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Service provider recommendation system in shared additive manufacturing: a case study on assistive technology platform in South Korea

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Abstract

In shared manufacturing platforms, self-organized individuals can actively participate as service providers, offering manufacturing capabilities to meet unique customer demands. When combined with additive manufacturing (AM) technologies, shared manufacturing presents substantial potential for delivering customized, one-of-a-kind products to customers with reduced barriers to access. Despite this promise, research specifically addressing shared AM environments and the unique needs of customers within them remains limited. Addressing this gap, this study develops a service provider recommendation framework tailored for shared AM contexts, aligning customer preferences with service provider capabilities. The framework includes a production scheduling model for AM that estimates cost and production completion time, integrating providers' operational constraints, machine attributes, and pricing structures. To examine the applicability of the proposed model, we applied it to benchmark data, demonstrating how the scheduling outcomes produce more practical and implementable solutions compared to idealized models. Applied to an open-source assistive technology (AT) platform in South Korea, the framework demonstrates how shared AM can better accommodate individualized customer needs in a user-centered manner. Additionally, by analyzing scheduling outcomes under different conditions, this study provides managerial insights for AM service providers, helping to improve decision-making, resource allocation, and operational efficiency in shared AM environments.

Keywords: shared manufacturing, service provider recommendation, production planning, additive manufacturing, assistive technology

1. Introduction

Shared manufacturing, a concept rooted in the sharing economy (Kumar, Lahiri, and Dogan 2018), enables individuals and businesses to access manufacturing resources through peer-to-peer (P2P) models (Yu et al. 2020b). By integrating shared production capabilities into decentralized networks, it enhances resource efficiency and promotes collaborative production, representing a shift from traditional, centralized manufacturing toward more flexible, customer-driven models.

The evolution of shared manufacturing can be traced to enterprise-driven resource sharing, where companies utilize production resources from their other facilities or external

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companies to improve efficiency (Becker and Stern 2016; Kusiak 2022). Over time, digitalization and smart manufacturing technologies—such as cloud manufacturing and digital twin—have expanded this concept. Cloud manufacturing enables companies to access distributed manufacturing capabilities through cloud computing (Wang et al. 2018; Simeone et al. 2019; Cao et al. 2023), while digital twins create virtual models of production systems for optimization before physical implementation (Wang et al. 2021; Leng et al. 2021).

Simultaneously, the demand for personalized products has surged. Consumers have transitioned from passive buyers to active participants, increasingly seeking goods tailored to their specific needs (Hu 2013; Jiang et al. 2016; Kim and Lee 2023). They are becoming more accustomed to specifying requirements, designing products, and exploring ways to produce customized items (Fan and Poole 2006). This shift, driven by economic, technological, and societal changes in consumer demand, has accelerated interest in shared manufacturing (Yu et al. 2020b).

Within this context, additive manufacturing (AM) can play a key role in lowering entry barriers and expanding accessibility, especially allowing small-scale users to engage without requiring extensive infrastructure or expertise. AM, commonly known as 3D printing, fabricates objects layer by layer directly from digital models (ASTM 2015), simplifying production process compared to subtractive methods (Cuellar et al. 2018). Its efficiency for small-batch production (Manogharan, Wysk, and Harrysson 2016; Lutter-Günther et al. 2015) aligns with the increasing demand for customization (Son, Kim, and Jeong 2021). AM also removes the need for large industrial infrastructure, allowing individuals and small businesses to manufacture customized items independently (Yoo, Ko, and Chun 2016). As such, AM enables mass customization, empowering consumers to actively participate in both the design and production (Kim and Lee 2023).

Despite its potential, research on shared AM remains scarce. Most studies focus heavily on platform design or technology, often overlooking the other two key stakeholders: customers and service providers. Even among the few studies on shared AM (Yang, Chen, and Kumara 2021; Lupi et al. 2023), customer behavior and provider-side operational issues are largely underexplored. This limits the ability of shared AM systems in meeting user needs—an essential factor for platform success.

To fill this gap, this study takes a user-centric view, identifying key factors influencing customer decisions when selecting AM service providers. It also incorporates AM service providers' side constraints by integrating practical management policies and pricing structures into the scheduling model. By reflecting real-world constraints, the model enhances its applicability, allowing service providers to generate feasible and implementable production schedules. Bridging both perspectives, this study enhances the adaptability of shared AM platforms, contributing to improved customer satisfaction and service provider operational efficiency.

This paper proceeds as follows: Section 2 reviews literature on shared manufacturing and AM production scheduling. Section 3 introduces the research framework, detailing the shared AM model and the service provider recommendation framework. Section 4 presents a multi-objective production scheduling model for AM to estimate costs and production completion time. Section 5 describes a basic application to benchmark data and a case-based experiment on an assistive technology platform in South Korea, analyzing scheduling outcomes under different conditions. Section 6 concludes with managerial insights, research contributions, and future directions.

2. Literature review

2.1. Shared manufacturing

The concept of shared manufacturing originates from the need to utilize manufacturing resources more efficiently. Early research focused on resource sharing within manufacturing systems of a company (Aissani, Trentesaux, and Beldjilali 2009; Kondoh and Salmi 2011), later expanding to encompass resource sharing among different companies (Adhau, Mittal, and Mittal 2013; Hsu et al. 2016; Li et al. 2018).

As technology advanced within the sharing economy, the concept of shared manufacturing evolved to allow anyone to participate as either a customer or a service provider. Yu et al. (2020a) categorized sharing levels into Product-Service System, Configuration-Service System, and Resource-Service System. At its highest level, shared manufacturing enables P2P access to services, with participants acting as ‘prosumers’ who are both producers and consumers within interconnected physical and digital systems.

Following this, technical developments for shared manufacturing have addressed security and trust issues inherent in P2P resource sharing. Yu et al. (2020b) proposed a Blockchain-based Shared Manufacturing framework with a Resource Operation Blockchain (ROB) and Smart Contract Network (SCN). Using a Proof-of-Participation mechanism, this framework improves security and operational efficiency. Wang et al. (2021) further applied digital twin technology to support sustainable resources allocation, promoting stable operations by maintaining provider anonymity and assessing credibility.

Other studies explored managerial and operational aspects. Li et al. (2023) used game models to analyze suppliers’ decisions between selling and sharing manufacturing capacity through third-party platforms. They found that high production or maintenance costs favor sharing and that suppliers simultaneously sell equipment and share capacity only when rental efficiency and costs are extreme. Wei and Wu (2022) addressed the two-machine hybrid flow-shop problem, developing dynamic programming algorithms to minimize makespan and total weighted completion time in a shared manufacturing environment. They classified the problem as NP-hard and provided comparative experiments with other algorithms.

While shared manufacturing has been explored in various contexts, few studies have integrated AM technologies into this concept. Lupi, et al (2023), pioneered the term 'shared AM' and developed a Business Process Model and Notation (BPMN) diagram, along with a Blockchain-based Shared Additive Manufacturing (BBSAM) protocol. Leveraging smart contracts and blockchain, the protocol enables decentralized and transparent AM supply chains. Their study also conducted a simulation using Italian AM market data to validate the BBSAM's performance.

2.2. Production planning and scheduling in additive manufacturing

Production planning and scheduling in AM often involves fabricating heterogeneous parts using both identical and non-identical AM machines. It presents unique challenges rarely encountered in traditional manufacturing, including diverse options and alternatives enabled by AM's flexibility (Fogliatto, Silveira, and Borenstein 2012). In this setting, studies on production planning and scheduling in AM address operational issues related to job allocation to machines, sequencing of jobs, and nesting parts within builds.

Li, Kucukkoc, and Zhang (2017) conducted one of the earliest studies in this field, developing a mathematical model that assigns parts to jobs and allocates these jobs to AM machines, minimizing average production cost per material volume. Their model accounts for heterogeneity in AM machines and parts and includes two heuristic methods. While pioneering, it primarily addresses fundamental aspects, laying the groundwork for future studies.

Subsequent research has explored single AM machine scenarios to investigate AM's unique complexities in more detail. Fera et al. (2018) introduced a modified genetic algorithm for optimizing time and cost in single-machine AM scheduling, particularly for Direct Metal Laser Sintering, where diverse geometries are managed simultaneously. Similarly, Arık (2022) examined scheduling issues related to part assembly operations, proposing a mixed-integer programming model and a heuristic to optimize batch scheduling on a single AM machine, considering machine tray constraints.

Meanwhile, other researchers have investigated scenarios involving multiple AM machines. For identical machines, Chergui, Hadj-Hamou, and Vignat (2018) focus on the planning, nesting, and scheduling to meet order due dates, developing a mathematical model and heuristic approach to solve the problem. Similarly, Kucukkoc (2019) developed mixed-integer linear programming models to minimize the makespan—the total time required to complete all scheduled jobs—by optimizing part allocation across parallel identical machines.

For non-identical AM machines, the focus shifts towards accommodating diverse capabilities such as speeds, output quality, and material handling properties. Altekin and Bukchin (2022) tackled the operational planning challenges of heterogeneous AM systems by proposing a multi-objective optimization framework to balance cost and production time, considering the unique attributes of each machine in the network. Lu, Hu, and Ng (2023) introduced a sub-second pixel-based packing algorithm for unrelated machines, enhancing efficiency by minimizing makespan and improving machine capacity utilization through precise part layout in AM processes.

Complementing these approaches, Antón et al. (2023) highlight the lack of a standardized approach for tackling the distinct production planning challenges posed by AM. To address this, they developed a comprehensive framework that integrates key operational elements of AM production planning, such as part placement, machine scheduling, and cost-time trade-offs. This framework formalizes AM-specific issues and offers a versatile foundation adaptable to various manufacturing scenarios.

Table 1 summarizes the key studies, comparing their objectives, machine configurations, and additional considerations. Compared to prior work, this study incorporates operational constraints and multi-material considerations while jointly optimizing production cost and completion time.

