen in Figure 57 (“The MESA Model” n.d.).

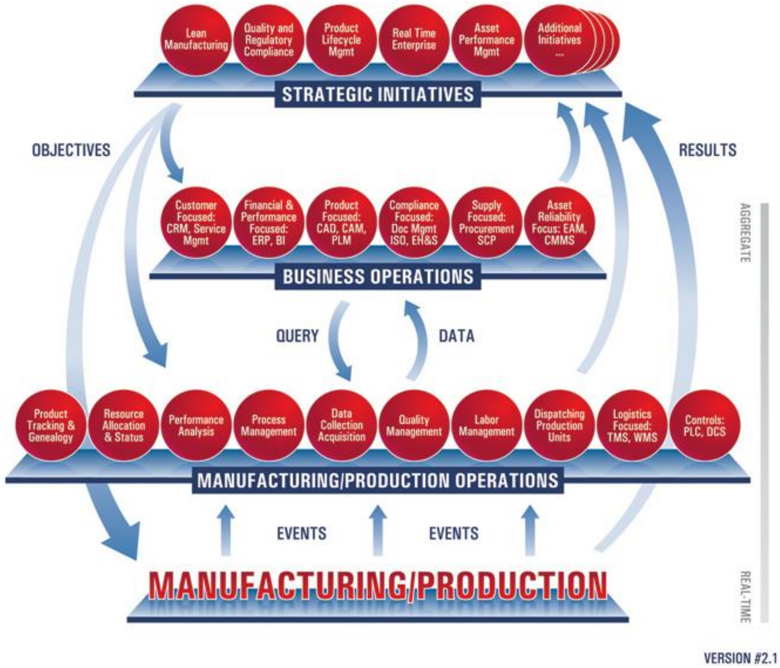


Figure 57: The general MESA framework relating manufacturing, business and strategy

In 2006, MESA conducted a survey of 135 manufacturers that culminated in a comprehensive report entitled “Metrics that Matter: Uncovering KPIs that Justify Operational Improvements.” The single most important performance criteria identified was a firm’s profitability. In addition, MESA highlighted several other areas that are consider critical to a business’ success (“Metrics That Matter: Uncovering KPIs That Justify” 2006). These seven metrics are listed below in order of importance as determined by the survey:

- Quality
- Customer service
- Throughput
- Asset utilization
- Compliance
- Flexibility
- Inventory

This collection of characteristics seems much more relevant FOSC model validation than the three previous methods. Nevertheless, there is a relationship between these metrics and the other methods. For example, it is easy to recognize some of the aspects of Dove's Agile model, particularly as embodied in the notion of operational flexibility. Therefore, MESA's Metrics that Matter was chosen as the most suitable tool for validation.

Table 3 presents the results of the MESA KPIs in the context of the FOSC model. There were two KPIs that had to be inferred. Quality and compliance are both presuppositions based upon the assumption that aerospace parts will have been already approved by a regulating authority. In other words, quality and compliance are prerequisites. Throughput was another item that was assumed as a non-issue, as discussed in the SCOR section.

Table 3: A qualitative validation of the FOSC model in terms of the MESA criteria

Attribute	Applicability	Comments
Quality	(assumed)	Assumed a precondition for AM parts due to the FAA flight-safety mandate for flight-critical hardware
Customer Service	*no*	(Characteristics is completely absent from the model)
Throughput	(n/a)	Considered sufficient but not directly measured as machine bandwidth is treated as a nonfactor
Asset Utilization	yes	Provided in the form of units produced per machine in conjunction to each machine's capacity
Compliance	(assumed)	Assumed a precondition since FAA conformity is required for all flight hardware within a certified article
Flexibility	yes	Manifest via the presence of multiple suppliers within the model, with businesses awarded based upon lowest cost
Inventory	*no*	Believed to be irrelevant since model assumes parts will be fabricated on demand with material readily available

From this score card, it is fairly obvious that the FOSC model does not perfectly align with the proposed MESA KPI metrics. Nevertheless, the rubric's fitness seems sufficient enough, especially in the context of the fact that there are few alternatives available. Based upon what has been identified, it seems that the FOSC model is "valid" insofar as it addresses satisfactorily many of the key topics for a manufacturing system.

A few final thoughts regarding the general lack of congruency between the FOSC model and the various supply chain and manufacturing methodologies available. First, the FOSC is basically a hybrid between manufacturing and supply chain. It also involves optimization, but it is much more than a standard ILP. This model is perhaps best characterized as a "manufacturing sourcing" model. Additive manufacturing is a new paradigm, so it stands to reason that evaluating its assimilation may require a unique series of metrics than what have been used historically.

Model Verification

Model verification process is straightforward – it is akin to checking the accuracy of the model's output. This involved using a second software model, and in this case, Python, to compare the results of the Excel model. The results are reproduced below. Both ILP models were in perfect agreement for various scenarios tested. One condition is replicated below in Figure 58 that captures sample input parameters for the Excel model.

Parameters	*CM*			*AM*
Facility:	**A**	**B**	**C**	**D**
Variable cost ($)	1	1.5	1.75	2.5
Fixed cost ($)	20	15	10	--
Capacity (prt)	5	10	15	5
Demand (prt)		30		3

Decision variables	**A**	**B**	**C**	**D**	
Units produced	5	10	15	3	*<< integer*
(used?)	1	1	1	1	*<< binary*

Resource allocation					**Used**		**Constraint**	**Limit**	**Type**
As	1				5	<=	5	5	Capty
Bs		1			10	<=	10	10	Capty
Cs			1		15	<=	15	15	Capty
Ds				1	3	<=	5	5	Capty
A+B+C+D	5	10	15	3	33	=	33		Dmd
Ds				3	3	>=	3		Dmd

Cost multiplier					Total Cost
Var ($)	1	1.5	1.75	2.5	98.75
Fxd ($)	20	15	10	--	

Figure 58: Sample input for verification analysis for FOSC Excel model

The demand of CM parts was varied from 10 to 30 units. An Excel plot of the data is reproduced in Figure 59. The output or the total cost of the assembly ranged from $35 to almost

$99. The step-increase at 18 units and 28 units corresponds to the need for the algorthium to transition to the next CM facility, consequently incurring another fairly large fixed cost.

The same behavior can be seen in the second figure below (Figure 60) for the Python output. In this figure, the blue line represents the total cost of the assembly and the orange line is the number of units produced by the AM facility. Under the condition where AM parts can substitute for CM parts, the extra two units of AM capacity is used to satisfy the CM demand. Because it is cost effective, the algorithum selects these parts before switching to the next CM facility. This will become an important phnomenon in the following section.

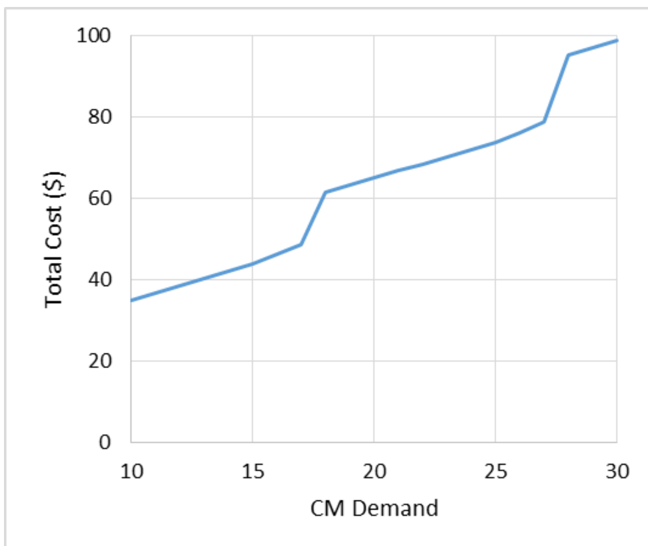


Figure 59: Plot of the total cost per the Excel model for varying CM demand

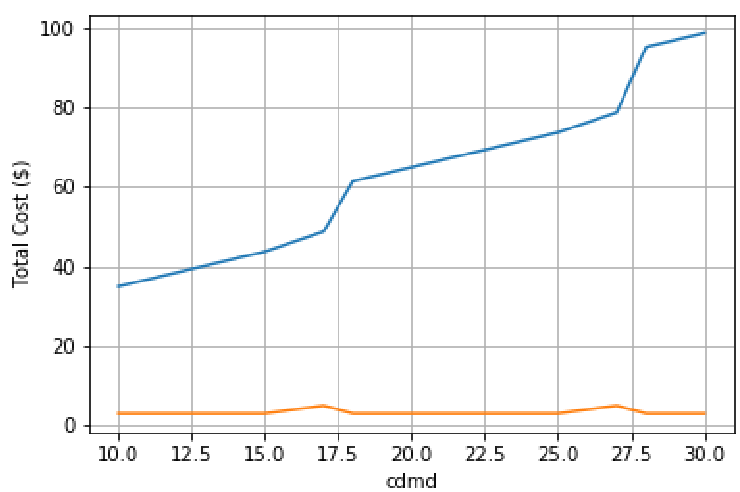


Figure 60: Corresponding plot of the total cost using the Python model

5. RESULTS

There were two primary challenges to refining the FOSC model. The first was to determine realistic parameters that would be representative of industry data. The second challenge was to decide which parameters to vary for the sensitivity analysis. Both challenges are cursorily introduced in this section, and the results are elaborated in the following section, Chapter 6.

It was explained in Chapter 4 that AM cost data are not readily available, and thus, a few assumptions are required. General heuristics were used to help establish a baseline case; for example, it is fairly understood that AM variable cost is greater that CM variable cost for large production runs. Similarly, it is reasonable to assume that CM fixed costs are significantly higher than the CM variable cost, also referred to as the product's marginal cost. Notwithstanding, the emphasis on the accuracy of these assumptions is eventually blunted by the fact that a sensitivity study was conducted, varying both the CM variable and fixed costs.

The model contains four parameters: variable cost, fixed cost, capacity and demand. For each parameter set, there is a CM and AM option, with the exception of fixed cost that only applies to conventional manufacturing. This results in 13 total parameters that can be modified. Therefore, the second challenge involves selecting the parameters for the sensitivity analysis. If one were to assume a high-medium-low scenario for each parameter, this would generate nearly 1.6 million outcomes. It is important to realize that the focus of the research is methodology development and not optimization *per se*. As such, the goal is not to find the global cost minimum, but rather to understand what variables and constraints are important when attempting to model the impact of additive manufacturing on the supply chain.

To make the analysis more tractable, of the 13 parameters, five were deemed most important – *AM variable cost*, *CM fixed cost* (three total), and *CM demand*. For the purposes of the sensitivity studies, the CM facilities were considered homogenous. This allowed the three CM fixed costs to be treated as a single variable, which in turn, resulted in a total number of parameters of three.

In addition to the three sensitivity studies, there were three parameter study conducted that evaluated the effects of changing the CM values for each of the three facilities. There can be very complicated coupling between these variables that materially affect the solution. The model parameters, and the two different studies described are reproduced below in Table 4.

Table 4: Summary of the FOSC model parameters and related studies

	Parameter	Study	Explanation
Additive Facility	*Variable cost*	S	Identified as one of the three key input parameters
	Fixed cost	--	(considered negligible)
	Capacity	--	Can be used to study increase in size of AM build chamber
	Demand	--	Can be used to study changes in technology maturity
Conventional (Facility A)	*Variable cost*	P	Was set to unity initial and used to normalize the other costs
	Fixed cost	S & P	Identified as one of the three key input parameters
	Capacity	P	Could have an important effect depending upon other facilities
	Demand	S	Identified as one of the three key input parameters
Conventional (Facility B)	*Variable cost*	P	Used to consider secondary effects due to additional facilities
	Fixed cost	P	Used to consider secondary effects due to additional facilities
	Capacity	P	Used to consider secondary effects due to additional facilities
	Demand	--	(all demand for CM is consolidate as a single entry)
Conventional (Facility C)	*Variable cost*	P	Used to consider secondary effects due to additional facilities
	Fixed cost	P	Used to consider secondary effects due to additional facilities
	Capacity	P	Used to consider secondary effects due to additional facilities
	Demand	--	(all demand for CM is consolidate as a single entry)

Key: S = sensitivity study, P = parameter study

5.1 Baseline Model

In light of the simplifying assumptions, the baseline model was developed and is presented in Figure 61 on the following page. A CM variable cost of 1 unit was assumed, then 10 units for the AM variable cost, and 500 for the CM fixed cost. Only these latter two variables will be modified in addition to changing CM demand. For this reason, these entries in the table were identified with normal black font, and the non-changing values were grayed out. This represents the initial or baseline FOSC model.

Parameters	CM			AM
Facility:	A	B	C	D
Variable cost ($)	1	1	1	10
Fixed cost ($)	500	500	500	--
Capacity (prt)	300	300	300	250
Demand (prt)	360			50

Decision variables	A	B	C	D	
Units produced	60	0	300	50	*<< integer*
(used?)	1	0	1	1	*<< binary*

Resource allocation					Used		Constrant	Limit	Type
As	1				60	<=	300	300	Capty
Bs		1			-	<=	-	300	Capty
Cs			1		300	<=	300	300	Capty
Ds				1	50	<=	250	250	Capty
A+B+C+D	60	0	300	50	410	=	410		Dmd
Ds				50	50	>=	50		Dmd

Cost multiplier					Total Cost
Var ($)	1	1	1	10	1,860
Fxd ($)	500	500	500	--	

Figure 61: The FOSC baseline model illustrating the facility selection process

There were five scenarios evaluated, three of which were designed as sensitivity studies. The first study was a critical point analysis intended to understand the behavior of CM versus AM part substitution as a function of CM demand. The second study is also a sensitivity analysis for the base case, where the AM variable cost, CM fixed cost, and CM demand are all varied sequentially by a fixed percentage. The third study is a modification of this same theme. The percentage change for each of the three categories were adjusted, as well as the initial CM demand value using values that were believed to be more insightful. The fourth study again is a sensitivity analysis, and involves actual cost-multiplier data as a function of TRL (i.e. technology maturity). And the fifth and final study is fundamentally different – only the CM values are modified. The CM variable cost, fixed cost, and the capacity are all changed asynchronously. The results for each of these five cases is presented in the following subsections.

5.2 Critical Point Analysis

The model is designed such that for simple cases, one can intuit when the algorithm will transition from CM parts to AM parts as capacity for CM parts becomes constrained. In this transition interval, depending upon the AM variable cost, it may be cost effective to use AM parts as a direct substitute for CM parts. This would obviate the need to pay for additional fixed cost required to sustain the capability to produce CM parts. In Figure 62 below, for the baseline parameters, this transition interval occurs between a CM demand of 300 and 350 parts, and then again for 600 and 650 parts. Each is marked accordingly on the plot. This structural adjustment follows the same pattern observed during the verification process (see Figure 59 for details).

