SYM-AM-23-069

Excerpt from the Proceedings
of the
Twentieth Annual Acquisition Research Symposium

Acquisition Research: Creating Synergy for Informed Change

May 10–11, 2023

Published: April 30, 2023

Approved for public release; distribution is unlimited.

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

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The research presented in this report was supported by the Acquisition Research Program at the Naval Postgraduate School.

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Decision Making for Additive Manufacturing in Sustainable Defense Acquisition

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Abstract

The research team developed a model-based acquisition decision support tool (i.e., the decision engine) for additive manufacturing materials and technologies selection. In order to

develop the framework, the team focused on a use case involving aircraft single-component (i.e., an aileron bellcrank) design and manufacturing. In the use case, the team identified the key decision factors in considering additive manufacturing alternatives against traditional manufacturing methods. Preliminary findings indicate that the decision engine provides the users with an algorithmic view of the variables to make an optimized decision regarding where and how additive manufacturing can have the most impact. To this end, the team designed the user interface in such a way that the decision engine visualizes the relative performance of each alternative considered, thereby assisting a stakeholder in the decision-making process. More specifically, the decision engine provides quantitative information about the usefulness of each alternative relative to others. As a result, the decision engine supports stakeholders in making informed decisions on additive manufacturing opportunities throughout the mission engineering and sustainment defense acquisition.

Introduction

Additive manufacturing provides an alternative approach to manufacturing products across the supply chain. Some of the benefits of using additive manufacturing are inventory reduction in the supply chain, increase in supply chain resilience through alternate options, quicker response to surge demands and warfighter readiness, and manufacturing products with complex design while actively reducing the number of serviceable components. From a sustainable acquisition standpoint, the team needed to figure out how to quantitatively approach the decision-making process of additive manufacturing for defense-related acquisition. That is, it is crucial to develop a model-based decision-support tool for the defense-related acquisition of additive manufacturing components and equipment.

As the team initiated the research effort of producing the decision framework, some of the questions we asked ourselves were as follows: Can the whole supply chain and sustainment strategy change, given the use of additive manufacturing instead of traditional manufacturing? In what timeframe? What are the limits (e.g., materials science, systems engineering, cost, reliability, infrastructure)? Obviously, these are open-ended and difficult questions to answer. To address these questions adequately while also ensuring component readiness through additive manufacturing in mission engineering, the team realized the importance of having a sufficiently narrowed-down digital environment with the capabilities we need. Thus, to narrow the scope of the research, the team focused on the digital data and framework surrounding the opportunity to exploit additive manufacturing as follows:

- Identification of necessary data in digital system models to understand how additive manufacturing could support system readiness and sustainment;
- Isolation of the most critical system elements from the perspective of sustainment; identification of the variables that are key to understanding criticality from this point of view;
- Development of a framework that would allow the focused allocation of additive manufacturing to impact system readiness and sustainment; and
- Development of a framework of items and contractual elements that would be critical for the DoD to negotiate during the contract phase (e.g., any intellectual property rights or options needed to support an additive manufacturing strategy for certain types of supplies and equipment).

Accordingly, we explored additive manufacturing as a systems engineering problem as follows: First, we identified the critical decision and analysis variables and created a framework to understand how these variables impact each other. Second, we transferred the above framework into an algorithmic view of these variables to make an optimized decision regarding where and how additive manufacturing can have the most impact. Third, we developed an interactive decision support tool (i.e., the decision engine in additive manufacturing) and tested its use in a user case. As a result, this research paper starts with the conceptual background of decision engine development. Then, the discussions transition to a use case, “Aircraft Single Component Design,” to demonstrate the decision engine’s effectiveness.

Decision Support Tool for Additive Manufacturing: Overall Scenario

Additive Manufacturing (AM) is playing an increasingly important role in DoD acquisition and sustainment. Decisions about additive manufacturing technology are made within various agencies ranging from the USD(A&S) to individual military departments. Decision makers range from high-level decision makers interested in overall mission effectiveness to field engineers who are responsible for operating specific equipment. There is a wide range of decisions related to additive manufacturing, such as decisions about whether to use additive manufacturing or traditional manufacturing, supplier selection, a decision on contract type; AM technology selection, machine and material selection, and process parameter selection (e.g., layer thickness, speed, part orientation).

Furthermore, the decision-making criteria vary widely from high-level attributes such as resilience and mission effectiveness to technical attributes such as part accuracy and structural performance. Other decision factors may include material availability, machine availability, machine maintainability, competition, technology capability, technology maturity, cost, number of parts, intellectual property ownership, and supply chain resilience.

While there are several initiatives to support specific types of decisions within the AM domain, there is a lack of a decision support tool that can be adopted or customized to support different decision makers for a range of AM-related decisions. Thus, in this task, the team addresses this limitation by developing the decision engine and demonstrating it using use cases that are relevant to mission engineering. The activities carried out in this project are illustrated in Figure 1. Please note that this research paper focuses on the decision support tool (decision engine) development, followed by the demonstration of the decision engine using “Aircraft Single Component Design,” which is shown in Figure 1 as the “AM Use Case 2.” For the “AM Use Case 1,” please see a separate paper (Q. Shi et al., 2022).