Table 1. Overview of relevant literature

Reference	Objective	Machines	Other considerations
Li, Kucukkoc, and Zhang (2017)	Min. production cost	Multiple non-identical machines	-
Fera et al. (2018)	Min. lateness & cost	Single machine	-
Arık (2022)	Min. makespan	Single machine	-
Chergui, Hadj-Hamou, and Vignat (2018)	Min. tardiness	Multiple identical machines	Bin packing
Kucukkoc (2019)	Min. makespan	Multiple identical machines	-
Altekin and Bukchin (2022)	Min. makespan & cost	Multiple non-identical machines	-
Lu, Hu, and Ng (2023)	Min. makespan	Multiple non-identical machines	Bin packing
The current paper	Min. cost & production completion time	Multiple non-identical machines	Operational constraints, multi-material

2.3. Research gaps

While shared manufacturing and AM-based production planning have been widely studied, important gaps still remain. This section identifies key limitations in existing literature and highlights areas for further exploration.

First, in shared manufacturing, significant gaps remain in applying AM technologies. AM technologies are highly accessible, requiring only design files and basic operational knowledge, which lowers entry barriers and encourages broader customer engagement. This accessibility makes it worthwhile to investigate how shared AM environments affect participants' decision-making and operational processes.

Additionally, most existing studies focus on the roles and strategies of service enablers who design and manage platforms, with limited attention to the customer perspective—particularly the factors influencing their choice of resources or service providers. This study addresses this gap by exploring customer preferences and decision-making when selecting AM service providers, aiming to enhance the user-centered focus of shared manufacturing platforms.

Second, AM production planning and scheduling research has largely focused on optimizing machine utilization, often overlooking real-world operational challenges encountered by managers and enterprises. For instance, most studies overlook downtimes due to maintenance or non-working hours typical in facilities such as 3D printing centers. These practical constraints significantly affect planning and scheduling, as AM equipment may not be continuously available—especially on weekends or during planned shutdowns.

Another significant gap is the limited integration of customer perspectives into AM production planning. Most existing studies emphasize production efficiency, often neglecting the impact of customer needs and service provider policies on production outcomes. This oversight is especially critical in service-oriented sectors, where customer satisfaction relies heavily on factors such as cost, lead time, and product quality. Our study addresses this gap by incorporating service providers' operational policies and pricing strategies into the scheduling model. This approach not only considers practical constraints, such as operational hours and production capacities, but also enhances the model's relevance by aligning it with customer preferences and leveraging AM's inherent flexibility.

3. Research framework

This section presents the overall structure of shared AM platform and the decision-making framework for service provider recommendations. Section 3.1 outlines the key characteristics of shared AM, distinguishing it from general shared manufacturing platforms and emphasizing differences in decision-making dynamics. Section 3.2 introduces a recommendation framework that supports customer decisions by optimizing service provider selection based on individual preferences.

3.1. Shared additive manufacturing

Shared AM is a type of sharing economy that adopts the triadic structure typical of sharing economy platforms (Kumar, Lahiri, and Dogan 2018). It involves three main actors: AM service providers, customers, and the service enabler (platform), each with a distinct role.

First, AM service providers are entities equipped with AM technologies and willing to offer manufacturing services through the platform. These providers may be individuals, companies, institutions, or schools that engage in AM services either as a primary business or as a supplementary source of income, such as through low-paying or part-time jobs (Kumar, Lahiri, and Dogan 2018). Whether operating full-time or part-time, their primary motivation is to maximize the utilization of their AM equipment to generate profit. To achieve this, they must share comprehensive information about their resources, pricing structures, operational policies, and workforce to ensure transparency.

Customers, another key actor in shared AM, are individuals or entities that seek customized manufacturing solution. Through the shared AM platform, they can access AM capabilities without investing in large-scale production facilities. Since traditional methods are typically cost-effective only at scale, AM offers a more efficient alternative for personalized or small-batch production (Fogliatto, Silveira, and Borenstein 2012; Son, Kim, and Jeong 2021). To effectively utilize the platform, customers must provide detailed design and manufacturing specifications compatible with AM machines.

Lastly, the platform itself serves as the service enabler, connecting customers seeking access to underutilized AM machines to the AM service providers (Kumar, Lahiri, and Dogan 2018). The platform keeps comprehensive information on all AM service providers, including basic details such as name, location, operating hours, available AM machines and other manufacturing equipment, and workforce. Additionally, in advanced systems, the platform may also track the real-time status of AM machines, monitoring expected job completion times to enhance operational efficiency (Yu, et al. 2020b). By coordinating these elements, the platform optimizes resource utilization and facilitates smooth interactions between providers and customers.

Table 2. Comparison of shared manufacturing and shared AM

	Shared manufacturing	Shared AM
Actors	Service provider, customer, service enabler	AM service provider, customer, service enabler
Technical barriers	Higher	Lower
Production process complexity	Suitable for complex production involving specialized industrial manufacturing processes	More adaptable for flexible and small-scale production
Service providers	Primarily professionals or companies with specialized manufacturing equipment	Wide range of participants, including companies, institutions, and individuals
Customers	Passive; reliant on service enabler for production coordination	Active; autonomous in selecting providers and managing orders
Service enabler	Active coordination of production tasks	Primarily acts as a facilitator, providing information and recommendations
Decision-making process	Centralized – managed by the service enabler	Decentralized – customers have more control over provider selection

Although shared manufacturing and shared AM both have three main actors, their roles and decision-making processes differ significantly due to AM's low technical barriers (Table 2).

Shared manufacturing platforms typically involve higher technical complexity, and are suited for orders requiring specialized expertise and multi-step workflows. These platforms accommodate conventional manufacturing processes and large-scale production, often demanding careful coordination. To manage this, the service enabler plays an active role, leveraging expertise to decompose customer orders into tasks and assign them to suitable resources (Wang et al. 2021). This approach optimizes workflow efficiency and reduces the burden on customers, as shown in Figure 1(a).

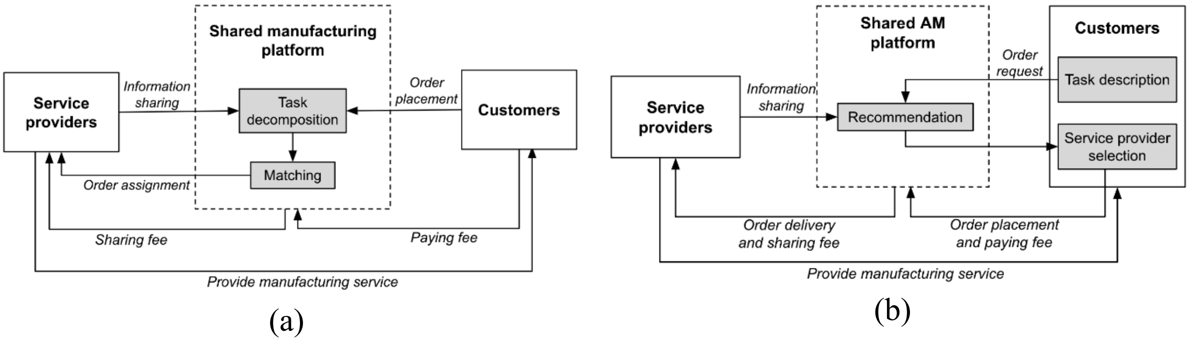

Figure 1. Frameworks for (a) shared manufacturing and (b) shared additive manufacturing platforms.

In contrast, shared AM platforms operate more decentrally, with the service enabler acting as a facilitator, while customers actively participate in decision-making. AM technologies offer greater accessibility and lower technical barriers, enabling customers to independently design and manufacture products (Pearce et al. 2010; Yoo, Ko, and Chun 2016; Jiménez et al. 2019). This makes shared AM ideal for small-scale, customized production, where customers can assess potential service providers based on factors such as service quality and price (Hamenda 2018), and reputation (Truong, Ackermann, and Klink 2021).

Instead of managing production, the shared AM service enabler primarily provides information and connectivity, as illustrated in Figure 1(b). However, the abundance of provider options can overwhelm customers. To support their decision-making, the service enabler may offer a recommendation module that suggests suitable service providers based on their preferences, thereby improving customer experience within the platforms.

3.2. AM service provider recommendation framework

The AM service provider recommendation framework, shown in Figure 2, operates in two phases. In Phase 1, the production scheduling model estimates the total cost and completion time for each candidate provider based on order details (e.g., product design, materials, manufacturing conditions) and AM service provider-specific information (e.g., machine types, availability, business hours, pricing). The model optimizes two objectives—minimizing total cost and production completion time—using weighted factors. Its primary purpose is not to derive an optimal production schedule but to provide customers with estimated cost and completion time per provider. Thus, the outputs are the two objective values.

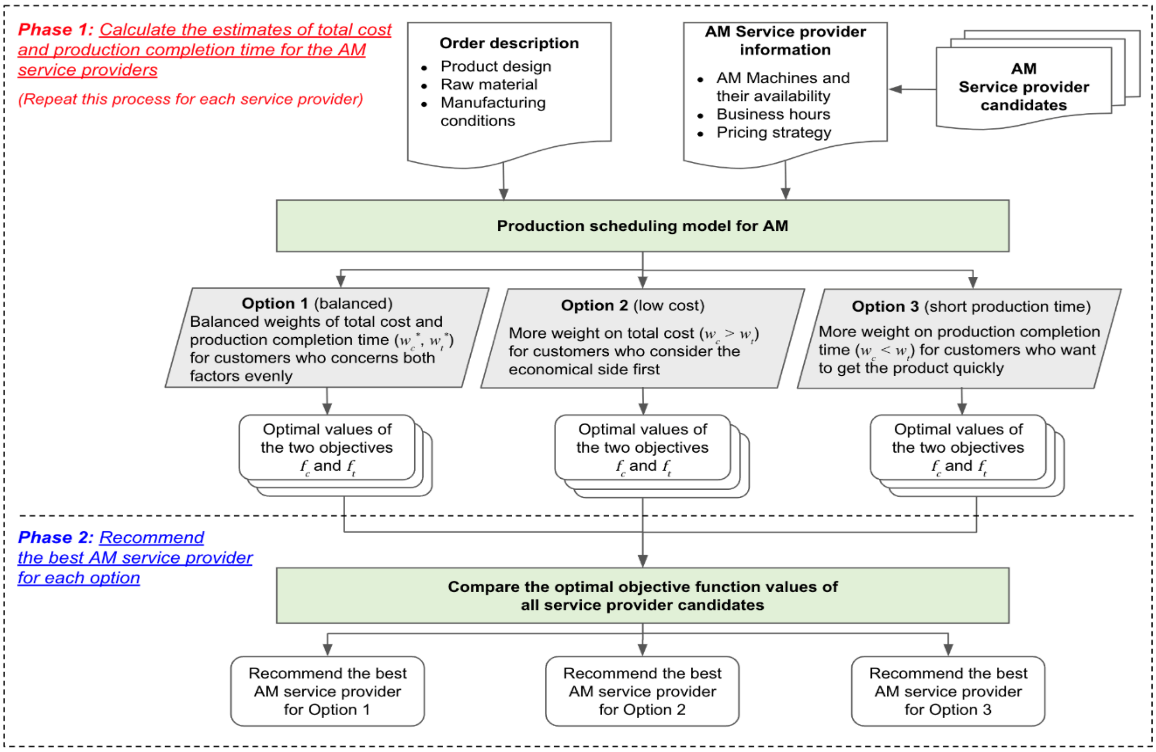

Figure 2. AM service provider recommendation framework

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A key feature of Phase 1 is the incorporation of customer preferences, reflected in three options that assign different weight to cost and time according to the customer's priorities.