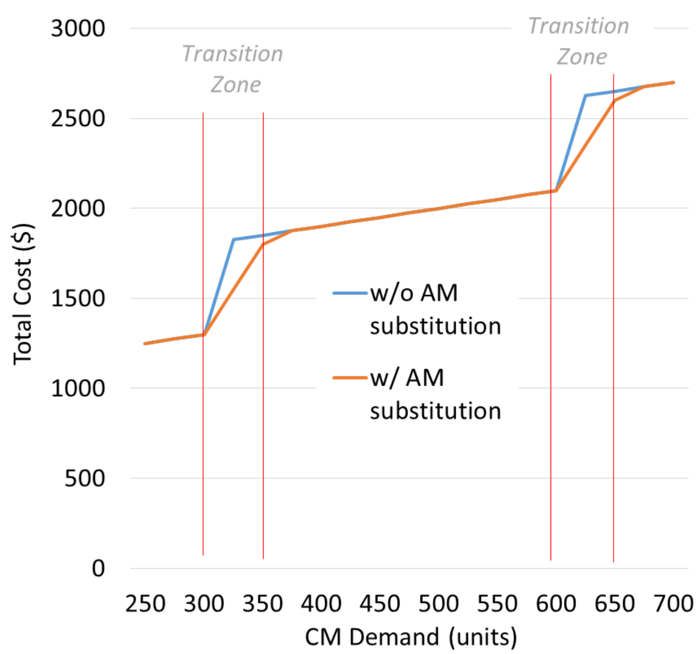


Figure 62: Critical point analysis of the baseline data as a function of CM demand

Perhaps the best manner in which to easily conceptualize the behavior of the algorithm is to chart the activity of the individual facilities. Table 5 below outlines the utilization of the four facilities with increasing CM demand. Binary operators are uses, hence a '1' represents the CM facilities that have been engaged in production.

In the two transition zones identified above in Figure 62, there are a series of AM parts that are produced as replacement parts. In particular, 25 AM parts that will be used to substitute for the extra 25 CM parts that would be required from a second CM facility. This occurs while transitioning from a CM demand of 300 to 325, and again at 325 to 350, 600 to 625, and final 625 to 650. Naturally, the algorithm is selecting the lowest cost option between procuring relatively expensive AM parts versus paying a large fixed cost to a CM facility to obtain cheaper CM parts. The implication of this will be discussed in Chapter 6.

Table 5: CM facility utilization and AM units produced as a function of CM demand

CM Demand	A	B	C	AM units	Total Cost ($)
250			1		1250
275			1		1275
300	1				1300
325			1	25	1550
350			1	50	1800
375	1		1		1875
400	1		1		1900
425	1		1		1925
450	1		1		1950
475	1		1		1975
500	1		1		2000
525	1		1		2025
550	1		1		2050
575		1	1		2075
600	1	1			2100
625	1		1	25	2350
650	1		1	50	2600
675	1	1	1		2675
700	1	1	1		2700

The purpose of this exercise was to verify the behavior of the model in the data range that would be consider more representative of industry cost data. As discussed, this is critical due to the general lack of AM-related cost data in the public domain. The model does indeed function as expected within this parameter range.

5.3 Initial Sensitivity Analysis

The initial sensitivity study involved the most comprehensive investigation in terms of the number of scenarios to ascertain the effects of changing the three parameters introduced previously, specifically AM variable cost, CM fixed cost, and CM demand. The goal was to identify which changes in parameters would cause the largest change in the total cost of the assembly (i.e. the price that the Tier 1-2 would pay). In this initial case, the three key parameters were modified relative to its baseline values, each sequentially by ±30%. These input values are outlined in Table 6 on the following page.

Table 6: Input values for the ±30% sensitivity study

Parameters	*Low*	*Baseline*	*High*
AM VC	7	10	13
CM FC	350	500	650
CM demand	245	350	455

The FOSC model was updated by changing only one parameter at a time, holding the other two fixed. It is important to note that although there were three CM facilities – and thus three CM fixed costs – they were all treated similarly, a concept presented in the introduction of this section. This results in three variables, and if one were to assume high-medium-low for each of these, the final result would be a data cube with dimensions of 3 x 3 x 3. These 27 final cost values were then studied in greater detail. The initial results are summarized below in Table 7 in the form of a heat map – the green shading indicates the lowest values and the red shading is the highest for that dataset.

Table 7: Total cost as a function of changing the three key input parameters

		CM demand		
AM VC	CM FC	245	350	455
7	350	945	1350	1505
7	500	1095	1500	1805
7	650	1245	1650	2105
10	350	1095	1550	1655
10	500	1245	1800	1955
10	650	1395	1950	2255
13	350	1245	1700	1805
13	500	1395	2000	2105
13	650	1545	2250	2405

These data can also be plotted in the form a three-dimensional surface, segmented as three separate plots in terms of the AM variable cost. Each surface has a progressively higher average total cost as represented by Table 7 above. In all three cases, the surfaces demonstrate a monotonic increase from its minimum value to the maximum value, and therefore lack inflection points. Figures 63 through 65 on the following two pages illustrate this phenomenon.

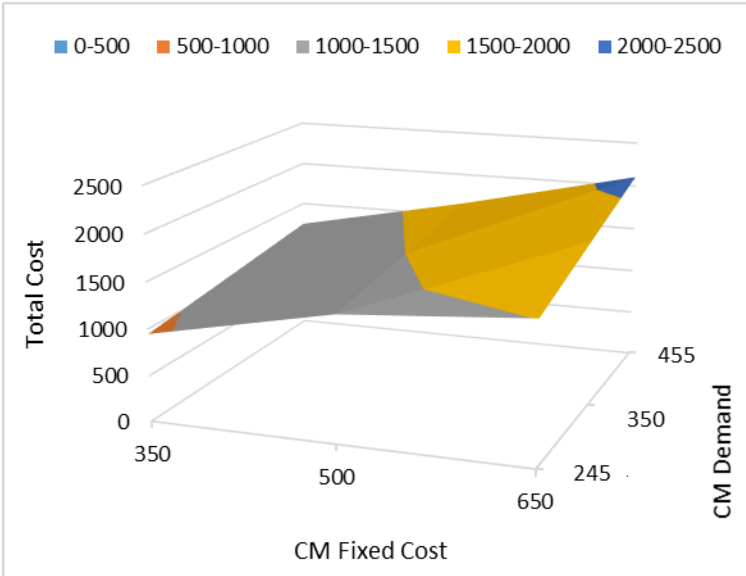


Figure 63: Total cost surface for AM variable cost of 7

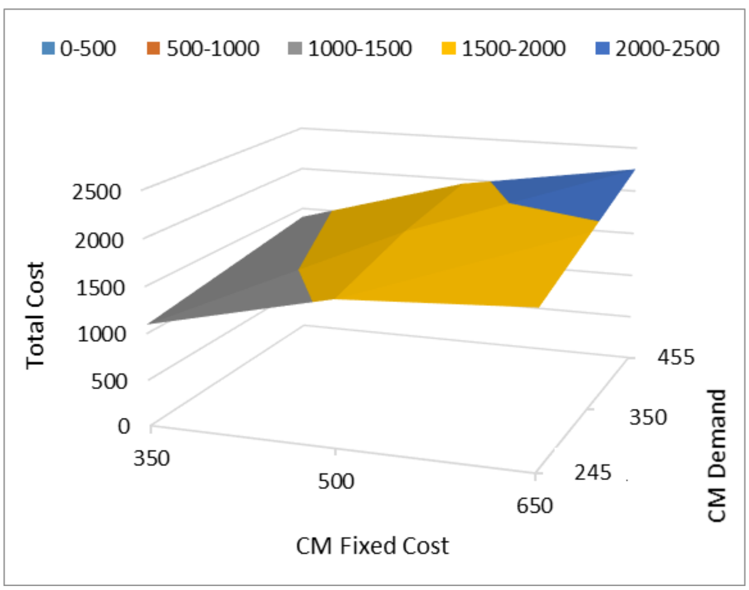


Figure 64: Total cost surface for AM variable cost of 10

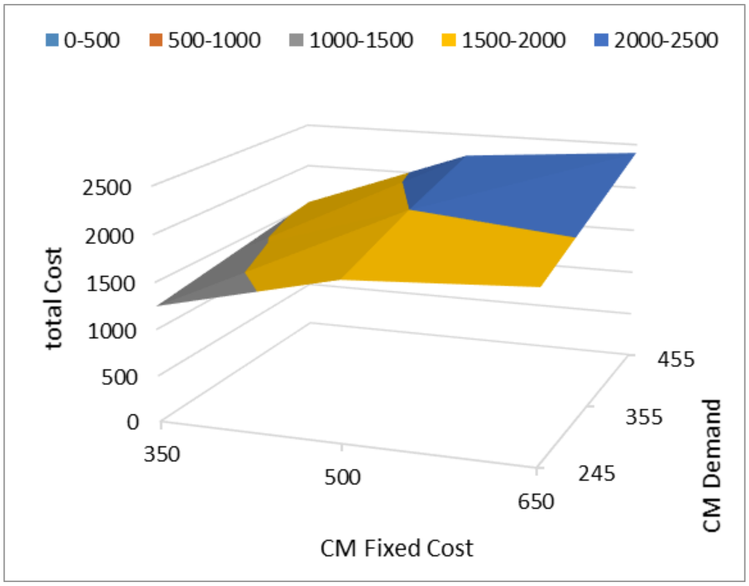


Figure 65: Total cost surface for AM variable cost of 13

Another approach to analyze the impact due to changes in CM demand is to plot the column data in Table 7. This shows the rate of change for varying demand as a function of the change of CM fixed cost. This results in shown graphically in Figure 66. Naturally, the slope indicates the rate of change; nevertheless, it is still difficult to decipher the net effects of these changes on the entire system. For this reason, a tornado plot was considered more desirable.

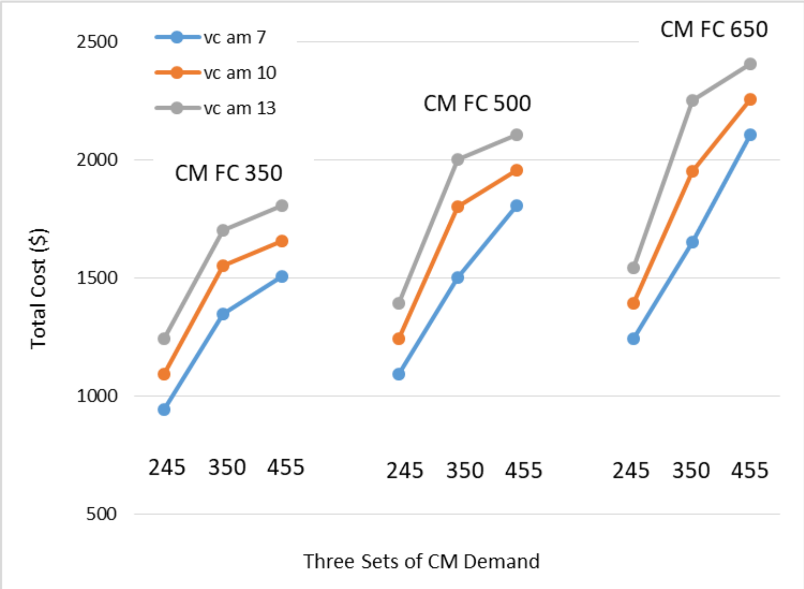


Figure 66: Total cost as a function of CM demand, segmented by CM fixed cost

Tornado plots are popular graphical tools as they can quickly illustrate the overall effects of changes in variables. In this case, data from Table 7 were plotted and organized from most impactful to least impactful with respect to the magnitude of these changes in cost. The results are plotted below in Figure 67. The maximum change in total cost is roughly $4000 and occurs with the highest AM variable cost (i.e. 13) coupled with the highest CM fixed cost (i.e. 650) as the CM demand increases from 245 to 455.

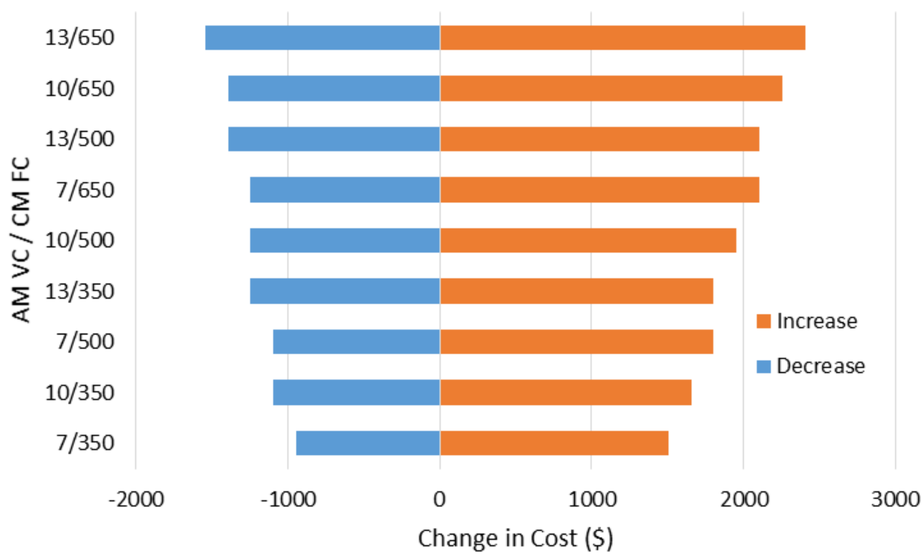


Figure 67: Tornado plot for sensitivity using ±30% and CM demand from 245 to 455

5.4 Modified Sensitivity Analysis

Gleaning insight from the initial sensitivity study, a second more focused sensitivity analysis was conducted. There were two fundamental changes – the first pertains to the AM variable cost, and the second change includes the CM capacity value. In particular, the issue of cost uncertainty for additive manufacturing needed to be addressed. To account for this, the range for the AM variable cost variation was doubled, increasing from ±30% to ±60%.

For the CM capacity component, a change was made to better understand the extreme or critical point in which the algorithm is required to add capacity to meet demand. This involved two steps. First, the initial CM demand was reduced from 350 parts to 315 parts to coincide with this “capacity transition” zone, or the step increase illustrated in Figure 62. The second step was to reduce the range of CM demand from ±30% to only ±3% of the starting value (i.e. 315). This in turn corresponds to an upper and lower limit of 305 to 325 CM parts, respectively. Finally, the variation in the CM fixed cost was left unchanged from the initial case (i.e. ±30%). The final values for three variables are summarized below in Table 8.

Table 8: Input values for the modified sensitivity study using ±60/30/3% changes

Parameters	*Low*	*Initial case*	*High*
AM VC	20	50	80
CM FC	350	500	650
CM demand	305	315	325

Figure 68 below is a tornado plot that clearly delineates the impact of these parameter changes. The maximum change in cost is roughly $11,000, and is associated with the largest value for the AM variable cost and largest value of the CM fixed cost, 80 and 650, respectively. There is a clear, predictable pattern, driven by the AM variable cost. These notable differences from the initial sensitivity study will be addressed in the Chapter 6.

