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MULTI-OBJECTIVE OPTIMIZATION OF ADDITIVE AND TRADITIONAL MANUFACTURING STRATEGIES UNDER UNCERTAINTY

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MULTI-OBJECTIVE OPTIMIZATION OF ADDITIVE AND TRADITIONAL MANUFACTURING STRATEGIES UNDER UNCERTAINTY

A THESIS APPROVED FOR THE

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To my parents, Rosalba and William for their unconditional love and sacrifices.To my aunt Blanca and my cousin Vanessa, for welcoming me with open arms and unwavering kindness.Your support, love, and presence made all the difference. This achievement is as much yours as it is mine.

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Contents

Abstract

This thesis addresses production scheduling challenges in additive manufacturing (AM) by using a multi objective optimization approach that simultaneously considers cost and time. While traditional models often focus on a single objective, our work integrates both, reflecting the real world tradeoffs manufacturers face. We develop a mathematical model that selects the appropriate manufacturing technologies and determines production quantities, ensuring that demand is met within specified time and budget limits.

A key focus of this study is understanding how economies of scale influence the optimal strategies as demand increases. As production volumes grow, the model captures how cost efficiencies emerge and how the tradeoffs between time and cost evolve. We apply Pareto frontier analysis to identify the best compromise solutions and perform a Monte Carlo simulation to assess the probability of exceeding time or cost targets, offering a deeper view of operational risks under uncertainty.

The paper is organized as follows. We first discuss the challenges of production planning in AM and the motivation for a multi objective framework. We then present the model structure and solution methods, followed by the results section covering Pareto analysis, economies of scale effects, and exceedance probabilities.We found that as demand increases, traditional manufacturing technologies become more cost effective due to economies of scale, while additive manufacturing remains competitive for smaller volumes and tighter time constraints. Additionally, the Monte Carlo analysis revealed that uncertainty in costs and processing times significantly affects the selection of optimal production strategies Finally, we conclude by discussing practical implications for manufacturers and directions for future research.

Keywords: Additive manufacturing, multi-objective optimization, decision making, aerospace spare parts

Chapter 1

Introduction

Additive manufacturing (AM), commonly known as 3D printing, has revolutionized how parts and components are designed, produced, and supplied across industries. From aerospace and defense to automotive and healthcare, the advantages of AM such as reduced material waste, geometric complexity, and digital flexibility, have prompted growing interest in replacing or complementing traditional manufacturing (TM) methods like casting and machining [1]. However, the economic and operational viability of AM is still highly situational. Decisions regarding the adoption of AM must balance multiple objectives, including cost, lead time, setup flexibility, and capacity utilization, all of which vary significantly based on scale, technology, and product type.

This paper presents a comprehensive, simulation driven multi objective optimization framework that evaluates the tradeoffs between cost and production time across a range of AM and TM technologies. Our work not only examines how economies of scale impact technology selection under various demand scenarios, but also introduces a Monte Carlo based sensitivity analysis to account for uncertainty in input data such as setup costs, unit prices, processing times, and production capacity. We incorporate both incremental discounting and bulk cost structures using piecewise linear functions, and analyze the global Pareto frontier across thousands of randomized simulations. To further enhance robustness, we employ exceedance probability curves, which reveal the likelihood of exceeding certain cost thresholds at different time levels, helping decision makers manage risk and performance expectations.

1.1 Motivation and Research Gap

The need for multi objective decision models in AM has been strongly recognized in the literature. A particularly relevant and timely contribution is the review by Framinan et al. (2022), which offers a broad and structured overview of how operations research (OR) methods have been applied in additive manufacturing [2]. Their work classifies more than 100 studies based on the type of OR technique used (e.g., mathematical programming, simulation, heuristics) and the planning level addressed (strategic, tactical, operational). It highlights a number of open challenges that directly inform this paper. namely, the scarcity of models that integrate cost and time objectives simultaneously, the underuse of stochastic approaches to reflect real world variability, and the need for decision support tools that work under uncertainty. Many of the studies covered in their taxonomy also serve as key references in this work. Their review provided not only a conceptual map of the field but also a clear motivation for our integrated, uncertainty modeling approach. Building on these observations, Altekin and Bukchin (2022) [3] developed one of the few mathematical formulations for a multi machine AM system, using mixed integer linear programming (MILP) to analyze the tradeoffs between cost and makespan in Direct Metal Laser Sintering (DMLS) environments. Their work emphasizes that treating cost and time independently can lead to suboptimal outcomes and underscores the complexity of job shop scheduling in heterogeneous AM facilities.

Precisely choosing the most appropriate AM technology or "printer selection" remains a non trivial challenge, complicated by the diverse capabilities of AM processes and their interaction with traditional manufacturing methods [4]. Early efforts to structure this decision making process included methods like the Analytic Hierarchy Process (AHP) [5]. Importantly, the inherent uncertainties in manufacturing data, be it material properties, processing times, or costs, were recognized early on, with foundational work exploring the use of interval, fuzzy, or stochastic approaches to capture this variability [6] [7] [8]. While these prior studies laid crucial groundwork, more recent machine selection frameworks, such as those employing AHP like Raja et al. (2022) in which they applied the Analytic Hierarchy Process (AHP) to select AM machines in small and medium enterprises, prioritizing product features and user criteria. [9]. Qin et al. (2023) provided an extensive review of multi attribute decision making methods (MADM) like AHP, TOPSIS, VIKOR, and MOORA for AM decisions, but noted that these methods often lack mechanisms to handle uncertainty or explore Pareto optimal tradeoffs [10]. Similar decision support systems have been built by Tsutsui et al. (2023) using multi criteria evaluation frameworks to integrate AM into sustainable defense acquisition scenarios. [11]

A unique contribution to the field comes from Shi et al. (2022, 2023), who proposed a system-of-systems (SoS) framework for evaluating AM in the context of space satellite systems. They introduced a utility theory based decision engine for selecting machine material pairs under various stakeholder preferences, illustrating the value of aligning system engineering with advanced optimization and risk modeling [12] [13]. However, these works remain primarily conceptual or limited to case specific demonstrations.

Beyond case based or conceptual studies, recent literature has increasingly focused on integrating additive manufacturing into broader supply chain and production strategy contexts, an area directly relevant to our approach. Several studies have explored how AM can reshape spare parts logistics through strategic configuration and technology selection. For example, Cantini et al. [14] developed a decision support system that evaluates centralized, decentralized, and hybrid supply chain models for spare parts, showing that hybrid configurations ,especially when paired with AM, can offer superior cost performance tradeoffs under demand uncertainty. Similarly, Meng et al. [15] used a mixed integer model to compare AM and conventional approaches in distributed spare parts networks, highlighting AM's responsiveness in high variety, low volume environments.

At the technology planning level, Sgarbossa et al. [16] and Hughes et al. [17] introduced decision frameworks that assess the viability of AM adoption for spare parts, based on parameters like complexity, volume, and lead time. Lin et al. [18] extended this line of thinking by proposing a blockchain integrated AM network, aiming to enhance traceability, security, and decentralized coordination.

From a logistical and operational standpoint, Qiang et al. (2017) [19] and Ransikarbum and Mason [20] (2017) formulated multi objective and multi criteria models for routing, scheduling, and AM investment decisions under cost, time, and criticality constraints. These models demonstrate that when properly configured, AM based networks can outperform traditional systems in responsiveness and resilience. Complementary studies by Khamhong et al (2019). introduced additional decision tools, ranging from Fuzzy AHP for printer selection [21] to DEA based orientation analysis [22, 23] and multi objective part to printer assignment frameworks [24] further enriching the decision science underpinning AM planning. Gradl et al. [25] offered an industry focused review on AM applications in gas turbines, emphasizing repairability and design freedom, while Koller et al. [26] synthesized over 30 studies to identify modeling gaps in decentralized AM for spare parts. They point out a persistent overreliance on cost centric objectives and a lack of simulation based validation gaps our work directly addresses through stochastic optimization and robustness analysis.

When it comes to supply chain and spare parts planning, studies such as Khajavi et al. (2014), Heinen and Hoberg (2017), and Li et al. (2017, 2019) have provided strong arguments for integrating AM into distributed production strategies. Khajavi et al. showed that AM could reduce response time and costs in aerospace logistics, particularly for low volume parts [27]. Heinen and Hoberg used cost and demand modeling to assess switchover shares for AM in spare parts management, concluding that AM is cost competitive for low demand SKUs even with higher unit prices [28]. Li et al. (2017) used system dynamics simulation to compare conventional, centralized, and distributed AM based spare parts supply chains, while their 2019 follow up expanded the analysis to make to order environments under heterogeneous demand using discrete event simulation [29] [30].

Simulation is another core methodology in AM optimization. Ghadge et al. (2018) and Liu et al. (2013) employed system dynamics and SCOR models respectively to study AM's impact on aerospace supply chains, focusing on sustainability and responsiveness improvements [31] [32]. Tsai and Chen (2016) introduced a simulation based multi objective optimization framework for inventory systems, combining ranking and selection procedures with utility theory to tackle stochastic environments, a methodology that inspires part of our Monte Carlo setup [33].

Meanwhile, researchers like Fera et al. (2018) have focused on metaheuristic optimization using genetic algorithms to optimize time and cost for AM machines under strict sequencing and job constraints [34]. Margolis et al. (2018) and Canales-Bustos et al. (2017) contributed multi objective network design models that include AM options to enhance supply chain resilience and reduce emissions, laying the groundwork for tradeoff analyses under sustainability criteria [35] [36].

Recent works by Mindt et al. (2022) and Minguella-Canela (2020) further highlight the importance of agent based modeling and digital decision support systems to holistically assess AM from both economic and stakeholder oriented angles [37] [38].

Building on these foundational works, this study makes four key contributions:

1. Multi objective modeling of AM and TM technologies under uncertain demand: We develop a robust MILP model that simultaneously minimizes total cost and production time, subject to budget, capacity, and batch production constraints. The model accommodates five competing manufacturing technologies, including three AM variants and two TM options.

2. Incorporation of economies of scale through dual cost structures: Both incremental discounts and bulk (piecewise linear) pricing structures are modeled, allowing us to compare how different economic assumptions affect technology preferences across varying demand levels.

3. Comprehensive uncertainty modeling using Monte Carlo simulation: We conduct 20,000 simulations where demand, setup costs, unit prices, processing times, and machine capacities are sampled from realistic distributions. This allows us to observe global Pareto frontiers and explore the robustness of solutions beyond deterministic setups.

4. Use of probability of exceedance analysis to assess solution reliability: We implement two complementary exceedance analyses to evaluate the probability of cost overruns across different target time windows. These curves provide a decision tool to assess solution stability and risk exposure under varying production constraints.

This approach helps bridge the gap between theoretical optimization and real world manufacturing decision making. Unlike many existing works that focus on static optimization or qualitative frameworks, our model offers a quantitative, data driven, and risk sensitive approach to manufacturing strategy planning. It captures the essential dynamics that manufacturing managers, supply chain planners, and technology adopters need to consider in order to make effective tradeoffs between time, cost, and reliability.

1.2 Economies of Scale in Manufacturing

Economies of scale are a key consideration in manufacturing strategy. They refer to the reduction in average cost per unit as production quantity increases, typically achieved through:

- Spreading fixed costs (e.g., tooling, setup) over more units.
- Higher labor and equipment utilization.
- Bulk purchasing and material discounts.

Traditional manufacturing processes, especially casting, strongly benefit from economies of scale. In contrast, AM's minimal setup requirements and digital nature make it advantageous for customized or low volume production but with flatter cost curves. Therefore, selecting between AM and TM technologies under different production scales is a multi faceted decision involving tradeoffs in cost, time, and performance—an ideal setting for multi objective optimization.

Chapter 2

Additive and Traditional Manufacturing Technologies

2.1 Definition and Contrast

Traditional manufacturing (TM) has underpinned industrial development since the first industrial revolution. Processes like casting, forging, machining, and molding have enabled mass production across sectors for centuries. Metal casting, in particular, dates back to ancient civilizations and remains one of the most prevalent methods for producing large metal parts due to its high repeatability and economies of scale.

