Identifying and Assessing Aerospace Parts for Production in Additive Manufacturing

by

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Submitted to the MIT Aeronautics and Astronautics Department

and

MIT Sloan School of Management
in partial fulfillment of the requirements for the degrees of

Master of Science in Aeronautics and Astronautics

and

Master of Business Administration

in conjunction with the Leaders for Global Operations program

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2021

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Abstract

Pratt & Whitney is a major aerospace Original Equipment Manufacturer (OEM) of gas turbine engines for both the commercial and military sectors. Additive Manufacturing (AM) presents Pratt & Whitney with the opportunity to improve their supply chain and increase performance. Yet, given the complexity of their product and the volume of parts required to make it, Pratt & Whitney faces a significant challenge in identifying appropriate parts to be produced additively from engineering, supply chain, and business standpoints.

The motivation of this project is to optimize an existing process which was limited to close review of a small number of parts into a cohesive and sustainable methodology that will identify parts across a large catalog that are suitable for sustained production in AM. This thesis describes a two-part methodology for identifying parts based on their suitability to be manufactured additively. The first part of the process ranks a large set of parts using the Analytic Hierarchy Process (AHP). The second part is a prescriptive expert review of the top parts at the end of which, a recommendation on whether to produce a part through AM can be made. This thesis includes a field study of a data set of 25,000 parts in which the AHP process was applied and analyzed. The field study succeeded in producing a ranked list of parts, the best of which moved on to further review by Pratt & Whitney for production consideration.

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Acknowledgments

Thank you to Pratt & Whitney for sponsoring this project and to the Pratt & Whitney engineers, operations personnel and technicians for bearing with me during my time there. A special thanks to my sponsors Paul Faughnan and Jesse Boyer for giving me their time and patience during this project, which fell during an especially difficult time for everyone during the onset of COVID-19. Also, thanks to Travis Gracewski for being a continuous resource for LGO interns at Pratt & Whitney over the years.

Thank you to my academic advisors, Prof Paulo Lozano and Prof Roy Welsch for their guidance and oversight during the project, which was instrumental in trying to add value when COVID limitations and restrictions made doing so all the more difficult. Lastly, many thanks to the Leaders for Global Operations faculty, staff and students. Learning from all of you during this time was a critical part of my internship experience.

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List of Acronyms

AHP . . . . Analytic Hierarchy Process

AM . . . . Additive Manufacturing

BTF . . . . Buy-to-Fly

CAD . . . . Computer-Aided Design

DED . . . . Directed Energy Deposition

IP . . . . Intellectual Property

MRL . . . . Manufacturing Readiness Level

OEM . . . . Original Equipment Manufacturer

PBF . . . . Powder Bed Fusion

Chapter 1

Introduction

Pratt & Whitney (a Raytheon Technologies Company) has been a world leader in the design, manufacture and service of aircraft engines and auxiliary power units for 95 years. In 2019, Pratt & Whitney reported 42,200 employees and net sales of $20.9B with $1.8B in adjusted operating profit. Like many organizations, particularly those in aerospace, COVID-19 has increased pressure to control costs with revenues reduced based on travel limitations. As such, there is reason more than ever to explore ways to add robustness to their supply chain. This chapter is an introduction to the current technical and business challenges that prompted the project, the motivations of the project, as well as an overview of the rest of the thesis.

1.1 Project Motivation and Problem Statement

AM presents an intriguing value proposition to aerospace manufactures. The technology excels in complexity, reducing raw material waste and providing weight savings; all of which are important aspects in succeeding as an OEM in aerospace. Pratt & Whitney has significant research capability in AM including touch points at laboratories within Raytheon Technologies business units, along with other AM centers in academia, government and industry. As an OEM of gas turbine engines, Pratt & Whitney manages a vast and complex supply chain. They produce a wide array of parts, all of which are subject to the strict regulations and controls inherent to the aerospace industry. Pratt & Whitney therefore faces a significant challenge in identifying appropriate parts to be produced additively from an engineering, supply chain and business standpoint. Furthermore, the technical data required to manufacture parts using traditional processes is not all encompassing of that required for AM.

To date, Pratt & Whitney has approached part selection for additive manufacturing using relatively simple spreadsheet tools to guide a process that was limited to focused part selection. This approach had the benefit of close inspection of parts that were nominated, including detailed assessments of the business case for transitioning the part to production through AM. However it lacked the breadth to holistically assess the Pratt & Whitney parts catalog to identify parts for AM that may not have been intuitive from either a technical or business perspective.

Many long-standing aerospace OEMs are in a continuous process of updating data management systems which is a non-trivial task given the volume of technical data they catalog and their decades long history. Furthermore, given the barriers to new technology implementation in manned aircraft due to government regulation, there are a very limited number of parts approved for flight. This makes use of traditional statistical methods like regression models, or sophisticated approaches, like machine learning, difficult to apply given challenges with curating the disparate data sets. Therefore, a novel approach is required when leaning on legacy data systems to identify parts for AM.

1.2 Problem Approach and Hypothesis

The approach to identify suitable parts for production in AM proposed in this thesis is to combine a database driven tool with a detailed expert review of the most promising parts. This thesis hypothesizes that leveraging the AHP will mitigate concerns with uncurated or incomplete data sets. Moreover, as OEMs and government regulators become more experienced with AM, OEMs can easily tune their search tools to identify parts that meet their need. Further, focusing the expert review on part attributes not easily captured in legacy data systems will improve efficiency and identify the parts most suitable for transition.

1.3 Thesis Overview

This thesis starts with an introduction to the current challenges in implementing part selection methodologies at Pratt & Whitney. Chapter two discusses contemporary research in the field and provides background information on the concepts and theories used in this research. The next chapter hypothesizes a theoretical framework for implementing the AHP in part selection for AM in aerospace. Chapter four is an application of the theories in chapter three using data from Pratt Whitney. Chapter five details the framework for an expert review that is proposed to be implemented on parts identified by using the AHP. The final chapter provides an overall conclusion to the thesis as well as recommendations for further work in this field.

Chapter 2

Literature Review

The purpose of this chapter is to review current and recent studies into the fields of metals additive manufacturing and related part selection methodologies to identify the current state of the art as well as areas that need further research. This will help to better delineate where this thesis fits into the already-existing body of scientific work. Furthermore, this chapter will provide background information on AM as well as the AHP in order to provide context for the methods discussed in later chapters.

2.1 Additive Manufacturing

Additive Manufacturing is the process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies [1]. Gibson et al further describe an eight step process inherent to AM [6]. Some of these steps will be referenced in Chapter 3 when discussing part selection considerations.

1. CAD: AM parts start with a software model that fully describes the external geometry. This can involve the use of nearly any Computer-Aided Design (CAD) software.

2. Conversion to STL: Nearly every AM machine accepts the STL file format. The concept behind this step though is that the CAD model must be output into a

file that describes the external closed surfaces of the part. This file will form the basis for calculation of the slices. Newer machines may use native CAD files, such machines can skip this step.

3. Transfer to AM Machine and STL File Manipulation: The STL file describing the part must be transferred to the AM machine. In order to do so there may need to be some manipulation of the file to ensure the correct size, position and orientation for the build.

4. Machine Setup: The AM machine must be properly set up to allow for the correct build parameters such as material constrains, energy source, layer thickness etc.

5. Build: Building the part is primarily an automated process carried out by the machine. However, an operator may be needed to ensure no errors occur, or to ensure that errors are identified and corrected.

6. Removal: Once the part is built it must be removed from the machine.

7. Post-processing: After parts are removed from the AM machine, they typically need additional cleaning or other treatment prior to use. This may include the removal of support structures required during the build.

8. Application: Parts may now be ready to use. However, they may also require additional treatment prior to use. Some treatments include: heat treatment, hot isostatic pressing, machining and coating. Note that while Gibson et al separate this step from post-processing, many organizations combine them.