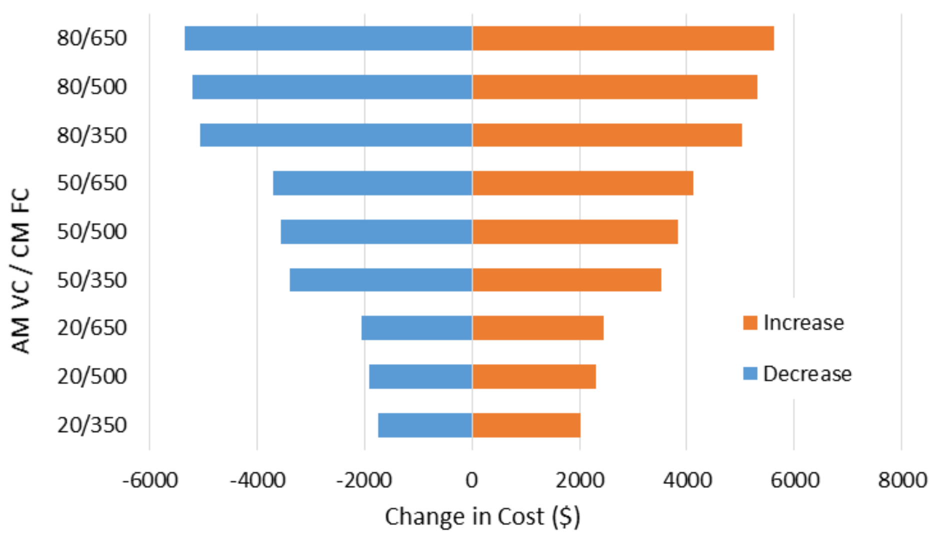


Figure 68: Tornado plot for the modified sensitivity analysis of ±60/30/3% case

5.5 Sensitivity Using TRL Data

The third sensitivity study is yet another variation of the previous two studies. In this case, although, actual cost multiplier data as a function of TRL were used. These data are reproduced in the following Figures 69 and 70 (Kenley and Nail 2005; Hoy and Hudak 1994) and cover cost uncertainty for new technology development and production, respectively. It is reasonable to assume these data are analogous to the fixed cost and variable cost of product development.

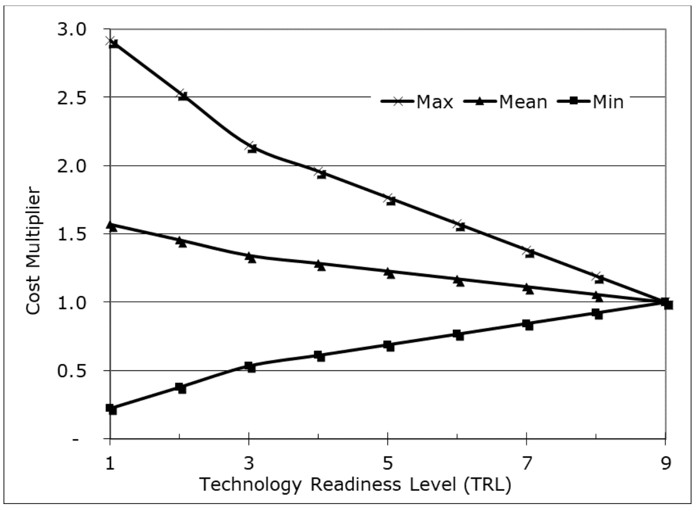


Figure 69: Cost multiplier as a function of TRL for development (or fixed costs)

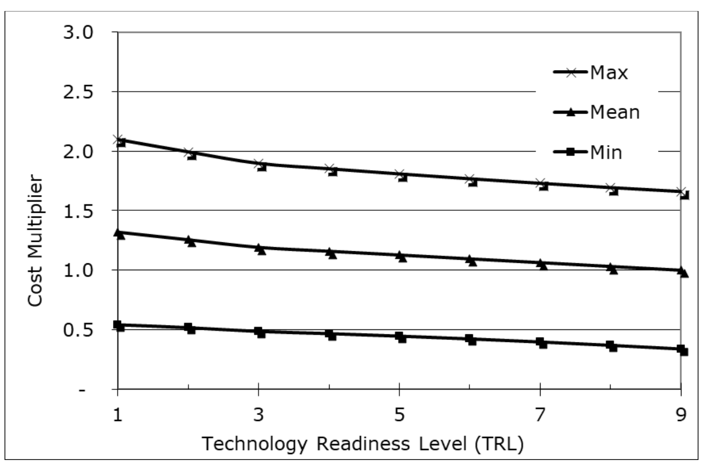


Figure 70: Cost multiplier as a function of TRL for production (or variable costs)

Using this analogy, it was assumed that the CM TRL was effectively at level 8, and that AM TRL was basically at level 4 for PBF. Both of these assumptions are conservative since they add to the uncertainty of cost (and schedule). The choice for PBF was based upon general guidance provided by the America Makes[12] initiative that endeavors to move metal AM technologies from TRL 4 to 7 ("National Network for Manufacturing Innovation Program: Strategic Plan" 2016). For more information on determining TRL, please see Appendix A of the book *Managing Technology and Product Development Programmes* (2019).

From the Figure 69, this represents a min-max range of cost multipliers from 0.92 to 1.19 for the CM fixed costs. Similarly, using Figure 70, this translated to a cost multiplier min-max range of 0.47 to 1.85 for the AM variable costs. These factors were applied to an initial case that was developed based upon the results of the previous two sensitivity studies. Applying the min-max criteria from above, final input values for the three key parameters were determined as summarized in Table 9 below.

Table 9: Input values for the TRL-related sensitivity study

Parameters	*Low*	*Initial case*	*High*
AM VC	5	12	19
CM FC	460	530	600
CM demand	305	315	325

Similar to the previous two sensitivity studies, these data were plotted as a tornado chart, and presented in Figure 71 on the following page. The total magnitude of change is roughly $4300, and corresponds to the maximum AM variable cost and maximum CM fixed cost. Similar to the previous study, there is a clear pattern where the cost of AM dominates the results.

[12] America Makes is a national accelerator and partner for research in additive manufacturing; the initiative stemmed from the 2011 the President's Council of Advisors on Science and Technology report on manufacturing.

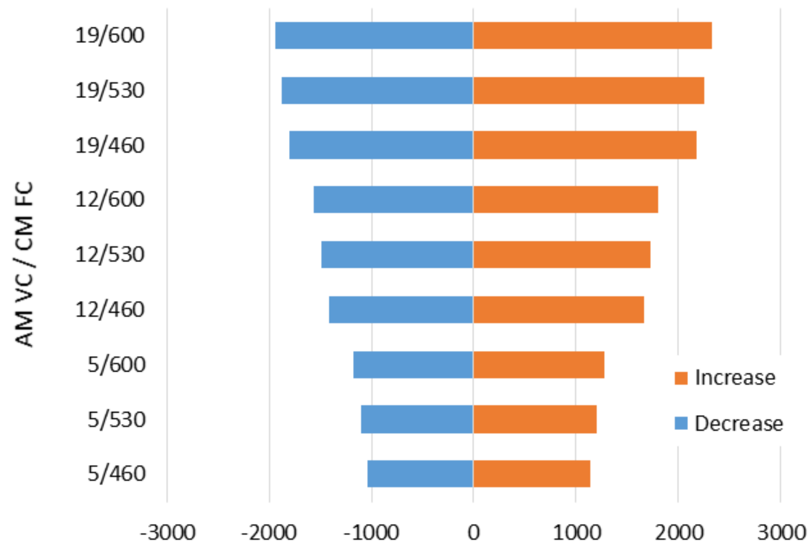


Figure 71: Tornado plot for the actual cost data associated with change in TRL4

5.6 Additional Parameter Variation

The fifth case asynchronously varies only the CM parameters, specifically the variable cost, fixed cost, and capacity. The intent it to understand the effects of coupling. The AM values remained fixed at their baseline condition. The updated CM values are displayed in Table 10. It is apparent from the table that the fixed cost and capacity either increase or decrease. These combinations should create a different outcome from the ILP for the baseline case. Moreover, the change of the variable costs between facilities makes the overall scenario more realistic.

Table 10: CM parameters for the asynchronous variation study

		CM A	CM B	CM C
Case 5.1	*VC ($)*	1	1.25	1.5
	FC ($)	500	450	400
	Capacity	300	250	200
Case 5.2	*VC ($)*	1	1.25	1.5
	FC ($)	500	450	400
	Capacity	200	250	300
Case 5.3	*VC ($)*	1	1.25	1.5
	FC ($)	400	450	500
	Capacity	200	250	300

The results of these changes are captured in Figure 72 below. In general, there is negligible different between the first two Cases, 5.1 and 5.2, but both behave differently from the third Case, 5.3. It would be hard to predict this result by inspection of the input parameters. For this reason, the ILP simulation was required. Recall, these changes are only due to the effects of the CM parameters, as the AM parameters were held constant in each case.

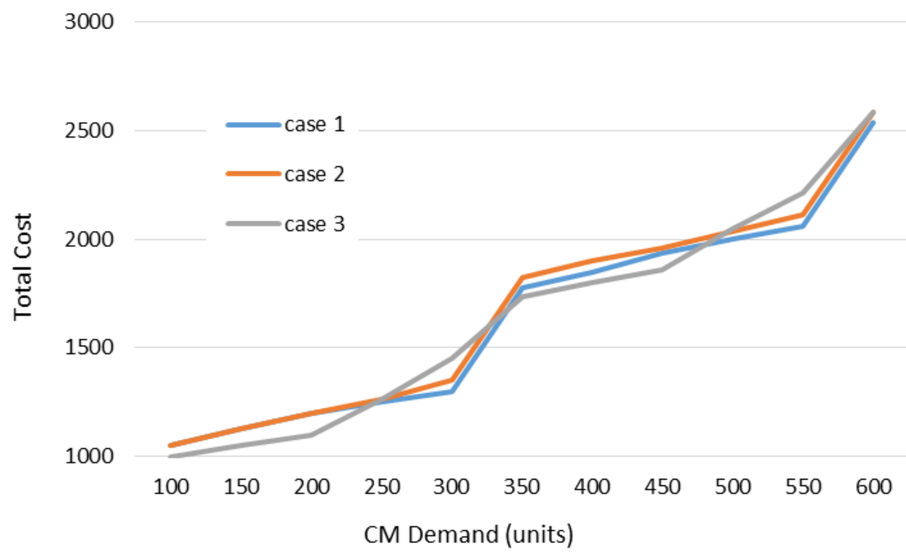


Figure 72: Effects of varying the three CM parameters on the total cost

Similar to the transition zone analysis, perhaps the best approach to determining the behavior of the system is to chart the individual behavior of the facilities. As such, there three tables were generated that track the engagement of the three facilities. Although Case 5.1 and 5.2 show a similar pattern in Figure 72 above, it is evident from Tables 11 and 12 that they have different participation from the three facilities. Likewise, in Table 13, there is unique pattern for allocation of parts from each facility. These three tables are located on the follow page.

It is worth quickly noting some unusual behavior associated with the subtle nuances of the Simplex algorithm. For example, one would anticipate that facility C would be used to produce the first 300 parts in Case 5.3, given the pattern from Case 5.1 and 5.2. A similar behavior is exhibited in Table 5 with a CM demand of 300 – the routine seems to randomly jump from facility C to facility A. This does not affect the final answer in either case, yet its presences is curious and unexplainable.

Table 11: CM facility utilization for Case 5.1

CM Demand	A	B	C	Cost $
100			1	1050
150			1	1125
200			1	1200
250	1			1250
300	1			1300
350	1		1	1775
400	1		1	1850
450	1	1		1937
500	1	1		2000
550	1	1		2062
600	1	1	1	2537

Table 12: CM facility utilization for Case 5.2

CM Demand	A	B	C	Cost $
100			1	1050
150			1	1125
200	1			1200
250		1		1262
300			1	1350
350	1		1	1825
400	1	1		1900
450	1	1		1962
500		1	1	2037
550		1	1	2112
600	1	1	1	2587

Table 13: CM facility utilization for Case 5.3

CM Demand	A	B	C	Cost $
100	1			1000
150	1			1050
200	1			1100
250		1		1262
300			1	1450
350	1	1		1737
400	1	1		1800
450	1	1		1862
500	1		1	2050
550		1	1	2212
600	1	1	1	2587

6. DISCUSSION

It has been posited that commercial aerospace is a challenging market for technology diffusion and new product development due to the extensive qualification process mandated to ensure product safety. The harsh operating environment and an extended operating life further complicate the engineering and design of the aeroengine. In addition, this artifact is produced within a complex production network, involving thousands of suppliers. The goal of this research was to answer the question concerning the disruption of metal additive manufacturing – a powerful new design and manufacturing paradigm – on this supply chain system.

6.1 Research Summary

This research is unique as it targets *serialized production* of AM parts in commercial aerospace, and not the low volume maintenance, repair and overhaul (MRO) spares market for military that is most common in the published literature. Additive manufacturing's two fundamental advantages are its ability to: a) create complex, structurally optimized parts that can potentially replace multiple CM parts; and, b) fabricate parts on demand due to the lack of need for tooling that would be required in the case of conventional manufacturing. This latter benefit is extremely attractive for the MRO of older, legacy aircraft that may be challenged with parts and tooling obsolesce; as such, it has become a fairly popular research topic.

A literature review indicated that there is no reasonable research precedence for modeling the supply chain for production parts. Consequently, a methodology was needed to fill this research void. The supply chain for serialized production of AM parts was characterized using a systems approach that comprised five steps.

The first fundamental step was to define the system of interest, which was limited to the aeroengine OEM and its primary and secondary suppliers. The next step was to determine the CM parts that are candidates for AM-part substitution. The third stage involved creating a simple plant workflow model to estimate the pecuniary implications for manufacturing suppliers. The most detailed modeling effort encompassed the fourth stage – an ILP economic model of a portion of the supply chain. The fifth and final stage was to validate the ILP's fitness and verify its accuracy. The ILP modeling was performed in both Excel and Python.

6.1.1 Model Formulation

The ILP was the crux of the investigation. It started with decomposing the aeroengine production network into a four-level – or tiered – pyramid with the aeroengine OEM at the apex. An important initial assumption was that the impact of additive manufacturing would only affect the interaction between the two interior tiers – namely, the Tier 3s fabricators and the Tier 1-2s assemblers. These two tiers constitute the basis of the ILP that was labeled the First-order Supply Chain (FOSC) model.