In contrast, Additive Manufacturing (AM) emerged in the 1980s with the advent of stereolithography (SLA). Initially used for prototyping, AM has evolved into a viable production method with technologies such as Powder Bed Fusion (PBF), Directed Energy Deposition (DED), and Binder Jetting now capable of producing end use parts. Over the past two decades, AM has gained traction in high value industries like aerospace, automotive, and biomedical due to its ability to fabricate complex geometries, reduce part counts, and enable design driven manufacturing. Additive manufacturing refers to a family of processes that create parts layer by layer directly from digital models. Unlike subtractive methods (e.g., CNC machining) or formative processes (e.g., casting or forging), AM minimizes material waste, shortens the product development cycle, and enables mass customization. However, AM often struggles to compete with TM in terms of unit cost and throughput for high volume production.

Traditional manufacturing, as considered in this study, centers on metal casting, a well established process that involves pouring molten metal into a mold to form parts. TM techniques excel in large batch production due to their maturity, speed, and cost effectiveness when amortized over many units. However, they are often constrained by long setup times, tooling costs, and design limitations.

2.2 Tradeoffs and Manufacturing Strategy

The choice between AM and TM depends on several factors, including:

- **Production volume:** AM is more cost effective at low volumes, while TM is superior at scale.
- **Lead time:** AM offers faster turnaround for prototypes or low run batches.
- **Complexity:** AM supports complex internal geometries without additional cost.
- **Part performance and tolerances:** TM generally offers tighter tolerances and consistent mechanical properties.

As such, many modern manufacturers are exploring hybrid production strategies that leverage both AM and TM depending on part characteristics and market demand.

2.3 Additive Manufacturing Processes Considered

2.3.1 Powder Bed Fusion (PBF)

Powder Bed Fusion (PBF) is one of the most common metal 3D printing methods. It works by spreading thin layers of metal powder and using a laser or electron beam to melt the areas needed to form the part. After each layer is finished, the platform lowers, and a new layer is added. This repeats until the part is complete.

PBF is great for making complex shapes with high detail and strong material properties, often close to those of traditionally made metal parts. However, it is slow, expensive, and limited in size. It also needs a special environment (like inert gas or vacuum) to avoid oxidation. Due to its precision, it is often used in aerospace and medical applications.

2.3.2 Binder Jetting

Binder Jetting also uses a powder bed, but instead of melting the powder, it applies a liquid binder to hold the particles together. The result is a fragile "green" part, which then goes through several post-processing steps like curing, removing excess powder, and sintering to make it strong.

This method is usually faster and cheaper than PBF, especially for making large batches or larger parts where ultra high precision is not needed. However, the final strength and accuracy depend a lot on how well the sintering process goes. It is a good choice when speed and cost matter more than high strength for tooling, prototypes, or less critical parts.

2.3.3 Selective Laser Melting (SLM)

Selective Laser Melting (SLM) is a type of Powder Bed Fusion that uses a laser to fully melt the metal powder and create dense, strong parts. It builds layer by layer, just like PBF, and is great for making very detailed and complex shapes.

SLM is known for high precision and strong parts, often used in critical applications like aerospace and medical implants. But it is also slow and uses a lot of energy. It needs strict control of the environment to avoid defects, and post-processing, such as heat treatment or surface finishing is usually required. It is best for low to medium production volumes when part quality and performance are the top priorities.

2.3.4 Hybrid Wire Arc Additive Manufacturing (hWAAM)

Hybrid WAAM builds metal parts by melting wire with an electric arc, similar to welding, and adding layers one at a time. The "hybrid" part comes from combining this process with machining steps during or after printing to improve accuracy.

hWAAM is much faster than powder-based methods and is great for making large parts. It also tends to be cheaper. The tradeoff is that the parts can be rough and not as precise, so they often need a lot of post-processing. Still, it is becoming popular in the aerospace and marine industries, especially for repairing or building big, heavy-duty parts.

2.3.5 Traditional Manufacturing: Metal Casting

Metal casting remains one of the most widely used methods for producing metal parts, especially when dealing with large volumes or complex geometries. The process involves pouring molten metal into a mold cavity made of sand, ceramic, or metal, where it solidifies into the desired shape. After cooling, the mold is broken or removed, and the part may undergo further finishing.

Casting offers high material utilization at scale, low per-unit costs for large production runs, and the ability to create parts that would be difficult or uneconomical to machine or print. However, it lacks the flexibility of additive manufacturing for low volume or custom components, as it typically requires significant tooling investment and longer setup times. For industries with stable, high volume demand, casting remains an efficient and economical choice.

Chapter 3

Methodology

This study develops an optimization framework that integrates a mixed integer ε constraint model with Monte Carlo sampling to explore the tradeoff between the total production cost and the processing time under uncertainty. The core mathematical program determines how many of each machine to install and how many batches of each part to run on each machine to satisfy aggregate demand, respect a fixed budget, and adhere to a user specified time limit. Uncertainty in demand, machine capacities, setup costs, processing times, and unit costs is captured via probability distributions; repeated sampling of these inputs produces a cloud of cost–time outcomes, from which Pareto optimal frontiers and exceedance curves are extracted.

In this section we detail the steps taken to build, analyze, and validate our optimization framework. We begin by describing the data we collected and how we formulate the core problem. We then introduce the ε-constraint model used to generate Pareto-optimal solutions, specify the objective function, and enumerate all model parameters and constraints. Next, we explain our sensitivity analysis via Monte Carlo sampling, and finally we present the construction of probability-of-exceedance curves.

3.1 ε-Constraint Multi-Objective Model

In this study, the problem involves two goals that usually pull in opposite directions: minimizing total cost and minimizing total production time. Choosing only the cheapest option might lead to unacceptable delays, while focusing only on speed could drive costs too high. To deal with this, we use a multi objective optimization approach.

Instead of mixing both goals into a single weighted objective, we applied the epsilon constraint method. This technique focuses on minimizing cost, while time is treated as a constraint with an upper limit (called epsilon). By adjusting the time limit across different simulation runs, we can generate a variety of solutions that show the trade offs between cost and time. This helps us map out the Pareto frontier, the set of best possible compromises between the two objectives.

The epsilon constraint method works well here because it avoids the need to guess arbitrary weightings between cost and time, and it lets us explore different service levels realistically. It also fits naturally into our Monte Carlo simulation framework, where time limits are randomly varied to see how solutions behave under different delivery pressures.

3.2 Modelling Economies of scale- Incremental discounts (Model 1)

Economies of scale are an important factor when comparing different manufacturing technologies. As production volume increases, unit costs typically decrease due to better resource utilization, amortization of setup costs, and discounts on material usage. To capture this behavior accurately, the incremental discounts model includes detailed **piecewise linear cost functions** for each machine.

For each machine $i \in \mathcal{M}$, the total variable cost is modeled as:

$$\text{varCost}_i = f_i(\text{vol}_i)$$

where vol_i is the total volume (number of parts) produced on machine i, and $f_i(\cdot)$ is a piecewise linear function defined over specific volume breakpoints.

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Formally, the cost function is structured as:

$$0 = v_{i,0} < v_{i,1} < v_{i,2} < \cdots < v_{i,n-1} < v_{i,n}, \quad c_{i,1}, \ldots, c_{i,n}$$

be your breakpoints and segment costs. Then

$$f_i(\mathrm{vol}_i) = \begin{cases} c_{i,1}\,\mathrm{vol}_i, & 0 \leq \mathrm{vol}_i < v_{i,1}, \\ c_{i,2}\,\mathrm{vol}_i, & v_{i,1} \leq \mathrm{vol}_i < v_{i,2}, \\ \quad\vdots & \quad\vdots \\ c_{i,k}\,\mathrm{vol}_i, & v_{i,k-1} \leq \mathrm{vol}_i < v_{i,k}, \quad k = 1, \ldots, n, \\ \quad\vdots & \quad\vdots \\ c_{i,n}\,\mathrm{vol}_i, & v_{i,n-1} \leq \mathrm{vol}_i \leq v_{i,n}. \end{cases}$$

where:

- $v_{i1}, v_{i2}, v_{i3} \ldots v_{in}$ are the volume thresholds (breakpoints),
- $c_{i1}, c_{i2}, c_{i3} \ldots c_{in}$ are the unit costs associated with each segment.

This design reflects that AM technologies typically benefit from lower volume discounts (starting at smaller batch sizes), while traditional casting only achieves significant cost reductions at much larger production volumes.

The piecewise relationships were implemented using Gurobi's `addGenConstrPWL` functionality, allowing the optimization model to automatically determine the correct cost level based on production volume decisions.

3.2.1 Objective Function

The main goal of the optimization model is to minimize the total production cost. The total cost is composed of two parts: the **setup cost** associated with installing each machine, and the **variable cost** associated with the volume of parts produced on each machine.

Formally, the objective function is:

$$\text{Minimize} \quad Z = \sum_{i \in \mathcal{M}} (F_i n_i + \text{varCost}_i) \tag{3.1}$$

where:

- F_i is the fixed setup cost for one machine of type i,
- n_i is the number of machines of type i installed,
- varCost_i is the total variable production cost incurred on machine i, based on the volume produced and the corresponding cost function.

The model aims to find the best allocation of parts and machines that minimizes the total cost while satisfying all operational constraints, such as demand fulfillment, budget limits, machine capacities, and production time (makespan) restrictions.
It is important to highlight that although the cost is the explicit objective function to minimize, the model also respects the production time constraints through the ϵ-constraint method, ensuring that time remains an active decision factor during optimization.

3.2.2 Parameters and Constraints

Parameters

The model uses the following parameters:

- $\mathcal{M}$: set of machine types, e.g., {AM hWAAM, AM Binder 1, AM Binder 2, AM PBF, TM Casting}.
- $\mathcal{P}$: set of part types, e.g., {part 1, part 2}.
- t_{ij}: processing time (in hours) required to produce one part j on machine i.
- c_{ik}: unit cost for machine i in bracket k.
- b_{ij}: number of parts in one batch of part j produced on machine i.
- x_{ij}: number of batches of part j assigned to machine type i

- D: total demand (number of parts required).
- F_i: fixed setup cost for one unit of machine i.
- $f_i(\cdot)$: piecewise linear variable cost function for machine i, defined over volume produced.
- B: total available budget.
- T: maximum allowed total production time (makespan limit).
- H_i: available processing hours per period for one unit of machine i (machine capacity).
- M: a large constant (Big-M) used for linking constraints.

Constraints

The optimization model includes the following constraints:

1. **Demand satisfaction:**
$$\sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{P}} b_{ij} x_{ij} \geq D \tag{3.2}$$
Ensures that the total number of parts produced meets or exceeds demand.

2. **Makespan (Time) constraint:**
$$\sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{P}} t_{ij} b_{ij} x_{ij} \leq T \tag{3.3}$$
Ensures that the total production time does not exceed the allowed time limit.

3. **Budget constraint:**
$$\sum_{i \in \mathcal{M}} (F_i n_i + \mathrm{varCost}_i) \leq B \tag{3.4}$$
Ensures that the total cost (setup plus variable) stays within the available budget.

4. **Machine capacity constraint:**
$$\sum_{j \in \mathcal{P}} t_{ij} b_{ij} x_{ij} \leq H_i n_i \quad \forall i \in \mathcal{M} \tag{3.5}$$

Guarantees that the assigned workload on each machine does not exceed its capacity.

5. **Machine activation constraint (Big-M constraint):**

$$x_{ij} \le M n_i \quad \forall i \in \mathcal{M},\, j \in \mathcal{P} \tag{3.6}$$

Allows production only if the corresponding machine is installed.

6. **Volume definition:**

$$\text{vol}_i = \sum_{j \in \mathcal{P}} b_{ij} x_{ij} \quad \forall i \in \mathcal{M} \tag{3.7}$$

Defines the total volume produced by each machine type.

7. **Piecewise linear cost:**

$$\text{varCost}_i = f_i(\text{vol}_i) \quad \forall i \in \mathcal{M} \tag{3.8}$$

Relates the variable production cost to the total volume produced on each machine via the piecewise linear function.