2.1.1 AM Part Progression

There are various ways to apply AM to production. Simpson [17] describes a three phase process.

- Phase 1: Replicate with AM - In this phase the goal is to reproduce a part exactly with AM and compare it to the conventionally manufactured part in terms of performance, cost etc.

- Phase 2: Adapt for AM - In this phase, the designer has the freedom to adapt the part for AM. The part still needs to achieve the same functionality, but the non-functional features can be modified to make the part less difficult to produce additively. Some examples of changes in this phase could be to add lattice structures or conformal cooling channels to improve heat transfer.

- Phase 3: Optimize for AM - In this phase, the designer has the freedom to redesign the part completely for AM or design a new component from scratch. Generally speaking the engineer is trying to design a component within a given design space that meets necessary requirements. This phase can use techniques like topology optimization which can better leverage the strengths of AM.

Reproducing parts through replication (phase 1) is often the least preferred method to implement AM, yet many organizations use this as a starting point to gain some familiarity with the technology. Furthermore, parts that are required to go through certification by government agencies (like the FAA) have further barrier to entry. So again, it can be beneficial for manufacturers to start with replication as a way to sensitize the industry to the technology. Therefore, this thesis will predominantly focus on replication.

2.1.2 AM Processes

There are many different AM processes used for metals and polymers. Two common processes for metals are PBF and DED. DED directs energy into a narrow, focused region to heat a substrate, melting the substrate and melting the material that is being deposited into the substrate's melt pool. DED processes are not used to melt material that is pre-laid in a powder bed, but rather to melt materials as they are being deposited [5]. DED is a versatile process that can be used to manufacture entire parts or even as a means to repair parts. Figure 2-1 shows a schematic of the DED process.

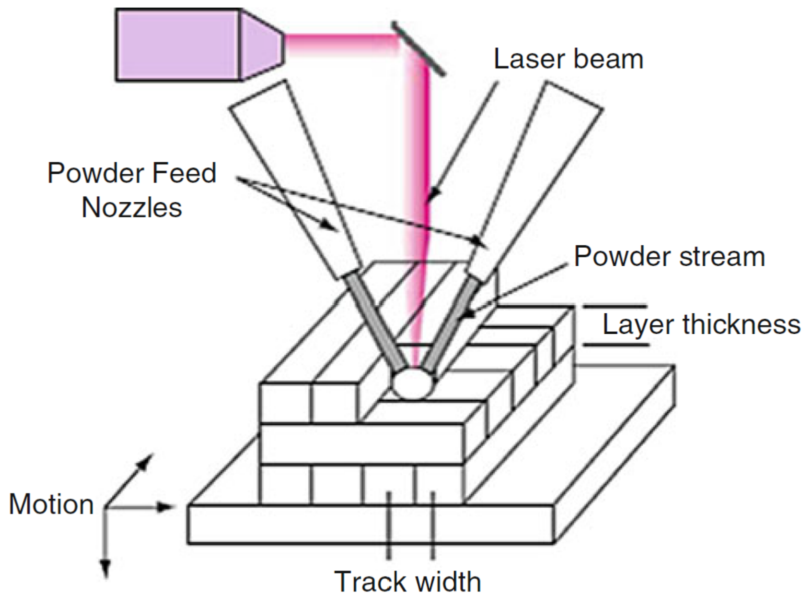

Figure 2-1: DED process schematic [5]. Note that while this schematic shows a laser as the energy source, electron beams are also widely used in industry.

PBF processes are widely used across AM and especially so in metals AM. They will be the principal process considered in this research and as such, the remainder of this section will discuss some benefits and limitations of PBF. Selective Laser Sintering (SLS) was the first commercialized PBF process, albeit for polymers, and was developed at the University of Texas at Austin. PBF processes include one or more thermal sources for inducing fusion between powder particles, a method for controlling powder fusion to a prescribed region of each layer, and mechanisms for adding and smoothing powder layers [7]. Lasers are the most common thermal source for PBF but electron beams are also widely used.

Figure 2-2 shows a schematic of an SLS PBF process. The general concept starts with a layer of powder deposited onto a substrate, the layer is melted with a laser or electron beam following the appropriate shape, the substrate is lowered one layer thickness, another layer is deposited and the process continues until the part is complete.

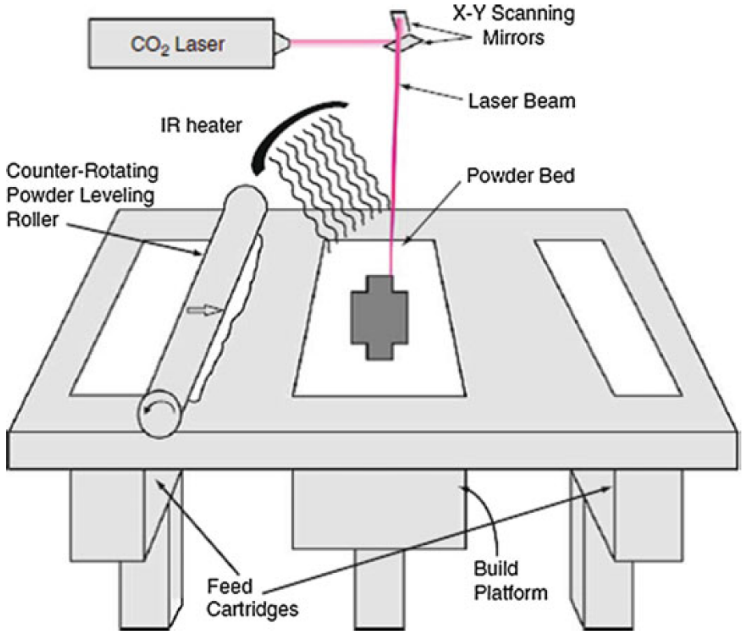

Figure 2-2: PBF process schematic [7]

Polymer AM processes often do not require support structures during the build process as the unused powder surrounding the part is enough to support it. Metal AM processes on the other hand, do often require supports. The part is typically affixed to a build plate and support structures are used to dissipate heat, provide support, and prevent warping during the cool down process. These supports then have to be removed following the build. This can add significant costs to the post build processes, especially if the supports are in contact with surfaces that need treatment due to flow requirements.

PBF AM processes typically can provide more accuracy in the plane parallel to the build plate. This is because detail in that plane is limited by the accuracy of the thermal source. In the direction normal to the build plate, accuracy is limited by the layer thickness. This differential in accuracy means that part orientation during build may be a limiting factor. If a part has very strict tolerances in three dimensions, it may preclude it from being built, depending on the tolerances of the AM build machine. Skewed orientations are possible but may not meet very strict requirements.

The ability to recycle unused powder during the PBF process can be a significant source of cost savings. Metal PBF parts are often more expensive than their bar stock counterparts, so reducing waste can be critical in making a business case for AM. Each layer during a build contains a significant amount of material that is not meant to be built into the part. The material closest to the part may undergo partial melting and may therefore be unable to be reused, but material farther from the part may be nearly intact. This drives the need for recycling, filtering and testing protocols to ensure quality and repeatability. Professional organizations like SAE and ASTM provide industry standards for organizations to adhere to, which is especially important in a well-regulated industry like aerospace.

As one of the most popular commercial AM processes, PBF benefits from ever evolving technology. Improvements include wider arrays of buildable materials, the use of multiple thermal sources to increase build speeds and ever-increasing chamber sizes which increases the maximum part sizes. Of particular importance for aerospace, post processing technology is also improving regularly. Post processing steps are often necessary due to the high stress and longevity required of many aerospace components, especially those used on passenger aircraft.

2.1.3 AM in Aerospace

Aerospace is a particularly attractive application of metals AM. Many aerospace companies have invested in AM development. There are significant drivers in aerospace to reduce weight and control manufacturing costs. The lightweight materials used in aerospace (such as titanium) are very expensive [8] therefore aircraft parts are a prime candidate for production through AM.