For the FOSC, it was concluded that four total facilities – three conventional manufacturing and one additive manufacturing – provided a sufficient level of abstraction. The model has 13 parameters that include the variable and fixed costs, as well as the capacity and demand for both the CM and AM facilities. As such, for a typical analysis involving three scenarios, high-medium-low, there would be 3^{13} or approximately 1.6 million possible outcomes. This was later simplified to three primary parameters based upon the author's judgement – the AM variable cost, CM fixed cost and CM capacity. The result was 3^3 combinations, or 27 different possible cost outcomes for total cost of the assembly.

The FOSC model is predicated upon four important assumptions. First, each tier is dedicated to a single task or function – Tier 3s, for instance, can only fabricate parts and not assemble them. Secondly, as parts fabricators, only Tier 3s can implement additive manufacturing; consequently, the supply chain response can be simplified to studying only the interaction between the Tier 3s and their immediate customers, the Tier 1-2s. This serves as the third assumption. The fourth assumption is that the ILP model is based solely on enterprise operating economics. The fifth and final assumption is that the supply chain is perfectly efficient, free of delays, quality escapes, and material availability issues, etc.

Using the FOSC model, four different scenarios were studied that correspond to increasing levels of technology maturation or changes in TRL. This is indicative of the general confidence in the technology as a whole. There were two important stages of development. First, the FOSC model included parts that were specifically designed for additive manufacturing. By consolidating CM parts, these custom-design AM parts are considered cost effective under certain sourcing conditions.

The second stage of adoption is completely unrelated to custom designed parts. This occurs when AM parts are used to directly substitute one-to-one for CM-designed parts –

according to the model, this results from the higher costs associated with CM fixed costs when adding more capacity. In such a situation, Tier 1-2s would be financially incented to source relatively small quantities of CM-equivalent parts from an AM facility. The alternative would be to engage a second CM facility to meet demand, and thus pay an additional fixed or setup cost. This can be cost prohibitive for small production quantities. This on-demand AM parts substitution scenario analysis constituted a bulk of the analytical study.

6.1.2 Model Results

The baseline FOSC model included data believed to be representative of industry, at least in terms of the relative magnitude between the various costs. Each was normalized with respect to the CM variable cost that was established as one unit of cost. There were five cases analyzed, two proved most significant. First, when the AM variable cost was considered low relative to the CM fixed cost, the combination of these parameters would dictate the supplier selection (e.g. Figure 67). On the other hand, when the AM variable cost was sufficiently high, this alone dominated the supplier selection process, as illustrated in both Figures 68 and 71.

Secondly, independent of the AM costs, the relative nature of the three CM parameters is vital. This is easy to intuit by inspection. Therefore, a thorough modeling effort should consider the relative change of these parameters. Contemplate the following business scenario as an example: a company is competing for market share for CM parts, and it has low variable and fixed costs, yet also has limited capacity.

For larger production orders, Tier 1-2s would be more inclined economically to choose a large company in order to consolidate its order. This follows a general trend within aerospace of supplier rationalization – there is a cost associated with maintain of supply since each has to be periodically qualified. The result of selecting a single supplier is also consistent with the ILP results as shown in Figure 72. The combination of capacity and fixed cost are critical strategic differentiators for CM facilities. On the other hand, realistically, facilities with large capacity typically have higher fixed and variable costs that need to be amortized over long production runs in order to be profitable.

6.1.3 Research Questions Revisited

The dissertation began by posing five research questions concerning the nature of aerospace supply chain in light of additive manufacturing. As previously explained, a multi-step methodology was developed to include an ILP economic model of a simplified supply chain. Both the model and the process of modeling made it possible to answer the various research questions. The following lists both the section in the document where the answers are provided, as well as a summary of the answer.

R1. *WHICH segments of aerospace are subject to AM disruption, and WHICH metal AM modalities are most likely to prevail?*

***Section 2.1 & 2.2*:** Amongst the five primary aircraft systems, the aeroengine was deemed the most susceptible to additive manufacturing mainly due to the fact that it is comprised of alloys that are difficult to machine. The small size of parts and their tolerances are other important criteria.

There are four fundamental metal AM modalities. Of these, PBF seems most likely to penetrate the aeroengine market – this includes both laser and E-beam systems. The greatest advantage of PBF is the ability to produce complex geometry parts with a high-level of dimensional accuracy that requires minimal machining. The key limitation is a relatively slow build rate or rate of deposition in comparison to other AM processes.

R2. *HOW can the entire production network (i.e. OEM plus supply chain) be decomposed to capture changes in design and manufacturing methods?*

***Section 4.2.1*:** The production network for aeroengine was modeled as a multi-tiered pyramid. The engineering and design originate from the OEM at the apex, and these data are pass down to its suppliers (which number in the thousands). According to the model, parts are produced by the Tier 3s and sent to the Tier 1-2s for assembly. These assemblies are then sent to the OEM for final installation into the aeroengine. A critical modeling assumption is that each tier is dedicated to a single manufacturing function. Thus, the Tier 3s were the only entities that could engage in additive manufacturing.

R3. *WHAT model can be developed that is sufficiently simple in terms of type and quantity of variables and parameters, yet can adequately predict network behavior?*

***Section 4.2.4*:** Only two tiers of the supply chain were modeled, the assemblers (i.e. Tier 1-2s) and the detailed parts manufacturers (i.e. Tier 3s). An efficient ILP model was devised by using just a single Tier 1-2 and only four Tier 3s. Similarly, the Tier 3s were comprised of three CM facilities and only one AM facility. The decision variable was the number of parts to be produce by the Tier 3s based upon the demand set by the assemblers (i.e. Tier 1-2s). The objective function was to minimize the cost of the total assembly as seen by the Tier 1-2s.

The Tier 3s have four different parameters. Two parameters pertain to cost (i.e. fixed and variable) and two concern part quantity (i.e. capacity and demand). A simplifying assumption was that the AM facility has a near-zero fixed cost due to the lack of need for tooling.

The behavior of the network was viewed in terms of the quantity and connectivity of nodes, each representing a Tier 3 facility. The final answer depended upon the demand as specified by the Tier 1-2s, and included one through four Tier 3s. This model could be easily scaled to include an unlimited number of facilities. It was shown that the selection pattern would remain consistent upon scaling the ILP.

R4. *WHAT is the impact of adopting additive manufacturing according to this model, and HOW sensitive is the network to parameter changes?*

***Section 5.3 & 5.4*:** There were four scenarios considered. Notwithstanding, the two most important scenarios modeled were sourcing parts that were specifically designed for additive manufacturing, and using additive manufacturing to build CM parts in essentially an on demand situation. Due to the economic implications to the Tier 3s, this latter case became a primary focus of the modeling effort. In particular, attention was placed on the situation where a small quantity of CM parts were required beyond a CM facility’s capacity. As such, Tier 1-2s might source from AM facilities to help minimize cost. This would create pricing pressure on CM facilities to remain competitive. A key assumption was an increase in AM technology maturity.

Various sensitivity studies were conducted by modifying cost, capacity, and demand. Network sensitivity is a function of the magnitude of the AM variable cost in relation to the CM fixed cost. It is easy to imagine that a low AM variable cost would readily allow CM part substitution. Furthermore, the relationship between capacity and demand is important because, on average, it is more economical to source from fewer CM facilities.

Finally, though not an output of the ILP, the Tier 3s will likely be adversely affected by the onset of additive manufacturing simply due to the reduction of parts required for newer assemblies. This part consolidation and part-count reduction has been seen with adoption of composites, for example, as discussed Section 2.1.2.

R5. *WHERE and HOW will changes in AM technology be manifested throughout the entire production network?*

Section 6.1**:** Realistically, additive manufacturing will be adopted throughout the production network as evidenced by GE and its examples in the opening chapters. One important consideration for aerospace is the qualification process for AM parts. The rigor of government regulatory approval process due to its concern for the safety of the flying public was discussed at length. Clearly, the government's acceptance of AM technology is the most critical to its adoption. The second most important entity is the OEM itself. Recall that the OEMs control the design authority and production certificate, and can carry the legally liable for any mishap related to mechanical failure. Only they can authorize design changes.

Adoption of additive manufacturing therefore will assuredly include the OEMs; furthermore, they too need a certain level of technological competence. In the FOSC model, it was assumed that only the Tier 3s had access to this technology. This key limitation will be discussed in more detail below.

6.2 Conclusions

The methodology developed and implemented fulfills an important research need based upon a fairly extensive literature search. To date, there has been no bottoms-up numerical model that addresses the motivating question about additive manufacturing and the supply chain. This technology does in fact show great promise to disrupt, although an essential aspect of its adoption depends upon the role of the supply chain to execute – nearly flawlessly for commercial aerospace – given the high standard of quality and emphasis on safety.

This model provides a first-order approximation of additive manufacturing's effects on suppliers. Its simplicity and flexibility enables a vast number of numerical studies that can be used to develop a company's strategy, regardless if dedicated to conventional or additive manufacturing, and independent of its size or location within the supplier network. Among other things, it predicts that CM facilities will face pricing pressure under certain production scenarios. It is worth mentioning that this general conclusion was supported by Professor Sunil Chopra of Northwestern University, an internationally-known expert in supply chain research.[13]

It is important to realize that the objective of the model was not to optimize costs for a certain set of conditions. The model is to be used more broadly as a strategic planning tool. One example would be a company that is considering whether to enter the AM market. Armed with knowledge about the CM competitive landscape – in terms of costs and capacity – the AM facility could determine the profitable pricing (i.e. variable cost plus margin) for its parts for a given level of part demand. Similarly, a CM facility could use this to access its own positioning relative to a potential new AM entrant. Indeed, this would be helpful tool when conducting a Porter's Five Forces analysis to assess a company's long-term strategic positioning (Porter 1979). In general, for those organizations competent with this technology, it significantly lowers the traditional barriers to entry into new parts markets as a direct result of the versatility of printing. As discussed, the application are nearly limitless.

Based upon conference presentations by Boeing at the SAE AeroTech spring 2018 conference, and Honeywell at SME RAPID summer conference that same year, OEMs are using AM part substitution to create pricing pressure on existing CM suppliers. Brandon Wegge, Chief Engineer at Boeing, explained how his company had used internal AM capability to help renegotiate prices on parts (Wegge 2019). A similar story was offered by Don Godfrey, Engineering Technical Fellow in additive manufacturing at Honeywell (Godfrey 2019). Most likely this occurred only for spares in the maintenance aftermarket, and not for serialized production parts. But this trend will continue to develop and will eventually impact mainline production as the AM technology continues to mature.

[13] Personal email correspondence, February 3, 2020.

6.3 Limitations

The methodology and model seem reasonably well formulated; although, as with any model or abstraction, there are limitations. There are three that warrant closer attention.

The most critical assumption is that all AM activities reside at the Tier 3 level. Indeed, the case study by GE alone proves otherwise. There is evidence that all aerospace OEMs are engaged in metal additive manufacturing to varying degrees. One anecdote shared by Don Godfrey of Honeywell during RAPID 2019 in Detroit is that his organization has forecasted an internal long-term demand that would require some 400 machines (Godfrey 2019). They are committed to install 100 machines, according to Godfrey, and plan to depend upon the supply chain to provide the balance of the AM capacity. Godfrey also quipped that their sourcing strategy would likely be 30 companies with 10 AM machines each, as opposed to 100 companies with only three machines. This is consistent with a broader trend in aerospace, and other industries such as automotive, of supplier rationalization (Michaels 2018).

Godfrey's pronouncement seems reasonable since there is a certain level of investment in digital infrastructure and workforce development that is required when operating these machines, particularly in a production environment. And it can be argued that smaller companies – many of these Tier 3s – lack the financial capacity, specific domain knowledge, and broader expertise to make this transition to an extensively digital environment. As a consequence, it seems more likely that only the larger companies will make these investments, or there will be a series of new entrants possibly financed by outside capital. The Swiss company Oerlikon serves as one such example.

The second most critical assumption is that AM parts will eventually serve as a direct substitute for CM parts. Current federal regulations do not permit part substitution since equivalency between AM and CM parts has yet to be proven. The grain structure between the two processes is fundamentally different, a topic discussed at length in Section 2.2.6. It is feasible that additive manufacturing will eventually mature to enable such a substitution, but this may take decades. The FOSC model presupposes this phenomenon as simply "sometime in the future." Thus, there is an assumed level of confidence in the technology required for the model's findings to be truly representative. It was for this reason the author elaborated at length about the engineering challenges that currently beguile the AM industry in Chapter 2. And this technology maturation requires effort and support from all stakeholders.

Even if CM parts were to become targets for substitution, it is unlikely that entire assemblies would be candidates. Changing an assembly could materially alter the artifact's load path, and in turn, its failure modes. Consequently, this would require an entire redesign and possibly a re-substantiation of the new AM-fabricated assembly. This would be prohibitively costly both in terms of time and money for the OEM.

The third and final noteworthy limitation is the ideal nature of the model itself. As mentioned, this includes several abstractions from reality as the model:

- excludes any supply chain inefficiencies
- assumes purchasing behavior is based solely on economics;
- does not consider the impact of time;
- treats all suppliers as equally qualified;
- discounts technology step-changes such as new AM materials;
- ignores strategic sourcing concerns including sole-sourcing; and,
- deems all other AM modalities as irrelevant.

Notwithstanding, this methodology as a whole offers a reasonable approximation for the factors that are considered more important in the context of CM versus AM debate. The model's results are insightful, and should help researchers continue to refine their methods for modeling AM adoption in aerospace.

One final comment is appropriate regarding technology readiness level (TRL). As mentioned, there is no consensus on the TRL for any of the AM modalities – even for the most ubiquitous manufacturing configuration, *laser PBF using 40μ Ti 6-4 powder* – because there is still considerable variation in the performance amongst the six major laser-based machine builders. Furthermore, the impact of additive manufacturing on the supply chain would only occur upon implementation into production; per the definition, this would only occur at TRL 9.

Suffice it to say, there is a certain level of confusion within the AM community concerning this technology-development metric. Generally speaking, the TRL for metal additive manufacturing is at a moderate level, perhaps in the 5 to 6 range. Thus, due to a lack of consensus, it was decided for this dissertation to simply use the term "technology maturity." TRL seems best suited for product development that is subject to specific decision gates associated with formal design reviews. This is consistent with its origins for NASA acquisitions' contracts dating back to the 1970s, and more recently, for procurement for the US Department of Defense. In general, the notion of TRL is not as commonly used in commercial aerospace.

6.4 Recommended Research

Perhaps the most obvious future task would obtain actual cost data for a CM part to compare directly to an AM part in order to properly calibrate the ILP model. As mentioned, cost data was essentially non-existent either because: a) there were few use cases, or b) the cases that do exist are being treated as confidential. Organizations such as SAE International are trying to work through this problem with its AMS AM Standards international efforts.