8. **Variable Domains:** The decision variables are constrained as follows:

$$x_{ij} \in \mathbb{Z}_+, \quad n_i \in \mathbb{Z}_+, \quad \text{vol}_i, \text{varCost}_i, T \ge 0 \tag{3.9}$$

where $\mathbb{Z}_+$ denotes the set of nonnegative integers.

3.3 Modelling Economies of scale — Binary Bracket Formulation (Model 2)

To provide greater modeling flexibility and explicitly control the cost structure, Model 2 implements economies of scale using **binary bracket logic**. This formulation uses a set of predefined volume intervals, where each bracket has an associated unit cost. Only one bracket can be active at a time for each machine, and binary variables ensure proper bracket selection.

For each machine $i \in \mathcal{M}$, the total variable cost is modeled as:

$$\text{varCost}_i = \sum_{k=1}^{K} c_{ik} \cdot \text{vol}_i \cdot z_{ik}$$

subject to:

$$\sum_{k=1}^{K} z_{ik} = 1 \quad \forall i \in \mathcal{M}$$

$$\ell_{ik} \cdot z_{ik} \leq \text{vol}_i \leq u_{ik} + M(1 - z_{ik}) \quad \forall i \in \mathcal{M}, \forall k \in \{1, 2, \dots, K\}$$

where vol_i is the total number of parts produced by machine i, and each bracket k corresponds to a cost segment defined by a unit cost c_{ik} and a volume range $[\ell_{ik}, u_{ik}]$. The binary variable z_{ik} indicates which cost bracket is active.

This method allows precise control over volume dependent pricing, making it especially useful for modeling nonconvex cost functions or enforcing pricing tiers used in real procurement or manufacturing contracts.

3.3.1 Objective Function

The main objective remains to minimize the total production cost, which consists of setup costs and volume-dependent variable costs:

$$\text{Minimize} \quad Z = \sum_{i \in \mathcal{M}} (F_i n_i + \text{varCost}_i) \tag{3.10}$$

where:

- F_i is the fixed setup cost for one machine of type i,
- n_i is the number of machines of type i installed,

- varCost_i is the variable production cost for machine i, based on the bracket selected and the volume produced.

As in Model 1, the objective is to find the optimal number of machines and part allocations that minimize total cost while satisfying demand, time, and budget constraints.

3.3.2 Parameters and Constraints

Parameters

Model 2 uses the same base parameters as Model 1, with the addition of bracket definitions:

- $\mathcal{M}$: set of machine types, e.g., {AM hWAAM, AM Binder 1, AM Binder 2, AM PBF, TM Casting}.
- $\mathcal{P}$: set of part types, e.g., {part 1, part 2}.
- t_{ij}: processing time (in hours) required to produce one part j on machine i.
- b_{ij}: number of parts in one batch of part j produced on machine i.
- x_{ij}: number of batches of part j assigned to machine type i
- D: total demand (number of parts required).
- F_i: fixed setup cost for one unit of machine i.
- B: total available budget.
- T: maximum allowed total production time (makespan limit).
- H_i: available processing hours per period for one unit of machine i (machine capacity).
- M: a large constant (Big-M) used for logical implications.
- c_{ik}: unit cost for machine i in bracket k.
- ℓ_{ik}, u_{ik}: lower and upper bounds of the volume range for bracket k on machine i.

Constraints

The constraints used in Model 2 include all baseline constraints from Model 1, along with additional bracket logic:

1. **Demand satisfaction:**

$$\sum_{i\in\mathcal{M}}\sum_{j\in\mathcal{P}} b_{ij}x_{ij} \geq D \tag{3.11}$$

2. **Makespan (Time) constraint:**

$$\sum_{i\in\mathcal{M}}\sum_{j\in\mathcal{P}} t_{ij}b_{ij}x_{ij} \leq T \tag{3.12}$$

3. **Budget constraint:**

$$\sum_{i\in\mathcal{M}} (F_i n_i + \mathrm{varCost}_i) \leq B \tag{3.13}$$

4. **Machine capacity constraint:**

$$\sum_{j\in\mathcal{P}} t_{ij}b_{ij}x_{ij} \leq H_i n_i \quad \forall i \in \mathcal{M} \tag{3.14}$$

5. **Machine activation constraint (Big-M constraint):**

$$x_{ij} \leq M n_i \quad \forall i \in \mathcal{M},\, j \in \mathcal{P} \tag{3.15}$$

6. **Volume definition:**

$$\mathrm{vol}_i = \sum_{j\in\mathcal{P}} b_{ij}x_{ij} \quad \forall i \in \mathcal{M} \tag{3.16}$$

7. **Bracket selection constraint:**

$$\sum_{k=1}^{K} z_{ik} = 1 \quad \forall i \in \mathcal{M} \tag{3.17}$$

8. **Volume bounds for active bracket:**

$$\ell_{ik} \cdot z_{ik} \leq \mathrm{vol}_i \leq u_{ik} + M(1 - z_{ik}) \quad \forall i \in \mathcal{M}, \forall k \tag{3.18}$$

9. **Variable cost expression:**

$$\mathrm{varCost}_i = \sum_{k=1}^{K} c_{ik} \cdot \mathrm{vol}_i \cdot z_{ik} \quad \forall i \in \mathcal{M} \tag{3.19}$$

10. **Variable Domains** The decision variables for Model 2 are:

$$x_{ij} \in \mathbb{Z}_+, \quad n_i \in \mathbb{Z}_+, \quad \mathrm{vol}_i, \mathrm{varCost}_i \geq 0, \quad z_{ik} \in \{0, 1\} \tag{3.20}$$

This binary-based formulation is more expressive than native PWL, allowing the model to represent real world pricing rules that rely on discrete volume tiers and cost thresholds.

3.4 Incorporating Lead Time

In our baseline model, we only accounted for processing time on each machine. To capture the effect of procurement or setup delays, we introduce a `lead time` parameter:

Machine	Lead Time (days)	Lead Time (hours)
AM hWAAM	2	48
AM Binder	2	48
AM slm	3	72
AM PBF	3	72
TM Casting	21	504

Table 3.1: Lead times for each technology (days and equivalent hours).

We then modify the total-time constraint by adding a fixed delay whenever a machine is used at all:

$$T = \sum_{i,j} x_{ij} \left(\mathrm{b}_{ij} \cdot t_{ij} \right) + \sum_{i} y_i \, \mathrm{lead\_time}_i \leq \varepsilon, \tag{3.21}$$

where $y_i \in \{0, 1\}$ indicates whether machine i is activated. Concretely, We add a binary decision variables y_i and constraints

$$x_{ij} \le M\, y_i \quad \forall i, j, \qquad n_i \ge y_i \quad \forall i$$

to force $y_i = 1$ whenever any batch is run or a copy is purchased.

By rerunning the models with the above modification, we can observe how the Pareto frontier and the share of AM vs. TM solutions shift when TM's long tooling delays are properly penalized. We expect AM technologies, with their much shorter lead times, to become relatively more attractive under tighter time budgets.

3.4.1 Scenario: 30% AM Setup Cost Reduction

In this scenario analysis we explore the impact of a substantial reduction in the capital cost of additive manufacturing equipment. Specifically, for each AM machine we apply a 30% discount to its fixed setup cost:

while leaving all other parameters (including unit production costs, lead times, capacity, etc.) unchanged.

By resolving (and resimulating) under these adjusted setup costs, we can observe how a 30% drop in AM equipment price affects:

1. The Pareto frontier (cost vs. time tradeoff),
2. The frequency with which AM technologies dominate over TM in the optimal solutions,
3. The value of flexibility that quicker AM lead times provide when capital is cheaper.

Comparing these results to the baseline run quantifies the competitiveness gain that capital cost reductions would have on additive manufacturing.

3.5 Data Collection and Problem Definition

The data used for this study came from two main sources. First, technical parameters such as batch sizes, processing times, and part masses were taken from the paper "Decision Making for Additive Manufacturing in Sustainable Defense Acquisition" by Tsutsui et al. (2023). Their work provided a clear case study based on aerospace parts, which matched the type of components we wanted to model. Using their data helped ensure that the production characteristics across the different AM and TM technologies were realistic and based on industry accepted values.

In this work, we evaluate the production of the Aileron Bellcrank, a real aerospace component originally made through metal casting. This use case is based on the same scenario presented by Tsutsui et al. (2023) [11], where an aerospace OEM needed to replace 100 out of production bellcranks for fleet sustainment. Since the original supplier had discontinued production, the company explored both traditional metal casting and additive manufacturing (AM) alternatives. To improve performance, the bellcrank was also redesigned through topology optimization using Autodesk Fusion 360. The goal of the optimization was to minimize the mass of the part while maintaining enough stiffness to meet the load requirements, taking advantage of the ability of additive manufacturing to create more complex geometries. The material, 6061 Aluminum, remained the same between the original and optimized designs.

Figure 3.1: Original aileron Bellcrank used

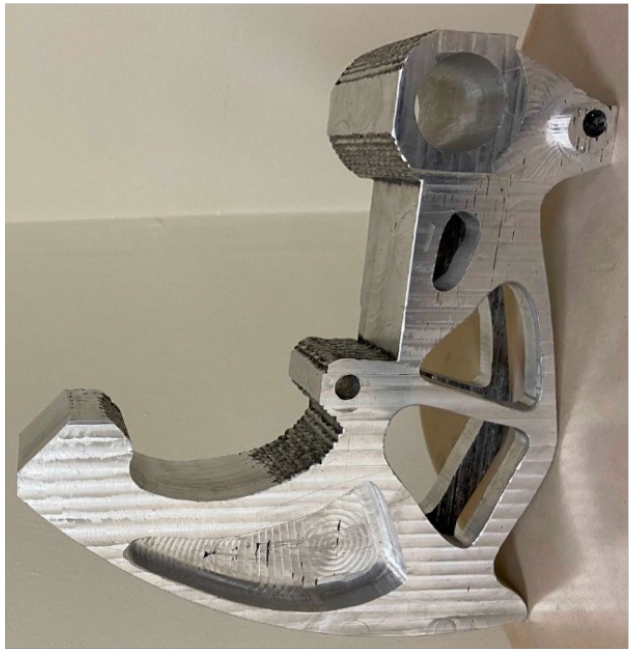

Figure 3.2: Optimized aileron Bellcrank used

Using this part ensures that the problem we study, choosing between AM and TM under cost and time constraints, reflects a real world industrial challenge faced by modern companies dealing with supply chain disruptions and rising manufacturing costs.

Second, the setup costs for the different manufacturing technologies were manually collected through online searches. We gather price estimates from machine manufacturers, supplier catalogs, and other public sources. Since exact numbers can vary across vendors and over time, we treated the collected prices as approximate base values and added some variability during the Monte Carlo simulation to reflect real world uncertainty.

Overall, we combined academic data with current market observations to build a dataset that is realistic enough for meaningful simulation while being flexible enough to explore different demand and cost scenarios.

3.5.1 Incremental discounts Cost

To capture economies of scale in a transparent, contract-style way, we assume that the supplier offers fixed percentage discounts once cumulative production crosses each volume breakpoint. Denote by v_{k-1} and v_k the lower and upper bounds of bracket k, with

$$\{v_0, v_1, \ldots, v_K\} = \{0, 25, 50, 100, 200, 400, 800, 1200, 2200\}.$$

Let $c_{i,1}$ be the baseline unit cost for machine i in bracket 1 (as taken from our source data). For brackets $k = 2, \ldots, K$, we define a bulk-discount rate δ_k and set

$$c_{i,k} \ = \ (1 - \delta_k)\ c_{i,1}.$$

A plausible discount schedule is:

Volume Range	$[0, 25)$	$[25, 50)$	$\cdots$	$[800, 1200)$	$[1200, 2200)$
Discount Rate	0%	5%	$\cdots$	18%	20%

Thus, for each machine i:

$$\begin{aligned}
c_{i,1} &= (\text{quoted base cost}),\\
c_{i,2} &= 0.95\, c_{i,1},\\
c_{i,3} &= 0.92\, c_{i,1},\\
c_{i,4} &= 0.90\, c_{i,1},\\
c_{i,5} &= 0.88\, c_{i,1},\\
c_{i,6} &= 0.85\, c_{i,1},\\
c_{i,7} &= 0.82\, c_{i,1},\\
c_{i,8} &= 0.80\, c_{i,1}.
\end{aligned}$$

These $c_{i,k}$ then define the cumulative cost breakpoints used in the model's `addGenConstrPWL` calls.