However, aerospace is not without its limitations when it comes to implementation of AM. As mentioned previously, aerospace components are subject to extreme stresses and have long lifespan requirements. Adding passengers to the equation makes quality, and regulation, very important. This can make adoption of new technologies difficult if their efficacy and consistency cannot be proven. The nature of AM processes makes this a non-trivial hurdle. Material specifications and testing of the metals used for subtractive or casting manufacturing processes has been well studied and verified over the life of the aerospace industry, so adding a less tested process can be difficult from a regulatory standpoint. Nonetheless, aerospace represents a prime candidate in furthering adoption and advancement of AM technologies.

2.2 Part Selection Methodologies

Part selection for AM is a challenging process that is complicated by several factors, not the least of which is part volume. High performance gas turbine engines are often made up of over 6,000 parts, and many are flown for decades. Therefore, an OEM can be required to provide replacements for over 100,000 SKUs. The large volume of parts implies that it is advantageous to develop methodologies to identify those parts that are most suitable to be produced additively. There are predominantly two strategies for identifying and selecting parts most suitable for additive production: bottom up and top down.

2.2.1 Bottom Up Selection

A bottom up selection process is driven largely by part users. In this method, parts are identified and nominated for production through AM by those closest to the part. They could be end users, manufacturing technicians or even supply chain representatives. Lindeman et al [12] describe a three-phase process for part selection using this methodology.

- Information Phase: Here the AM technology is introduced to the interested parties. Many aspects of this phase are educational in nature and experts can be used to demonstrate the advantages and limitations of the technology with examples. This phase can also include creative workshops where part selection groups can begin nominating parts for production. The goal of this phase is to give participants a basic understanding of the technology and the ability to begin internal part screening.

- Assessment Phase: During this phase the number of parts is narrowed down. This screening is accomplished by applying a trade-off methodology matrix. The parts can then be ranked according to assessments done by the part owners and AM experts.

- Decision Phase: The decision phase aims to find the part that represents the biggest benefit for specific AM adapted redesign. This phase will also include in depth technical analysis of requirements as well as business related concerns that are inherent to any production decision.

Organizations that are more experienced with AM may not require an in depth or lengthy phase one. Moreover, some organizations may go through cycles of these three steps as they experience employee turnover or other knowledge management challenges. Lastly, Lindeman focuses on the later stages of the additive part progression, namely adapt and optimize for AM. This can be a very effective methodology for these phases as close inspection of part requirements and expert analysis are likely required in order to identify and redesign parts.

2.2.2 Top Down Selection

The bottom up approach has the benefit of thorough inspection and detailed analysis. However, applying such an approach to a large parts catalog can be cost prohibitive due to the time involved with assessing each part. Therefore, a different approach is required. A top down approach starts at the macro level. Here a database of parts is assessed in aggregate with the goal of identifying those most suitable for production through AM.

Applying a top down part selection approach to the later stages of the AM part progression can be very difficult as the parts would require adaptation for AM production. In phase one (replicate), part catalogs can be more readily used to identify conventionally manufactured parts for AM. Here, each part's specific technical specifications will more closely resemble those of its additive replacement part. In contrast, only the performance requirements would be analogous when considering parts for adaptation or optimization.

Leveraging regression models or machine learning algorithms can be powerful, however curated data is required. The limited number of parts that are currently FAA approved make this difficult for an aerospace OEM so other techniques must be leaned on to algorithmically assess and rank parts based on their suitability to be transferred from conventional manufacturing processes to AM. Knofius et al [11] used an application of the AHP to select parts for additive production in service logistics. Their study ranked 6,190 parts. The parts were first filtered on base requirements necessary to meet AM limitations and then ranked on how much their supply chain would be improved if they were switched to AM production.

2.3 Analytic Hierarchy Process

The AHP was developed by Thomas Saaty in the 1970s. The AHP "is a theory of measurement concerned with deriving dominance priorities from paired comparisons of homogeneous elements with respect to a common criterion or attribute. Such measurement can be extended to non-homogeneous elements through 'clustering.' In a multi-criterion setting, the AHP can be used to scale elements in a hierarchy structure with mutually independent elements in each level, or in a network system of components allowing for dependence within and between components. Thus, a hierarchy is a special case of the more general system formulation, the network. Applications of the AHP have included parallel hierarchies (one for benefits and one for costs), and solitary hierarchies (projected and idealized planning, resource allocation). More complex applications of the AHP include the case of an infinite number of elements, and the modelling of neural firing and its synthesis." [16] Ultimately, the AHP provides an analytical and numerical framework for making decisions in complex systems. The AHP does not produce absolute scores for alternatives, rather it provides a relative score based on defined criteria.

As an example, consider a decision-making problem with m alternatives and n

criteria. To apply AHP, we would begin with the decision maker (in the case of this research, an expert in AM) expressing how two criteria compare to each other using the scale in Figure 2-3. Psychologists suggest that the 1-9 rating scale gives the appropriate level of detail without giving the decision maker difficulties expressing their opinion were they provided a larger scale. The number of comparisons required for n criteria is $\frac{n^2-n}{2}$. Many studies limit the number of criteria to 7 in order to avoid decision fatigue on the part of the decision maker in an effort to ensure consistency in their rating. by forming a pairwise comparison matrix of the criteria. Once the decision maker provides their input, it is compiled into a pairwise comparison matrix.

The Scale

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgement slightly favor one activity over another
5	Essential or strong importance	Experience and judgement strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order or affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgements	When compromise is needed
Reciprocals	If activity i has one of the above nonzero numbers assigned to it, when compared to activity j, then j has the reciprocal value when compared with i	

Figure 2-3: AHP criteria comparison table
[15]

Once the comparison matrix is compiled, it needs to be checked for consistency. Conflicts can arise due to the human involvement with the criteria ratings. For example, if the decision maker using Figure 2-3 rates criteria A as 7 in comparison to criteria B and rates B as a 6 in comparison to criteria C, they would be expected to later rate A as more important than C. However, if the decision maker instead rates criteria C as more important than criteria A, this lack of consistency needs to be quantified. Furthermore, if the decision maker's overall consistency falls below a certain threshold, their ratings could be invalidated writ large. Chapter 3 will discuss consistency checks in greater detail, this example is used to develop a conceptual understanding.

Following the consistency check of the criteria comparison matrix, a priority vector is computed to determine relative weights for each criterion. There are three common methods to accomplish this: the eigenvector method, the normalized column sum method, and the geometric mean method [13]. Of these, the eigenvector method is the most commonly used and was proposed by Saaty [15].

Next a pairwise comparison matrix is developed for each respective criterion comparing the m alternatives. This leaves n comparison matrices of size $m \times m$. Each matrix is checked for consistency similar to the method described when considering the criteria and local priority vectors are computed for each criterion. Lastly, global alternative priorities are calculated by combining the local priority vectors. The application of the AHP produces a rank ordered list of the m alternatives. It is naturally dependent on the inputs of the decision maker, but it applies structure to the decision-making process and some steps lend themselves to automation, which can greatly extend the decision makers reach.

Chapter 3

AHP Methodology for Part Selection

Pratt & Whitney, as a part of Raytheon Technologies, has substantial internal AM research capability in both human capital and infrastructure. However, Pratt & Whitney has a nearly 100 year long history, its products are comprised of thousands of parts and provides legacy support to these products for decades. This means manually assessing its entire active parts catalog in order to identify parts when implementing additive into their supply chain is difficult and cost prohibitive.