From a more scholarly perspective, the most likely second recommendation would be to improve the scenario analysis, investigating more comprehensively the effects of parameter changes. One option would be to conduct a design of experiment (DOE) using *Monte Carlo* to simulate a much larger portion of the 1.6 million combinations. This would give the investigator greater insight into the nature of the interactions of the 13 parameters.

A third enhancement could be to add complexity to the model by considering the effects of time. One of the great advantages of the additive manufacturing is its ability to produce parts quickly – recall that it was first developed for rapid prototyping. This could be related either to the lack of need of tooling, or the ability to produce parts in closer proximity to the customer. The aspect of time is an important consideration as evidenced by the amount of supply chain research related to this topic, as well as feedback the author has received during this research.

Along the same lines, another worthwhile enhancement to the model would be to add additional facilities. It was stated that the four-element model was a sufficient first-order approximation. Adding more entities would make the model dynamic more representative of reality, especially in the context of such a large and diverse industry like commercial aerospace.

A fifth and final consideration would be to vary the location of the AM process within the production network. As mentioned, this was a fundamental limitation to the model. The current ILP model cannot account for AM activities at other tiers within the entire network. One solution might be to allocate a percentage of the AM activities across the three tiers, including the OEM. This would assuredly add an element of reality, although it may also greatly complicate the ILP formulation. Nevertheless, with the Python code made available, some of these suggested changes could be relatively straightforward for an adept programmer.

APPENDIX

System Decomposition Material

Table 1A: Maier's distinguishing traits of system of system applied to commercial aerospace

SoS Characteristic	Aerospace Commercial Aircraft Supply Chain
Geographic Dispersion	Globalized manufacturing base spread over multiple continents
Managerial Independence	Individual suppliers at all tiers retain their managerial independence yet depend on the success of a single product.
Heterogeneity	Various aspects of the supply chain function differently on a spectrum from raw material extraction to pure R&D.
Evolutionary Behavior	New technologies provide intrinsic change. Emerging markets and policy provide extrinsic change.
Emergent Behavior	Design improvements and changes occur from the bottom up and well as top down.

Table 2A: ROPE table for the aeroengine manufacturing system

	Resource	Operations	Policy	Economics
α	*Tier 4 ~ Mill, foundry, forger, extruder*	Produce raw material and basic structural preforms; main materials titanium, super alloy (nickel-based); global footprint	Strongly governed by environmental regulations; move towards less-stringent developing economies; China is newcomer	Energy intensive operations with large capital investment; forced to operate at 'mill minimums' to main profitability; typ. $2-10B revenue
β	*Tier 3 ~ Detailed parts manufacturing*	Small shops (typically <75 employees) that machine metal parts to blueprints – known as "build-to-print"	Themes dominated by small-business issues (e.g. employee retention); most regionally located in a cluster near OEM	Low margins (~10%) due to competition and low barriers to entry; shops usually dedicated to aerospace (i.e. AS9100 cert); with typ. $25-200M revenue
γ	*Tier 2 ~ Subassembly &* *Tier 1 ~ Major assembly*	Medium to large-sized corps than machine large structures and assemble major components	Regional corps with moderate labor challenges and environmental issues due to special process (e.g. chem-mill, heat treatment)	[T2] Somewhat higher margins than its counterparts (low to mid double digits), typ. $1-5B rev. [T1] Margins low double digits; typ. $2-10B revenue
δ	*OEM ~ Final assembly*	Dominated by US and EU, with oligopoly (e.g. GE, Rolls, P&W, Snecma); focused on systems integration and final assembly	Long standing entities (e.g. P&W 95 y/o, Rolls 104 yrs since first aeroengine); challenged with material sourcing, and environmental factors	High cost structure due to legacy and largest overhead; high cost due to logistics and marketing; focus on outsourcing over past 2 decades; typical margins mid-single digits; typ. $10-25 Descartes rev

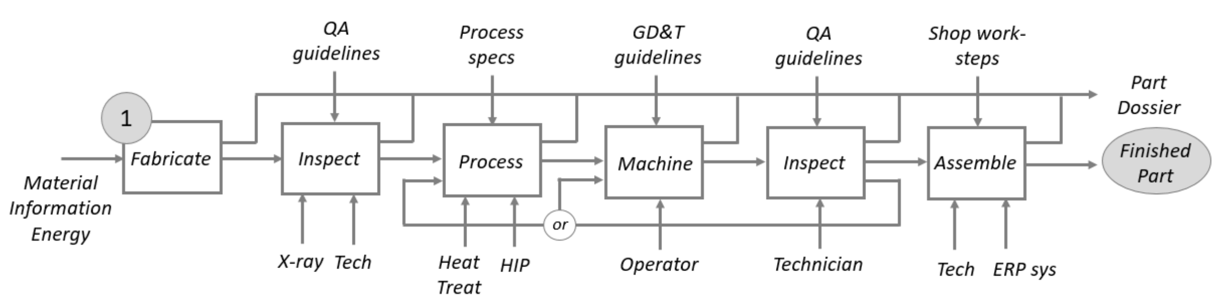


Figure 1A: IDEF0 for manufacturing system

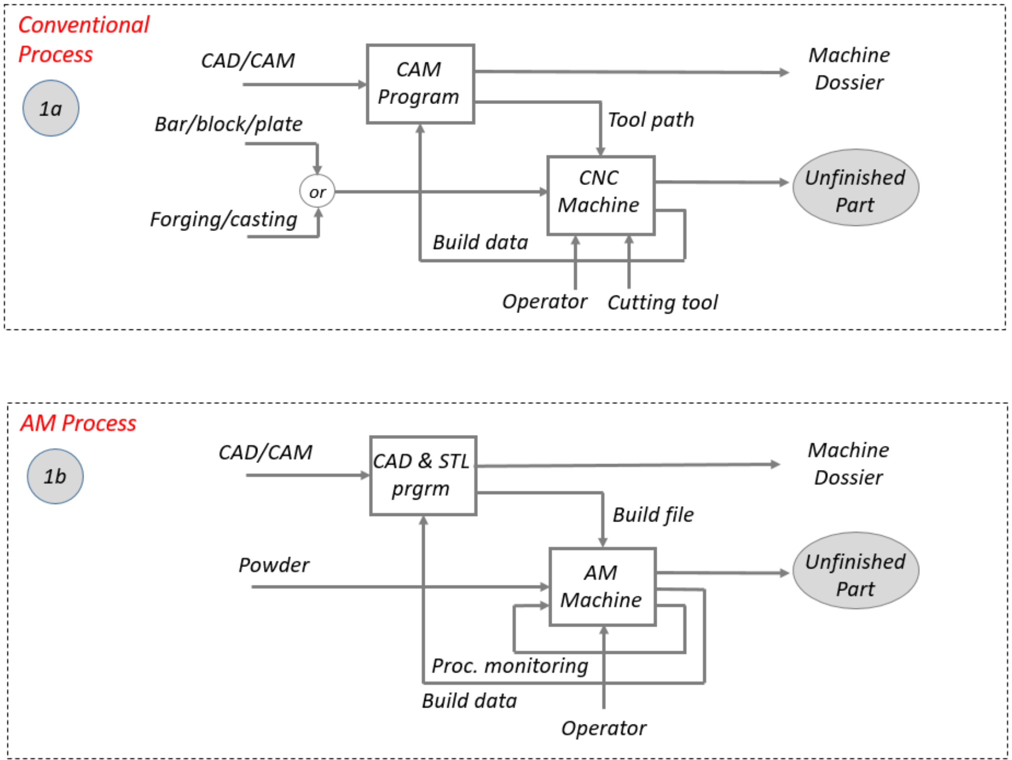


Figure 2A: IDEF0 for CNC machining vs AM system

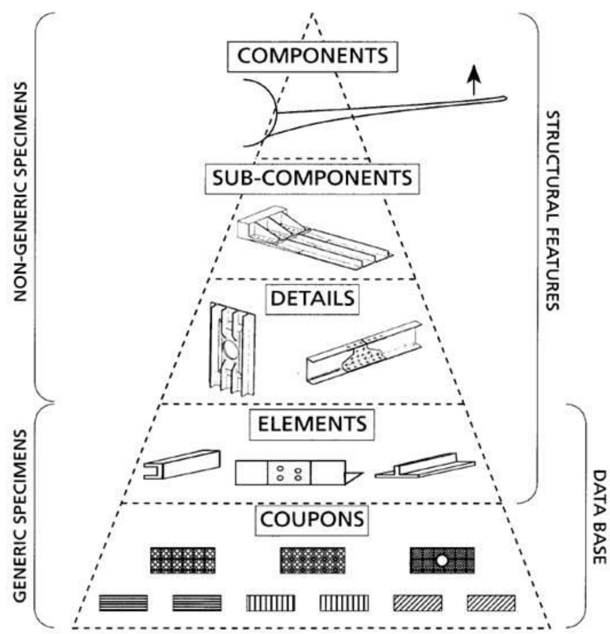


Figure 3A: Schematic of the FAA certification process

Python Model

```
*** Code ***
ILP model for corporation to include both fixed and variable costs.
This version is 3 corps use conventional mfg (C) for parts, plus 1 corp
using additive mfg (A) parts.
"""

from pulp import LpProblem, LpMinimize, LpVariable, LpInteger, LpStatus, value
import matplotlib
matplotlib.use("agg")
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

warning = "!!For specified parameters, unable to produce the required amount!!"
warning_bool = False

def parseInput(input):
    parsed_inputs = {}
    parsed_inputs["variable"] = input.iloc[1, 1]
    parsed_inputs["start"] = int(input.iloc[2, 1])
    parsed_inputs["end"] = int(input.iloc[3, 1])
    parsed_inputs["cap"] = list(input.iloc[6, 1:5].astype(float))
    parsed_inputs["fc"] = list(input.iloc[7, 1:5].astype(float))
    parsed_inputs["vc"] = list(input.iloc[8, 1:5].astype(float))
    parsed_inputs["admd"] = int(input.iloc[10, 1])
    parsed_inputs["cdmd"] = int(input.iloc[11, 1])
    return parsed_inputs

# read in the desired parameters for the function
# all inputs are kept constatnt location
parsed_inputs = {}

input = pd.read_csv("Input1.csv", header = None)
parsed_inputs = parseInput(input)

values = np.arange(parsed_inputs["start"], parsed_inputs["end"], 1)
y_vals = []
a_vals = []

for Variable in values:
    parsed_inputs[parsed_inputs["variable"]] = Variable
    # create PuLP (Python Linear Program) object
    prob = LpProblem('SC Prob', LpMinimize)

    # set total number of tier 3 corps, C & A
    corpC = 3
    I = range(corpC)
    corpA = 1
    J = range(corpA)

    # initialize decision var (x) and binary var (y) for non-zero production
    # x is TM parts, z is AM parts
    x = [None for i in I]
    y = [None for i in I]
    z = [None for j in J]

    for i in I:
        nm_lst = ['CorpC ', str(i), ' Output']
```

```
    nm = ''.join(nm_lst)
    # LpVariable requires: name, lower bound, upper bound, type
    x[i] = LpVariable(nm, 0, None, LpInteger)
    # binary variable - identify if corp is 'enabled' (i.e. 1 vs 0)
    ynm_lst = ['CorpC ', str(i), ' Enabled?']
    ynm = ''.join(ynm_lst)
    y[i] = LpVariable(ynm, 0, 1, LpInteger)

# print(w[0])
for j in J:
    # print(j)
    nm_lst2 = ['CorpA ', str(j), ' Output']
    nm2 = ''.join(nm_lst2)
    z[j] = LpVariable(nm2, 0, None, LpInteger)

# cnst: capacity (parts), varble & fixed costs ($), with 'corp' numb elements
# C is CM and A is AM
capC = parsed_inputs["cap"][0:3]
varC = parsed_inputs["vc"][0:3]
fxdC = parsed_inputs["fc"][0:3]

capA = [parsed_inputs["cap"][3]]
varA = [parsed_inputs["vc"][3]]

# set total demand
dmdC = parsed_inputs["cdmd"]
dmdA = parsed_inputs["admd"]
dmdTot = dmdC + dmdA

# define objct fnct
prob += sum([x[i] * varC[i] + fxdC[i] * y[i] for i in I]) + sum(
    [z[j] * varA[j] for j in J]), 'Cost of CM and AM sourcing'

# specify demand cnst
prob += sum([x[i] for i in I]) + sum([z[j] for j in J]) == dmdTot, 'CM dmd rqmt'

# Constraint to force A manufacturing to make at least all the dmdA parts
prob += sum([z[j] for j in J]) >= dmdA, 'AM dmd rqmt'

# eliminate corp when output is zero (i.e. binary condition)
for i in I:
    nm_lst = ['CorpC ', str(i), ' Capacity']
    nm = ''.join(nm_lst)
    prob += x[i] <= capC[i] * y[i], nm

for j in J:
    nm_lst2 = ['CorpA ', str(j), ' Capacity']
    nm2 = ''.join(nm_lst2)
    prob += z[j] <= capA[j], nm2

prob.writeLP('prob.lp')
prob.solve()
print()
print("dmdA:",dmdA," dmdC:",dmdC, " dmdTot:",dmdTot)
print('Status:', LpStatus[prob.status])
if(prob.status == -1):
    warning_bool = True
for v in prob.variables():
    print(v.name, '=', v.varValue)
    if(v.name == 'CorpA_0_Output'):
        a_vals.append(v.varValue)

print('Total cost of production ($) = ', value(prob.objective))
```

```
    y_vals.append(value(prob.objective))
if(warning_bool):
    print(warning)
else:
    fig, ax = plt.subplots()

    # plot total price
    ax.plot(values, y_vals)

    # plot the number of components produced by D
    ax.plot(values, a_vals)

    ax.set(xlabel=parsed_inputs["variable"], ylabel='Assembly Cost ($)',
           title='Cost of Production')
    ax.grid()

    fig.savefig("SCM_output.png")
```

```
*** Input File ***

Supply chain Model
Variable ->  cdmd
start  10
end    31

Facilities   A      B      C      D
cap          5      10     15     5
fc           20     15     10     0
vc           1      1.5    1.75   2.5

admd   3
cdmd   24
```