3.5.2 Bulk-Discount Cost Structure

In Model 2 we use eight volume brackets $\{v_0, \ldots, v_8\} = \{0, 25, 50, 100, 200, 400, 800, 1400, 2200\}$ and assign a flat per-part rate $c_{i,k}$ in each bracket. Concretely, for all AM machines, we adopt:

k	1	2	...	8
$[v_{k-1}, v_k)$	$[0, 25)$	$[25, 50)$	...	$[1400, 2200)$
$c_{i,k}$ ($/part)	1000	950	...	786

and for TM Casting:

k	1	2	...	8
$[v_{k-1}, v_k)$	$[0, 25)$	$[25, 50)$	...	$[1400, 2200)$
$c_{i,k}$ ($/part)	2500	2375	...	417

These $c_{i,k}$ values are chosen to reflect a realistic bulk-pricing schedule:

- The first segment uses published "list" rates (e.g. $1,000 for AM, $2,500 for TM).
- Subsequent brackets apply modest discounts (e.g. 5%, 8%, ..., 20%) on that base rate.
- The final bracket ($k = 8$) represents the deepest discount once very large volumes are reached.

Table 3.2: Machines and their setup costs [39] [40]

Machine	**Cost (USD)**
AM hWAAM	380000
AM Binder	350000
AM SLM	400000
AM PBF	500000
TM Casting	430000

3.6 Sensitivity Analysis and Monte Carlo Simulation

To capture the effects of uncertainty in demand, costs, processing times, and machine capacities, a comprehensive Monte Carlo simulation framework was developed. This approach allows for a robust sensitivity analysis by simulating a wide range of possible real world conditions and observing their impact on the optimal manufacturing decisions.

A total of 50,000 simulation runs were performed. In each run, the following parameters were randomly sampled:

- **Demand** was drawn from a negative binomial distribution, reflecting high variability typical in aerospace and spare parts markets.
- **Time constraint** (epsilon) was sampled from a uniform distribution between 300 and 10,000 hours
- **Setup costs** for each machine were sampled from normal distributions with a 20% standard deviation, truncated to ensure positive values.
- **Processing times** for each machine-part combination were sampled from normal distributions with a 20% standard deviation.
- **Piecewise unit costs** were sampled for each machine using normal distributions (15% standard deviation), allowing variability in economies of scale.
- **Machine capacities** were sampled from normal distributions with 10% standard deviation, ensuring positive and realistic capacity values.

These probability distributions are consistent with those proposed in the literature for modeling uncertainty in spare parts and manufacturing systems [41].

For each sampled scenario, a new instance of the optimization model was built and solved using Gurobi. If the model returned an optimal solution, key results including total cost, total time, and the sampled parameters were stored for further analysis.

The Monte Carlo sensitivity analysis provides a robust picture of how variability in input parameters influences the choice between additive and traditional manufacturing technologies. It also enables risk aware decision making by illustrating not just average outcomes, but the full range of possible results across thousands of real world like conditions.

3.7 Risk–Based Analysis via Exceedance Curves

3.7.1 Cost Exceedance Analysis

To better understand the risk of exceeding our production budget under different time constraints, we generate *exceedance curves* using results from the Monte Carlo simulations. For a given target time T, we collect all simulation runs whose total time T_i falls within a small window around T. Then, for any candidate cost threshold $\hat{c}$, we calculate the fraction of those runs that ended up costing more than $\hat{c}$:

$$\text{Exceedance probability} = \frac{\text{Number of runs with cost} > \hat{c}}{\text{Number of runs with } T_i \approx T}$$

Each curve corresponds to a different time target (e.g., 4000 h, 5000 h, 6000 h) and shows how likely it is to exceed a given budget. A curve that shifts left implies that, under tighter deadlines, even moderate budgets are more likely to be exceeded.

We can also flip the question. Instead of asking “what is the risk of going over a certain cost?”, we can ask: “what cost keeps the exceedance risk below a desired level p?” For each time target T, we find the cost threshold that only the most expensive $p\%$ of runs exceed:

$$\text{Threshold}_p(T) \;=\; \text{value exceeded by the top } p\% \text{ of costs at time } T$$

By plotting these thresholds against time, we generate a second set of curves—each one showing how the minimum required budget increases as the deadline tightens for a given risk level (e.g., 5%, 10%).

Together, these two exceedance plots offer a practical picture of the time–cost–risk tradeoff, helping decision makers balance deadlines, budgets, and uncertainty in a data driven way.

3.7.2 Importance of Exceedance Curves

These curves are particularly valuable in risk-averse planning: one can choose a target deadline and a maximum acceptable overrun probability, then read off the required contingency.

- *Two perspectives on the same joint distribution.* The “Cost–Exceedance” view slices horizontally at fixed T and shows how risk varies with budget. The "Time–Cost" view slices vertically at fixed p and shows how required budget scales with tighter deadlines.

- *Decision support under uncertainty.* Real programs rarely operate at "average" conditions; managers need to understand both the probability of cost overruns given a deadline and the budget needed to achieve a specified confidence level.

- *Flexibility.* By varying T and p, one can map out a risk analysis, supporting trade-off tables, contract negotiations, and contingency planning.

Combined, these exceedance-based plots complement Pareto-frontiers by embedding uncertainty directly into the time–cost tradeoff. They transform a point-estimate optimization into a spectrum of risk-controlled decisions.

Chapter 4

Results

4.1 Incremental discounts (Model 1)

4.1.1 No lead time constraints

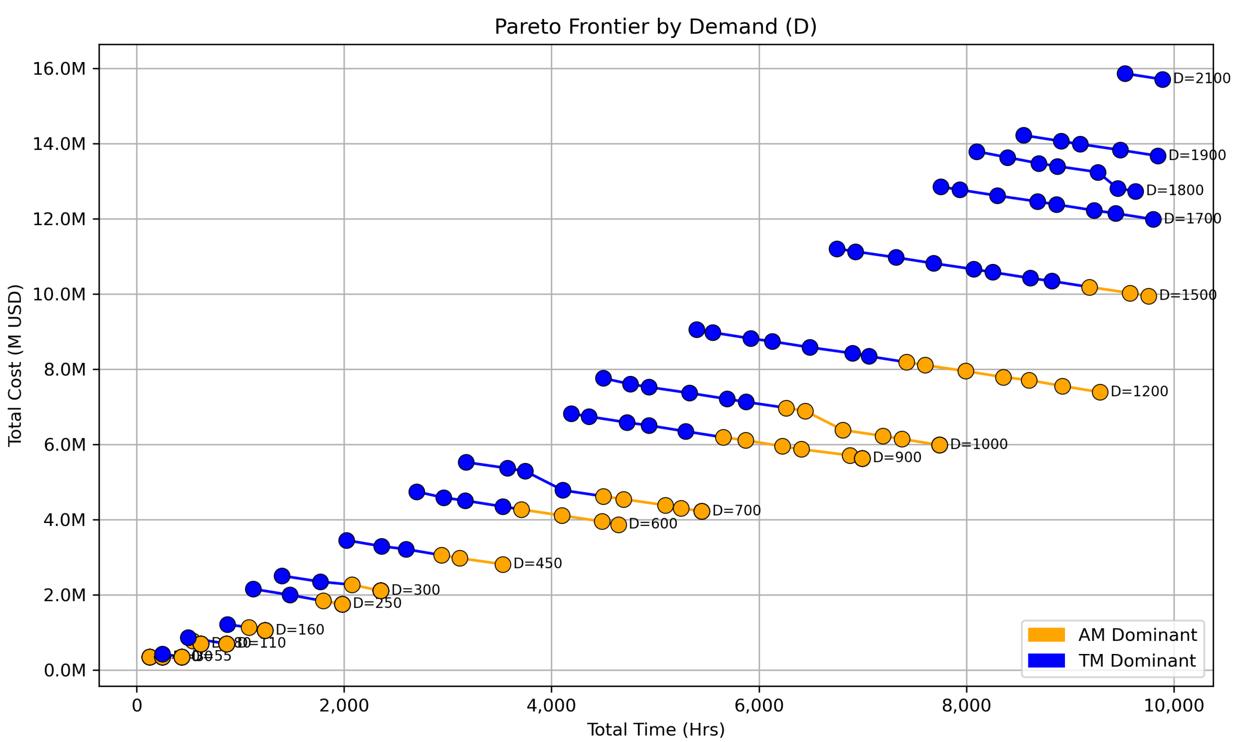

Figure 4.1: Pareto Incremental no lead time

Demand	AM Machines Req	TM Machines Req
10	1	0
30	1	0
55	1	1
80	2	1
110	2	1
160	3	1
250	5	1
300	6	1
450	8	1
600	10	2
700	10	3
900	12	5
1000	12	6
1200	12	10
1500	9	18
1700	7	24
1800	5	27
1900	4	30
2100	2	35

Table 4.1: Number of AM and TM machines required per demand level under incremental discounts model (rounded up to nearest integer)

Figure 4.1 shows, for each demand level D, the Pareto-optimal tradeoff between total makespan and total cost under our incremental discount AM model (no lead time). Points colored orange indicate solutions in which AM capacity supplies the majority of parts; blue points indicate TM dominance.

Table 4.1 translates those points into the actual number of AM and TM machines installed at each demand. A few clear patterns emerge:

- For very small orders ($D \leq 55$) a single AM machine is both fastest and cheapest.

- In the midrange ($80 \leq D \leq 600$), AM remains the cost leader: the model adds more AM units (and only one or two TM machines) to satisfy time/budget, leveraging deeper volume discounts.

- Beyond about $D = 700$, TM casting takes over: the number of TM units grows rapidly, AM count actually falls, and total cost increases more slowly with time,reflecting TM's superior throughput at high volumes.

In other words, incremental discounts make AM highly competitive up to roughly 600–700 parts; above that threshold, TM's raw speed is more valuable even at a higher cost per part.

Cost–Time Sensitivity

Examining the slopes of the Pareto curves across different D reveals how much extra budget is required to shave off additional hours. In the midrange, the curve is relatively flat: one can reduce makespan by several hundred hours with only modest cost increases. At the extremes (very low or very high D), the curve steepens sharply, indicating that further time savings become prohibitively expensive.
These insights give a concrete rule of thumb:

- *Small runs*: choose AM exclusively.

- *Moderate runs*: add AM until discounts taper, then supplement with a few TM units.

- *Large runs*: switch primarily to TM casting.