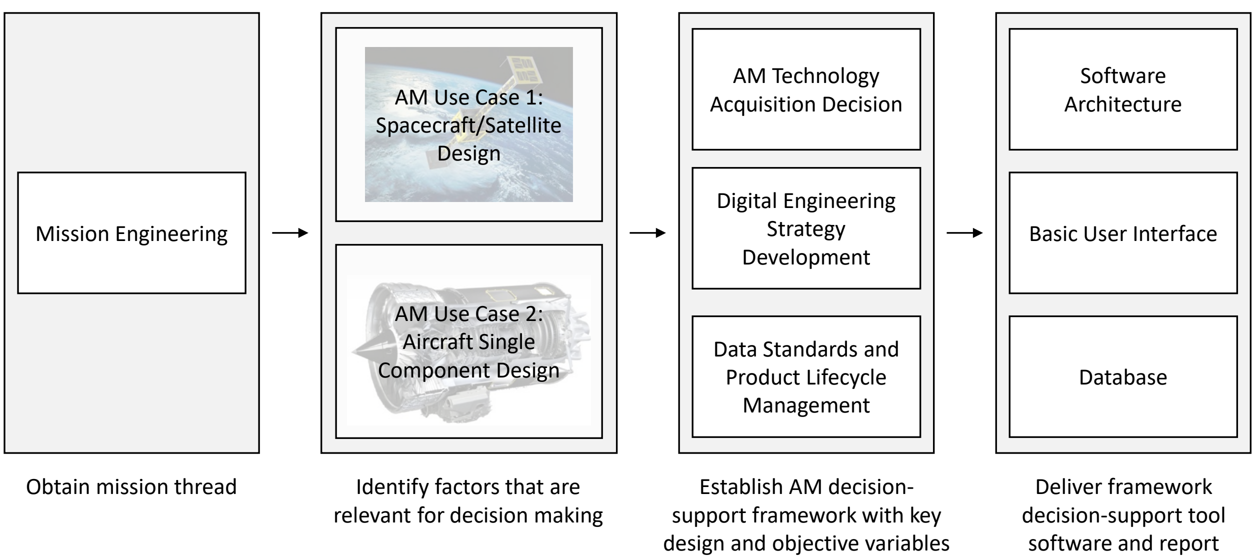

Figure 1. Overall Development Process

Visualization of Decision Engine

Each decision to be made by a decision maker can be split into two types of components: the objectives of the decision maker (e.g., what their goals are, what they want to improve, minimize, and prevent from happening) and the alternatives (the different options the decision maker can choose from). Each alternative is composed of the relevant attributes to the decision problem, examples of which can be seen in the use cases. The final output from the decision engine is a bar chart displaying the expected utility values of each alternative considered and is intended to assist the decision maker by providing them with quantitative information about the usefulness of each alternative relative to others.

For this project, we make several assumptions that impact the implementation of the decision engine. One assumption is that each decision has a finite number of alternatives. This assumption implies that the decision engine tool would not be suitable for choosing the optimal parameters in a continuous design space. However, if the options could be constrained to a finite subset of parameters, then this tool could be used. Another assumption is that the attributes of any alternative are utility-independent. If two attributes were not utility independent, then as the value of one attribute changes, the utility that the decision maker gets from another attribute will change. The assumption of utility independence is standard in the literature (Fernández et al., 2005) and greatly reduces the complexity of implementation and makes the process of using the engine significantly easier for an end-user.

The process of using the decision engine is described in the context of decisions being made in a hierarchy, with one individual making the final decision and an individual or team of technical engineers who determine the information relevant to the decision context. The general steps for the decision-making process are outlined in Fernández et al. (2005). In the context of a hierarchy, we assume that the decision makers and technical engineers are distinct groups, but they could, in practice, be the same. The decision maker should set out the specifics of the decision, answering questions such as:

- What exactly is the decision being made?
- What are the specific objectives or goals that want to be achieved from this decision?
- What kind of attributes will be important when comparing multiple alternatives?

Once the decision context has been clearly established by the decision maker, the technical engineers may begin translating this information into data usable by the engine. The information about the decision scenario is fed into the decision engine via .json files, which are a type of structured data file that is human-readable. There are two categories of files used by the decision engine: the decision objective file and the alternative information files.

Decision Objective File

The first type of file is the decision objective file, and there is typically only one of these in each decision-making context. The decision objective file contains information specific to the decision context and the decision maker. In this file, each attribute being considered by the final decision maker has some general information listed, such as its name, description, and units of measurement, as well as information relating to the utility function of the decision maker. This information describes the general shape of the utility function, such as the risk attitude of the decision maker and whether it is monotonically increasing, decreasing, or neither. Lastly, specific numerical data about each utility function is provided. Each utility function takes the form of the equation $u_i(x) = a + bx + ce^{dx}$, where i is the index of the attribute being considered, x is the attribute's value, $u_i(x)$ is the utility of attribute i with value x, and a, b, c, and d are the specific parameters of the utility function. The decision objective file contains these parameters a, b, c, and d. The information about the decision context must be collected from the final decision maker or someone else with a clear understanding of the goal of the decision.