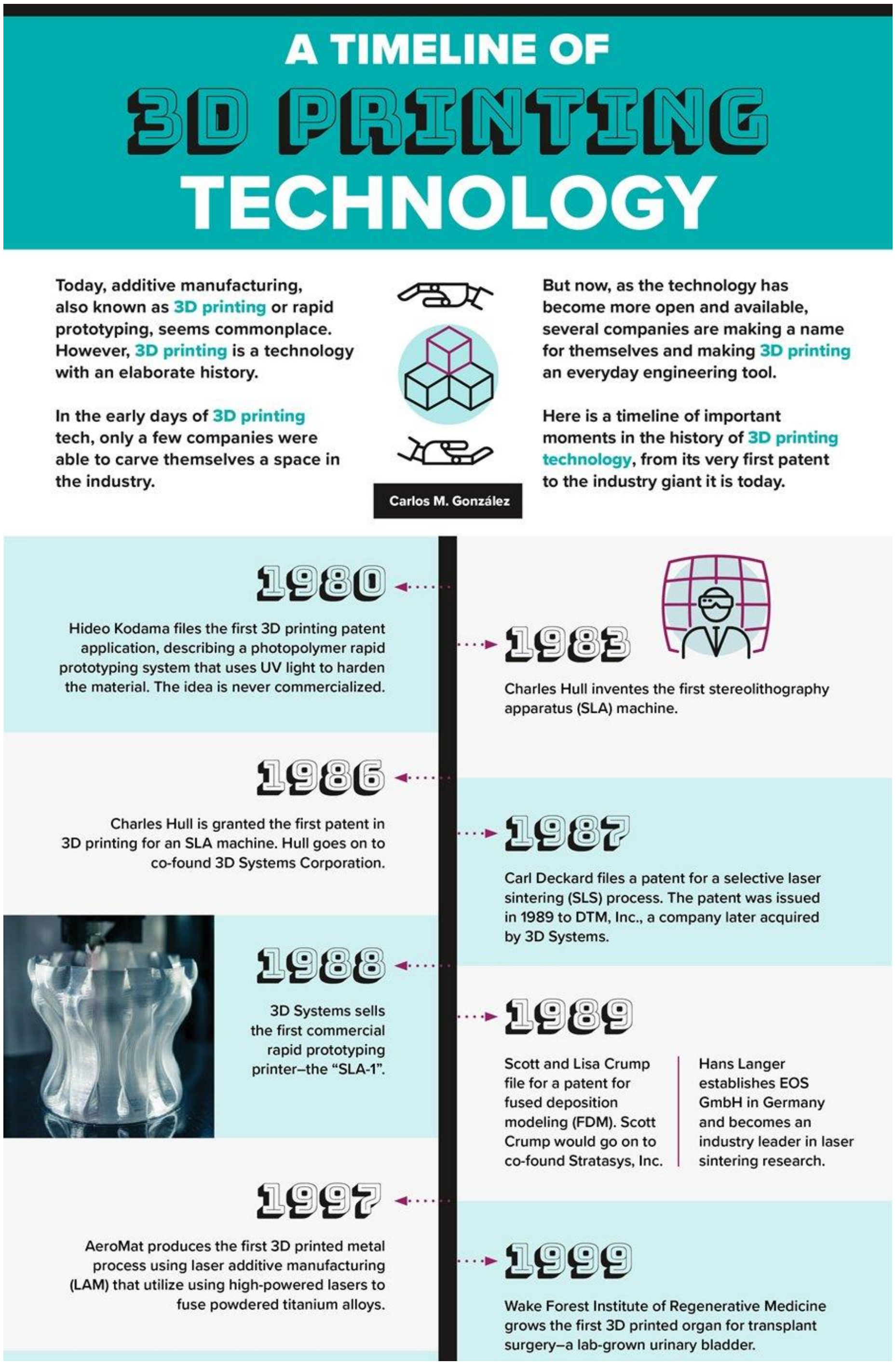
```
*** Sample Output ***

dmdA: 3  dmdC: 29  dmdTot: 32
Status: Optimal
CorpA_0_Output = 3.0
CorpC_0_Enabled? = 1.0
CorpC_0_Output = 5.0
CorpC_1_Enabled? = 1.0
CorpC_1_Output = 10.0
CorpC_2_Enabled? = 1.0
CorpC_2_Output = 14.0
Total cost of production ($) =  97.0
```

AM Market Material

https://amfg.ai/2019/02/27/additive-manufacturing-industry-landscape-2019/

Figure 4A: Market segmentation for the various AM modalities



https://www.asme.org/topics-resources/content/infographic-the-history-of-3d-printing

Figure 5A: Additive manufacturing timeline (1 of 2)

Figure 5A: Additive manufacturing timeline CONT (2 of 2)

REFERENCES

Aerospace Manufacturing and Design. 2019. “5 Questions with Robert Hill,” October 2019.

AFRL. 1981. “ICAM Architecture Part II - Function Modeling Manual (IDEF0).”

Aguayo, Rafael. 1991. *Dr. Deming: The American Who Taught the Japanese about Quality*. Simon and Schuster.

APICS Supply Chain Council. 2017. “SCOR Quick Reference Guide V12.0.” www.apics.org/docs/default-source/scc-non-research/apicsscc_scor_quick_reference_guide.pdf.

Arnold, Katelyn. 2019. “GE Announces Additive Manufacturing Breakthrough in Commercial Aviation.” Additive Manufacturing Magazine. 2019. https://www.additivemanufacturing.media/news/ge-announces-additive-manufacturing-breakthrough-in-commercial-aviation.

Aviationweek.Com. 2015. “Technology Laureate : GE Aviation ’ s Greg Morris , Early Additive Adapter,” 2015.

Axtell, Robert. 2000. “Why Agents? On the Varied Motivations for Agent Computing in the Social Sciences Agent. Working Paper.” *Center on Social and Economics Dynamics - The Brookings Institution*, no. 17: 1–23. http://www.brookings.edu/~/media/research/files/reports/2000/11/technology axtell/agents.pdf.

Bahnini, Insaf, Mickael Rivette, Ahmed Rechia, Ali Siadat, and Abdelilah Elmesbahi. 2018. “Additive Manufacturing Technology: The Status , Applications, and Prospects.” *International Journal of Advanced Manufacturing Technology* 97: 147–61.

Baldwin, Carliss, and Kim Clark. 2000. *Design Rules: The Power of Modularity*. Vol 1. MIT Press.

Barz, A., T. Buer, and H. D. Haasis. 2016. “A Study on the Effects of Additive Manufacturing on the Structure of Supply Networks.” *IFAC-PapersOnLine* 49 (2): 72–77. https://doi.org/10.1016/j.ifacol.2016.03.013.

Beamon, Benita M. 1999. “Measuring Supply Chain Performance.” *International Journal of Operations & Production Management* 19 (3): 275–92.

Biggs, Norman, E. Keith Lloyd, and Robin J. Wilson. 1986. *Graph Theory, 1736-1936*. Oxford University Press.

Bihlman, Bill. 2015. “The Boeing 787 Program Launch Debacle.” Lubbock.

———. 2016. “Material Trends in Commercial Aerospace Impacting Titanium.” Paris.

———. 2017. “The State of Advanced Manufacturing in Commecial Aerospace.” Taipei.

Bixby, Robert E. 2012. “A Brief History of Linear and Mixed-Integer Programming Computation.” *Documenta Mathematic* Extra Volu: 107–21.

Bonabeau, Eric. 2002. “Agent-Based Modeling : Methods and Techniques for Simulating Human Systems Eric Bonabeau Proceedings of the National Academy of Sciences of the United States of America , Vol . 99 , No . 10 , Supplement 3 : Arthur M . Sackler Colloquium of the National Ac.” *National Academy of Sciences of the United States of America* 99 (10): 7280–87.

Booth, Joran W., Jeffrey Alperovich, Tahira N. Reid, and Karthik Ramani. 2016. “The Design for Additive Manufacturing Worksheet.” In *ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, V007T06A041. Charlotte. https://doi.org/10.1115/DETC2016-60407.

Booth, Joran W, Jeffrey Alperovich, and Tahira N Reid. 2017. “The Design for Additive Manufacturing Worksheet.” *Journal of Mechanical Design* 139 (October): 1–9. https://doi.org/10.1115/1.4037251.

Bourell, David L. 2016. “Perspectives on Additive Manufacturing.” *Annual Review of Materials Research* 46:1–18. https://doi.org/10.1146/annurev-matsci-070115-031606.

Brooks, Robert. 2015. “Alcoa Details Research, Process Strategy to Maximize 3DP.” Forging Magazine. 2015. https://www.forgingmagazine.com/forming/article/21923191/alcoa-details-research-process-strategy-to-maximize-3dp.

Brown, Alan S. 2018. “Chain Reaction: Why Additive Manufacturing Is about to Transform the Supply Chain.” *ASME*, October 2018.

Buede, Dennis, and William Miller. 2016. *The Engineering Design of Systesms: Models and Methods*. 3rd ed. John Wiley & Sons. https://doi.org/10.1109/fusion.1993.518356.

Busachi, Alessandro, John Erkoyuncu, Paul Colegrove, Richard Drake, Chris Watts, Filomeno Martina, Nikolaos Tapoglou, and Helen Lockett. 2018. "A System Approach for Modelling Additive Manufacturing in Defence Acquisition Programs." *Procedia CIRP* 67 (2012): 209–14. https://doi.org/10.1016/j.procir.2017.12.201.

Campbell, Donald T. 1957. "Factors Relevant to the Validity of Experiments in Social Settings 1." *Psychological Bulletin* 54 (4): 297–312.

Cedoz, Robert, Ann Bolcavage, Akin Keskin, John F Matlik, Daniel R Hartman, Nate Cooper, Kong Ma, et al. 2014. "Integrated Computational Materials Engineering from a Gas Turbine Engine Perspective." *Integrating Materials and Manufacturing Innovation* 3 (1): 1–24. https://doi.org/10.1186/2193-9772-3-13.

Chadzynski, Pawel Z., Barclay Brown, and Patrick Willemsen. 2018. "Enhancing Automated Trade Studies Using MBSE, SysML and PLM." *INCOSE International Symposium* 28 (1): 1626–35. https://doi.org/10.1002/j.2334-5837.2018.00572.x.

Checkland, Peter, and Sue Holwell. 1998. "Action Research: Its Nature and Validity." *Systemic Practice and Action Research* 11 (1): 9–21. http://arj.sagepub.com/content/1/1/9.short.

Costabile, G., M. Fera, F. Fruggiero, A. Lambiase, and D. Pham. 2016. "Cost Models of Additive Manufacturing: A Literature Review." *International Journal of Industrial Engineering Computations* 8 (2): 263–82. https://doi.org/10.5267/j.ijiec.2016.9.001.

Costantino, Nicola, Mariagrazia Dotoli, Marco Falagario, Maria Pia, and Agostino Marcello. 2012. "Int . J . Production Economics A Model for Supply Management of Agile Manufacturing Supply Chains $." *Intern. Journal of Production Economics* 135 (1): 451–57. https://doi.org/10.1016/j.ijpe.2011.08.021.

Cunningham, N. 1994. "Deming and the Vindication of Knowledge in the Philosophy of C.I. Lewis." *Quality Management Journal* April: pp 7-15.

Davies, Sam. 2018. "GE Additive Sets out Its Role in the Growth of AM as an Industry-Standard Production Tool." TCT Magazine. 2018. https://www.tctmagazine.com/3d-printing-news/ge-additive-role-am-industry-standard-production/.

DebRoy, T., H. L. Wei, J. S. Zuback, T. Mukherjee, J. W. Elmer, J. O. Milewski, A. M. Beese, A. Wilson-Heid, A. De, and W. Zhang. 2018. "Additive Manufacturing of Metallic Components – Process, Structure and Properties." *Progress in Materials Science* 92: 112–224. https://doi.org/10.1016/j.pmatsci.2017.10.001.

Debroy, T, T Mukherjee, J O Milewski, J W Elmer, B Ribic, J J Blecher, and W Zhang. 2019. "Scientific, Technological and Economic Issues in Metal Printing and Their Solutions." *Nature Materials* 18 (October). https://doi.org/10.1038/s41563-019-0408-2.

DeLaurentis, Dan, and Robert K. Callaway. 2004. "A System-of-Systems Perspective for Public Policy Decisions." *Review of Policy Research* 21 (6): 829–37. https://doi.org/10.1111/j.1541-1338.2004.00111.x.

DeLaurentis, Daniel. 2005. "Understanding Transportation as a System-of-Systems Design Problem," no. January: 1–14. https://doi.org/10.2514/6.2005-123.

DeLaurentis, Daniel A., William A. Crossley, and Muharrem Mane. 2011. "Taxonomy to Guide Systems-of-Systems Decision-Making in Air Transportation Problems." *Journal of Aircraft* 48 (3): 760–70. https://doi.org/10.2514/1.c031008.

Deming, W. E. 1986. *Out of the Crisis*. Cambridge: MIT. Center for advanced engineering study.

Denning, Steve. 2013. "What Went Wrong At Boeing?" *Forbes*, June 2013. https://www.forbes.com/sites/stevedenning/2013/01/21/what-went-wrong-at-boeing/#4ec8ebe97b1b.

Diegel, O., A. Nordin, and D. Motte. 2019. *A Practical Guide to Design for Additive Manufacturing*. Springer S. Springer, Singapore.

Dotoli, Mariagrazia, Maria Pia Fanti, Senior Member, and Carlo Meloni. 2005. "Design and Optimization of Integrated E-Supply Chain for Agile and Environmentally Conscious Manufacturing." *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 36 (1): 62–75.

Dove, Rick. 2012. "Agile 101: Agile System/Process Architecture Pattern." International Council on Systems Engineering.

Dove, Rick, and Ralph Labarge. 2014. "Fundamentals of Agile Systems Engineering – Part 1." Las Vegas: International Council on Systems Engineering, International Symposium.

Dutta, B, and F H Sam Froes. 2017. "The Additive Manufacturing of Titanium Alloys." *Metal Powder Report* 72 (2): 96–106. https://doi.org/10.1016/j.mprp.2016.12.062.

El-Khoury, Bernard, and C. Robert Kenley. 2014. "An Assumptions-Based Framework for TRL-Based Cost and Schedule Models." *Journal of Cost Analysis and Parametrics* 7 (3): 160–79. https://doi.org/10.1080/1941658x.2014.982232.

Engler-Modic, E. 2018. “3D Printing Streamlines Aviation Supply Chains.” *Aerospace Manufacturing and Design*, October 2018.

FAA. 2020. “Transport Airplane Issues List.” https://www.faa.gov/aircraft/air_cert/design_approvals/transport/media/rpttailistforpublicweb.pdf.

Farid, Amro M. 2007. “Reconfigurability Measurement in Automated Manufacturing Systems,” 302.

Feldmann, Carsten, and Andreas Pumpe. 2017. “A Holistic Decision Framework for 3D Printing Investments in Global Supply Chains.” *Transportation Research Procedia* 25: 677–94. https://doi.org/10.1016/j.trpro.2017.05.451.

Fera, M., R. Macchiaroli, F. Fruggiero, and A. Lambiase. 2018. “A New Perspective for Production Process Analysis Using Additive Manufacturing — Complexity vs Production Volume.” *The International Journal of Advanced Manufacturing Technology* C (95): 673–85.

Flinn, Peter, ed. 2019. *Managing Technology and Product Development Programmes*. John Wiley & Sons.