4.1.2 Incremental Discounts with Lead Time Constraints

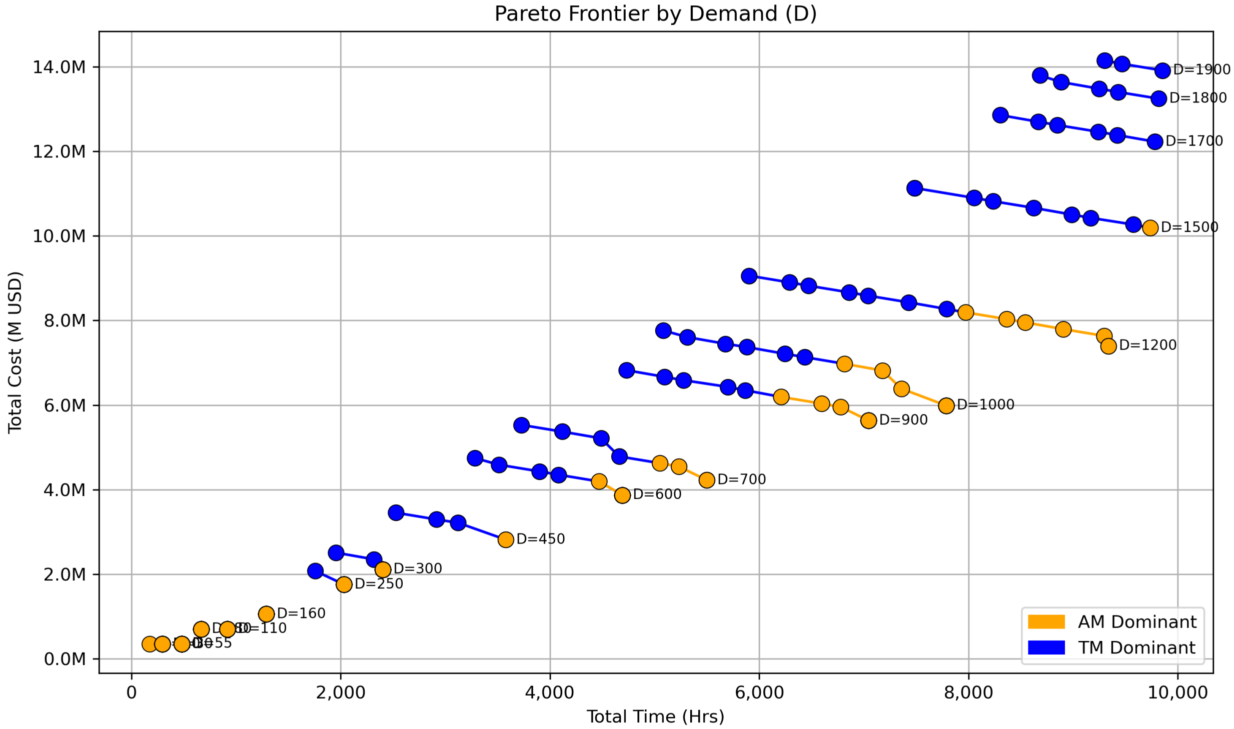

Figure 4.2: Pareto Incremental lead time

Demand	AM Machines Req	TM Machines Req
10	1	0
30	1	0
55	1	0
80	2	0
110	2	0
160	3	0
250	5	1
300	6	1
450	8	1
600	10	2
700	10	3
900	12	5
1000	12	6
1200	11	11
1500	7	20
1700	5	25
1800	4	29
1900	3	31

Table 4.2: Number of AM and TM machines required per demand level under incremental discounts model with lead time constraints

Figure 4.2 shows the Pareto frontier for each demand level under the incremental-discounts model once we impose lead-time constraints. Recall that each AM machine incurs a lead-time of 48–72 hours, whereas TM_Casting incurs 504 hours. We absorb these into the total-time constraint via binary "used" variables, so that starting any machine adds its lead time to the makespan.

Key observations Imposing the lead-time constraint shifts the frontier upward and to the right compared to the no-lead-time case (Figure 4.1). In particular:

- At low demands (10–80 parts), TM remains unattractive: the long setup delay makes AM solutions strictly better in both cost and time.

- At moderate demands (160–600 parts), TM-dominant points still appear, but only at high makespan allowances. Under tighter deadlines, AM machines—despite higher per-part cost—are favored because they can begin production sooner.

- At high demands (900–2100 parts), TM dominates only when time budgets exceed roughly 5000 hours; otherwise, the lead-time overhead forces the model to install more AM capacity, raising cost but meeting deadlines.

Comparison to no lead time model: Compared with the model in Section 4.1.1, the lead-time version:

- *Reduces* the region where TM-dominant solutions are optimal, since TM's long startup delay erodes its cost advantage at tight deadlines.

- *Increases* AM machine counts at each demand level to compensate for lost productive hours during setup.

- *Raises* minimum achievable cost for given makespan: every curve in Figure 4.2 lies above its counterpart in Figure 4.1.

Together, these results highlight the critical role of lead time in technology selection: even if TM has lower per-part variable cost at large volumes, its slow startup can make AM the more practical choice under real-world scheduling constraints.

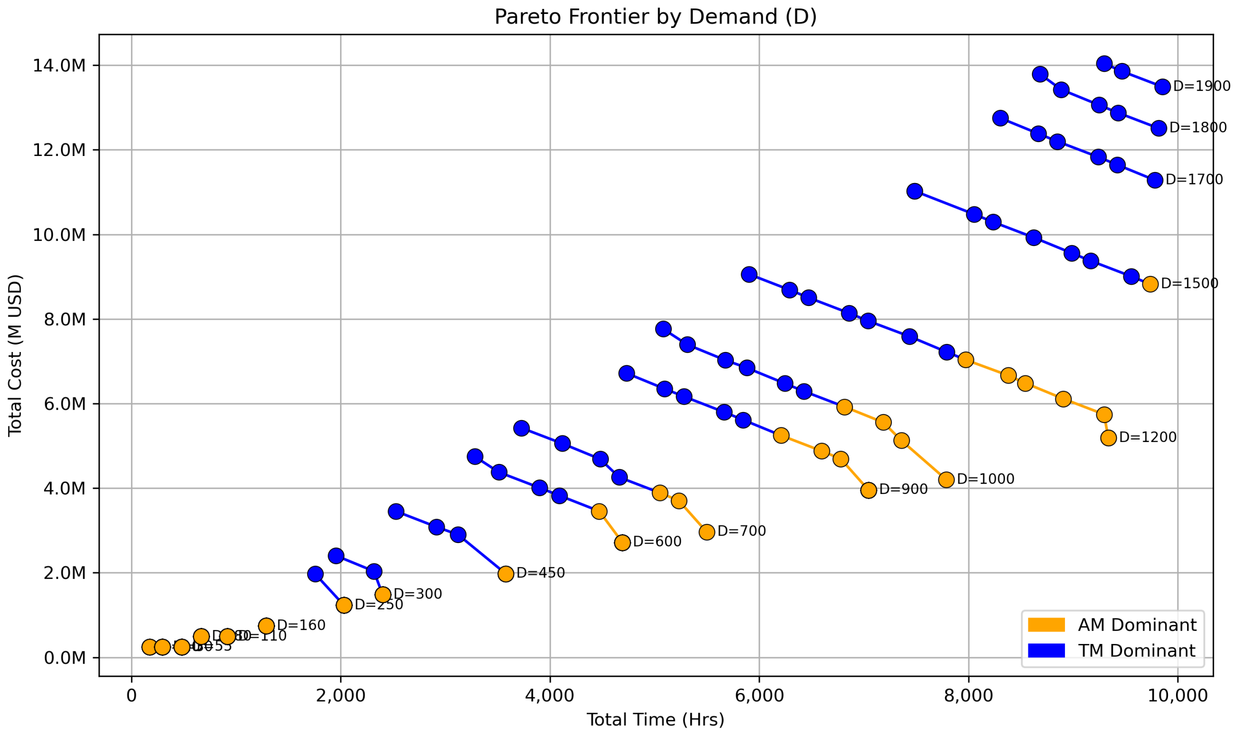

Figure 4.3: Pareto Incremental lead time reduced cost

Demand	**AM Machines Req**	**TM Machines Req**
10	1	0
30	1	0
55	1	0
80	2	0
110	2	0
160	3	0
250	5	1
300	6	1
450	8	1
600	10	2
700	10	3
900	12	5
1000	12	6
1200	11	11
1500	7	20
1700	5	25
1800	4	29
1900	3	31

Table 4.3: Number of AM and TM machines required per demand level under incremental discounts with 30% AM setup cost reduction (rounded up to nearest integer)

4.1.3 Effect of 30% Reduced AM Setup Cost

To evaluate the potential impact of future cost reductions in Additive Manufacturing (AM) technologies, we simulated the same optimization model under a 30% reduction in AM setup costs. Figure 4.3 and Table 4.3 present the updated Pareto frontier and machine requirements, respectively, and are compared directly to the baseline results in Figure 4.2 and Table 4.2.

Overall, the results between the baseline and the reduced setup cost scenarios are quite similar. Although some minor improvements in total cost are observed in certain medium demand levels (e.g., $D = 900$ and $D = 1000$), these shifts are not consistent or significant enough to suggest a strong competitiveness gain for AM. The number of AM and TM machines required remains the same across all demand levels, indicating that capacity and time constraints still dominate the decision making process and that the material or unit costs also have to be lower in the future for AM to gain more terrain against TM.

In summary, a 30% reduction in AM setup costs alone is not sufficient to drive a meaningful shift in technology dominance or cost-time efficiency. More substantial cost reductions or improvements in AM throughput would likely be necessary to make AM significantly more competitive, especially at higher demand levels.

4.2 Bulk Discounts (Model 2)

4.2.1 Bulk Discounts (No Lead Time Constraints)

Figure 4.4 and Table 4.4 show the results of the bulk discount model with no lead time constraints. Compared to the incremental discount version analyzed earlier (Figure 4.1, Table 4.1), the cost-time patterns and dominance behavior are quite similar overall. However, a few notable differences are worth pointing out:

- In both models, AM dominates for small to mid sized orders (up to about $D =$ 600–700), and TM takes over as demand grows. However, under bulk discounts, AM appears slightly *more persistent* in the $D =$ 900–1000 range. This is likely due to the flatter cost brackets, which allow AM to stay competitive for slightly longer.

- Machine usage patterns are nearly identical across demand levels. For example, both models allocate 12 AM machines and 6 TM machines at $D = 1000$, and ramp up TM capacity steeply from $D = 1200$ onward. This suggests that discount structure has a modest effect on dominance, but not on machine requirements.

- In the bulk discount model, the Pareto curves appear marginally smoother and more linear in the mid-to-high demand levels, reflecting the all-or-nothing pricing of bulk brackets compared to the stepwise accumulation in the incremental model.

In summary, both discounting mechanisms lead to the same high-level conclusion: Additive Manufacturing is cost-effective for small and medium production runs, while Traditional Manufacturing becomes more attractive for large scale orders. The choice of discount scheme (incremental vs. bulk) makes only a minor difference in terms of machine allocation and overall dominance behavior.

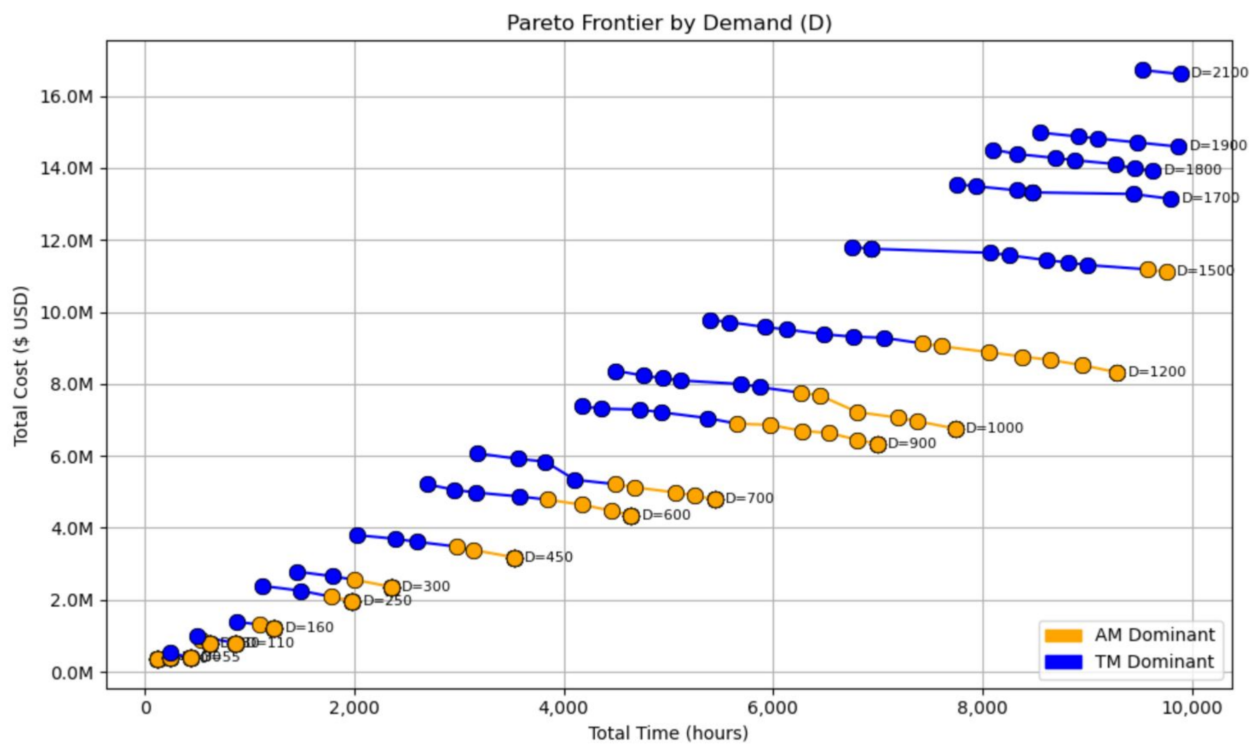

Figure 4.4: Pareto Bulk no lead time

Demand	**AM Machines Req**	**TM Machines Req**
10	1	0
30	1	0
55	1	1
80	2	1
110	2	1
160	3	1
250	5	1
300	6	1
450	8	1
600	10	2
700	10	3
900	12	5
1000	12	6
1200	12	10
1500	8	19
1700	6	25
1800	5	27
1900	4	30
2100	2	35