Option 1 is a balanced choice, intended for customers who value both cost and time equally. This option assigns balanced weights for cost and production completion time during the initialization step of the scheduling model, allowing customers to obtain products at a reasonable price within a moderate timeframe.

Option 2 is cost-focused, designed for customers prioritizing affordability and willing to wait longer for a lower price (Lenker et al. 2013). In this option, cost weight is higher than in Option 1.

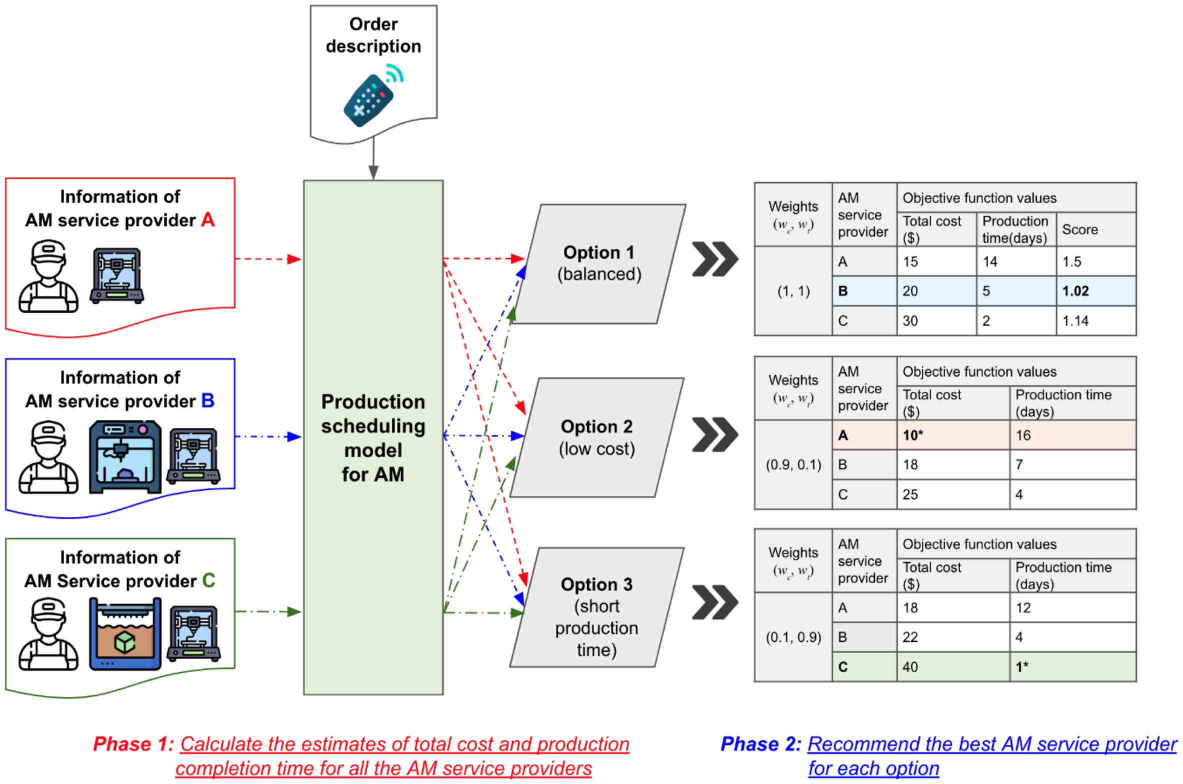
Option 3 prioritizes rapid delivery for customers who need their product urgently and are prepared to pay a premium for faster service (Dolan and Henderson 2014; Larsson Ranada and Lidström 2019). Here, time weight is emphasized, and cost weight is reduced.

Accordingly, the framework yields three distinct sets of optimal cost and production completion time value. As this process repeats for each AM service provider, Phase 1 compiles three sets of objective values across all candidates, accommodating varied customer preferences.

Phase 2 involves comparing the optimal objective values of all service provider candidates to recommend the best AM service provider for each option. The recommendation from Option 1 is tailored to customers with balanced preferences, whereas Options 2 and 3 focus on customers prioritizing low cost and short completion time, respectively. This structured approach ensures that customer preferences are aligned with the most suitable AM service providers, enhancing the relevance and effectiveness of the recommendations.

Figure 3 provides an illustrative example of the recommendation framework in action, with three hypothetical AM service provider candidates: A, B, and C. Each provider differs in terms of machine types, operating hours, pricing policies, and other parameters. Within the model, the weights for the two objectives—cost and lead time (w_c, w_t) —are preset through the model's initialization: Option 1 has weights of (1, 1), Option 2 prioritizes cost with weights of (0.9, 0.1), and Option 3 prioritizes time with weights of (0.1, 0.9). Using order details and the specific attributes of AM service provider A, the optimal production plans are calculated for each option (the following values are set for illustrative purposes). For Option 1, the optimal plan for service provider A would cost \$15 and take 14 days. Under Option 2, the cost of service provider A is reduced to \$10 but requires 16 days, while Option 3 results in a \$18 cost with a lead time of 12 days. This process is then repeated for other service providers, B and C, yielding a total of nine results by the end of Phase 1.

In Phase 2, the results from each service provider candidate are compared to identify the best option for each customer preference. To facilitate comparison, a score is calculated for each provider by normalizing cost and production time against the highest values observed in the results. Specifically, each provider’s cost and production time are divided by the maximum cost and production time, respectively, and then summed to obtain the final score.



Weights (w_c, w_t)	AM service provider	Total cost ($)	Production time(days)	Score
(1, 1)	A	15	14	1.5
	B	20	5	**1.02**
	C	30	2	1.14

Weights (w_c, w_t)	AM service provider	Total cost ($)	Production time (days)
(0.9, 0.1)	**A**	**10***	16
	B	18	7
	C	25	4

Weights (w_c, w_t)	AM service provider	Total cost ($)	Production time (days)
(0.1, 0.9)	A	18	12
	B	22	4
	C	40	**1***

Figure 3. Illustrative example of the AM service provider recommendation

For Option 1, which balances cost and production time, service provider B is recommended as it achieves the lowest score of 1.02. Under Option 2, where cost efficiency is prioritized, service provider A offers the most economical option with a cost value of $10. Lastly, for Option 3, which favors shorter production time, service provider C proves optimal with the shortest production time, one day. At the conclusion of Phase 2, the framework presents the customer with the top service provider recommendation for each option, along with their respective cost and production time estimates. This allows the customer to review the three options and select the most suitable service provider and option combination for their needs.

4. Multi-objective production scheduling model for AM

This section presents a multi-objective production scheduling model for AM, designed to estimate total cost and production completion time for each AM service provider and deliver this information to customers.

The model reflects several characteristics unique to shared AM, distinguishing it from general scheduling models.

First, it incorporates AM-specific flexibility: assigning parts to machines, batching parts into jobs, and operating without strict precedence constraints. Traditional manufacturing often involves multi-step workflows (e.g., tooling, machining, finishing) with complex dependencies. In contrast, AM enables direct fabrication from digital models, reducing task interdependencies (Son, Kim and Jeong 2021). The model also integrates nesting by grouping parts based on dimensions, materials, and volume, reflecting AM's ability to handle various geometries and materials with reduced part-machine dependency.

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Second, the model incorporates provider-level constraints such as non-continuous machine availability and variable operating hours. Many shared AM service providers operate on small-scale or irregular schedules, a factor often overlooked in conventional models. By accounting for these, the proposed model enhances realism and applicability shared AM platforms.

The scheduling model builds on prior research, incorporating both established and novel features:

- *Part batching and job scheduling*: The model handles part batching and job scheduling, ensuring that parts are grouped into jobs and assigned to machines efficiently (Li, Kucukkoc, and Zhang 2017; Kucukkoc 2019).
- *Non-identical parts*: The model accounts for the variability in part dimensions and processing requirements, addressing the challenge of scheduling non-identical parts, a common consideration in AM scheduling research (Li, Kucukkoc, and Zhang 2017; Kucukkoc 2019).
- *Heterogenous machines*: Reflecting real-world settings, the model incorporates machines with differing specifications, such as setup times, fabrication speed, and base area capacities (Altekin and Bukchin 2022; Lu, Hu, and Ng 2023), to evaluate their impact on job allocation.
- *Multi-material processing*: The ability to handle multiple materials is integrated into the model, reflecting advancements in AM technology (Toksarı and Toğa 2022).

Additionally, this study introduces two key distinctive elements for real-world applicability:

- *Restricted operating hours and non-continuous machine scheduling*: This model uniquely integrates operational constraints, such as service provider operating hours and non-continuous machine usage, to reflect practical limitations. By considering these factors, the model transitions from an idealized scheduling approach to one that better represents real-world service environments.
- *Dynamic cost structure reflecting real-world pricing policies*: Unlike previous models, this study incorporates a detailed pricing policy. It includes fixed costs associated with ordering and a tiered pricing structure based on service duration and material usage, offering a more realistic cost evaluation for AM operations.

Figure 4 illustrates the concept model: distributed parts are grouped into jobs based on specific criteria such as material compatibility and dimensions, then assigned to AM machines with varying capabilities, such as forming time and material handling capacity. Subsequently, the model schedules jobs considering providers' daily operating hours and opening days, balancing the machine availability time with the service provider's operational policies. For instance, if a job ends during the day but the provider is closed, no new job is scheduled—introducing realistic discontinuities.