Alternative Information Files

The other files used by the decision engine contain information about the alternatives being considered. Each file contains information about the attributes relevant to the specific decision being made. For the alternative attribute information, the data can either be collected manually by technical engineers or automatically if there is access to a relevant database. Currently, each attribute is given either as a constant value or as a uniform distribution if there is uncertainty about the attribute's value. We plan to implement additional distributions in the future to enable a more accurate representation of the uncertainty in various attributes. Figure 2 shows the way information flows into the two types of files and then into the decision engine. Figure 3 depicts the main screen of the decision engine's user interface, which allows the selection of use cases for analysis. These use cases come from folders containing JSON data files, so these can be added to, removed from, or updated as needed. After the user selects a use case on the main screen (Figure 3), another user interface appears. The use case specific user interface is shown in the Use Case section below.

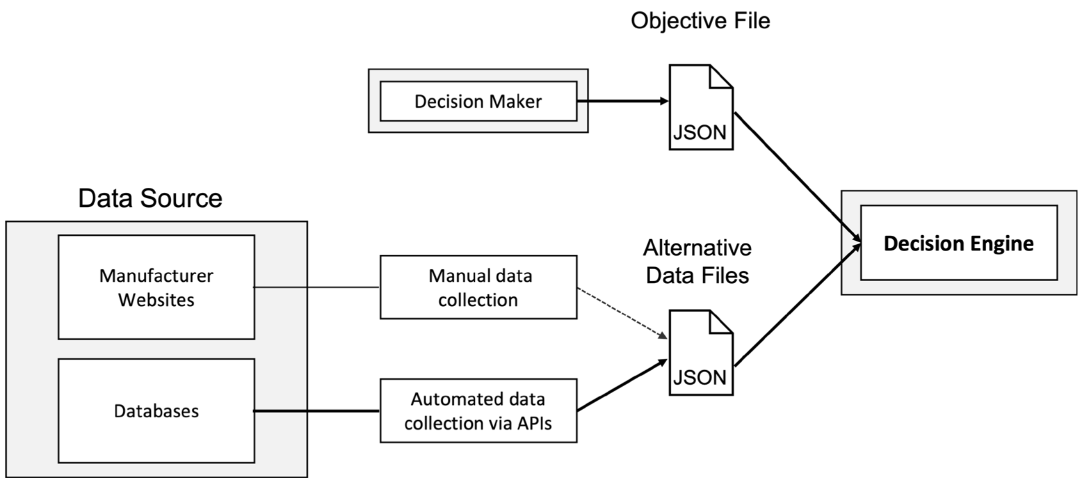

Figure 2. Decision Engine Information Flow

Figure 3. Main Screen for "Decision Engine for Additive Manufacturing"

Use Case: Aircraft Single Component Design

Background/Overview

The research team was approached by a large aerospace original equipment manufacturer (OEM) looking to leverage additive manufacturing (AM) to replace damaged, out-of-production parts for fleet sustainment. Specifically, this OEM is looking for a means to produce 100 replacement aileron bellcranks on a legacy aircraft. Traditionally made through metal casting, the original part supplier has discontinued production. Because the continuous operation of the fleet is critical, the company is eager to find a new means of sourcing the part quickly. In this transition period, the company is interested in assessing the utility of the traditional manufacturing metal casting approach against those of metal additive manufacturing methods, as additive manufacturing typically has lower lead times and supply chain costs (Gradl et al., 2022). The goal of this use case study is to apply the decision engine to compare the utility of several manufacturing approaches for low-volume production of a custom aircraft part for fleet sustainment. The information of this use case was adapted from past collaborative work with the OEM, and thus the simulated decisions represent an example of a real issue modern companies may face with respect to the desire to cut rising costs and/or sourcing parts that have become obsolete on the market.

Problem Statement

The original design of the bellcrank is shown on the left side of Figure 4. The dimensions of the bellcrank used in this case study have been augmented from the actual part so as to protect the OEM’s intellectual property. The decision engine is used to evaluate the utility of producing these parts using *traditional metal casting* and several different additive manufacturing solutions, including:

Hybrid wire arc additive manufacturing (hWAAM): In this hybrid process, a wire arc welding head selectively deposits metal in a layer-wise fashion. A CNC milling spindle selectively removes material at each layer to refine the part quality and surface finish. Following fabrication, the fully dense metal part needs moderate heat treatment prior to use.

Metal binder jetting (mBJT): In this process, the binder is selectively ink-jetted into a metal powder bed to fabricate a green part. Following printing, post-processing steps include binder curing, part de-powdering, binder pyrolysis, and metal sintering.

Sand Binder Jetting (sBJT): In this process, binder jetting is used to 3D print molds from foundry sand. Following printing, the printed molds are de-powdered and assembled for traditional metal casting processing.

Metal laser powder bed fusion (L-PBF): In this process, a laser selectively melts the metal powder in a layer-wise fashion. The printed part is fully dense and can be inserted into the application following post-processing steps, including de-powdering, heat treatment, support removal, and surface finishing.

This case study is separated into two decision scenarios as follows:

Scenario 1: Part Replication

In the first scenario, the company is comparing the utility of different manufacturing techniques to produce 100 replicates of the bellcrank geometry using 6061 Aluminum. In this decision, the company is only evaluating alternative manufacturing processes to replicate the same geometry and material as in the original design shown on the left side of Figure 4.