Table 4.4: Number of AM and TM machines required per demand level in the bulk discount model (no lead time constraints) (rounded up to nearest integer)

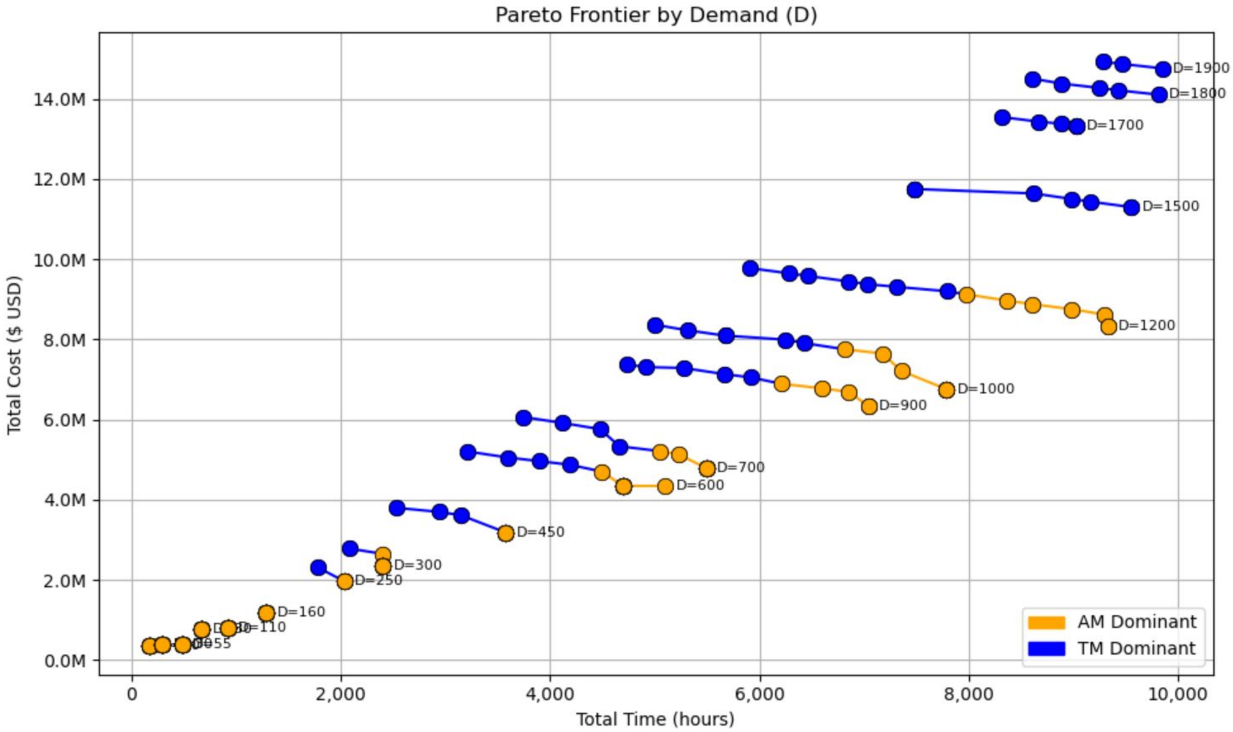

Figure 4.5: Pareto Bulk lead time

4.2.2 Bulk Discount Model with Lead Time Constraints

Demand	AM Machines Req	TM Machines Req
10	1	0
30	1	0
55	1	0
80	2	0
110	2	0
160	3	0
250	5	1
300	6	1
450	8	1
600	10	2
700	10	3
900	12	5
1000	12	6
1200	11	11
1500	6	20
1700	4	27
1800	4	29
1900	3	31

Table 4.5: Number of AM and TM machines required per demand level under bulk discounts with lead time constraints

Figure 4.5 and Table 4.5 show the results for the bulk discount model under lead time constraints. As in previous lead time scenarios, each machine adds a fixed setup delay to the total makespan 48–72 hours for AM machines and 504 hours for TM casting.

The lead time penalties have a clear effect on the frontier. Compared to the no lead time version, the cost-time tradeoffs shift upward and to the right, especially at higher demands. AM tends to dominate more frequently, particularly in the midrange ($D = 300$–900), where its shorter startup times allow it to meet tighter deadlines more effectively than TM.

At lower demands ($D \leq 110$), AM is still the obvious choice—it is both faster and cheaper. TM becomes competitive only at higher demand levels and looser time constraints. For instance, at $D = 1000$–1200, both technologies appear along the frontier depending on the time budget.

Overall, lead time constraints reduce the range where TM is optimal and increase the number of AM machines required. While the bulk discount structure helps TM catch up in cost at higher volumes, its long setup delay still makes AM more practical under tight scheduling scenarios.

4.2.3 Bulk Discount Model with Lead Time and Reduced AM Setup Cost

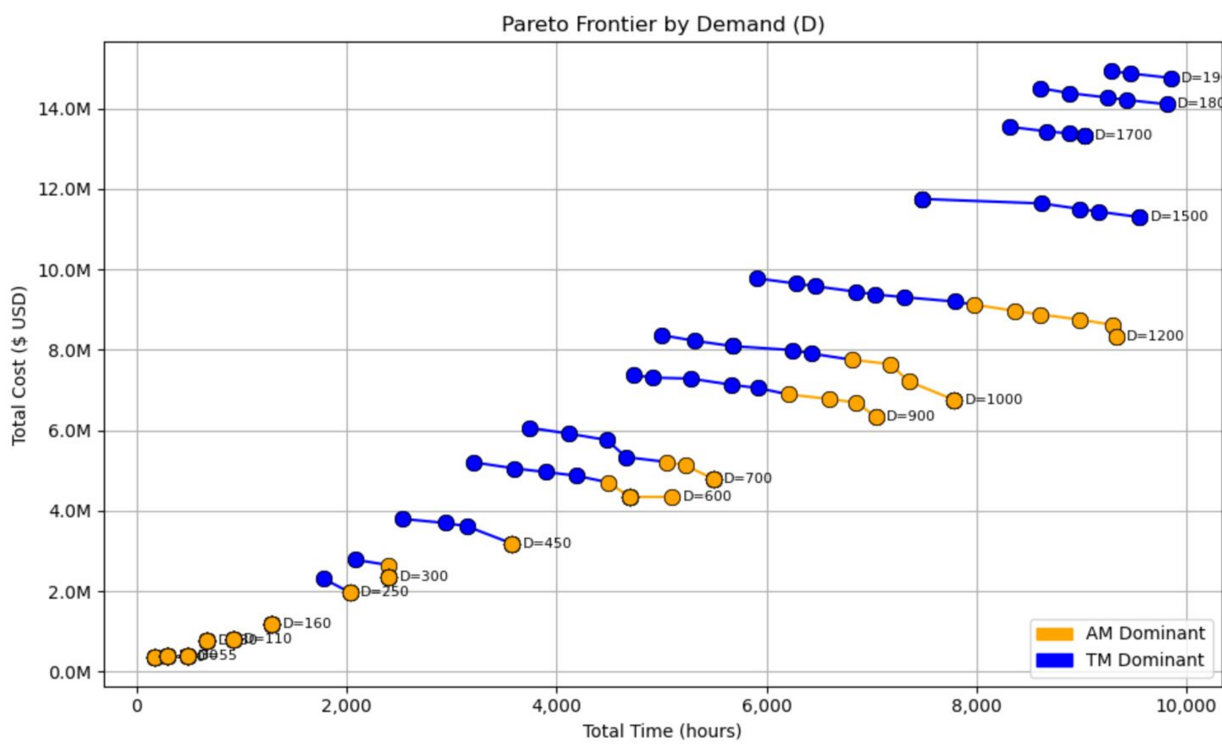

Figure 4.6: Pareto Bulk lead time reduced cost

Demand	AM Machines Req	TM Machines Req
10	1	0
30	1	0
55	1	0
80	2	0
110	2	0
160	3	0
250	5	1
300	6	1
450	8	1
600	10	2
700	10	3
900	12	5
1000	12	6
1200	11	11
1500	6	20
1700	4	27
1800	4	29
1900	3	31

Table 4.6: Number of AM and TM machines required per demand level under bulk discounts with 30% AM setup cost reduction (rounded up to nearest integer)

Figure 4.6 and Table 4.6 show the results of applying a 30% reduction in AM setup costs under the bulk discount model with lead time constraints.

The overall behavior remains consistent with the baseline bulk lead time model: AM dominates at low and moderate demands, while TM becomes necessary for higher volumes. However, with the reduced AM setup costs, we see a slight expansion of the AM dominant region—particularly around $D = 900$–1200. Costs along the frontier are modestly lower, and AM solutions appear more frequently under tighter time constraints.

Notably, this mirrors what was observed in the incremental discount model with reduced AM setup cost: the reduction improves AM's position in the midrange but does not fundamentally shift the overall balance. The number of AM and TM machines required also remains nearly identical, indicating that capacity constraints and lead times still drive machine allocation more than fixed setup costs alone.

In short, this confirms that reducing AM setup cost by 30% makes AM more competitive in specific scenarios, especially when time is limited and demand is moderate. But for large scale production, TM's throughput advantage continues to dominate.

4.3 Montecarlo Analysis Simulation

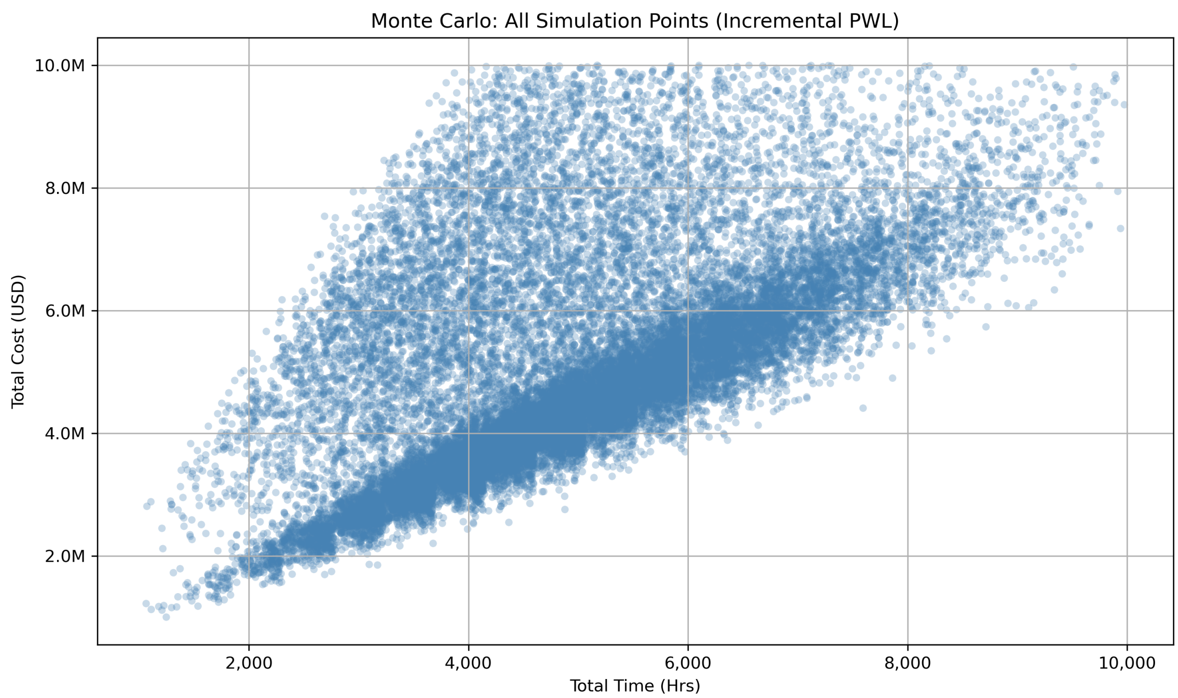

Figure 4.7: General Monte Carlo

Moreover, Figure 4.7 shows the result of a 40,000-sample Monte Carlo simulation on the incremental discount model, incorporating uncertainty in demand, time, setup cost, and unit cost rates. Each point represents one feasible simulation outcome—a unique combination of sampled inputs and resulting optimized total cost and time.