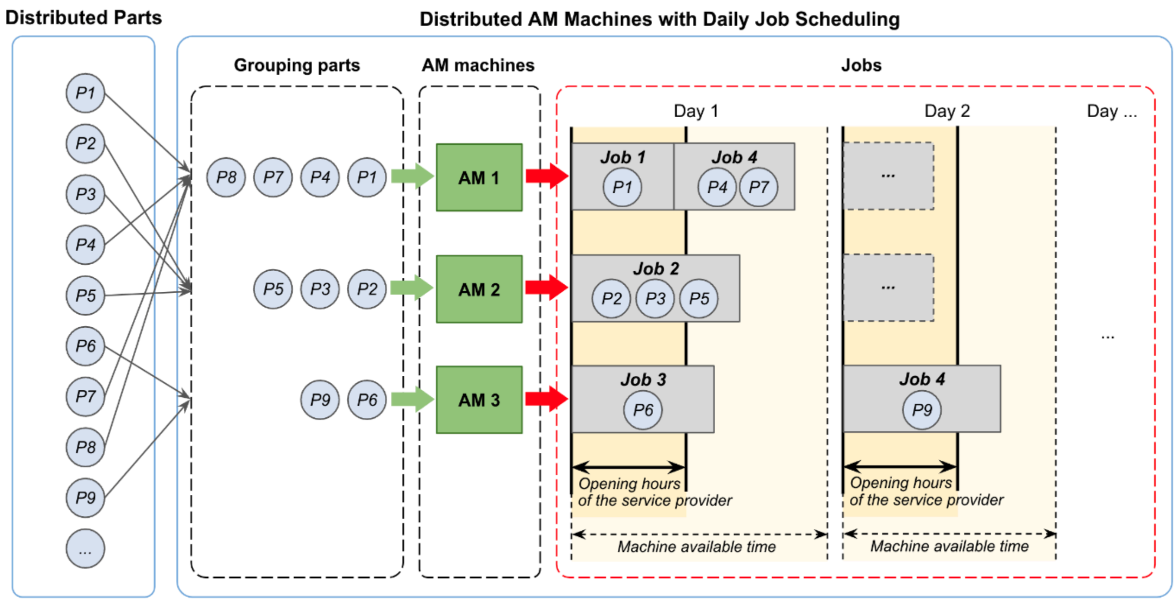

Figure 4. Concept model of production scheduling for additive manufacturing operation

The model is formulated as a mixed-integer linear programming (MILP) model with dual objectives: minimizing cost and minimizing production completion time. The total cost encompasses both fixed costs (e.g., ordering fees) and variable costs (e.g., machine use, materials), derived from actual AM service providers' pricing policies. The production completion time is influenced by AM machine properties (e.g., setup, forming times) and service providers' operational policies (e.g., operating hours, schedules). These two objectives are integrated into a single objective function using weight factors that reflect cost versus time priorities.

The output is an optimal daily production schedule with cost and production completion time (in days). Key factors influencing order cost and production completion time are assumed to be known. The following assumptions apply:

AM Service provider and machine-related assumptions

- The AM service provider's operating hours and working schedule are known.
- Detailed information about each AM machine (e.g., model, materials, setup time, forming time per unit of volume) is known.
- Setup time is applied every beginning of AM operation.

General process related assumptions

- Only parts with the same materials can be simultaneously printed as a job.
- Finalization time (post-processing, assembly, packaging) is assumed to be constant across all AM providers.
- Material changing time is not considered.

Related sets, parameters, and decision variables are presented in Appendix 1.

The two objectives of the AM production scheduling model—minimizing total cost and minimizing production completion time—are expressed in Equations (1) and (2), respectively. The total cost function f_c includes the service provider's basic ordering fee, machine usage costs, and material-related costs. Material-related costs specifically refer to additional charges incurred when using material types beyond the standard offerings provided by the AM service provider.

The production completion time function f_t is calculated based on the makespan for fabricating parts, along with any extra days required to complete production if needed.

$$\textbf{minimize} \quad f_c = c^{order} + \sum_{k,t} C_{kt} + \sum_{r} c_r \left(\Omega_r - 1\right) \tag{1}$$

$$\textbf{minimize} \quad f_t = \sum_{t} \left(t \times MS_t + d_t^{next} D_t^{extra}\right) \tag{2}$$

Part assignment and job-machine relationship

$$\sum_{j} X_{ij} = 1 \qquad \forall i \tag{3}$$

$$Y_{jkt} \sum_{i} b_i X_{ij} \leq \beta_k \qquad \forall j, k, t \tag{4}$$

$$\sum_{k,t} Y_{jkt} \leq 1 \qquad \forall j \tag{5}$$

$$I \times \sum_{k,t} Y_{jkt} \geq \sum_{i} X_{ij} \qquad \forall j \tag{6}$$

Equation (3) is the part occurrence to ensure that each part is assigned to exactly one job, while Equation (4) prevents the total parts assigned from exceeding the machine's capacity. These two constraints are adapted from the work of Li, Kucukkoc, Zhang (2017).

Equation (5) ensures that a job is not assigned across multiple machines or times, preventing duplicate allocations. Equation (6) links the binary variables X_{ij} and Y_{jkt}, ensuring that if any part is assigned to job j on day t of machine k, the corresponding job must also be active.

Operational time: machine availability and opening hours

$$P_{jkt} = Y_{jkt} \left(s_k + \delta_k \sum_{i} v_i X_{ij}\right) \qquad \forall j, k, t \tag{7}$$

$$T_{kt} = \sum_{j} P_{jkt} \qquad \forall k, t \tag{8}$$

$$T_{kt} \leq h_t \qquad \forall k, t \tag{9}$$

$$T_{kt}^{long} = \left\{P_{jkt}\right\} \qquad \forall k, t \tag{10}$$

$$T_{kt} - T_{kt}^{long} \leq o_t \qquad \forall k, t \tag{11}$$

$$T_{kt} \leq T_{kt}^{hour} \qquad \forall k, t \qquad (12)$$

$$T_{kt} + K_{kt} \geq T_{kt}^{hour} \qquad \forall k, t \qquad (13)$$

Equations (7) to (11) address the calculation of manufacturing time and machine availability focusing on two distinct concepts: working and operational hours.

To accurately account for the time required to complete each job, Equation (7) calculates the processing time for job j on machine k during day t. This processing time includes the machine's setup time s_k, which occurs for every job, as well as the fabrication time required for all parts assigned to the job. Equation (8) then calculates the total working time of machine k on day t, summing the processing times of all jobs assigned to the machine. According to Equation (9), this total working time must not exceed the available working time h_t for the day. Machine available time refers to the total time a machine can be shared for production on a given day. For example, if a machine is allocated for only 4 hours of shared use on day t, the total processing time for all jobs assigned to the machine that day cannot exceed 8 hours. In cases where the machine is available for 24 hours but new orders are not accepted over the weekend, the effective machine availability can span up to 72 hours starting from Friday.

On the other hand, opening hours o_t refer to the daily operational hours of the service provider, regardless of the total machine availability. Even if a machine is available 24 hours a day, if the service provider's opening hours are limited to 8 hours (e.g., 9 AM to 5 PM), the last part must start production within this time frame. Equation (10) calculates the longest fabrication time (T_{kt}^{long}) among all jobs assigned to machine k on day t. Using this variable, Equation (11) ensures that all fabrication processes are scheduled to begin within the service provider's operating hours. For example, if a part requires 10 hours to complete and another requires 9 hours, the second part cannot begin production after the first on the same day, as the service provider would already be closed.

Finally, Equations (12) and (13) round up the total working time of AM machine on day t to an integer variable (T_{kt}^{hour}). This integer variable is used to calculate the machine usage fee in the subsequent equations (14) and (15).

Equation (7) has a product of two binary variables, which is then replaced by the following three constraints.

$$P_{jkt} \leq bigM \times Y_{jkt} \qquad \forall j, k, t \qquad (7\text{-}1)$$

$$P_{jkt} \leq s_k Y_{jkt} + \delta_k \sum_i v_i X_{ij} \qquad \forall j, k, t \qquad (7\text{-}2)$$

$$P_{jkt} \geq s_k Y_{jkt} + \delta_k \sum_i v_i X_{ij} - bigM\left(1 - Y_{jkt}\right) \qquad \forall j, k, t \qquad (7\text{-}3)$$

Among the constraints, Equation (10) has a max constraint. In that, it is replaced with the following three constraints using auxiliary binary variable u_{jkt}.

$$\sum_{j} u_{jkt} = 1 \qquad \forall k, t \qquad (10\text{-}1)$$

$$T_{kt}^{long} \geq P_{jkt} \qquad \forall j, k, t \qquad (10\text{-}2)$$

$$T_{kt}^{long} \leq P_{jkt} + 24\left(1 - u_{jkt}\right) \qquad \forall j, k, t \qquad (10\text{-}3)$$

Equation (10-1) ensures that at least one u_{jkt} is 1 for each machine k and day t, and Equation (10-2) ensures that the longest fabrication time T_{kt}^{long} is greater than or equal to the processing time P_{jkt} of job j if it is being fabricated on machine k on day t. Equation (10-3) ensures that if job j is not fabricated on machine k on day t (i.e., $P_{jkt} = 0$), then T_{kt}^{long} can be at most 24 times the negation of u_{jkt}, ensuring consistency in the linearized model.

Machine usage fee

$$c_{k}^{basic} K_{kt} \leq C_{kt} \qquad \forall k, t \qquad (14)$$

$$c_{k}^{basic} K_{kt} + c_{k}^{extra}\left(T_{kt}^{hour} - \tau_{k}^{AM}\right) \leq C_{kt} \qquad \forall k, t \qquad (15)$$

Equation (14) applies the basic usage fee for machine k if it is used on day t. Equation (15) accounts for the machine usage fee incurred when the total processing time exceeds the threshold τ_{k}^{AM}. For example, if the minimum usage time threshold for a machine is 6 hours and the basic usage fee is \$5, the service provider charges \$5 even if the processing time is only 1 hour. However, if it takes more than 6 hours, the customer must pay an extra usage fee c_{k}^{extra} for each additional hour beyond the threshold.