Scenario 2: Topology Optimized Redesign vs. Original Design

In the second scenario, the company is evaluating the utility of different manufacturing techniques to produce 100 redesigned bellcranks, which have been optimized for lightweighting. Specifically, topology optimization software (Autodesk Fusion 360, n.d.) has been employed in which part mass is generatively removed from the original design as guided by an iterative evaluation of the stresses within the part (Shanmugasundar et al., 2021). The optimization algorithm sought to minimize part mass while still retaining sufficient part stiffness to meet the load specifications. The resulting topology optimized geometry is shown on the right side of Figure 4. In this scenario, the effects of a change in part geometry enabled by additive manufacturing are explored while the material (Aluminum 6061) is held constant.

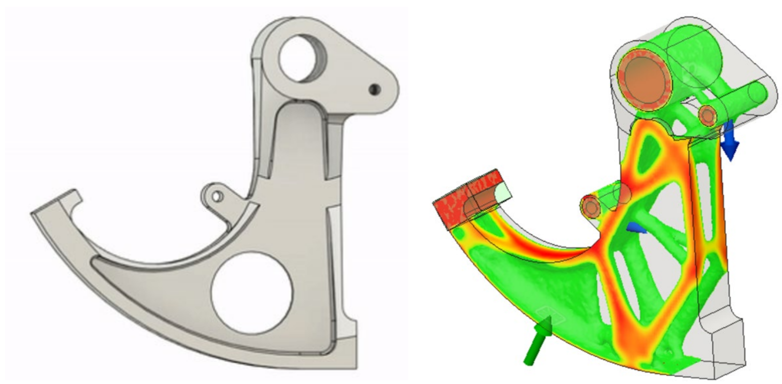

Figure 4. Aileron bellcrank

(Left) CAD model of the original aileron bellcrank. The bellcrank is traditionally manufactured through the traditional metal casting of 6061 Aluminum.

(Right) Topology optimization was used to redesign the aileron bellcrank for mass minimization. Colored regions indicate where material should be placed within the volume. Red regions represent regions of high stress; green regions represent areas of low stress. The material used in the optimization is the same as that in the original design, 6061 Aluminum. The grey bounding box around the optimized geometry is included to illustrate the mass savings enabled by topology optimization.

Attributes

In decreasing order of importance, the customer is concerned with the minimization of cost, time, and part mass. These customer concerns form the attributes of the decision. In addition to these customer concerns, part bounding box size was added as an attribute to ensure that the part could fit within the allowable build volume of each additive manufacturing process. Thus, the attributes of the decision are part bounding box size, total cost, total time, and part mass.

Utility Functions

Utility functions generated for each attribute are shown in Table 1. A minimum point, an intermediate point, and a maximum point were used to fit the functions. A utility function was not fitted for the part bounding box attribute. Instead, this function had the form of a binary "on/off" condition where, if the bounding box volume of the manufacturing process being considered is below the requirement, the utility of that process is zero regardless of the utility values.

For the *total cost*, a monotonically decreasing linear function was chosen because utility for the customer decreases proportionally as manufacturing cost increases. For both *total time* and *part mass*, a concave function was chosen because utility for the customer decreases more sharply as each of these attributes increases. The utility functions are summarized in Table 1. Figure 5, Figure 6, and Figure 7 show the points used to fit utility functions for cost, time, and mass, respectively. In these figures, please note that the data points were obtained from customer surveying.

Table 1. Utility Functions

Attribute	**Utility Function Type**	**Utility Function: $u(x) = a + bx + ce^{dx}$**			
		a	b	c	d
Part Bounding Box (mm x mm x mm)	On/Off	-	-	-	-
Total Cost ($)	Linear	1	-2e-6	0	0
Total Time (hours)	Exponential (Concave)	0	0	1.002	-0.00198
Mass (kg)	Exponential (Concave)	0	0	1.019	-0.41000