Francois, M M, A Sun, W E King, N J Henson, D Tourret, C A Bronkhorst, N N Carlson, et al. 2017. “Modeling of Additive Manufacturing Processes for Metals: Challenges and Opportunities.” *Current Opinion in Solid State & Materials Science* 21 (4): 198–206. https://doi.org/10.1016/j.cossms.2016.12.001.

Frazier, William E. 2014. “Metal Additive Manufacturing : A Review.” *Journal of Materials Engineering and Performance* 23 (June): 1917–28. https://doi.org/10.1007/s11665-014-0958-z.

Gates, Dominic, Lewis Kamb, Steve Miletich, and Christine Clarridge. 2019. “Boeing Ousts Muilenburg amid 737 MAX Crisis; Observers Wonder If New CEO Calhoun Will Bring the Right Sort of Change.” *Seattle Times*, December 23, 2019. https://www.seattletimes.com/business/boeing-aerospace/boeing-ousts-ceo-dennis-muilenberg/.

“GE Offers $1.4B to Acquire Arcam, SLM Solutions Group.” 2016. Aerospace Manufacturing and Design. 2016. https://www.aerospacemanufacturinganddesign.com/article/ge-acquires-arcam-slm-solutions-090716/.

Ghadge, Abhijeet, Samir Dani, and Roy Kalawsky. 2010. "A Framework for Managing Risks in the Aerospace Supply Chain Using Systems Thinking." *2010 5th International Conference on System of Systems Engineering, SoSE 2010*, 0–5. https://doi.org/10.1109/SYSOSE.2010.5544082.

Girdhar, Anupam. 2001. "Expansion of Group Technology Part Coding Based on Functionality." *PhD Dissertation*. University of Cincinnati. https://doi.org/10.1017/S002221510010115X.

Gisario, Annamaria, Michele Kazarian, Filomeno Martina, and Mehrshad Mehrpouya. 2019. "Metal Additive Manufacturing in the Commercial Aviation Industry : A Review." *Journal of Manufacturing Systems* 53 (August): 124–49. https://doi.org/10.1016/j.jmsy.2019.08.005.

Godfrey, Donald. 2019. "RAPID Conference Presentation." Detroit: Society of Manufacturing Engineers.

Gorelik, Michael. 2017. "Additive Manufacturing in the Context of Structural Integrity." *International Journal of Fatigue* 94: 168–77. https://doi.org/10.1016/j.ijfatigue.2016.07.005.

Gorod, Alex, Brian Sauser, and John Boardman. 2008. "System-of-Systems Engineering Management: A Review of Modern History and a Path Forward." *IEEE Systems Journal* 2 (4): 484–99. https://doi.org/10.1109/JSYST.2008.2007163.

Guizzardi, Giancarlo. 2005. *Ontological Foundations for Structural Conceptual Models*. *CTIT PhD Thesis Series*. Vol. 05–74. https://doi.org/10.1007/978-3-642-31095-9_45.

Hall, Arthur D. 1969. "Three-Dimensional Engineering," no. 2: 156–60.

Haskins, Cecilia. 2014. "A Historical Perspective of MBSE with a View to the Future." *INCOSE International Symposium* 21 (1): 493–509. https://doi.org/10.1002/j.2334-5837.2011.tb01220.x.

Herzner, Fred. 2017. *What Did We Know? What Did We Do? Making Decisions in Large Organizations*. Edited by Dustin Klein. Smart Business Network.

Herzog, Dirk, Vanessa Seyda, Eric Wycisk, and Claus Emmelmann. 2016. "Additive Manufacturing of Metals." *Acta Materialia* 117: 371–92. https://doi.org/10.1016/j.actamat.2016.07.019.

Hindle, Giles A., and Richard Vidgen. 2018. "Developing a Business Analytics Methodology: A Case Study in the Foodbank Sector." *European Journal of Operational Research* 268 (3): 836–51. https://doi.org/10.1016/j.ejor.2017.06.031.

Hopp, Wallace J. 2011. *Supply Chain Science*. Waveland Press.

Horvath, Joan. 2014. "A Brief History of 3D Printing." In *Mastering 3D Printing*, 3–10. Berkeley, CA: Apress. https://doi.org/10.1007/978-1-4842-0025-4_1.

Hoy, Kirk, and David Hudak. 1994. "Advances in Quantifying Schedule/Technical Risk." Arlington.

Huan, Samuel H, Sunil K Sheoran, and Ge Wang. 2004. "A Review and Analysis of Supply Chain Operations Reference (SCOR) Model." *Supply Chain Management: An International Journal*. https://doi.org/10.1108/13598540410517557.

"International Standard ISO/IEC/IEEE 24765." 2017. Vol. 9. Switzerland.

Jackson, Beau. 2018. "GE Aviation Celebrates 30,000th 3D Printed Fuel Nozzle." 3dprintingindustry.Com. 2018. https://3dprintingindustry.com/news/ge-aviation-celebrates-30000th-3d-printed-fuel-nozzle-141165/.

Jackson, Michael C. 2007. *Systems Approaches to Management*. Springer Science & Business Media.

Johnson, Clarence L. "Kelly." 1985. *Kelly: More Than My Share of It All*. Edited by Maggie Smith. Washington: Smithsonian Institution.

Jones, A., A. Deshmukh, S. Kumara, and M. Li. 2008. "Engineering Complex, Information-Based, Networked Industrial Systems: A Research Roadmap." *JCISE on Engineering Informatics* 8 (11005–1).

Kang, Jin wu, and Qiang xian Ma. 2017. "The Role and Impact of 3D Printing Technologies in Casting." *China Foundry* 14 (3): 157–68. https://doi.org/10.1007/s41230-017-6109-z.

Kaur, Harpreet, Surya Prakash Singh, and Abhijit Majumdar. 2019. "Modelling Joint Outsourcing and Offshoring Decisions." *International Journal of Production Research* 7543: 1–32. https://doi.org/10.1080/00207543.2018.1471245.

Kellner, Tomas. 2018. "The Blade Runners: This Factory Is 3D Printing Turbine Parts For The World's Largest Jet Engine." GE Reports. 2018. https://www.ge.com/reports/future-manufacturing-take-look-inside-factory-3d-printing-jet-engine-parts/.

Kenley, C. Robert, Timothy M. Dannenhoffer, Paul C. Wood, and Daniel A. DeLaurentis. 2015. "Synthesizing and Specifying Architectures for System of Systems." *INCOSE International Symposium* 24 (1): 94–107. https://doi.org/10.1002/j.2334-5837.2014.tb03137.x.

Kenley, C Robert, and James Nail. 2005. "Quantifying Cost Risk Early in the Life Cycle."

Kim, Duck Bong, Paul Witherell, Robert Lipman, and Shaw C. Feng. 2015. "Streamlining the Additive Manufacturing Digital Spectrum: A Systems Approach." *Additive Manufacturing* 5: 20–30. https://doi.org/10.1016/j.addma.2014.10.004.

Kleiner, S., and C. Kramer. 2013. "Model Based Design with Systems Engineering Based on RFLP Using V6." In *Smart Product Engineering*, edited by M. Abramovici and R. Stark. Springer Berlin Heidelberg.

Koch, Claudia. 2017. "Standardization in Emerging Technologies: The Case of Additive Manufacturing." *ITU Kaleidoscope: Challenges for a Data-Driven Society*, 1–8.

Koenig, Bill. 2020. "3D Printing Cleared for Takeoff." SME. 2020. https://www.sme.org/technologies/articles/2020/january/3d-printing-cleared-for-takeoff/.

Kok, Y., X. P. Tan, P. Wang, M. L.S. Nai, N. H. Loh, E. Liu, and S. B. Tor. 2018. "Anisotropy and Heterogeneity of Microstructure and Mechanical Properties in Metal Additive Manufacturing: A Critical Review." *Materials and Design* 139: 565–86. https://doi.org/10.1016/j.matdes.2017.11.021.

Kuhn, Thomas S. 2012. *The Structure of Scientific Revolutions*. 4th ed. University of Chicago press.

Kumar, Jyothish, and Krishnadas Nair. 2017. "Current Trends of Additive Manufacturing in the Aerospace Industry." *Advances in 3D Printing and Additive Manufacturing Technologies*, 39–54. https://doi.org/10.1007/978-981-10-0812-2_4.

Laureijs, Rianne, Jaime Bonnin Roca, Sneha Narra, Colt Montgomery, Jack Beuth, and Erica R.H. Fuchs. 2016. "Metal Additive Manufacturing: Cost Competitive Beyond Low Volumes." *Journal of Manufacturing Science and Engineering* 139 (August 2017): 1–9. https://doi.org/10.2139/ssrn.2815047.

Leal, R, F M Barreiros, L Alves, F Romeiro, J C Vasco, and M Santos. 2017. "Additive Manufacturing Tooling for the Automotive Industry." *The International Journal of Advanced Manufacturing Technology*, 1671–76. https://doi.org/10.1007/s00170-017-0239-8.

Lindemann, Christian, and Rainer Koch. 2016. "Cost Efficient Design and Planning for Additive Manufacturing Technologies." In *27th Annual International Solid Freeform Fabrication Symposium*, 93–112.

Maier, M. 1998. "Architecting Principles for Systems-of-Systems." *Systems Engineering* 1 (4): 267–84. https://doi.org/10.1002/(SICI)1520-6858(1998)1:4%3C267::AID-SYS3%3E3.0.CO;2-D.

Mann, Ted. 2016. "3-D Printing Expands to Metals, Showing Industrial Promise." *The Wall Street Journal*, November 11, 2016. https://www.wsj.com/articles/3-d-printing-expands-to-metals-showing-industrial-promise-1478860204.

Martukanitz, Richard, Pan Michaleris, Todd Palmer, Tarasankar DebRoy, Zi Kui Liu, Richard Otis, Tae Wook Heo, and Long Qing Chen. 2014. "Toward an Integrated Computational System for Describing the Additive Manufacturing Process for Metallic Materials." *Additive Manufacturing* 1: 52–63. https://doi.org/10.1016/j.addma.2014.09.002.

Mas, Fernando, Jesus Racero, Manuel Oliva, and Domingo Morales-palma. 2018. "A Preliminary Methodological Approach to Models for Manufacturing." In *IFIP International Conference on Product Lifecycle Management*, 540:273–83. Springer International Publishing. https://doi.org/10.1007/978-3-030-01614-2.

Mastrocinque, Ernesto, Baris Yuce, Alfredo Lambiase, and Michael S. Packianather. 2014. "A System of Systems Approach to Supply Chain Design." *Applied Mechanics and Materials* 496–500: 2807–14. https://doi.org/10.4028/www.scientific.net/amm.496-500.2807.

McKean, David, James D. Moreland, and Steven Doskey. 2019. "Use of Model-Based Architecture Attributes to Construct a Component-Level Trade Space." *Systems Engineering* 22 (2): 172–87. https://doi.org/10.1002/sys.21478.

McManus, Hugh L., Daniel E. Hastings, and Joyce M. Warmkessel. 2008. "New Methods for Rapid Architecture Selection and Conceptual Design." *Journal of Spacecraft and Rockets* 41 (1): 10–19. https://doi.org/10.2514/1.9203.

"Metrics That Matter: Uncovering KPIs That Justify." 2006.

Michaels, Kevin. 2018. *AeroDynamic: Inside the High-Stakes Global Jetliner Ecosystem*. AIAA.

MMPDS. 2018. "Public Minutes of the St 31 MMPDS Coordination Meeting." Atlanta. https://www.mmpds.org/wp-content/uploads/2019/01/31stMMPDSMtg-PUBLIC-MINUTES.pdf.

Molitch-Hou, Michael. 2017. "GE Additive Unveils Largest Metal Powder Bed Fusion 3D Printer." Engineering.Com. 2017. https://www.engineering.com/3DPrinting/3DPrintingArticles/ArticleID/16007/GE-Additive-Unveils-Largest-Metal-Powder-Bed-Fusion-3D-Printer.aspx.

Morris, CW. 1938. "Foundations of Theory of Signs." In *International Encyclopidia of Unified Science*, 77–138.

Mour, Ankur, C. Robert Kenley, Navindran Davendralingam, and Daniel DeLaurentis. 2014. "Agent-Based Modeling for Systems of Systems." *INCOSE International Symposium* 23 (1): 973–87. https://doi.org/10.1002/j.2334-5837.2013.tb03067.x.

Mourtzis, Dimitris. 2019. "Simulation in the Design and Operation of Manufacturing Systems : State of the Art and New Trends." *International Journal of Production Research* 0 (0): 1–23. https://doi.org/10.1080/00207543.2019.1636321.

Moylan, Shawn, Christopher U Brown, and John Slotwinski. 2020. "Recommended Protocol for Round-Robin Studies in Additive Manufacturing." *Journal of Testing and Evaluation* 44 (2): 1009–18. https://doi.org/10.1520/JTE20150317.

NASA. n.d. "NCAMP Database." Accessed February 17, 2020. https://www.wichita.edu/research/NIAR/Research/ncamp.php.

"National Network for Manufacturing Innovation Program: Strategic Plan." 2016.

Nazir, Aamer, and Jeng-ywan Jeng. 2019. "A High-Speed Additive Manufacturing Approach for Achieving High Printing Speed and Accuracy." *Mechanical Engineering Science* 0 (43): 1–9. https://doi.org/10.1177/0954406219861664.

Newman, Mark E.J. 2002. "The Structure and Function of Networks." *Computer Physics Communications* 147 (1–2): 40–45. https://doi.org/10.1016/S0010-4655(02)00201-1.

Niaki, Mojtaba Khorram, and Fabio Nonino. 2017. "Impact of Additive Manufacturing on Business Competitiveness: A Multiple Case Study." *Journal of Manufacturing Technology Management* 28 (1): 56–74. https://doi.org/10.1108/JMTM-01-2016-0001.

Nobil, Amir Hossein, Sajjad Jalali, and Seyed Taghi Akhavan Niaki. 2018. “Financially Embedded Facility Location Decisions on Designing a Supply Chain Structure: A Case Study.” *Systems Engineering* 21 (6): 520–33. https://doi.org/10.1002/sys.21452.

Norris, Guy. 2017. “GE Testing For Boeing 777X Engine Moves Into High Gear.” *Aviation Week & Space Technology,* 2017. https://aviationweek.com.

O’Donnell, F. J., and A. H.B. Duffy. 2002. “Modelling Design Development Performance.” *International Journal of Operations and Production Management* 22 (11): 1198–1221. https://doi.org/10.1108/01443570210450301.

Oettmeier, Katrin, and Erik Hofmann. 2017. “Additive Manufacturing Technology Adoption: An Empirical Analysis of General and Supply Chain-Related Determinants.” *Journal of Business Economics* 87 (1): 97–124. https://doi.org/10.1007/s11573-016-0806-8.

Olexa, Russ. 2001. “The Father of the Second Industrial Revolution.” *Manufacturing Engineering* 127 (2): 42–54.