Therefore Pratt & Whitney, and other major aerospace OEMs, have an identified need to automate the process. This chapter outlines the process of applying the AHP to part selection for AM within an aerospace OEM. It will hypothesize the criteria an established aerospace OEM may consider when using the AHP to identify parts for AM from both a technical and business perspective while using legacy data systems which capture part specifications best suited for traditional manufacturing technologies (i.e. subtractive manufacturing, casting, forging etc.). The criteria discussed in the following sections are not meant to serve as an exhaustive list, but rather a starting point for where the intersection of relevant data for AM part selection and available data on legacy systems may coincide. Following the criteria review, this chapter will provide the steps necessary to produce a rank ordered list of parts while using the AHP.

3.1 Technical Data

The technical data required to support traditional manufacturing processes is not all encompassing of the data that is required to produce a part additively nor does it include all necessary information for accurate cost estimation for AM. For instance, if a part requires supports during the build process for thermal stress relief in a powder bed fusion machine, this cannot be easily assessed using dimensional data in a part schematic. Similarly, some parts may be very difficult to produce additively because they have tolerance requirements along two axes that an AM machine may be able to meet on only one axis. Yet, there are drivers from a technical perspective that would indicate a higher probability of success in AM that can be reasonably aggregated from databases that were built from legacy data. This section will propose data points that are both available in many databases and may indicate success in AM.

3.1.1 Material Specification

Material specifications cover materials, material tolerances, and quality control procedures and processes. They delineate chemical composition and provide detailed technical requirements. Many OEMs lean on SAE Aerospace Material Specifications (AMS) as an industry standard for materials. The material specification for each part is included with part data regardless of the manufacturing process and may be easily callable.

For OEMs that produce materials that undergo extreme stresses, for example, manufacturers of jet engines, rockets, or turbo-machinery, material property requirements may be a major limiter by which parts or assemblies cannot be made through current additive technologies. Beyond absolute feasibility, the material specification may indicate how difficult a particular material is to work with either during a build, or in post processing, especially for parts with extensive surface treatment requirements.

3.1.2 Box Dimensions

Part box dimensions refer to the smallest rectangular box a completed part could fit in. Box dimensions can be used alone to glean important information regarding printability of a part, and can be paired with other data to be used as a proxy for complexity consideration, although complexity will be covered later in this chapter.

Box dimensions can first serve as a good data point for filtering out unprintable parts. Polymer AM machines as well as directed energy disposition machines tend to be able to accommodate larger parts than metal PBF machines. However, as discussed previously, PBF machines are the most commonly used machines in metals AM. They typically have build plate size limitations in the order of 40 cm. Box dimensions can be used to find the largest part dimensions to determine whether or not it can fit within the limits of the build plate, or build chamber.

Box dimensions can further help identify how many parts can be printed per build. Some nesting techniques used in polymer builds can be impractical with metals due to thermal concerns, and even less feasible for parts that have the mechanical and thermal cycle requirements that many parts in commercial aviation have. As such, the relative box dimension sizes of these parts may serve as a good starting point in identifying how many may fit on a single build plate, and subsequently, how production may scale.

3.1.3 Weight

Aerospace OEMs may look to improve their Buy-to-fly (BTF) ratio, which is the ratio between the mass of raw material needed for a given production and the final mass of the manufactured part [8]. Currently, by using the conventional manufacturing processes, the Buy-to-Fly (BTF) ratio for aircraft components is in the range of 12:1 – 25:1 and results in very poor material efficiency [10]. In general, this can create efficiencies in switching to production through AM. The BTF ratio for AM PBF produced parts depends on a number of factors including post processing requirements and percentage of powder that is able to be recycled per build. Yet, regardless of the process, AM powders tend to cost more per unit weight than their equivalent in bar stock or other metal species, so lower weight parts can favor AM.

3.1.4 Flow Requirements

Many parts are required to support different kinds of flow in aerospace, be it air, fuel, oil or any other fluid. The type of fluid and flow rate necessitate surface treatments and geometries to support their requirements. Users may want to use a scale, where they rank no flow parts more highly than those that are required to support air flow, and rank parts required to support air flow higher than those that need to support fuel flow. Or they may want to filter any parts that are required to pass flows because of feasibility concerns or cost concerns associated with necessary AM post processing. Ultimately, meeting the required surface finish for some flows may be easier to support via post processing than others, so decision makers may want to factor this into part selection if the data is available.

3.1.5 Complexity

The addition of complex features often does not increase a part's cost of production. Cost tends to either fall with complexity or stay relatively constant. This is likely due to lower costs in materials and faster build times. Conversely, complexity tends to increase the cost of parts made using Computer Numeric Control (CNC) machines [14]. Therefore, attempting to estimate the complexity of a part using technical data may intimate that there will also be a business case for printing.

Conner et al defined complexity for an AM part as:

$$C = (1 - \frac{V_p}{V_b}) + (1 - \frac{A_s}{A_p}) + (1 - \frac{1}{\sqrt{1 + N_c}}) \tag{3.1}$$

Where V_p = part volume, V_b = bounding box volume, A_s = surface area of a sphere with the same volume as the part, A_p = surface area of the part, and N_c = number of holes/cores within the part [3]. Complexity decreases as the part volume approaches that of its bounding box. It further decreases as the part's surface area approaches that of a sphere of the same volume, which has the lowest possible ratio of surface area to volume. Lastly we see that complexity increases with the number of holes or cores in the part.

Some of these data points may not easily be aggregated from existing databases, yet some can be derived from existing data. Part volume can be derived from using the part weight, and the material specification, which will include density. It should be noted that the material density may vary from the listed material specification depending on what processes the part goes through, but it can still be a good estimate to work with. Part area may or may not be readily available in aggregate depending on the database being used. The same can be said for the number of cores. However, portions of the equation can be used to get a relative estimate of complexity based on the data available.

3.2 Business Considerations

Technical considerations will determine if a part *can* be produced additively. But business considerations will indicate whether or not a part *should* be produced additively. There are many cost drivers of AM that will be difficult to assess using conventional manufacturing or supply chain data. These drivers can be better analyzed during an expert review process (Chapter 5). Yet, there are still a number of factors included in conventional manufacturing and supply chain data that may indicate a part's business case for production in AM.

3.2.1 Cost

Part cost can be used as a starting point. Given the relationship between cost and complexity discussed in Section 3.1.5 we can estimate that parts produced relatively inexpensively through conventional manufacturing are less likely to find a business case using AM. For example, nuts, bolts, washers, etc. would be difficult to produce cost competitively while using AM. Therefore, more expensive parts have a better probability of finding a business case within AM.

3.2.2 Supply Chain

OEMs may look beyond strict cost savings when making a business case for AM. Adding robustness to the supply chain for a given part can be a large enough driver to transition to AM even if the part is currently being made more cost effectively. Some examples of supply chain improvements are moving away from single source suppliers or insulating the supply chain from macro variability by diversifying across different suppliers or regions may be a big enough driver to implement AM. Quantifying these supply chain requirements and combining that with technical data is no small task.

OEMs often keep track of the number of parts that are currently back ordered from suppliers who are either not meeting their contract terms or are unable to meet a new need from the OEM. Taking this data and multiplying it by the cost of the part will give the total value of the back-ordered parts. This is a valuable data point in quantifying some of the costs associated with limits in the supply chain. Other supply chain considerations that are useful but may be more difficult to determine depending on the data system being used are: the number of suppliers currently providing a part, cost increases to a part over time (which can be quantified using a CAGR) or quality issues with a part or supplier. Ultimately, the role the supply chain plays in implementing AM for a given OEM will be dependent on their specific priorities and needs.

3.2.3 Intellectual Property

Many OEMs do not own the Intellectual Property (IP) for all of the parts in their products. Some IP may be licensed or owned by suppliers or the government. This means that there can be varying degrees of difficulty in producing the parts additively which can present unique challenges. Quantifying how difficult the IP issues will be to work through is no small task and even harder to do in aggregate over thousands of parts. One solution could be to treat IP as a strict filter to determine whether or not a part will even be considered. If the IP is owned by the OEM or the government, the part can be considered, if it is not, the part is disqualified.