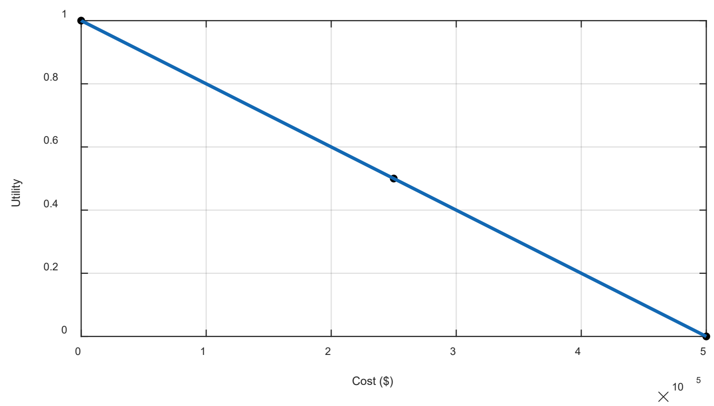

Figure 5. Fitted Utility as a Function of Cost

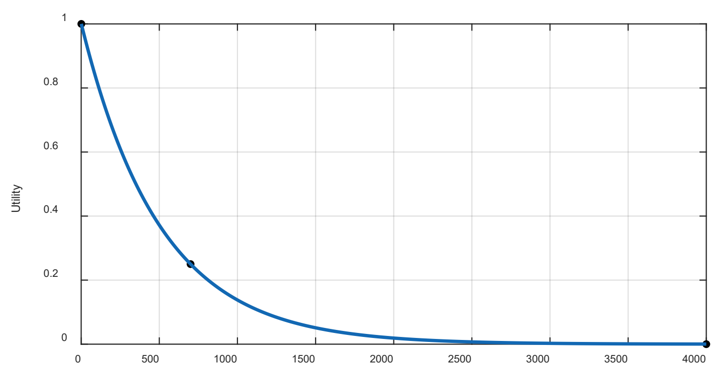

Figure 6. Fitted Utility as a Function of Time

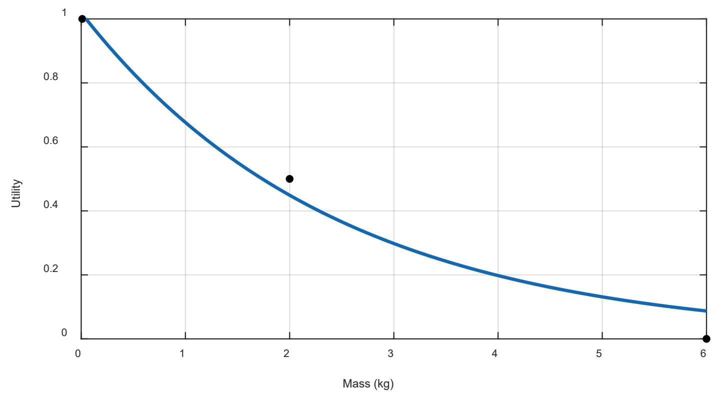

Figure 7. Fitted Utility as a Function of Mass

A weight was assigned to each attribute's utility function to represent the customer's preferences for the relative importance of each attribute. In Scenario 1, in which manufacturing processes are evaluated for their utility to replicate the original part geometry and material, the customer has a slightly stronger preference for reducing cost than time. On the other hand, in Scenario 2, in which the utility of replicating the original part geometry via metal casting is compared to the additive manufacturing processes' ability to fabricate the topology optimized part geometry (Figure 4, right), the customer has a near equal preference for minimizing cost, time, and part mass. These weighting values are shown in Table 2.

Table 2. Weights of Attributes Generated From Customer Requirements

Attribute	**Scenario 1: Weight**	**Scenario 2: Weight**
Total Cost	0.6	0.4
Total Time	0.4	0.3
Mass	-	0.3

Decision Engine Data Inputs

Part Bounding Box

The bounding box size of the part was obtained by measuring the length, width, and height of the part's computer-aided design (CAD) model. The bounding box of the bellcrank measures 350 mm x 350 mm x 87 mm; thus, the requirements for this attribute are these dimensions. The bounding box size is the same for both scenarios.

Total Cost

Cost estimates for traditional metal casting were obtained from a vendor's website (Liaoning Borui Machinery Co., n.d.). The estimated cost for manual green sand casting of a large complex shape is $2,500 per part. Cost estimates for the additive manufacturing processes were generated by a cost model from *Additive Manufacturing Technologies: Rapid Prototyping to Direct Digital Manufacturing* (Gibson et al., 2015) given by:

$$Cost = P + O + M + L$$

where

P is the prorated machine purchase cost;

O is the machine operation cost;

M is the material cost; and

L is the labor cost.

In order to calculate these four sub-costs, information on part geometry, material specification from suppliers, and machine process parameters are needed. At a high level, the model first uses part geometry information to calculate total scan length (the total linear distance traveled by the print head during fabrication), which is estimated from the part volume, the average cross-sectional area of each layer, and deposition diameter. The estimated scan length is then used in combination with known process parameters (i.e., scan speed, deposition head diameter, and layer height) to estimate the total part build time. Once the build time is obtained, estimates for the cost of machine purchase, operation, materials, and labor can be calculated. Process parameters were sampled from works in the literature for each manufacturing process. Process parameters for hWAAM were adapted from X. Shi et al. (2017). Process parameters for binder jetting were adapted from Bai et al. (2017). Process parameters for powder bed fusion were adapted from Uddin et al. (2018). Cost estimates were rounded to the nearest hundred dollars, and an error of ±10% in estimated cost is assumed in order to account for discrepancies.

Total Time

Times estimates for traditional metal casting were obtained from information published on the Impro website (Impro). Time estimates for the additive manufacturing processes were calculated using build time models from the *Additive Manufacturing Technologies: Rapid Prototyping to Direct Digital Manufacturing* textbook (Gibson et al., 2015). Build time is estimated from the total printing scan length and process parameters specific to each additive manufacturing process, such as layer height, hatch spacing, deposition head diameter, and scan speed. Values for hWAAM process parameters were adapted from X. Shi et al. (2017). Values for binder jetting process parameters were adapted from Bai et al. (2017). Values for powder bed fusion process parameters were adapted from Uddin et al. (2018).

In addition to machine build time, the time required for human hands-on labor, which includes printer facilitation and post-processing, is accounted for in each process. The estimated human time varies for each process and depends on the process and post-processing needs. The pertinent assumptions are listed in Table 3 and Table 4 for Scenario 1 and Scenario 2, respectively.

Part Mass

The part mass is obtained from the CAD model of the bellcrank. In Scenario 1, since the part design and material are unchanged from that of the original, the part mass produced by each process is the same as the original part, 4.02 kg.