Linking binary variables for production and operation

$$Z_{t} \leq \phi_{t} \qquad \forall t \qquad (16)$$

$$Z_{t} \geq Y_{jkt} \qquad \forall j, k, t \qquad (17)$$

$$\sum_{j,k} Y_{jkt} \geq Z_{t} \qquad \forall t \qquad (18)$$

$$K_{kt} \geq \sum_{j} Y_{jkt}/J \qquad \forall k, t \qquad (19)$$

Equation (16) indicates that the fabrication process can only occur on an operating day for the service provider. Equations (17) and (18) link the two variables, Y_{jkt} and Z_{t}. Equation (17) states that if a job occurs on day t, then Z_{t} must be 1, indicating that day t is a production day. Conversely, Equation (18) ensures that if Z_{t} is set to 1, there must be at least one part fabrication process occurring on that day. Similarly, if AM machine k is operated on day t for any part fabrication, the binary variable K_{kt} must be 1 by Equation (19).

Makespan and production completion time

$$MS_t \geq Z_t - \sum_{t+1}^{T} Z_t \qquad \forall t \qquad (20)$$

$$T_t^{long\_day} = max\{T_{kt}\} \qquad \forall t \qquad (21)$$

$$bigM \times D_t^{extra\_aux} \geq T_t^{long\_day} - o_t + a \qquad \forall t \qquad (22)$$

$$D_t^{extra} = MS_t D_t^{extra\_aux} \qquad \forall t \qquad (23)$$

Equations (20) to (23) address the makespan and the production completion time. In Equation (20), the binary variable MS_t indicates the makespan and takes a value of 1 if and only if there is no fabrication process occurring on the following days. The Equation (21) defines the variable $T_t^{long\_day}$, which represents the longest working hour among the AM machines on day t. This variable helps determine whether additional days are required to complete the production process after all part fabrications are finished.

Equations (22) and (23) calculate the extra days needed to finalize the production process after all part fabrications are completed. The time required for assembly and finalization, represented by the parameter a. may exceed the remaining operational hours on the same day if production ends close to the service provider's closing time. In such cases, these tasks must be carried over to the next working day, necessitating extra days.

To capture this, we introduced an auxiliary variable $D_t^{extra\_aux}$ in Equation (22) to indicate whether extra days may be required to finalize the production. This auxiliary variable is calculated for each day t, regardless of whether day t is the actual makespan. It merely evaluates the possibility of requiring extra time for finalization on each day.

In contrast, the actual number of extra days required due to insufficient time to finalize the production on the makespan day is determined by the variable D_t^{extra}. According to Equation (23), this variable takes the value of 1 only when the day t is the makespan ($MS_t = 1$) and additional time is needed to complete the production ($D_t^{extra\_aux} = 1$). This equation is replaced by three sub-constraints, (23-1) to (23-3), which ensure both conditions are satisfied.

$$D_t^{extra} \leq MS_t \qquad \forall t \qquad (23\text{-}1)$$

$$D_t^{extra} \leq D_t^{extra\_aux} \qquad \forall t \qquad (23\text{-}2)$$

$$D_t^{extra} \geq MS_t + D_t^{extra\_aux} - 1 \qquad \forall t \qquad (23\text{-}3)$$

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Also, Equation (21) is replaced with the following three linear constraints using auxiliary binary variable v_{kt}, similar to Equation (10).

$$\sum_k v_{kt} \geq 1 \qquad \forall t \qquad (21\text{-}1)$$

$$T_t^{long\_day} \geq T_{kt} \qquad \forall k, t \qquad (21\text{-}2)$$

$$T_t^{long\_day} - T_{kt} \leq 24\left(1 - v_{kt}\right) \qquad \forall k, t \qquad (21\text{-}3)$$

Raw material selection and availability

$$R_{jktr} \leq \gamma_{kr} \qquad \forall j, k, t, r \quad (24)$$

$$R_{jktr} \leq \alpha_{ir} + \left(1 - X_{ij}\right) \qquad \forall i, j, k, t, r \quad (25)$$

$$\sum_r R_{jktr} = Y_{jkt} \qquad \forall j, k, t \qquad (26)$$

$$\Omega_r \geq \frac{\sum_{j,k,t} R_{jktr}}{(J \times K \times T)} \qquad \forall r \qquad (27)$$

Equations from (24) to (27) relate to raw materials used for part fabrication. Equation (24) ensures that the material chosen for part fabrication is compatible with the machine. Equation (25) guarantees that a job j can use material r only if all assigned parts are compatible with it. If any part i assigned to job j ($X_{ij} = 1$) is incompatible with material r ($\alpha_{ir} = 0$), the right-hand side of the constraint becomes zero, thereby forcing R_{jktr} to be zero. Conversely, if all assigned parts can be produced using material r, the constraint does not impose any restriction on R_{jktr}, allowing it to take a value of 1 when the job is scheduled. Equation (26) ensures only one type of material is chosen for each job. Finally, Equation (27)(27) indicates whether material r is used in production by aggregating the values of R_{jktr}.

Planning horizon and start condition

$$\sum_{i,j} Y_{jk1} \geq 1 \qquad (28)$$

$$\sum_t \left(t \times MS_t + d_t^{next} D_t^{extra}\right) \leq T \qquad (29)$$

Equations (28) and (29) define constraints related to the conditions of start and end of the production in the planning horizon. Equation (28) specifies that the production must begin on the first day of the planning period, requiring at least one part fabrication starts on that day. Equation (29) limits the production completion time to be within the planning horizon.

Variable constraints

$$X_{ij}, Y_{jkt}, R_{jktr}, Z_t, MS_t, K_{kt}, \Omega_r, D_t^{extra}, D_t^{extra\_aux} \in \{0, 1\}$$
$$P_{jkt}, T_{kt}, T_{kt}^{hour}, T_{kt}^{long}, T_t^{long\_day}, C_{kt} \geq 0 \qquad \forall i, j, k, t, r \quad (30)$$
$$T_{kt}^{hour} \; is \; integer.$$

Lastly, Equation (30) is a basic constraint on the variables.

Objective function normalization and weighted combining

Next, the total cost and production completion time functions, f_{cost} and f_{time}, are normalized to bring them to a comparable scale. The normalization process uses the worst possible value of each objective, f_c^{max} and f_t^{max}, determined at their respective worst-case scenarios within the feasible region. In this model, the worst possible value of an objective function is obtained when the other objective is sorely considered in the model. The following Equation (31) shows the combined objective F by normalizing the two objective functions f_c and f_t.

$$\textbf{minimize} \quad F = \frac{f_c}{f_c^{max}} + \frac{f_t}{f_t^{max}} \tag{31}$$

At last, the weighted objective is calculated as shown in Equation (32).

$$\textbf{minimize} \quad F = w_c \frac{f_c}{f_c^{max}} + w_t \frac{f_t}{f_t^{max}} \tag{32}$$

5. Case-based experiment

This section presents a basic application and a case-based experiment to evaluate the effectiveness of the AM service provider recommendation framework using the case of the Open-Source AT Platform in South Korea. The framework is applied along with the production scheduling model, aggregating estimated costs and completion time to identify optimal service providers for different customer preferences.

5.1. Basic application

To ensure the applicability and practical behavior of the proposed model, a basic application was conducted using the dataset from Kucukkoc (2019). This highlights the proposed model's distinct features and its ability to address AM scheduling problems effectively.

The details of the parts and machines are provided in Appendix 2 (Table A1) and Appendix 3 (Table A2). The dataset includes 20 parts with base area and volume data from Kucukkoc (2019). As the original study did not consider material diversity, assignable materials were randomly assigned to the parts (Table A1). The two machines have an identical forming time but differ in setup times and base area capacities. It is assumed that both machines are capable of handling both material 1 and material 2, and it requires 2 hours for the assembly and finalization stage.

Additional parameters not included in the original study were defined: a base order fee of 10,000 KRW, a basic usage cost of 5,000 KRW for the first 5 hours of operation, and 1,000 KRW per hour thereafter. An extra 1,000 KRW fee applies for each additional material used.

The machines are assumed to be available for 24 hours per day, while the AM service provider operates only 14 hours daily, on Monday and Wednesday. This setup allows the observation of discrete scheduling patterns. The planning horizon spans 29 days starting from Monday.

To normalize the two objectives, worst-case scenarios were first identified. When minimizing completion time only, the total cost reached 852,000 KRW, with a production completion time of 22 days. Conversely, when minimizing cost only, the cost was 702,000 KRW, but completion required 29 days. Thus, 852,000 KRW and 29 days were used as the worst possible values for normalizing the objective functions. The basic application was conducted using the basic setting, where equal weights were assigned.

The test was conducted on a system with an Intel(R) Core(TM) i7-10700 CPU @ 2.90GHz, featuring 8 physical cores and 16 logical processors, utilizing up to 16 threads. The experiments employed the following versions of Python and associated packages: python: 3.12.4, pandas: 2.2.2, numpy: 1.26.4, gurobipy:11.0.3. Due to the complexity of the problem and the presence of numerous integer variables, the solver was executed for 600 seconds.

The results indicate that the 20 parts were grouped into 11 jobs (Table 3). The makespan reached 23.95 hours on Day 21, and with finalization, production completed on Day 22. In comparison, the model of Kucukkoc (2019) resulted in a makespan of 397.88 hours, completing the production on Day 17. The 4-day difference stems from a key modeling difference: while the earlier model assumes uninterrupted operation, the proposed model incorporates the provider's actual operating schedule. As a result, job assignments are not continuous, leading to a longer production completion time. At the same time, material availability also influenced the outcome.

Table 3. Basic application results

Job (j)	Part (i)	Machine (k)	Day (t)	Material (r)	Processing time (P_{jkt}) - hr
1	4, 8	2	17	2	119.95
2	11, 12	1	10	1	72.80
3	19	1	3	2	74.40
4	10, 14	1	17	2	112.94
5	6, 7, 15, 20	2	3	1	115.99
6	1	2	1	2	26.70
7	18	2	10	1	89.71
8	5, 9	2	9	1	44.88
9	2, 3, 16	2	15	1	35.99
10	17	1	9	2	7.63
11	13	1	1	1	10.72

Figure 5 shows the Gantt chart illustrating discrete job assignments under real-world constraints. The shaded yellow areas represent the opening hours of the AM service provider—12 hours each on Monday and Wednesday. Outside these hours, no new job is assigned, so there are some gaps. The chart also highlights how jobs requiring different materials are assigned to machines based on material-handling capability. The makespan of 119.95 hours (Day 21), with completion on Day 22, demonstrates the model's scheduling efficiency and its ability to generate practical, managerially feasible solutions aligned with real-world operational constraints.