3.3 Criteria Ratings

The criteria priority vector will quantify how important each criterion is to the decision maker. As mentioned previously, this can be calculated multiple ways. This research will use the eigenvector method. Were the pair-wise comparison matrices sparse, we may consider another method, but given the nature of our comparisons, the eigenvector method should deliver efficient and accurate results. This section will discuss how to calculate the priority vector given available data sources as well as acceptable limits for consistency across the pair-wise comparison matrix.

3.3.1 Decision Maker Ratings

Decision criteria can be selected based on the data that is available and the goal of the decision maker. For example, if the goal is to improve the supply chain, then more criteria related to the supply chain may be selected. Regardless of the criteria chosen, the decision maker(s) must give ratings for all pairwise comparisons between criteria. Figure 3-1 is a completed example rating using Figure 2-3 as the scale. The criteria here are a subset of those listed in the previous section.

Participant 1 | 1

Name | Weight | Date

α: 0.1 | CR: 5% | Consistency Ratio

i	j	Criteria A	Criteria B	more important ? A or B	Scale (1-9)
1	2	Complexity	Weight	B	7
1	3		Box Volume	B	3
1	4		Cost	B	6
1	5		Material Spec	B	8
1	6		OTD	B	4
1	7				
1	8				
2	3	Weight	Box Volume	A	3
2	4		Cost	A	2
2	5		Material Spec	B	2
2	6		OTD	A	3
2	7				
2	8				
3	4	Box Volume	Cost	B	3
3	5		Material Spec	B	4
3	6		OTD	B	2
3	7				
3	8				
4	5	Cost	Material Spec	B	3
4	6		OTD	B	2
4	7				
4	8				
5	6	Material Spec	OTD	A	5
5	7				
5	8				
6	7				
6	8				
7	8				

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong Importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, it dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
2,4,6,8 can be used to express intermediate values		

Figure 3-1: AHP criteria ratings by decision maker [9]. Note: the ratings in this table are not from Pratt & Whitney experts, they are inputs from the author only for illustrative purposes.

After the decision maker provides comparative ratings for the criteria, a pairwise comparison matrix can be compiled from the results. Figure 3-2 is an example of a pairwise comparison matrix compiled from the inputs in Figure 3-1.

		Complexity 1	Weight 2	Box Volume 3	Cost 4	Material Spec 5	OTD 6
Complexity	1	1	1/7	1/3	1/6	1/8	1/4
Weight	2	7	1	3	2	1/2	3
Box Volume	3	3	1/3	1	1/3	1/4	1/2
Cost	4	6	1/2	3	1	1/3	1/2
Material Spec	5	8	2	4	3	1	5
OTD	6	4	1/3	2	2	1/5	1

Figure 3-2: Pairwise comparison matrix compiled using the inputs from Figure 3-1 [9]

3.3.2 Consistency Check

The subjective nature of the decision maker's criteria ratings necessitates a review of their inputs to ensure major errors will not be propagated further into calculations. To accomplish this, a consistency check can be performed as follows. Given a pairwise comparison matrix, its maximum eigenvalue, λ_{max}, is equal to n (for an $n \times n$ matrix) if and only if the matrix is consistent. The value of λ_{max} is greater than n if the matrix is inconsistent [13]. Saaty [15] proposed a consistency index $CI(X)$ as:

$$CI(X) = \frac{\lambda_{max} - n}{n - 1} \tag{3.2}$$

However, experimental results showed that the expected value of CI for a random matrix of size $n+1$ is on average greater than the expected value of CI for a random matrix of size n. Therefore, CI needs to be scaled in order to normalize the consistency check across different sized matrices. [13]. To do so we introduce RI_n, a real number that estimates the average CI obtained from a large data set of randomly generated matrices of size n. Given a pairwise comparison matrix of size n, the Consistency Ration (CR) can now be calculated as:

$$CR(X) = \frac{CI(X)}{RI_n} \tag{3.3}$$

Figure 3-3 includes random indices for matrices up to size 7×7. These were calculated by Saaty, who also suggests that a $CR \leq 0.1$ is acceptable, and a $CR > 0.1$ is inconsistent and will not produce reliable results. The random indices in Figure 3-3 as well at the 10% cutoff for CR will be used for calculations in Chapter 4.

n	RI
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32

Figure 3-3: Random indices used for this example as well as the case study in Chapter 4 [15].

Any number of open source solvers can be used to calculate λ_{max}. Using *SciPy* in *Python* and a random index of 1.24, the CR for the decision maker's inputs in the example in Figure 3-1 is 0.049 which is within acceptable limits.

3.4 Priority Vectors

This section will outline how to calculate the relative importance of each criteria as well as how to compare each part using the eigenvector method. It will expand on concepts covered in Section 2.3.

3.4.1 Compile Pairwise Comparison Matrices

Pairwise comparison matrices need to be compiled for each criterion. The resultant matrices will be similar to Figure 3-2 but the size of the matrix will be the # of parts $\times$ # of parts. In the example above, if 25 parts were being considered, there would be 6 individual 25×25 matrices, one for each criterion which compares each part's specific criteria score against that of the other parts. These matrices can be compiled algorithmically, as the inputs are all discrete data points. A category like 'material spec' may need to have scores assigned to each listed material specification in order to facilitate this process. A consistency check is not required for these matrices because they are being generated numerically and will inherently be consistent.

3.4.2 Calculate the Priority Vectors

There is now a pairwise comparison matrix for the criteria weights [1] as well as pairwise comparison matrices comparing each part to the other parts for each criterion. A priority vector will now need to be calculated for each matrix. The eigenvector method will be used, as it is the most appropriate for data sets of this type, as well as the most widely used method. According to this method, a priority vector (also known as the Perrono-Frobenius eigenvector) is the principal eigenvector of X, the pairwise comparison matrix. Given a matrix X whose elements are obtained as ratios between weights, we multiply it by w [13].

$$Xw = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \vdots & \cdots & \cdots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} nw_1 \\ nw_2 \\ \vdots \\ nw_n \end{bmatrix} = nw$$

Figure 3-4: Matrix X of size $n \times n$ multiplied by the principal eigenvector w [13].

This formulation now implies that n is an eigenvalue and w is an eigenvector of X. n is taken as the largest eigenvalue of X. The eigenvector w can be calculated from matrix X by solving the equation system in Figure 3-5.

[1]Note: 'weight' in this section refers to the relative significance of a given input to another, and is not related the mass of the part.

$$\begin{cases} Xw = \lambda_{max} \\ w^T \left[1, 1, \cdots, 1\right]^T = 1 \end{cases}$$

Figure 3-5: Equation system used to obtain the eigenvector w [13].

There are a number of software packages that can be used to calculate these vectors.

3.5 Combine Results and Quantify Error

The section above provided local priority vectors for each criterion which are comprised of each part's score in that criteria. These vectors need to be combined and weighted using the criteria priority vector which was a result of the decision maker's priorities. This final vector is the global priority vector v.

To transform the local priority vectors into a global ranking we first consider $S = [s_1\ s_2\ \cdots\ s_n]$ where the j^{th} column of S is vector s_j = the local priority vector for criteria j. Vector s_j is essentially the vector containing the normalized score for each part in that particular criteria. The global priority vector, v, is the final score for each part. It is defined as $v = Sw$ where w is the criteria priority vector. To transform the vector to a ranking, the vector only needs to be sorted into descending order.

Section 3.3.2 discussed acceptable limits for consistency on the part of the decision maker while providing their criteria ratings. Even if the CR is within acceptable limits, if the CR is above 0, there is a margin of error that needs to be captured. Tomashevskii proposed the following method to capture the error for a given weight [18]:

$$\Delta\omega_i = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(\frac{n}{\lambda_{max}}a_{ik}\omega_k - \omega_i\right)^2}\ ,\ i = 1, ..., n \tag{3.4}$$

If we normalize by the weight we have:

$$\frac{\Delta\omega_i}{\omega_i} = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(\frac{n}{\lambda_{max}}a_{ik}\frac{\omega_k}{\omega_i}-1\right)^2}\ ,\ i = 1, ..., n \tag{3.5}$$

Applying the equations to the example from Figure 3-1 produces the following results.