In Scenario 2, the additive manufacturing processes' utility is re-evaluated for their ability to fabricate topology optimized design with reduced mass (Figure 4, right). According to Maurer (n.d.), topology optimization can be used to reduce the mass of components by up to one-third. Thus, the topology-optimized design has an estimated part mass of 2.68 kg. The more complex geometry generated from topology optimization is not manufacturable using traditional metal casting, and thus the part mass for the casting process is kept at 4.02 kg. An uncertainty of 1% in mass is assumed to account for discrepancies and tolerances in manufacturing.

Table 3. Data Inputs for Scenario 1

Attribute (units)	Require ment	AM: hWAAM DMS 2Cubed Al6061[1]	AM: Binder Jet ExOne X160Pro Al6061[2]	AM: Binder Jet ExOne X160Pro Sand+Al6061	AM: PBF DMP Factory 500-LaserForm Al6061[3,4]	TM: Casting Al6061
Part Bounding Box (mm x mm x mm)	87 x 350 x 350	610 x 610 x 610	800 x 500 x 400	800 x 500 x 400	500 x 500 x 500	-
Parts per batch (no.)	-	6	8	5	5	-
Part Mass (kg)	-	4.02	4.02	4.02	4.02	4.02
Total Cost ($)	$100,000	$34,600	$98,500	$58,900	$164,100	$250,000[5]
Prorated Machine Cost ($)	-	$1,000	$500	$800	$5,700	-
Operation Cost ($)	-	$11,800	$5,700	$9,100	$51,700	-
Materials Cost ($)	-	$9,800	$85,100[6]	$32,800	$90,500[6]	-
Labor Cost ($)	-	$11,900	$7,300	$16,200	$16,200	-
Total Time for 100 Parts (hours)	900	930	774	1,377	2,186	2,000[7]
Machine Time (hours)[8]	-	590	566	915	1,724	-
Human Time (hours)	-	340[9]	208[10]	462[11]	462[12]	-

(Uncertainty assumptions: ±10% for cost and time, ±1% for mass)

[1] 2Cubed printer information from Diversified Machine Systems (n.d.)

[2] X160Pro printer information from *ExOne X1 160PRO Review - Industrial Metal and Ceramic 3D Printer* (n.d.)

[3] Factory-500 printer information from GF Machining Solutions (n.d.)

[4] Data from Uddin et al. (2018)

[5] Sand mold cost estimate from Liaoning Borui Machinery Co. (n.d.)

[6] Data from MSE Supplies (n.d.)

[7] Data from Impro Precision (n.d.)

[8] Gibson (Gibson et al., 2015)

[9] Estimate roughly 10 hours of post-processing per batch of printed parts. Includes time for print set up, part removal, and finishing machining

[10] Estimate roughly 15 hours of post-processing per batch of printed parts. Includes time for print set up, de-powdering, and time to set up curing and sintering of parts

[11] Estimate roughly 22 hours of post-processing per batch of printed parts. Includes time for print set up, de-powdering, curing, and casting

[12] Estimate roughly 8 hours of post-processing per batch of printed parts. Includes time for print set up, part removal, and machining

Table 4. Data Inputs for Scenario 2

Attribute (units)	Requirement	AM: hWAAM DMS 2Cubed Al6061	AM: Binder Jet ExOne X160Pro Al6061	AM: Binder Jet ExOne X160Pro Sand+Al6061	AM: PBF DMP Factory 500-LaserForm Al6061	TM: Casting Al6061
Part Bounding Box (mm x mm x mm)	87 x 350 x 350	610 x 610 x 610	800 x 500 x 400	800 x 500 x 400	500 x 500 x 500	-
Part Mass (kg)	4.02	2.68[13]	2.68[13]	2.68[13]	2.68[13]	4.02
Total Cost ($)	$100,000	$31,300	$79,000	$48,000	$134,000	$250,000
Prorated Machine Cost ($)	-	$1,000	$500	$800	$5,700	-
Operation Cost ($)	-	$11,800	$5,700	$9,100	$51,700	-
Materials Cost ($)	-	$6,500	$56,700	$21,900	$60,400	-
Labor Cost ($)	-	$11,900	$7,300	$16,200	$16,200	-
Total Time for 100 Parts (hours)	900	930	774	1,377	2,186	2,000
Machine Time (hours)	-	590	566	915	1,724	-
Human Time (hours)	-	340	208	462	462	-

(Uncertainty assumptions: ±10% for cost and time, ±1% for mass)

Results: Decision Engine Recommendations

Scenario 1: Part Replication

The attribute weights, attribute data, and utility functions were input into the decision engine in order to calculate the utility of each manufacturing process for Scenario 1. The Scenario 1 data inputs for the decision engine are summarized in Table 3. The expected utility of each process is plotted in the bar graph in Figure 8.

It is observed from these results that traditional casting has the lowest utility (0.31), while hybrid wire arc additive manufacturing (hWAAM) has the highest utility (0.62). This result follows expectations, as the total cost and time for hWAAM are lower than those of the other processes (Table 3). Because the customer prioritizes cost minimization in their attribute weighting, it is reasonable to expect a process that has a lower cost to have a higher utility.

The expected utility of each manufacturing technique is plotted. The hWAAM process offers the highest utility, while traditional casting offers the lowest utility.