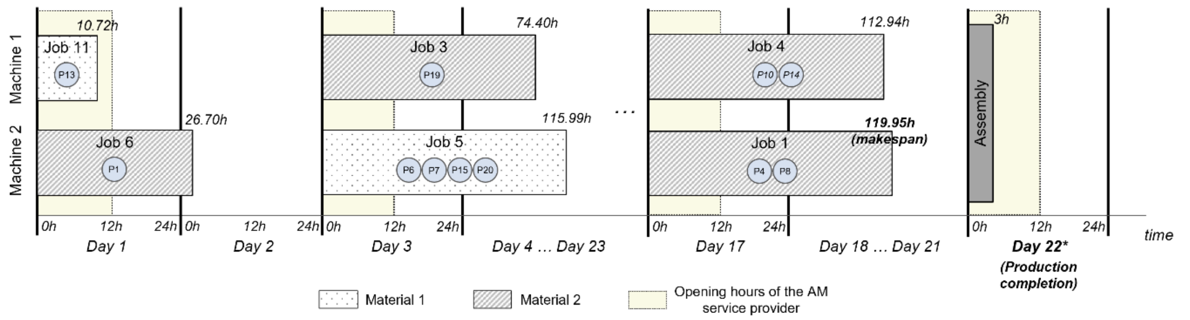

Figure 5. Gantt chart of basic application results

To test model consistency under idealized conditions, a supplementary experiment assumed 24-hour machine availability, with production completion time as the sole objective. The resulting makespan was 366.60 hours, shorter than the 397.88 hours in Kucukkoc (2019), which included powder-layering time based on job height. Our model, by contrast, is designed for broader AM technologies and excludes such process-specific constraints. The result confirms that the proposed model remains valid even under ideal conditions, while offering broader applicability.

Overall, the basic application demonstrates that the proposed model produces more practical and feasible scheduling solutions. Unlike previous approaches under idealized conditions, this model incorporates provider-specific operating hours, multi-material handling, and dynamic pricing, which are often overlooked in earlier studies. These considerations enable more realistic and actionable decisions in shared AM environments.

5.2. Experimental design

In recent years, the emergence of design-sharing platforms for AM has transformed how products are conceptualized and delivered, especially in the AT field. Such platforms offer customized solutions that improve the daily lives and independence of individuals with disabilities. In South Korea, the Korea National Rehabilitation Center launched an open-source sharing platform for assistive devices in 2022 (Figure 6) (Kim et al. 2024; Ro et al. 2024). Originally offered as a free service, the AT open platform allows users to share their needs or ideas for AT solutions. It promotes the use of accessible technologies like 3D printing and simple assembly, enabling affordable and easily obtainable design of new assistive devices. As of October 2024, 645 demands have been submitted to the platform, leading to over 300 developed and shared designs (The Korea National Rehabilitation Center, n.d.).

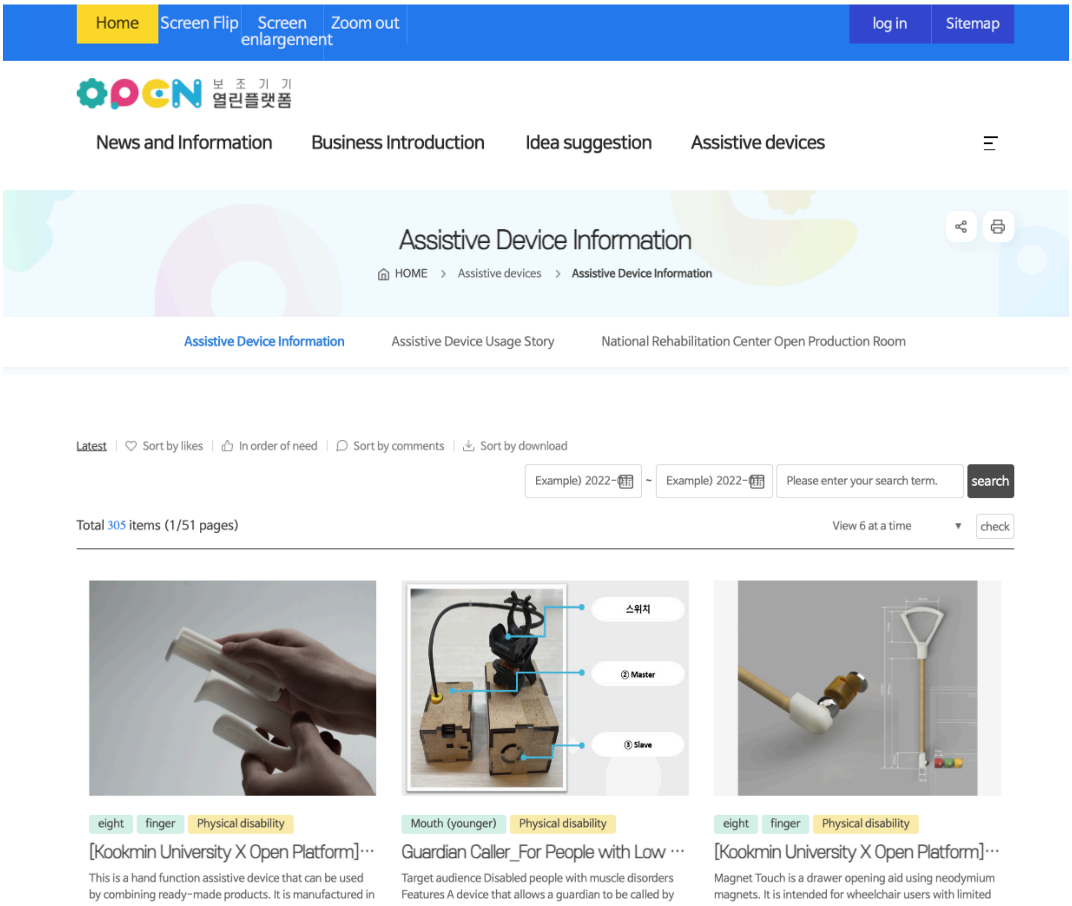

Figure 6. Assistive Technology Open Platform in South Korea

More recently, the Center has sought to introduce local makers capable of transforming AT designs into physical devices (Jeong 2024). This initiative ensures that shared designs are not only distributed but also produced for those in need, thereby expanding the platform's ability to meet diverse AT demands. As the platform evolves, it is expected to function as a shared AM platform serving two primary user groups: customers in need of assistive devices (e.g., elderly individuals, people with disabilities, and their caretakers) and service providers equipped with AM machines to produce these devices.

To support this transformation, the platform is exploring ways to match customers with AM service providers capable of fabricating the shared AT designs. To address this challenge, this study applies the proposed framework to assess its effectiveness in supporting service provider selection and production scheduling within this shared AM context.

For the experiment, a device called K-LipSync was selected as the sample product (Figure 7). The device is an alternative mouse for people who have difficulty using their hands to operate a computer mouse (Kim 2022). The shared design includes eleven housing parts manufactured by AM machines (Appendix 4, Table A3), along with electrical components for signal processing.

(a) Product design (b) Example of use

Figure 7. Sample product 'K-LipSync'

Three types of AM service providers were considered to represent different operational characteristics (Table 4). Each provider is assumed to operate one or more machines from the three types of AM machines shown in Figure 8, which differ in terms of price, performance, and material availability (Table A4 in Appendix 5). The service providers also differ in pricing strategies and operational policies—key factors likely to influence customer preferences.

Table 4. AM service provider candidates

AM service provider number	**Type**	**Basic ordering cost c^{order}** (₩)	**AM machines**				
			Machine index	**Machine name**	**Minimum usage time threshold** τ_j^{AM} (hr)	**Machine usage basic fee** (₩)	**Machine usage extra fee** (₩/hr)
1	Makerspace	5,000	1	Cubicon Style Plus	5	4,000	1,000
			2	Cubicon Style Plus	5	4,000	1,000
			3	Cubicon Style Plus	5	4,000	1,000
			4	Stratasys F120	2	5,000	2,000
2	3D Printing company	10,000	1	3D Systems Figure 4	1	20,000	8,000
			2	3D Systems Figure 4	1	20,000	8,000
			3	3D Systems Figure 4	1	20,000	8,000
			4	Stratasys F120	3	5,000	2,000
3	Individual	5,000	1	Cubicon Style Plus	1	1,000	500

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(a) Cubicon style plus (economical FDM) (b) Stratasys F120 (high-end FDM) (c) 3D Systems Figure 4 (high-end SLA)

Figure 8. Additive manufacturing machines

AM Service Provider 1 refers to a makerspace in South Korea, typically serving both hobbyists and startups with prototype designs. For these two types of customers, it is equipped with both economical AM machines for general use and mid- to high-end printers for prototype development. For this experiment, it is assumed that three Cubicon Style Plus machines and one Stratasys F120 are available for shared manufacturing. According to its pricing policy, there are no surcharges for using multiple material types. The makerspace operates from 9 AM to 5 PM on weekdays, while the machines are available 24 hours a day.

AM Service Provider 2 represents a professional 3D printing company, serving clients that require prototypes before large-scale production. To meet these needs, this service provider is equipped with high-end AM machines capable of rapidly fabricating high-quality prototypes. Due to the advanced nature of these machines, their usage costs are significantly higher than those of other providers. Additionally, a surcharge of 1,000 KRW is applied for each material type beyond the base. The company operates for 9 hours on weekdays, with machines available 24 hours daily.

AM Service Provider 3 represents an individual who owns a few economical AM machines, primarily used for hobbies or making daily items. Operational hours vary by personal schedule—some may only run machines after their regular jobs, while others may dedicate full days to shared manufacturing. For the experiment, it is assumed that this provider operates one AM machine, for 4 hours on weekdays and 12 hours on weekends. The machine is available 24 hours every day. Their prices are set as the lowest among the three types, while they apply a surcharge of 2,000 KRW per extra material type.