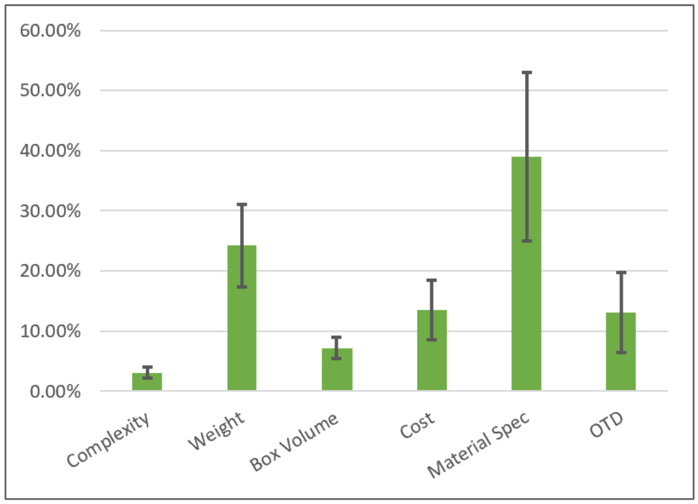

Figure 3-6: Resultant priority vector and error derived from the inputs in Figure 3-1 [9]

This priority vector can now be combined with the local ratings to form a global ranking of the alternatives, or parts in this example. There is a subjective nature to this process due to the inputs from the decision maker. However, it can still be an efficient way to extend the expertise of the decision maker to a wide range of parts that they would have otherwise been unable to assess by personally analyzing each part. It is important to make efforts to codify error and test the ranking for robustness to ensure useable results are being produced. This Chapter discussed error and Chapter 4 will examine how to test for robustness in the field study.

Chapter 4

Field Study

The methodology in Chapter 3 was applied to a field study at Pratt & Whitney. The study included a catalog of 25,000 parts from multiple jet engines. Specific details related to technical data, part specifications or information systems has been removed in order to protect intellectual property. However, the results related to the application of the AHP for this study are captured in this chapter.

4.1 Criteria Priority Vector

The criteria priority vector was calculated using inputs from two separate AM experts who rated four separate criteria, Criteria A-D. The two decision makers provided their criteria rantings independent of one another. As such, their level of consensus was measured to ensure the results were not skewing to a mean that perhaps neither would have preferred. The experts had a 94.4% consensus on a 0 to 1 scale, where 0 is no consensus and 1 is full consensus. The consensus indicator, S^* was calculated using a process proposed by Goepel [9] which relies on Shannon entropy such that

$$S^* = \frac{\dfrac{M - \exp(H_{\alpha\ min})}{\exp(H_{\gamma\ max})}}{\dfrac{1 - \exp(H_{\alpha\ min})}{\exp(H_{\gamma\ max})}} \tag{4.1}$$

With: $H_{\alpha,\beta,\gamma}$ = the Shannon entropy for the ratings of all K decision makers and N criteria:

$$H_\alpha = \frac{1}{K} \sum_{j=1}^{K} \sum_{i=1}^{K} -p_{ij} \ln p_{ij} \tag{4.2}$$

$$H_\gamma = \sum_{j=1}^{K} \bar{p}_j \ln \bar{p}_j \tag{4.3}$$

$$H_\beta = H_\gamma - H_\alpha \tag{4.4}$$

$$\bar{p}_j = \frac{1}{N} \sum_{j=1}^{K} p_{ij} \tag{4.5}$$

$$M = \frac{1}{\exp(H_\beta)} \tag{4.6}$$

Goepel considers $S^* \geq 85\%$ as very high consensus, meaning there was significant agreement between the two experts surveyed in this study.

In order to aggregate the decision maker's inputs, the geometric mean [9] c_{ij} was calculated:

$$c_{ij} = \frac{\sum_{k=1}^{N} w_k \ln a_{ij(k)}}{\sum_{k=1}^{N} w_k} \tag{4.7}$$

The resultant pairwise comparison matrix which includes the combined values is shown in Figure 4-1. The matrix in Figure 4-1 has a 3.7% consistency ratio, which meets the acceptable threshold of 10%, discussed in Section 3.3.2.

		Criteria A 1	Criteria B 2	Criteria C 3	Criteria D 4
Criteria A	1	1	1/6	6/7	1/5
Criteria B	2	6	1	4 1/2	2 4/9
Criteria C	3	1 1/6	2/9	1	1/5
Criteria D	4	5 1/2	2/5	4 3/4	1

Figure 4-1: Field study criteria pairwise comparison matrix derived from surveys provided by two Pratt & Whitney AM experts

Figure 4-2 is the priority vector calculated using the eigenvector method. It shows two dominant priorities and two which are less critical. The impact of the criteria priority will be discussed more deeply in the following section.

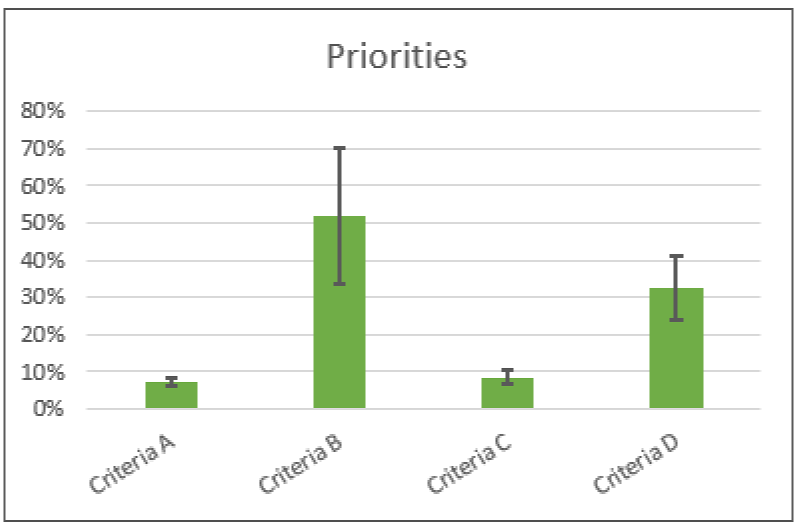

Figure 4-2: Field study criteria priorities derived from surveys provided by two Pratt & Whitney AM experts

4.2 Results

The initial 25,000 parts were filtered to remove parts that could not be printed due to technical limitations as well as parts that were missing data. Material specification was the most significant of the filters applied. The next most significant driver of removing parts from the ranking was missing data. Filters for part size and type (i.e. nuts, bolts and washers) were also applied, but only removed a small percentage of parts from consideration .

The parts with missing data were assessed to ensure there were no systemic issues related to part type (i.e. 'bracket', 'vane' etc.) or material specification. There were no systemic issues identified, implying the missing data may have been an artifact of the techniques used to aggregate the data from Pratt & Whitney systems. Subsequently, 523 parts remained and were then ranked using the criteria weights derived in Section 4.1. Of the 523 parts that were ultimately ranked, there were 447 unique results, with many of the duplicates being the same part but from different engines. The specific part rankings cannot be discussed here due to proprietary concerns but further examination of their validity was performed.

4.2.1 Validation

In order to validate the part ranking results a process similar to that of Knofius [11] was followed. Six parts were randomly selected from the ranked list: two from the top third, two from the middle third, and two from the bottom third. An AM expert was presented with a survey of the six parts (without their AHP ranking included) and asked to rate each part on a 1-3 scale based on how interesting the part is from an AM perspective: 1-most interesting, 2-possibly interesting, 3-least interesting. Figure 4-3 shows a comparison between where the AHP output ranked the part and how the expert rated the part.