Scenario 2: Topology Optimized Redesign vs. Original Design

The attribute weights, attribute data, and utility functions were input into the decision engine in order to calculate the utility of each manufacturing process for Scenario 2. The Scenario 2 data inputs for the decision engine are summarized in Table 4. The expected utility of each process is plotted in the bar graph in Figure 9. Once again, traditional casting has the lowest utility (0.22), while hybrid wire arc additive manufacturing (hWAAM) has the highest utility (0.52).

[13] Data from Maurer (n.d.)

However, note that the gap in utility between hWAAM (0.52) and binder jetting with 6061 Aluminum (0.51) has decreased significantly, suggesting that the two manufacturing processes are now comparable in this scenario. Between Scenario 1 and Scenario 2, the difference in utility between the two processes is 0.04, indicating that the introduction of topology optimization into the decision process can have an impact on recommendation output by the engine. This change is largely due to the fact that the bulk of the cost for the binder jetting process comes from the powder material feedstock, which can be quite expensive (~$185/kg; MSE Supplies, n.d.). However, in hWAAM, the cost of material is substantially less (~$20/kg) as it uses conventional welding wire (*WeldingSupply 1100-116-3*, n.d.).

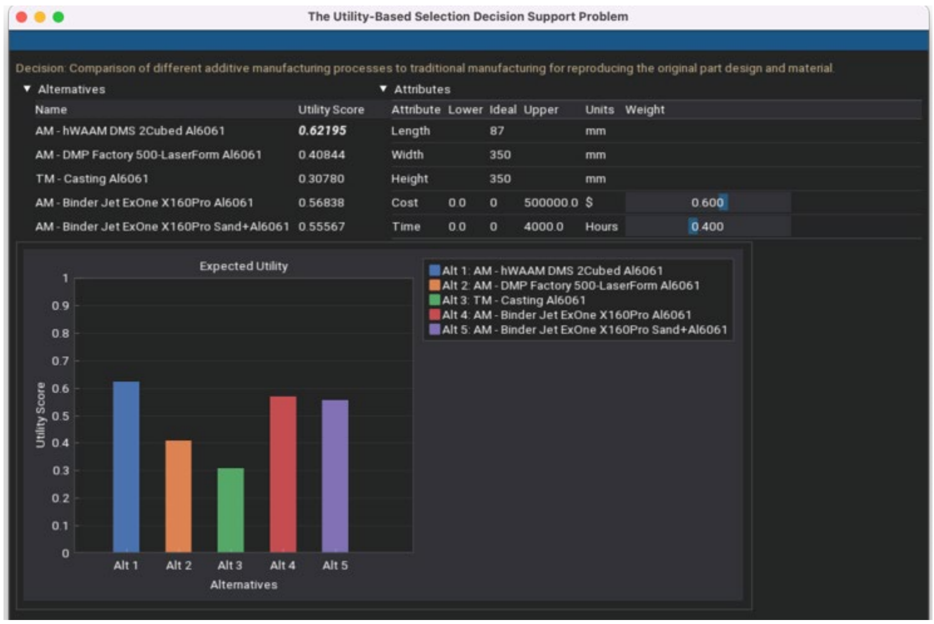

Figure 8. Decision Engine Outputs for Scenario 1

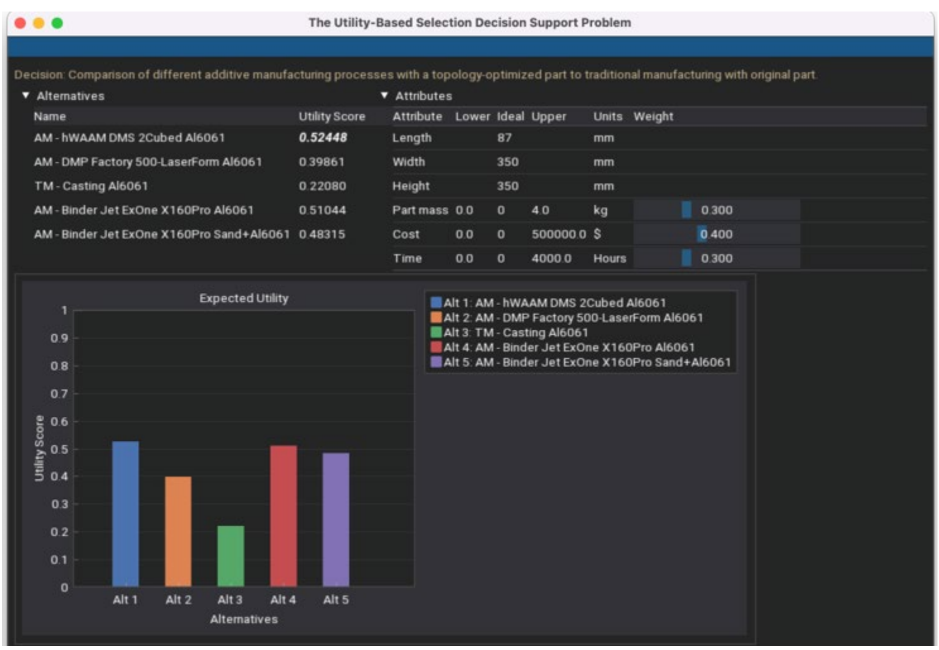

Figure 9. Decision Engine Outputs for Scenario 2

The expected utility of each manufacturing technique is plotted. The hWAAM process still offers the highest utility; however, due to decreased material costs from design mass reduction, the binder jetting process now has comparable utility. Traditional casting is still predicted to have the lowest utility.