To reflect a variety of manufacturing needs, four AM materials were selected: Polylactic Acid (PLA), Acrylonitrile Butadiene Styrene (ABS), Polyethylene Terephthalate Glycol (PETG), and photopolymer resin. These materials are matched to the three machine types. PLA and ABS are commonly used in Fused Deposition Modeling (FDM) machines for their stability. Although various types of photopolymer resins exist, this experiment treats them as a single category for simplicity. Biomedical concerns restrict material selection for parts that contact the lips—specifically parts 9, 20, and 31)—which must be made using PETG or photopolymer resin, while other parts have no such restriction.

Regarding the customers' preferences on the two objectives, there can be two contrasting options when it comes to assistive devices. In this context, we introduced distinct weight settings for the cost-preferred and time-preferred options, alongside the basic option with equal weights on total cost and production completion time (1, 1). The cost-preferred option assigns weights of (0.9, 0.1), catering to customers willing to endure long completion times—sometimes lasting several months—due to required consultations, personalization process, and government subsidy screenings, as long as it results in significant cost savings (Lenker et al. 2013). Conversely, the time-preferred option applies weights of (0.1, 0.9) for customers who prioritizes rapid delivery, even at a higher cost (Dolan and Handerson 2014; Larsson Ranada and Lidström 2019). This setup enables a comprehensive comparison of M service provider performance under different customer priorities, ensuring a thorough evaluation of the recommendation framework.

The planning horizon comprises 10 days, beginning on a Monday. The order requires three sets of the 11 parts, totaling 33 parts to be produced. After fabrication, 3 additional hours are required to assemble the parts and finalize the product. The experimental setup align with those used in the basic application.

5.3. Results

The results of the production scheduling model are summarized in Table 5. First, the worst possible values of the objectives were obtained for each AM service provider. For AM Service Provider 1, minimizing cost alone resulted in a production completion time of 10 days, while minimizing time led to a total cost of 230,000 KRW. These two were set as the worst-case values of AM Service Provider 1. Similar values for the other service providers are underlined in Table 5. Using these, the objectives were normalized and weighed to get the results for the three preference options.

To compare the results and identify the best service provider for each option, a score was calculated by combining the normalized values of cost (f_1) and time (f_2) using the designated weights. Normalization involved dividing each value by the maximum observed value. For example, for AM Service Provider 1 under the basic option, the cost (69,000 KRW) was divided by 119,000 and the completion time (2 days) by 4, and the sum of these two normalized values yields a score of 1.08. Accordingly, the service provider with the lowest score was selected as the best for that option.

The results indicate that under the basic option (equal weights), AM Service Provider 1 emerged as the best, offering a cost of 69,000 KRW with a completion time of two days (score: 1.080). AM Service Provider 2 provided the same completion time of two days at a higher cost of 119,000 KRW (score: 1.500). Meanwhile, AM Service Provider 3 achieved the lowest cost (39,500 KRW) along with the longest completion time of 4 days, resulting in a score of 1.332.

For the cost-preferred option, where cost minimization was prioritized with a weight of 0.9, AM Service Provider 3 was identified as the best (score: 0.417), offering the lowest cost of 39,500 KRW while having the longest production completion time. AM Service Provider 1 followed with 68,000 KRW and 3 days. AM Service Provider 2, despite having the same completion time as Provider 1, incurred the highest cost (112,000 KRW).

Table 5. AM service provider recommendation result

			One-hand results		Normalized and weighted results		
			Cost only	Time only	Basic option	Cost-preferred option	Time-preferred option
Weights (w_1, w_2)			(1, 0)	(0, 1)	(1, 1)	(0.9, 0.1)	(0.1, 0.9)
Service provider	AM Service Provider 1 (Makerspace)	Total Cost (f_1, KRW)	65,000	237,000	69,000	68,000	69,000
		Production Completion Time (f_2, days)	<u>10</u>	2	2	3	2
		Score	-	-	**1.080***	0.620	0.486
	AM Service Provider 2 (3D printing company)	Total Cost (f_1, KRW)	111,000	<u>789,000</u>	119,000	112,000	194,000
		Production Completion Time (f_2, days)	<u>10</u>	1	2	3	1
		Score	-	-	1.500	0.975	**0.325***
	AM Service Provider 3 (Individual)	Total Cost (f_1, KRW)	39,500	<u>63,000</u>	39,500	39,500	39,500
		Production Completion Time (f_2, days)	<u>10</u>	4	4	4	4
		Score	-	-	1.332	**0.417***	0.920

For the time-preferred option, where production completion time was prioritized with a weight of 0.9, AM Service Provider 2 emerged as the most time-efficient, completing production in just one day. However, this efficiency comes with a higher cost of 194,000 KRW. AM Service Provider 1 offered the service at a lower cost of 69,000 KRW within 2 days. Meanwhile, AM Service Provider 3 was estimated to have the longest production completion time (4 days).

It is noteworthy that for all three service providers, the cost under the time-preferred option was closer to that of the cost-only option than to the time-only one, which may seem counterintuitive. This arises from the cost function structure that includes both fixed base costs and variable costs tied to machine usage time. Consequently, minimizing cost often shortens production time to some extent, since the two objectives are not entirely independent—cost-efficient schedules frequently reduce completion time.

The normalization process also contributes to this effect. While completion time is bounded by the 10-day planning horizon, total cost can vary more widely due to inefficiencies in machine assignment. This broader range amplifies cost differences in normalized results, making the time-preferred option appear closer to cost-preferred ones. Overall, the outcome reflects that although cost and completion time are structurally related, they are not fully dependent.

Beyond the numerical comparison, a closer examination of the production schedules provides further insights into how each service provider adapts to different conditions. Among the three providers, AM Service Provider 2 showed the greatest variation in its production schedules across the options, adapting its machine usage according to the weight settings.

Under the basic option (Table 6), Machine 4 (Stratasys F120) was utilized extensively on Day 1 to reduce cost, while Machine 3 (3D Systems Figure 4) contributed to meeting the completion time and accommodate the material restriction associated with the straw part. This strategy allowed the production process to be completed within two days, including final assembly on Day 2.

A closer look at job processing times reveals further scheduling adjustments. On Day 1, two jobs (Job 1 and Job 3) were assigned to Machine 4 (Stratasys F120), with a total processing time of 22.84 hours. Given the provider's daily operating limit of 9 hours and Job 3's long duration of 16.10 hours, the operator prioritized Job 1 (6.74 hours) to complete it within working hours. Job 3 was then initiated before closing and allowed to run overnight. The completed output of Job 3 was retrieved during the next day's opening hours.

Table 6. Production schedule of AM Service Provider 2 under the basic option

Job (j)	Part (i)	Machine (k)	Day (t)	Material (r)	Processing time (P_{jkt}) - hr
1	1, 10, 19, 24, 29, 30, 32	4	1	ABS	6.74
2	6, 9, 20, 22, 29	3	1	Photopolymer resin	2.76
3	11, 12, 14, 15, 16, 23, 25, 26	4	1	ABS	16.10
4	2, 3, 4, 13, 28	4	2	ABS	5.96
5	5, 7, 8, 17, 18, 20, 21, 27, 31	3	1	Photopolymer resin	2.23

Under the cost-preferred option (Table 7), the results show a more conservative machine usage strategy, distributing tasks over three days to reduce costs. Machine 4 (Stratasys F120), which had a lower operating cost but slower fabrication speed than Machine 3 (3D Systems Figure 4), was primarily used. Machine 3 was employed selectively to accommodate material restrictions, with its usage minimized where possible. Part fabrication concluded 5.93 hours into Day 3, and an additional 3 hours were required for finalization, totaling 8.93 hours—just within the provider's 9-hour opening schedule.

Regarding the last scheduled jobs each day, Job 2 was the last on Machine 4 during Day 1, following the same scheduling logic as in the basic option. On Day 2, both Job 5 (6.79 hours) and Job 6 (3.01 hours) could be scheduled in any order, as each fit within the 9-hour limit.

Table 7. Production schedule of AM Service Provider 2 under the cost-preferred option

Job (j)	Part (i)	Machine (k)	Day (t)	Material (r)	Processing time (P_{jkt}) - hr
1	4, 5, 6, 13, 24, 26, 32	4	3	ABS	5.93
2	3, 10, 12, 14, 16, 19, 23, 25, 27, 30	4	1	ABS	16.49
3	7, 18, 21	4	1	ABS	1.27
4	8, 9, 20, 22, 29, 31	3	3	Photopolymer resin	2.99
5	1, 2, 11, 17, 28	4	2	ABS	6.79
6	15, 33	4	2	ABS	3.01

Finally, in the time-preferred option, AM Service Provider 2 leveraged all four machines to complete production within a single day (Table 8). The total fabrication times for the machines were 5.95, 4.77, 5.94, and 5.75 hours, respectively. Once fabrication concluded at 5.95 hours, 3 additional hours were required for finalization, bridging the total production time to 8.95 hours into the first day, barely fitting within the 9-hour opening schedule.

Table 8. Production schedule of AM Service Provider 2 under the time-preferred option

Job (j)	Part (i)	Machine (k)	Day (t)	Material (r)	Processing time (P_{jkt}) - hr
1	1, 8, 7	3	1	Photopolymer resin	2.09
2	15, 19, 29	2	1	Photopolymer resin	1.33
3	2, 10, 13, 18, 32	4	1	ABS	2.95
4	6, 7, 16, 26, 28	2	1	Photopolymer resin	1.62
5	25, 31	1	1	Photopolymer resin	1.83
6	3, 22	2	1	Photopolymer resin	1.82
7	14, 21	3	1	Photopolymer resin	1.39
8	9, 24, 33	1	1	Photopolymer resin	1.88
9	20, 23	1	1	Photopolymer resin	2.24
10	4, 5, 27	4	1	ABS	2.80
11	11, 12, 30	3	1	Photopolymer resin	2.46

In contrast to AM Service Provider 2, which exhibited significant adjustments in its production schedule, AM Service Providers 1 and 3 showed relatively minimal variations. Despite different objective weightings, their schedules remained largely consistent. This stability can be attributable to limited machine diversity and pricing structures that offered little incentive for adjustment.