Figure 4-3 shows 50% of the parts rated by the expert matched the AHP rank. The remaining parts were one rating point off, with the tendency for the expert to rate them more highly than the AHP ranking. The expert's ratings likely differ from the AHP results due to additional information available to the expert that was not included in the ranking due to database limitations. Furthermore, the tendency to rate higher than the output may be affected by all of the parts meeting feasibility requirements for printing, whereas most parts from a jet engine do not meet those requirements.

Part No.	AHP Rank Position	Expert Rating
I	1st Third	1 - Most Interesting
II	1st Third	2 - Possibly interesting
III	2nd Third	1 - Most Interesting
IV	2nd Third	2 - Possibly interesting
V	Last Third	2 - Possibly interesting
IV	Last Third	3 - Least Interesting

Figure 4-3: Comparison of expert rating for parts ranked using the AHP during the field study

4.3 Sensitivity Analysis

The subjective nature of the decision maker ratings necessitates a sensitivity analysis to test if small changes or inaccuracies by the decision maker will have substantial impacts on the overall rankings. These potential inaccuracies are less significant if the rankings are generally unchanged in relation to small changes in the criteria priority vector. To test this, the ranking was recomputed while changing the criteria priority vector and then compared to the original ranking using Spearman's Rho, which is a measure of correlation. Equation 4.8 shows how Spearman's Rho is calculated, with D_i equal to the difference between a ranked pair, and n equal to the number of ranked pairs.

$$\rho = 1 - \frac{6 \sum {D_i}^2}{n(n^2 - 1)} \tag{4.8}$$

Figure 4-4 shows a sensitivity analysis of the four criteria. Criteria B and D were varied by ±10%, whereas criteria A and C were varied by -5%, +15% due to their starting point near 5%. The dotted black line denotes the original weight in the priority vector for the given criteria. There, each curve intersects a Spearman's Rho of 1 as a matter of course, because Spearman's Rho is equal to 1 for perfect correlation. It should be noted that weights cannot be altered in isolation of one another, given the weights in the priority vector must add up to 1. Therefore, the original weights of the criteria were scaled to account for the changes in each individual weight when calculating a new ranking. For example, when criterion A was increased by 10%, criteria B-D were decreased by $3\frac{1}{3}$% to accommodate the change. It is a matter of subjectivity to qualify in words how correlated two variables are when using Spearman's Rho, but values over 0.75 often indicate 'high correlation' [4]. Figure 4-4 shows that even when varying a particular criterion by 15%, Spearman's Rho is still well over 0.90, indicating that there are not significant changes in the output rank and the ranking is robust to perturbations in the priority vector.

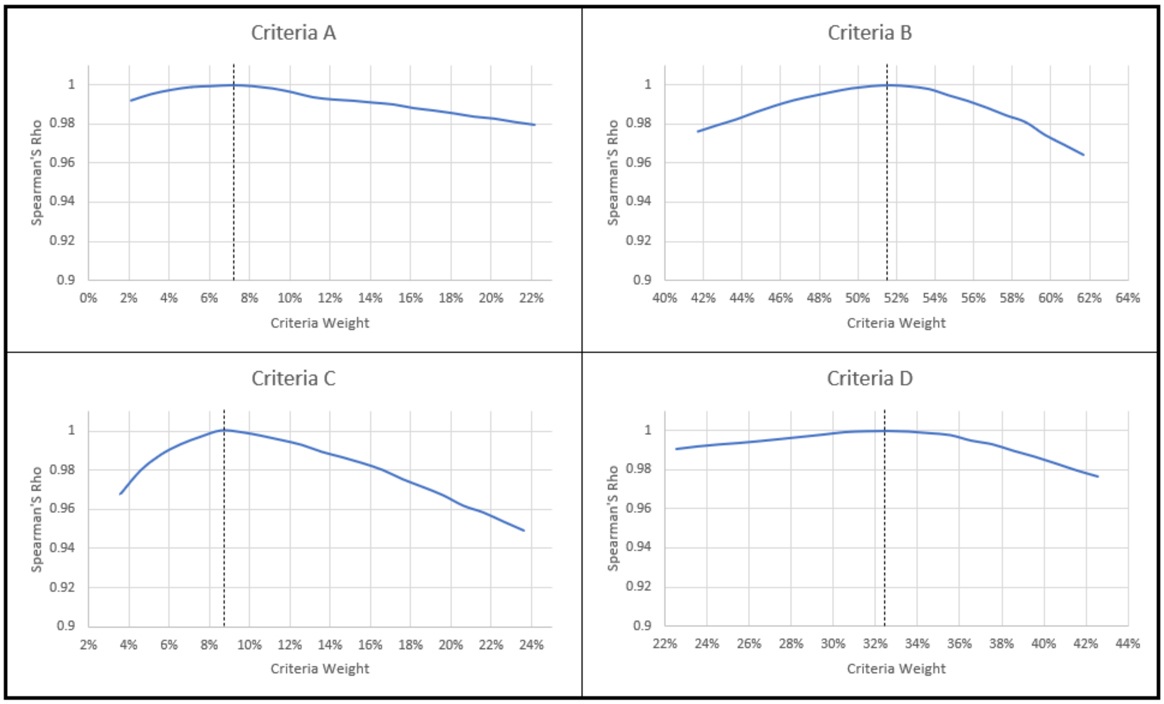

Figure 4-4: Comparison of variable weight to Spearman's Rho. The dotted black line denotes the value used in the field study.

4.4 Field Study Conclusions

This field study provided the opportunity to test the theories presented in Chapter 3. The part ranking produced using the AHP provided generally unique and robust results. However, while section 4.2.1 showed that the results were relevant, it also highlighted some limitations in using restrictive databases to assess these parts. In particular, AM build and cost concerns could not be directly measured because they are not included in the data that is necessary for building and pricing parts using traditional manufacturing processes. Therefore, these results will likely be most useful when combined with additional expert review to capture these missing dimensions, which will be discussed in detail in Chapter 5.

Chapter 5

Expert Analysis Process

Pratt & Whitney has been evaluating parts for AM using close expert review. Their previous part reviews were all encompassing because they had not fully utilized automated techniques to filter and identify parts based on data that is available. Therefore, the methodology described here will be more limited than a pure bottom up part selection process because some of the assessment (i.e. the criteria that data was available for) has already been accomplished. This phase of the part selection process will therefore focus specifically on attributes that are historically difficult to capture using aggregated data from traditional manufacturing processes.

5.1 Methodology and Framework

The expert review can generally be conducted in one of three ways. The first is a working group style, where all experts meet to assess parts together, providing input and reaching a conclusion in one event. The second is a dis-aggregated style, where each expert provides their input to a shared work space that contains part score/assessment sheets for each part. Parts can then be selected for production by a decision maker based on the experts' inputs. Lastly, a combined approach can be taken. In a combined approach various experts can provide their respective input into part score/assessment sheets, then the assessments can be reviewed by a decision board to select the best parts with relevant experts available to provide additional context as needed.

The biggest limitation of the expert review process is the time it takes to accomplish. Therefore, the combined approach is recommended for most organizations. This allows experts to provide the bulk of their input without requiring synchronization with others, but provides a discrete time where questions can be answered and a decision can be made supported by the best available data. The content of the review should be heavily influenced by the gaps in the data used during the AHP portion of the selection process. This specific content of the review will then be highly dependent on the organization and their maturity in AM.

The review criterion proposed in this section encompass criteria that would typically be hard to include in the AHP process, however this list is not all encompassing. The criteria are broken down into three areas, each of which may be able to be assessed by one expert. The areas are engineering requirements, AM requirements, and business considerations.

Each criterion can have a score associated with it. For example, in the comparative lead time criteria described below, an improvement of six months may warrant a score of 5, whereas an improvement of a week may warrant a score of 1. The details of an organization's score card will be highly dependent on the organization and its priorities. Therefore, recommendations in this chapter will be limited to the criteria and methods to aggregate the results.