Mass reduction of the bellcrank design through topology optimization has reduced the amount of material required to manufacture the part by one-third, which in turn has driven the total cost of the binder jetting process down by roughly 20%. An image of the optimized component, manufactured with hWAAM, is provided in Figure 10. Thus, this particular scenario highlights the possible changes in utility ranking of different processes as a result of subtle changes in the attributes by the introduction of topology optimization enabled in additive manufacturing processes.

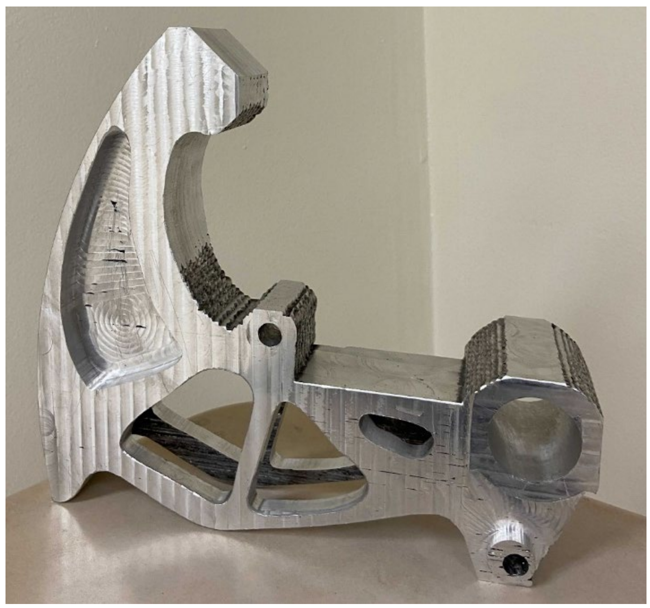

Figure 10. Topology Optimized Bellcrank Produced by hWAAM

(Note: The surface finish indicates that the AM part was post-processed using a milling machine.)

Final Thoughts on the Use Case: Aircraft Single Component Design

In this use case, a fleet sustainment decision by an aerospace company was explored. Within this decision, two possible scenarios for the design and manufacturing of an aileron bellcrank were explored. The first scenario enabled a comparison between traditional casting and different additive manufacturing processes' utilities in replicating the original bellcrank geometry and material.

In Scenario 2, the decision was re-evaluated with considerations that additive manufacturing processes can be used to produce a redesigned bellcrank geometry that was optimized for lightweighting. In both scenarios, the hybrid wire arc additive manufacturing process had the highest utility as it offered a sufficiently large build volume and offered the lowest cost and lead time among the alternatives. Between Scenario 1 and Scenario 2, a decrease in the relative ranking in utility between the two top manufacturing processes, hWAAM and binder jetting, was observed, indicating that additional consideration of additive manufacturing's ability to manufacture topology optimized parts in the decision process can impact engine outputs.

In the future, a third scenario that could be explored would be looking at how changing both the design and the material of the part for each process changes the utility. The change in material would change the design output by topology optimization, so each process/material combination would be tied to a unique design. Integration of the topology optimization process with the decision tool in an iterative fashion would also be a natural extension of this work.

Conclusions

The research focused on the data and framework surrounding the opportunity to exploit additive manufacturing as a systems engineering problem. The discussion started with a description and conceptual background on the decision support tool. Then, we discussed the use case, Design, Manufacturing, and Maintenance of Aircraft Components. To further understand use case, we identified the critical decision and analysis variables and created a framework to understand how these variables impact each other. Then, we transferred the above framework into an algorithmic view of these variables to make an optimized decision regarding where and how additive manufacturing can have the most impact. Finally, we developed an interactive decision support tool (i.e., the decision engine) in additive manufacturing so that the decision makers can use the quantitative data to make a proper decision.

As future work, further possibilities of the decision engine development include: (1) driving the decision engine using Model-based Systems Engineering (MBSE); (2) Integration of the decision engine with System-of-Systems (SoS) Analytic Workbench (AWB) for Mission Engineering; (3) Integration of the decision engine with AM machine/material databases (e.g., Senvol, PW Communications); (4) Integration of the decision engine with generative design tools to explore part redesign opportunities (and associated savings) via the use of AM (e.g., Autodesk Fusion 360); and (5) Expansion of decision engine to other DoD's area of interest, such as crisis management as discussed during the Additive Manufacturing Workshop in June 2022 at the MxD Headquarters in Chicago, IL (Brown, 2022).

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Acknowledgments

The authors acknowledge financial support from the U.S. Department of Defense through SERC/AIRC on research task WRT 1049.4, contract no. HQ0034-19-D-0003, and report no. AIRC-2022-TR-006.

In addition, the authors thank the following individuals who have contributed to the AIRC WRT-1049.4 project: Dr. Nathan Hartman, Dr. Ananth Iyer, Mr. Steven Dunlop, Ms. Dalia Bekdache, Mr. Clint Hanthorn, Mr. Dutt Thakkar, Ms. Ashritha Setlur, Mr. Atharva Sonanis, and Dr. Lindsey Bezek.

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