At AM Service Provider 3, flexibility was inherently limited by the availability of only one type of AM machine. With no alternative machines to optimize for cost or time, scheduling remained uncharged regardless of the weight settings.

Although AM Service Provider 1 had two types of AM machines, the difference in performance and cost was not substantial enough to affect scheduling decisions. According to Table A4, the forming time per unit volume for Style Plus, F120, and Figure 4 was 0.259, 0.151, and 0.054, respectively. Thus, F120 is approximately 1.7 times faster than Style Plus, while Figure 4 (used by AM Service Provider 2) is nearly five times faster than Style Plus.

Furthermore, the pricing structure at AM Service Provider 1 offered relatively modest cost differences: 2,500 KRW per hour for F120 and 800 KRW per hour for Style Plus, a threefold difference. In contrast, AM Service Provider 2 charged 20,000 KRW for the first hour of Figure 4 and 1,667 KRW per hour for F120, a price gap exceeding tenfold. Due to these smaller cost-performance gap at Provider 1, selecting a faster machine did not significantly influence either cost or scheduling efficiency.

As a result, unlike Provider 2—where machine selection was critical in adapting to different priorities—Provider 1's scheduling remined relatively static across the options.

6. Conclusion

This study examined the integration of AM within a shared manufacturing environment from a customer-focused perspective. With AM technologies lowering barriers and enhancing accessibility, customers are expected to take a more active role in decision-making. To support this transition, we developed an AM service provider recommendation framework tailored to the shared AM context. This framework systematically evaluates key decision factors, aligning customer needs with service provider capabilities.

To facilitate recommendations, we proposed a production scheduling model that incorporates real-world constraints such as machine heterogeneity, operational policies, and dynamic pricing structures. Applied to a real-world AT case in South Korea, the framework demonstrated effectiveness in addressing production challenges. The case-based experiment showed that how shared AM can optimize scheduling decisions by balancing cost-efficiency and timely production, ultimately improving service accessibility for customers.

The findings of this study offer several managerial insights for AM service providers, offering guidance on how to optimize their roles and strategies to enhance service efficiency, responsiveness, and user satisfaction.

First, AM service providers should define their aim—whether monetizing idle resources or pursuing shared AM as a core business. This decision affects how they allocate resources, set pricing strategies, and position themselves in the market. Providers can differentiate themselves by offering cost-effective, fast, or balanced services. Machine diversity improves scheduling flexibility, allowing them to better adapt to customer needs, whereas limited options constrain adaptation under fluctuating demand.

Second, pricing and operational constraints also play a critical role in scheduling decisions. A substantial cost-performance gap among machines enhances scheduling flexibility and allows more strategic guidance in customer choices, although it may add

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complexity of managing diverse AM machines. Moreover, the way providers manage their operational hours is also crucial; those with extended hours can distribute workloads more effectively, while those balancing shared AM with other operations may benefit from stricter time limits to avoid scheduling conflicts.

This study makes several contributions to the emerging field of shared AM, where dedicated research remains limited.

The first contribution is the extension of shared manufacturing to reflect AM-specific characteristics, including flexible production capabilities, material diversity, and service provider heterogeneity. While previous research has emphasized platform or providers perspectives, this study incorporates the customer's viewpoint, addressing how customer preferences shape service selection.

The second contribution is introducing a novel production scheduling model that integrates real-world constraints—including non-continuous machine operations, service provider-specific policies, and tiered pricing mechanisms—enhancing its practical applicability.

A further contribution is the application our framework to a real-world case, offering insights into how shared AM can effectively support individualized production needs in service-oriented manufacturing settings.

While this study provides valuable insights, several limitations suggest directions for future research. First, our approach primarily assumes a single-provider setup per order. However, orders involving multiple parts might benefit from being processed by different providers with specialized capabilities. Future research could explore multi-provider coordination.

Second, while this study focuses on production completion time, it does not account for the full lead time, which includes the delivery phase. From the customer's perspective, the total time to get the product is often more critical than just production duration. Factors such as the service provider's location, customer location, and shipping options directly influence lead time, impacting customer satisfaction. Future research could incorporate these logistical considerations to enhance the model's practical applicability.

Third, this study applies fixed weights for cost and production completion time in the objective function. As customer preferences may vary depending on context, determining appropriate weightings and integrating them into decision-support tools remains a key challenge. Future research should explore methods such as preference elicitation or multi-criteria decision-making to address this issue.

Finally, future research could develop algorithms with a broader range of customer preferences—such as quality expectations, geographical proximity, service provider reputation, and customer loyalty. Algorithms using machine learning and optimization techniques could generate faster, personalized recommendations, dynamically adapting to evolving customer needs in shared AM.

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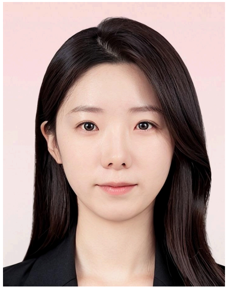
Notes on contributors



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Data availability statement
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendixes
Appendix 1

Sets

i	Part, $i \in \{1,..., I\}$
j	Job, $j \in \{1,..., J\}$
k	Available machine of the service provider, $k \in \{1, ..., K\}$
t	Time period (day), $t \in \{1,..., T\}$
r	Raw material, $r \in \{1,..., R\}$

Parameters

c^{order}	Basic ordering cost of the service provider
c_k^{basic}	Machine usage basic fee of machine k
c_k^{extra}	Machine usage extra fee of machine k per hour
c_r	Extra material handling fee
s_k	Setup time of machine k at the service provider
v_i	Volume of part i
b_i	Base area of part i
β_k	Base area of the build chamber of machine k
δ_k	Forming time of machine k for a unit volume
a	Assembly and finalizing time for the product
h_t	Available time of the AM machines on day t (integer)
o_t	Opening hours of the service provider on day t (integer)
τ_k^{AM}	Minimum usage time threshold of AM machine k (integer)
ϕ_t	Whether the day t is an opening day for the service provider (binary)
d_t^{next}	Next working day of the day t (integer, ≥ 1)
α_{ir}	Whether raw material r can be used to manufacture part i or not (binary) ($\sum_r \alpha_{ir} \geq 1$)
γ_{kr}	Whether machine k can handle raw material r or not (binary) ($\sum_r \gamma_{kr} \geq 1$)
M	Big M

Decision Variables

X_{ij}	Whether part i is assigned to job j or not (binary)
Y_{jkt}	Whether job j is processed by AM machine k on day t or not (binary)

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R_{jktr}	Whether job j is processed by AM machine k on day t with raw material r or not (binary)
Z_t	Whether the part manufacturing process is held on day t or not (binary)
P_{jkt}	Fabrication time of job j at AM machine k on day t
MS_t	Whether the day t is the makespan of the part manufacturing (binary)
K_{kt}	Whether AM machine k is used on day t or not (binary)
T_{kt}	Working hour of machine k on day t
T_{kt}^{hour}	Working hour of machine k on day t (integer)
T_{kt}^{long}	The longest part fabrication time of AM machine k on day t
$T_t^{long\_day}$	The longest working hour among the AM machines on day t
Ω_r	Whether material r is used in the production process (binary)
C_{kt}	Machine usage cost of AM machine k on day t
D_t^{extra}	Whether extra working days are required after the makespan to finish the production (binary)
$D_t^{extra\_aux}$	Auxiliary variable to link the variable D_t^{extra} and makespan MS_t (binary)

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Appendix 2

Table A1. Details of the parts (adapted from Kucukkoc (2019))

Part (i)	Base rea (b_i) – cm^2	Volume (v_i) – cm^3	Raw material
1	209.06	826.08	2
2	550.11	952.60	1
3	23.63	71.91	1
4	99.53	703.08	2
5	56.85	272.92	1
6	742.97	1583.98	1
7	50.02	125.7	1
8	300.66	3144.39	2
9	435.66	1142.25	1
10	131.88	1840.39	2
11	349.83	2204.41	1
12	84.97	121.82	1
13	48.27	315.00	1
14	269.66	1786.36	2
15	175.77	1885.00	1
16	122.62	102.83	1
17	178.34	214.79	2
18	569.53	2867.59	1
19	464.89	2378.05	2
20	134.08	124.66	1

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Appendix 3

Table A2. The machine specific parameters (adapted from Kucukkoc (2019))

Machine (k)	Forming time (δ_k) - hr/cm^3	Setup time (s_k) - hr	Base area (β_k) - cm^2	Available material
1	0.030864	1.0	800	1, 2
2	0.030864	1.2	1200	1, 2

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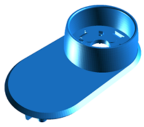
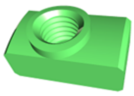
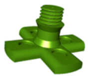
Appendix 4

Table A3. Housing part information

Part number	**1**	**2**	**3**	**4**
Name	Top cover	Top cover(side)	Bottom cover	Bottom cover(side)
Image				
Size (w×d×h, mm)	56×101×32	56×101×11	56×101×18	56×101×15
Volume (mm^3)	22,270	5,896	14,715	8,582
Base area (mm^2)	5,656	5,656	5,656	5,656
Part number	**5**	**6**	**7**	**8**
Name	Circle part	Cam adapter	Slide	Crosspart unified
Image				
Size (w×d×h, mm)	40×40×5	13×12×25	10×13×6	40×40×21
Volume (mm^3)	4,141	2,725	249	4,384
Base area (mm^2)	1,600	156	130	1,600
Part number	**9**	**10**	**11**	
Name	Straw	Pipe adapter	Button	
Image				
Size (w×d×h, mm)	40×40×62	29×29×29	25×31×8	
Volume (mm^3)	9,881	1,789	9,699	
Base area (mm^2)	1,600	841	775	

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Appendix 5

Table A4. AM machine properties

AM machine	**Building type**	**Base area of the chamber** (cm^2)	**Setup time** (min)	**Forming time per unit of volume** (hr/cm^3)	**Material availability**
Cubicon Style Plus	Fused deposition modeling (FDM)	225	10	0.259	PLA, PETG
Stratasys F120	Fused deposition modeling (FDM)	645.16	15	0.151	ABS
3D Systems Figure 4	Digital light processing (DLP)	87.6	45	0.054	Photopolymer resin