Pal, Snehashis, Hanuma Reddy Tiyyagura, Igor Drstvenšek, and Cheruvu Siva Kumar. 2016. “The Effect of Post-Processing and Machining Process Parameters on Properties of Stainless Steel PH1 Product Produced by Direct Metal Laser Sintering.” *Procedia Engineering* 149 (June): 359–65. https://doi.org/10.1016/j.proeng.2016.06.679.

Pollock, Tresa. 2019. “At the Crossroads of Additive Manufacturing, Analytics and Advanced Materials.” https://engineering.purdue.edu/Engr/AboutUs/News/Events/DistinguishedLectures/2020/pollock-lecture.

Porter, Michael E. 1979. “How Competitive Forces Shape Strategy.” *Harvard Business Review*.

Pratt & Whitney. 1988. *The Aircraft Gas Turbine Engine and Its Operation*. Edited by Hugh Prather. 5th ed. United Technologies Corporation.

“Pratt & Whitney to Focus on Powered-by-Hour Business Model.” 2015. The Economic Times. 2015. https://economictimes.indiatimes.com/industry/transportation/airlines-/-aviation/pratt-whitney-to-focus-on-powered-by-hour-business-model/articleshow/48908789.cms?from=mdr.

Rahman, Mustafizur, Yoke San Wong, and A. Rahmath Zareena. 2003. “Machinability of Titanium Alloys.” *JSME International Journal Series C* 46 (1): 107–15. https://doi.org/10.1299/jsmec.46.107.

Renishaw. n.d. "Additive Manufacturing Solutions Centres." Accessed March 7, 2020. https://www.renishaw.com/en/additive-manufacturing-solutions-centres--37039.

Rice, Richard C, Randall J Goode, J. Bakuckas, and S. Thompson. 2003. "Development of MMPDS Handbook Aircraft Design Allowables." In *7th Joint DOD/FAA/NASA Conference on Aging Aircraft*.

Richter, Klaus, and Johannes Walther, eds. 2017. *Supply Chain Integration Challenges in Commercial Aerospace*. Springer.

Roca, Jaime Bonnín. 2017. "Leaders and Followers: Challenges and Opportunities in the Adoption of Metal Additive Manufacturing Technologies." https://doi.org/10.1184/R1/6720371.v1.

SAE International. 2018. "Additive Manufacturing Standards Development." SAE International. https://www.sae.org/servlets/works/committeeHome.do?comtID=TEAAMSAM.

Scheithauer, Dieter, and Kevin Forsberg. 2013. "V-Model Views." *INCOSE International Symposium* 23 (1): 502–16.

Schniederjans, Dara G. 2017. "Adoption of 3D-Printing Technologies in Manufacturing: A Survey Analysis." *Intern. Journal of Production Economics* 183 (October 2016): 287–98. https://doi.org/10.1016/j.ijpe.2016.11.008.

Schoonenberg, Wester CH, Inas S. Khayal, and Amro M. Farid. 2019. *A Hetero-Functional Graph Theory for Modeling Interdependent Smart City Infrastructure*. Springer.

Scott, Alex, and Terry P. Harrison. 2016. "Additive Manufacturing in an End-to-End Supply Chain Setting." *3D Printing and Additive Manufacturing* 2 (2): 65–77. https://doi.org/10.1089/3dp.2015.0005.

Seifi, Mohsen, Michael Gorelik, Jess Waller, Nik Hrabe, Nima Shamsaei, Steve Daniewicz, and John J. Lewandowski. 2017. "Progress Towards Metal Additive Manufacturing Standardization to Support Qualification and Certification." *Jom* 69 (3): 439–55. https://doi.org/10.1007/s11837-017-2265-2.

Seifi, Mohsen, Ayman Salem, Jack Beuth, Ola Harrysson, and John J. Lewandowski. 2016. "Overview of Materials Qualification Needs for Metal Additive Manufacturing." *Jom* 68 (3): 747–64. https://doi.org/10.1007/s11837-015-1810-0.

Siebenmark, Jerry. 2018. “Spirit Aero, Norsk Add 3-D Titanium Part to Boeing 787.” Aviation International News Online. 2018. https://www.ainonline.com/aviation-news/air-transport/2018-12-26/spirit-aero-norsk-add-3-d-titanium-part-boeing-787.

Simon, Herber. 1996. “Chapter 7.” In *Science of the Artificial*. MIT Press.

Simpson, Timothy W., Christopher B. Williams, and Michael Hripko. 2017. “Preparing Industry for Additive Manufacturing and Its Applications: Summary & Recommendations from a National Science Foundation Workshop.” *Additive Manufacturing* 13: 166–78. https://doi.org/10.1016/j.addma.2016.08.002.

Sing, Swee Leong, Jia An, Wai Yee Yeong, and Florencia Edith Wiria. 2016. “Laser and Electron-Beam Powder-Bed Additive Manufacturing of Metallic Implants : A Review on Processes , Materials and Designs.” *Journal of Orthopaedic Research* 34 (3): 369–85. https://doi.org/10.1002/jor.23075.

Singamneni, Sarat, Yifan Lv, Andrew Hewitt, Rodger Chalk, Wayne Thomas, and David Jordison. 2019. “Additive Manufacturing for the Aircraft Industry: A Review.” *Journal of Aeronautics & Aerospace* 8 (1): 1–13. https://doi.org/10.4172/2329-6542.1000214.

Slotwinski, J A, E J Garboczi, P E Stutzman, C F Ferraris, S S Watson, and M A Peltz. 2014. “Characterization of Metal Powders Used for Additive Manufacturing.” *Journal of Research of the National Institute of Standards and Technology* 119: 460–93.

Sprock, Timothy, Leon McGinnis, and Conrad Bock. 2018. “Production and Logistics Systems Modeling Challenge Team.”

Sridharan, Ramaswami. 1995. “The Capacitated Plant Location Problem.” *European Journal Of Operational Research* 2 (87): 203–13.

Steele, Martin J. 2013. “NASA Handbook for Models and Simulations: An Implementation Guide for NASA-STD-7009A.”

Steiner, Rick. 2014. “Common SysML Conceptual Stumbling Blocks.”

Stevenson, A, M Baumers, J Segal, and Sarah Macdonell. 2017. “How Significant Is the Cost Impact of Part Consolidation within AM Adoption?” In *28th Annual International Solid Freeform Fabrication Symposium*, 2551–62.

Summers, Joshua D., and Jami J. Shah. 2010. “Mechanical Engineering Design Complexity Metrics: Size, Coupling, and Solvability.” *Journal of Mechanical Design* 132 (2): 021004. https://doi.org/10.1115/1.4000759.

Tamaskar, Shashank, Kartavya Neema, and Daniel Delaurentis. 2014. “Framework for Measuring Complexity of Aerospace Systems.” *Research in Engineering Design* 25 (2): 125–37. https://doi.org/10.1007/s00163-014-0169-5.

Tang, Zilin Elizabeth, Marc Goetschalckx, and Leon McGinnis. 2013. “Modeling-Based Design of Strategic Supply Chain Networks for Aircraft Manufacturing.” *Procedia Computer Science* 16: 611–20. https://doi.org/10.1016/j.procs.2013.01.064.

Tell, Philip von. 2017. *The Rise of Industrial 3D-Printing*.

“The ASTM International/ISO Partner Agreement.” 2011. 2011. https://www.astm.org/industry/additive-manufacturing-overview.html.

“The MESA Model.” n.d. Strategic Initiatives & Research Areas. Accessed February 16, 2020. http://www.mesa.org/en/modelstrategicinitiatives/MSI.asp.

“The Minds behind GE Additive: Greg Morris.” 2018. 2018. https://www.ge.com/additive/stories/minds-behind-ge-additive-greg-morris.

Thurber, Matt. 2010. “Boeing’s New Care Program Is Worth Its Weight in Gold.” AIN Online. 2010. https://www.ainonline.com/aviation-news/air-transport/2010-07-17/boeings-new-care-program-worth-its-weight-gold.

Tofail, Syed A M, Elias P Koumoulos, Amit Bandyopadhyay, Susmita Bose, Lisa O Donoghue, and Costas Charitidis. 2018. “Additive Manufacturing : Scientific and Technological Challenges, Market Uptake and Opportunities.” *Materials Today* 21 (1): 22–37. https://doi.org/10.1016/j.mattod.2017.07.001.

Togwe, Thembani, Bereket Tanju, and Timothy J. Eveleigh. 2018. “Using a Systems Engineering Framework for Additive Manufacturing.” *Systems Engineering* 21 (5): 466–75. https://doi.org/10.1002/sys.21447.

Tomblin, J S, J D Tauriello, and S P Doyle. 2002. “A Composite Material Qualification Method That Results in Cost, Time, and Risk Reduction.” *Journal of Advanced Materials -Covina-* 34: 41–51.

Uhlmann, Eckart, Robert Kersting, and Tiago Borsoi. 2015. “Additive Manufacturing of Titanium Alloy for Aircraft Components.” *Procedia CIRP* 35: 55–60. https://doi.org/10.1016/j.procir.2015.08.061.

Wegge, Brandon. 2019. “SAE AeroTeck Conference Presentation.” Charleston: SAE International.

Weisberg, David E. 2008. "A Brief Overview of the History of CAD."

Werner, Debra. 2017. "FAA Prepares Guidance for Wave of 3D-Printed Aerospace Parts." SpaceNews. 2017. https://spacenews.com/faa-prepares-guidance-for-wave-of-3d-printed-aerospace-parts/.

West, Timothy D., and Mark Blackburn. 2017. "Is Digital Thread/Digital Twin Affordable? A Systemic Assessment of the Cost of DoD's Latest Manhattan Project." *Procedia Computer Science* 114: 47–56. https://doi.org/10.1016/j.procs.2017.09.003.

White, Sarah K. 2018. "What Is SCOR? A Model for Improving Supply Chain Management." CIO. 2018. https://www.cio.com/article/3311516/what-is-scor-a-model-for-improving-supply-chain-management.html.

Wildemann, H, and F Hojak. 2017. "Main Differences and Commonalities between the Aircraft and the Automotive Industry." In *Supply Chain Integration Challenges in Commercial Aerospace Industry,* edited by K Richter and N Witt, 119–38. Springer.

Williams, Christopher B, Jitesh H Panchal, and David W Rosen. 2003. "A General Decision-Making Method for the Rapid Manufacturing of Cutomized Parts." In *ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference,* 1–11. Chicago.

Witherell, Paul. 2017. "Additive Manufacturing Data and Emerging Analytics Opportunities."

Wohlers, Terry. 2016. "History of Additive Manufacturing."

Wu, NaiQi, Ning Mao, and YanMing Qian. 2000. "An Approach to Partner Selection in Agile Manufacturing *." *Journal of Intelligent Manufacturing*, no. 729.

Yang, Li, Keng Hsu, Brian Baughman, Donald Godfrey, Francisco Medina, Mamballykalathil Menon, and Soeren Wiener. 2017. "Additive Manufacturing of Metals: The Technology, Materials, Design and Production," 45–61. https://doi.org/10.1007/978-3-319-55128-9.

Yusuf, Shahir Mohd, Samuel Cutler, and Nong Gao. 2019. "Review: The Impact of Metal Additive Manufacturing on the Aerospace Industry." *Metals* 9 (12): 35.

Ziegler, Moritz Julius, Kilian Seifried, Philipp Kuske, and Moritz Fleischmann. 2019. "TRUMPF Uses a Mixed Integer Model as Decision Support for Strategic Production Network Design." *INFORMS Journal on Applied Analytics* 49 (3): 213–26.

VITA

Bill Bihlman founded Aerolytics LLC, a management consultancy, in 2012. Its focus is marketing strategy for aerospace *materials*, *structures* and *component manufacturing* firms. He started his career in 1995 as an engineer with Raytheon Aircraft. Subsequently, he was Senior Consultant with AeroStrategy. Bill began his PhD at Texas Tech in 2015, transferring to Purdue in 2017. Bill holds a BS and MS in Mechanical Engineering from Purdue, an MBA and MPA from Cornell. He is a certified Green Belt in Six Sigma, a licensed private pilot, and is actively involved with SAE (AM Standards and AeroTech). Recent conference presentations include:

2020
Invited – aerospace raw material conference, *Roskill*, Germany
Invited – specialty metals conference, *Minor Metals Assoc*., Charleston SC

2019
"Next Generation Commercial Aircraft: Aluminum vs Carbon Fiber," *ARABAL*, Bahrain
"Additive Manufacturing in an f'(x) World: Navigating Change," *Keynote - GE Additive*, Germany
"Prevailing Trends in Manufacturing for Commercial Aerospace," *SAE Intl*, China
"Modeling Additive Mfgr Impact on Aerospace" (also track Chairman)," *SAE Aerotech*, Charleston SC
Invited – global aluminum conference, *APRAL*, Russia

2018
"Manufacturing Innovation in Aerospace Panel Overview" (Intro as Co-chair), *SAE Intl*, Japan
"Understanding the Requisite Ecosystem to Qualify Aerospace AM Parts," *INFORMS*, Las Vegas NV
"Systems Approach to Understanding AM's Impact on Aero Supply Chain," *INCOSE GLRC*, Indpls IN
"Manufacturing's Evolution and Its Impact on Aero Titanium," *Intl Titanium Assoc*, Las Vegas NV
"LSAM Machine Technology Overview," *CMSC's Extrusion Deposition AM Workshop*, W Laf IN
"Additive Manufacturing's Role in the Future of Aerospace," *SAE Intl*, China
"Additive Manufacturing for Aerospace - Opportunities and Challenges," *Credit Suisse*, NYC NY
"The Adoption of Additive Manufacturing: What Differentiates Aero vs Auto," *SAE Intl*, Cleveland OH

2017
"The State of Advanced Manufacturing in Aerospace," *Intl Intelligent Machines*, Taiwan
"Additive Manufacturing for Commercial Aerospace," *Dassault Systemes*, Chicago IL
"AM for Aerospace: Influencing Factors, Where It's At and Where It's Going," *SAE Intl*, Knoxville TN
"Material & Mfg for Commercial Aero: Present & Future," *Intl Machine Tool Show*, Taiwan

2016
"Aerostructure Materials: To What Extent Is Aluminum Relevant," *ARABAL*, United Arab Emirates
"Assessing CFRP's Role within Commercial Aerospace," *Composites World*, Scottsdale AZ
"Materials Choices in Aerospace & Demand Prospects for Aluminum," *Metal Bulletin*, Spain
"Material & Manufacturing for Commercial Aerospace: Present & Future," *TRAM*, Chicago IL
Industrial Roundtable: Additive Manufacturing Users (Conference Panelist), *ASME*, Charlotte NC
"Aeroengine Materials: Current and Next Generation," *Intl Nickel Study Group*, Portugal
"Material Trends in Commercial Aerospace Impacting Titanium," *Intl Titanium Assoc*, France