The cloud of points illustrates the broad range of outcomes that can arise when uncertainty is introduced into the system. A few key observations stand out:

- The density of points is highest in the midrange, between 3,000 and 7,000 hours and \$3M–\$7M, suggesting that under most sampled scenarios, the model tends to concentrate feasible solutions within that band.

- The lower boundary of the cloud exhibits a classic Pareto-like shape: as total time increases, total cost can be reduced,though with diminishing returns. This represents the best tradeoffs achievable under uncertainty.

- A wide spread is visible, particularly at high total times: some high cost solutions still exist even when time budgets are large. This likely reflects scenarios with high demand or unfavorable cost/time samples that force reliance on expensive capacity.

- While there is visible concentration in the midrange, the overall spread is wide, especially in cost, indicating that different combinations of demand, costs, and processing times can lead to highly variable outcomes. This highlights the importance of incorporating uncertainty into planning decisions rather than relying on deterministic averages.

4.4 Exceedance Curves

Figures 4.8 and 4.9 illustrate how cost overrun risk behaves under different time constraints, based on filtered Monte Carlo simulation data for demand around 1000 units.

Figure 4.8 shows how tighter time constraints (e.g., 4000–4500 hours) are associated with steeper and left shifted curves, meaning that the probability of exceeding a given cost threshold is significantly higher. In contrast, looser time budgets (e.g., 5500–6000 hours) provide more room for optimization, lowering the risk of costly outcomes. For instance, at a cost threshold of \$9M, the probability of exceeding budget drops from nearly 100% at 4000 hours to below 20% at 6000 hours.

Figure 4.9 flips the perspective: for each exceedance level (5%, 10%, etc.), it shows the minimum budget needed to stay within that risk, as a function of the available time. The

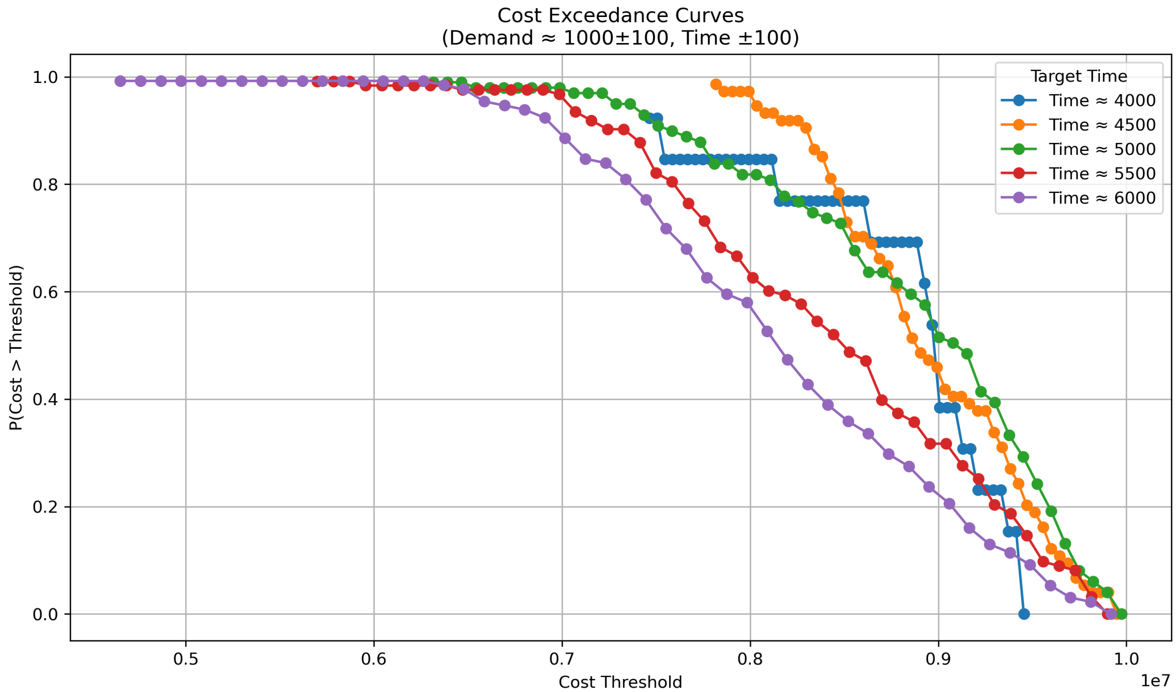

Figure 4.8: Probability of exceedance curves

curves decrease with increasing time, confirming that longer makespans reduce the cost required to meet reliability targets. The gap between curves also highlights how much extra budget is needed to reduce risk—for example, lowering risk from 25% to 5% may require an additional \$0.5–\$0.7M depending on the time constraint.

These curves make it clear that cost and time are tightly coupled under uncertainty. For planners with fixed deadlines, the plots provide a way to select budgets that match acceptable risk levels. Conversely, if budget is fixed, they help identify the minimum schedule buffer needed to avoid overruns with high confidence.

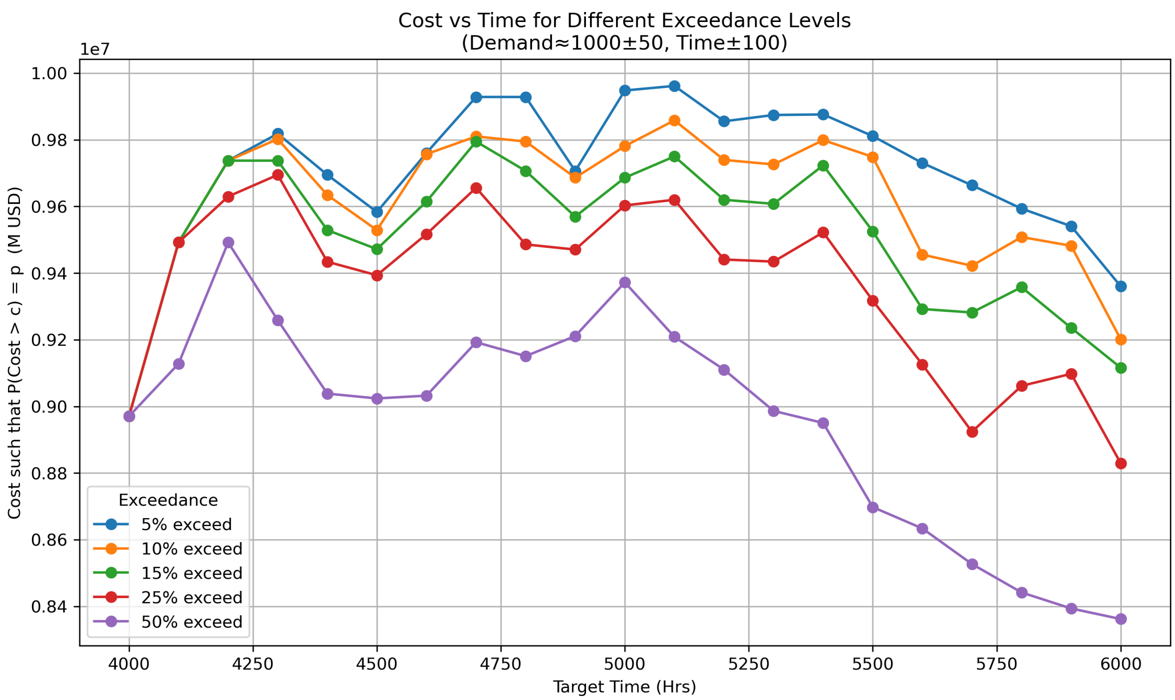

Figure 4.9: Probability of exceedance thresholds

Chapter 5

Discussion

The results of this study reveal clear patterns in how Additive Manufacturing (AM) and Traditional Manufacturing (TM) perform under varying demand levels, lead time constraints, and discount structures. Overall, AM proves highly competitive at low to moderate volumes due to its lower setup times and ability to respond quickly. For small production runs—especially below 600 to 700 parts—AM consistently offers both lower cost and faster makespan. TM becomes more favorable only as demand increases substantially, when its higher throughput starts to outweigh the long setup delays and higher upfront investment.

Introducing lead time constraints has a noticeable effect on the technology mix. Because TM requires significantly more time to start production, its viability drops sharply under tighter time budgets. In contrast, AM's shorter setup windows allow it to meet schedule requirements more easily, even when its per-unit costs are higher. As a result, the time constrained versions of both discount models show increased reliance on AM and reduced use of TM, especially in midrange demand scenarios. This underscores the importance of accounting for startup delays when planning production under strict deadlines.

Reducing AM setup costs by 30% leads to minor improvements in overall cost and slightly extends the range where AM dominates, particularly around 900–1200 units. However, the improvement is modest: the number of machines required remains unchanged, and the same general trends persist. This suggests that lowering fixed costs alone does not substantially shift the balance in favor of AM—more significant improvements in AM's speed, reliability, or per part costs may be necessary to make it a dominant option for larger runs.

Between the two pricing structures, incremental and bulk discounts yield broadly similar results. The point at which TM overtakes AM remains largely the same, and machine allocation patterns are nearly identical. However, the cost curves under bulk discounts tend to be slightly smoother and AM retains competitiveness for a bit longer in the transition zone. This indicates that while the discount structure affects marginal cost efficiency, it does not fundamentally change the technology selection decision or machine planning.

The Monte Carlo simulation reinforces the importance of incorporating uncertainty into production planning. Even modest variability in demand, costs, or processing times can lead to large differences in total cost and time outcomes. The wide spread in the simulation cloud makes it clear that deterministic solutions may significantly underestimate risk. Exceedance curves provide a useful way to visualize this: tighter deadlines result in much higher chances of going over budget, while increasing the time budget reduces that risk. Similarly, for a fixed risk tolerance, the curves show how much budget is needed to meet reliability targets. This kind of probabilistic analysis enables planners to make informed tradeoffs between cost, time, and risk.

Altogether, this study demonstrates that neither AM nor TM is universally superior. Each has strengths depending on the context, AM is agile and well suited for smaller or time sensitive jobs, while TM excels at scale. When real world uncertainties and constraints are accounted for, a hybrid strategy that adapts to demand and lead time requirements often proves to be the most effective approach.

Despite the insights gained, this study has several limitations. First, the simulation assumes that demand and other input parameters follow known distributions, which may not fully capture the complexity or unpredictability of real world conditions, especially in volatile markets like aerospace spare parts. Second, while the optimization considers time and cost tradeoffs, it does not explicitly model other operational concerns like quality, material constraints, or workforce availability.

Additionally, this study does not include post-processing steps required for AM parts, which can significantly impact both cost and production time. In the context of aerospace applications, where quality and safety standards are stringent, post-processing and certification processes can add considerable delays and costs that are not reflected in our current model.

Future work could incorporate these stages for a more complete picture of AM feasibility.

Chapter 6

Conclusion

This research investigated the tradeoffs between Additive Manufacturing (AM) and Traditional Manufacturing (TM) in aerospace production environments through a multi-objective optimization framework. By incorporating both cost and time objectives using the ε-constraint method, and combining this with Monte Carlo simulation and exceedance analysis, the study provides a comprehensive approach for informed manufacturing decision-making under uncertainty and scale effects.