5.1.1 Engineering Requirements

Engineering requirements considered in this section should be important requirements that were not captured in the AHP assessment. This portion of the review does not need to be performed by engineers with extensive experience in AM as long as they are equipped with the limitations and requirements from an AM expert. Specific requirements that may be reviewed in this section are flow and structural. Flow requirements are a very important factor for aerospace OEMs as discussed in Chapter 3. Structural limits are another important factor that require assessment again because of the high-performance needs in the industry.

It is beneficial for engineering requirements to be reviewed early in the expert review process. There are some unambiguous requirements that will disqualify a part. It is important to identify these as early as possible, because the AM requirements and business considerations may be relatively labor intensive, so pruning parts early can be an effective way to control overall costs.

5.1.2 AM Requirements

Review of AM factors will require an AM expert and may include a significant time investment. These factors can be the most difficult to capture elsewhere and therefore require close inspection by an expert. Major considerations are:

- Build Orientation: Chapter 2 discussed the different limitations on accuracy depending on the axis in the AM build machine. This means careful inspection of part specifications will need to be conducted to ensure requirements can be met. CAD software may be applied to parts to determine if an acceptable orientation can be found. Ultimately, orientation limitations should be considered as early as possible in the AM assessment, because they may lead to elimination of the part as a candidate for AM

- Supports Required: It is likely that some support structure will be required when building a part using metals AM. An expert may be able to quantify, through modeling if necessary, how many supports will be required. This can be expressed in a number of ways, including the percentage of the final material requirements (material required for the part and the support structure) that is dedicated to support structure. Further, the support structure needs can be combined with flow and surface treatment requirements to begin to assess the feasibility of post processing requirements. If supports are needed on surfaces that will need to be treated to support high velocity flows, this may make their post processing more expensive, and possibly even cost prohibitive.

- AM Estimated Cost: Estimating the cost of producing a part additively is a difficult process with a number of variables. Organizations will use different models depending on their industry and size. The cost model for an OEM will likely be very different than that of a small-scale supplier. Therefore, it is incumbent on each organization to develop their own model, however the model's output will be very important in determining if there is a business case for AM. Important factors that go into cost estimation for AM are material development and cost, labor and machine rates, estimated build times and post processing needs. These factors have inputs from the criteria above, but additional analysis will be needed to complete a useful model for each part.

- Lead Time: Some organizations may extend their business case to include improvements to the supply chain. In order to assess this, an estimate will be required for lead time if the part is transitioned to AM. Some contributing factors for lead time will be internal build capacity and finish requirements. The organization will need to determine how much (if any) capacity is available internally to build the part, or if it will be outsourced to a supplier. Finish requirements may also play a big role in lead times as post processing surface treatments are complex, detailed and often proprietary, therefore outsourcing to suppliers is often necessary.

- Estimated Time to MRL 9/10: Manufacturing Readiness Level (MRL) levels are a system of criteria used to identify and manage manufacturing risk in acquisition and during new technology development as it transitions to weapon system applications [2]. They are defined by the U.S. Department of Defense and used by many organizations to develop a common assessment tool to identify the maturity of a manufacturing process. In MRL levels 9 and 10, the focus is on full rate production and aspects of lean production as well as continuous production. In these steps the manufacturing process is quite mature. Assessing how long it will take to get to MRL 9 or 10 may be quite difficult to determine accurately. Yet if an organization prioritizes the speed at which a part will get to full scale production via AM, an estimate may be necessary.

5.1.3 Business Considerations

The determination on whether or not a part is transitioned to AM often will be decided by the business case for the move. To assess this, there needs to be a comparison of current costs and timelines with those estimated if there is a transition to AM. Many of the AM cost estimates can be best made by AM experts, however they can then be compared to current state costs and lead-times by supply chain representatives. These criteria can be used by supply chain experts to ultimately assess the business case for transition to AM.

- Cost Differential: The current costs associated with the part can be compared to those estimated above to determine if there will be a cost advantage.
- Lead Time Differential: Similar to cost differential, the current lead time can be compared to the estimated lead time provided earlier to identify improvements. Improvements to lead time may motivate an organization to transition to AM even if there is not a noteworthy improvement to cost as improvements in the responsiveness of the supply chain can be realized monetarily outside of strict part costs.
- Cost Increases: Even if there is not an advantage between the current cost to produce a part and the cost estimate for additive, if costs have been increasing, it may intimate a future advantage. Typically manufacturing costs are expected to go down over time, but scarcity, volatility and regulation can cause them to go up. Therefore, exploring AM for a part may be beneficial.
- Vendor Issues: Large OEMs in aerospace are supplied by many vendors. There can be multiple vendors approved to supply a particular part or just one. A scarcity of suppliers gives the supplier leverage over the OEM in pricing that the OEM may want to mitigate by exploring additive options. Furthermore, having a single source supplier for a critical part exposed an OEM to significant risk in the event the supplier encounters technical or business issues that impact performance, again providing the supplier with leverage over the OEM.

5.2 Final Selection and Challenges

There are a number of techniques that can be applied to aggregate part scores and select the best parts once each expert has provided their input. Decision makers may simply choose to sum each part's expert scores and select the parts with the highest total, or they may want to reintroduce the AHP. In this process, a decision maker would be required to rate the criteria used for the review, then a criteria priority vector can be calculated and applied to the part scores, producing a ranking similar to that provided using the data in the initial top-down selection process.

An expert review is exposed to a number of limitations. To start, an expert review requires experts to be present in an organization and for them to have the bandwidth necessary to conduct the review. Smaller organizations may be hampered by the lack of experts. In the same way, experts at larger organizations, like major OEMs, may lack the the time required to conduct a thorough review due to other responsibilities.

The review process also introduces more subjective ratings into the process beyond the criteria ratings used for the criteria priority vector in the AHP process. Yet, given data limitations, the review process is ultimately necessary in order to capture characteristics that were not previously included and make a final decision on a part.

Chapter 6

Conclusion

This thesis aimed to provide a comprehensive methodology for part selection in AM for organizations that are relying on imperfect or limited data sets. The application of the AHP to Pratt & Whitney's part catalog enables them to expand their part selection process from a focused review of limited parts, to one that can consider large portions of their part catalog. Combining the AHP results with an expert review process allows close inspection of the parts that are best suited for additive production while reducing expert time spent on less desirable parts.

The sensitivity analysis conducted as part of the field study in Chapter 4 showed that the part ranking results were generally robust to fluctuations in the priority vector which was calculated based on survey data from AM experts. However, the field study also demonstrated that the ranking results were effective but not perfect. Data limitations likely played a role in this, but the error introduced by the rating system may also have had an impact. Ultimately, using the AHP for part selection seems to be an effective first step for organizations seeking to expand their part selection methodology to approaches beyond close inspection of individual parts.

6.1 Future Research Opportunities

Future research in this area could seek to reduce subjective human input as well as expand part selection from replication to adaption and optimization for AM. The first steps in reducing human input could be including more robust data sets into the AHP selection process in order to reduce the workload during the expert review. Organizations may be able to leverage other predictive statistical methods for top down part selection like regression or machine learning as AM becomes more prevalent in aerospace and regulatory agencies approve more parts for manned flight. While Section 4.3 demonstrated that the methods used in this thesis were relatively robust to changes in the priority vector, there is certainly still room for improvement as curated data sets become available that can be used to predict success without expert input.

Adaption and optimization for AM are considered to provide the best technical and business case for AM. Therefore, future research should look to include those phases in part selection methodologies. This may be difficult given regulatory concerns in aerospace and the technical difficulty of identifying parts and subsystems that are suitable for adaption through automated processes. The technical challenge is likely why Lindemann's [12] methodology, which focuses on part adaption and optimization, is highly dependent on close inspection by experts.

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