The findings show that AM is the most advantageous choice for low to moderate production volumes, particularly under tight time constraints. Its low setup time and flexibility make it highly suitable for small-batch or urgent orders, where TM's long lead times would otherwise cause delays. In scenarios without time constraints, AM remains cost-effective up to approximately middle production volumes , after which TM casting begins to dominate due to its throughput and economies of scale.

Introducing lead time constraints reveals a substantial shift in technology preference. TM's setup delay often outweighs its cost advantage, pushing the optimizer to rely more heavily on AM to meet deadlines. This effect is most pronounced in midrange demand scenarios, where the ability of AM to start production faster proves critical. Even when a 30% reduction in AM setup cost is simulated, the impact on overall strategy is modest, demand level thresholds and machine allocations remain largely unchanged. This suggests that other factors, such as per-unit costs or improvements in AM throughput, would be needed to significantly change the balance.

Between the incremental and bulk discount models, technology preference and machine allocation remain consistent. The bulk discount model results in slightly smoother cost-time frontiers and marginally extends the competitiveness of AM in certain scenarios, but the general trends do not shift. This reinforces the idea that while cost structures influence efficiency, they do not drastically alter which technology is preferred.

Monte Carlo simulation highlights the importance of incorporating uncertainty into production planning. Even modest variations in demand, setup cost, or machine time can lead to wide differences in total cost and makespan. The resulting scatter of solutions underscores the risks of relying solely on deterministic models. To address this, exceedance curves were used to evaluate cost overrun probabilities under different time budgets. These curves provide practical tools for planners to align their budget and schedule decisions with acceptable levels of risk.

In summary, the study finds that neither AM nor TM is universally better. Instead, optimal decisions depend on demand size, time flexibility, cost structures, and risk tolerance. A hybrid strategy, leveraging AM for flexibility and TM for scale—often yields the best outcomes in real-world scenarios.

Nonetheless, the model has limitations. It assumes known distributions for uncertain inputs and omits several real-world constraints such as workforce availability, material shortages, and supply disruptions. Additionally, particularly for this application, the analysis excludes post-processing and certification steps required for aerospace-grade AM parts, which can significantly affect both cost and delivery times. These factors are particularly critical in regulated industries, where compliance and quality assurance can introduce major operational overhead. Future work should incorporate these considerations for a more complete and realistic representation of production environments.

Bibliography

[1] I. G. Ian Gibson, "Additive manufacturing technologies 3d printing, rapid prototyping, and direct digital manufacturing," 2015.

[2] J. M. Framinan, P. Perez-Gonzalez, and V. Fernandez-Viagas, "An overview on the use of operations research in additive manufacturing," *Annals of Operations Research*, vol. 322, no. 1, pp. 5–40, 2023.

[3] F. T. Altekin and Y. Bukchin, "A multi-objective optimization approach for exploring the cost and makespan trade-off in additive manufacturing," *European Journal of Operational Research*, vol. 301, no. 1, pp. 235–253, 2022.

[4] Y. Wang, R. Blache, and X. Xu, "Selection of additive manufacturing processes," *Rapid prototyping journal*, vol. 23, no. 2, pp. 434–447, 2017.

[5] M. Braglia, A. Petroni *et al.*, "A management-support technique for the selection of rapid prototyping technologies," *Journal of Industrial Technology*, vol. 15, no. 4, pp. 2–6, 1999.

[6] J. O. Wilson and D. Rosen, "Selection for rapid manufacturing under epistemic uncertainty," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, vol. 47411, 2005, pp. 451–460.

[7] H. Lan, Y. Ding, and J. Hong, "Decision support system for rapid prototyping process selection through integration of fuzzy synthetic evaluation and an expert system," *International Journal of Production Research*, vol. 43, no. 1, pp. 169–194, 2005.

[8] M. G. Fernandez, C. Conner Seepersad, D. W. Rosen, J. K. Allen, and F. Mistree, "Decision support in concurrent engineering—the utility-based selection decision support problem," *Concurrent Engineering Research and Applications*, vol. 13, no. 1, pp. 13–27, 2005.

[9] S. Raja, A. John Rajan, V. Praveen Kumar, N. Rajeswari, M. Girija, S. Modak, R. Vinod Kumar, and W. D. Mammo, "Selection of additive manufacturing machine using analytical hierarchy process," *Scientific Programming*, vol. 2022, no. 1, p. 1596590, 2022.

[10] Y. Qin, Q. Qi, P. Shi, S. Lou, P. J. Scott, and X. Jiang, "Multi-attribute decision-making methods in additive manufacturing: the state of the art," *Processes*, vol. 11, no. 2, p. 497, 2023.

[11] W. Tsutsui, Q. A. Shi, I. Walter, A. Wei, C. Williams, D. DeLaurentis, and J. Panchal, "Decision making for additive manufacturing in sustainable defense acquisition," *Naval Engineers Journal*, vol. 135, no. 4, pp. 47–58, 2023.

[12] Q. Shi, W. Tsutsui, D. Bekdache, J. H. Panchal, and D. DeLaurentis, "A system-of-systems (sos) perspective on additive manufacturing decisions for space applications," in *2022 17th Annual System of Systems Engineering Conference (SOSE)*. IEEE, 2022, pp. 282–288.

[13] Q. Shi, W. Tsutsui, I. Walter, J. Panchal, and D. DeLaurentis, "A decision support framework for additive manufacturing of space satellite systems," in *2023 IEEE Aerospace Conference*. IEEE, 2023, pp. 1–15.

[14] A. Cantini, M. Peron, F. De Carlo, and F. Sgarbossa, "A decision support system for configuring spare parts supply chains considering different manufacturing technologies," *International Journal of Production Research*, vol. 62, no. 8, pp. 3023–3043, 2024.

[15] K. Meng, P. Lou, X. Peng, and V. Prybutok, "Multi-objective optimization decision-making of quality dependent product recovery for sustainability," *International Journal of Production Economics*, vol. 188, pp. 72–85, 2017.

[16] F. Sgarbossa, M. Peron, F. Lolli, and E. Balugani, “Conventional or additive manufacturing for spare parts management: An extensive comparison for poisson demand,” *International Journal of Production Economics*, vol. 233, p. 107993, 2021.

[17] W. Hughes, W. Zhang, and Z. Ding, “Multiobjective optimization for hurricane retrofit to improve coastal community structural and socioeconomic resilience,” *Natural Hazards Review*, vol. 23, no. 4, p. 04022033, 2022.

[18] J. Lin, C. Yu, and J. Lu, “A bi-objective optimization method to minimize the makespan and energy consumption on parallel slm machines,” in *2023 IEEE 19th International Conference on Automation Science and Engineering (CASE)*. IEEE, 2023, pp. 1–6.

[19] Q. Li, I. Kucukkoc, and D. Z. Zhang, “Production planning in additive manufacturing and 3d printing,” *Computers & Operations Research*, vol. 83, pp. 157–172, 2017.

[20] K. Ransikarbum, S. Ha, J. Ma, and N. Kim, “Multi-objective optimization analysis for part-to-printer assignment in a network of 3d fused deposition modeling,” *Journal of Manufacturing Systems*, vol. 43, pp. 35–46, 2017.

[21] P. Khamhong, C. Yingviwatanapong, and K. Ransikarbum, “Fuzzy analytic hierarchy process (ahp)-based criteria analysis for 3d printer selection in additive manufacturing,” in *2019 Research, Invention, and Innovation Congress (RI2C)*. IEEE, 2019, pp. 1–5.

[22] K. Ransikarbum, R. Pitakaso, and N. Kim, “A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi-objective optimization,” *Applied Sciences*, vol. 10, no. 15, p. 5159, 2020.

[23] K. Ransikarbum and P. Khamhong, “Integrated fuzzy analytic hierarchy process and technique for order of preference by similarity to ideal solution for additive manufacturing printer selection,” *Journal of Materials Engineering and Performance*, vol. 30, no. 9, pp. 6481–6492, 2021.

[24] K. Ransikarbum, R. Pitakaso, N. Kim, and J. Ma, “Multicriteria decision analysis framework for part orientation analysis in additive manufacturing,” *Journal of Computational Design and Engineering*, vol. 8, no. 4, pp. 1141–1157, 2021.

[25] P. Gradl, D. C. Tinker, A. Park, O. R. Mireles, M. Garcia, R. Wilkerson, and C. Mckinney, "Robust metal additive manufacturing process selection and development for aerospace components," *Journal of Materials Engineering and Performance*, vol. 31, no. 8, pp. 6013–6044, 2022.

[26] J. Koller, R. Häfner, and F. Döpper, "Decentralized spare parts production for the aftermarket using additive manufacturing-a literature review," *Procedia CIRP*, vol. 107, pp. 894–901, 2022.

[27] S. H. Khajavi, J. Partanen, and J. Holmström, "Additive manufacturing in the spare parts supply chain," *Computers in industry*, vol. 65, no. 1, pp. 50–63, 2014.

[28] J. J. Heinen and K. Hoberg, "Assessing the potential of additive manufacturing for the provision of spare parts," *Journal of Operations Management*, vol. 65, no. 8, pp. 810–826, 2019.

[29] Y. Li, G. Jia, Y. Cheng, and Y. Hu, "Additive manufacturing technology in spare parts supply chain: a comparative study," *International Journal of Production Research*, vol. 55, no. 5, pp. 1498–1515, 2017.

[30] Y. Li, Y. Cheng, Q. Hu, S. Zhou, L. Ma, and M. K. Lim, "The influence of additive manufacturing on the configuration of make-to-order spare parts supply chain under heterogeneous demand," *International journal of production research*, vol. 57, no. 11, pp. 3622–3641, 2019.

[31] A. Ghadge, G. Karantoni, A. Chaudhuri, and A. Srinivasan, "Impact of additive manufacturing on aircraft supply chain performance: A system dynamics approach," *Journal of Manufacturing Technology Management*, vol. 29, no. 5, pp. 846–865, 2018.

[32] P. Liu, S. H. Huang, A. Mokasdar, H. Zhou, and L. Hou, "The impact of additive manufacturing in the aircraft spare parts supply chain: supply chain operation reference (scor) model based analysis," *Production planning & control*, vol. 25, no. 13-14, pp. 1169–1181, 2014.

[33] S. C. Tsai and S. T. Chen, "A simulation-based multi-objective optimization framework: A case study on inventory management," *Omega*, vol. 70, pp. 148–159, 2017.

[34] M. Fera, F. Fruggiero, A. Lambiase, R. Macchiaroli, V. Todisco *et al.*, "A modified genetic algorithm for time and cost optimization of an additive manufacturing single-machine scheduling," *International Journal of Industrial Engineering Computations*, vol. 9, no. 4, pp. 423–438, 2018.

[35] J. T. Margolis, K. M. Sullivan, S. J. Mason, and M. Magagnotti, "A multi-objective optimization model for designing resilient supply chain networks," *International Journal of Production Economics*, vol. 204, pp. 174–185, 2018.

[36] L. Canales-Bustos, E. Santibañez-González, and A. Candia-Véjar, "A multi-objective optimization model for the design of an effective decarbonized supply chain in mining," *International Journal of Production Economics*, vol. 193, pp. 449–464, 2017.

[37] N. Mindt, A. Der, M. Wiese, M. Mennenga, and C. Herrmann, "Multi-level framework for the assessment of additive manufacturing for spare parts supply," *Procedia CIRP*, vol. 105, pp. 416–421, 2022.

[38] J. Minguella Canela and I. Buj Corral, *Decision support models for the selection of production strategies in the paradigm of digital manufacturing, based on technologies, costs and productivity levels.* IntechOpen, 2019.

[39] Lyafs (3DPTEK), "Metal 3d printer price," https://www.lyafs.com/metal-3d-printer-price, 2025, accessed July 1, 2025.

[40] Jiangmen Zhenli Machinery Co., Ltd, "ZLC-1300T 1300t cold-chamber investment die-casting machine," https://jmzhenli.en.made-in-china.com/product/awhGeqoDAiRX/China-1300t-Cold-Chamber-Investment-Die-Casting-Machine-Price.html, 2025, accessed July 1, 2025.

[41] A. A. Syntetos, M. Z. Babai, and N. Altay, "On the demand distributions of spare parts," *International Journal of Production Research*, vol. 50, no. 8, pp. 2101–2117, 2012.