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VIRTUAL PLANNING OF A METAL ADDITIVE MANUFACTURING FACTORY USING TECHNO-ECONOMIC HYBRID SIMULATION MODELS

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ABSTRACT

Factory simulation can guide leaner production operations and resilient supply chains by informing capital allocation and real-time decision-making. This is especially true for emerging production methods, like additive manufacturing (AM), where a lack of expertise and relative technological novelty make it difficult to quantitatively assess technology economics across applications. While reported cost models provide detailed analysis on the AM printing process, accurate modeling requires specific evaluation of process-level and production-level considerations that significantly impact factory dynamics and cost. Advances in factory simulation modeling therefore promise the development of comprehensive and actionable cost models. This paper reviews progress in simulation-based costing, hybrid simulation, and automated model generation, and proposes an integrated approach for cost modeling using an AM-based factory. We demonstrate the feasibility of this approach by simulating the production of two common AM part geometries, and evaluate the associated cost and time performances of different factory configurations.

1 INTRODUCTION

Additive Manufacturing (AM) has enabled new manufacturing design freedoms and irrevocably changed the perception of what humans can create (Conner et al. 2014). Its intrinsic process flexibility also promises leaner and more resilient factories and supply chains. Despite strong industry growth, AM remains limited relative to its potential. High per-part costs, driven by a multitude of factors, limit the application potential of AM to a mix of specific high-value components in various industries. Identifying these applications is challenging, and researchers have come up with different cost-productivity models to support decision-making. We consider both the origin of these models, and their modern form.

In early studies on AM, Hopkinson and Dickens (2003) calculated the costs of producing one part type via various AM methods, categorized the costs (machine, labor, and material) and compared with injection molding costs to identify cost-advantageous production volumes for AM. However, as pointed out in a follow-up work by Ruffo et al. (2006), the authors overlooked costs associated with machine depreciation that deflect the cost curve at low production volumes. Ruffo et al. (2006) also found a saw-tooth shape of the cost curve reflecting the effect of the batch size (i.e., the number of parts per build) on both fixed and variable costs, thereby improving AM cost modeling accuracy. Later, Baumers et al. (2015) discussed an impediment to AM scale-up being low productivity of AM, which is considerably less than that achieved by conventional manufacturing methods such as casting and molding.

For Laser Powder Bed Fusion (LPBF) of metals, which is a widely used metal AM technique, researchers have developed models with a wider scope and more detail. For example, Garzaniti et al. (2019) have captured a complete AM workflow and used an exhaustive list of recurring and non-recurring costs

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associated with LPBF. However, the authors did not study the influence of production planning decisions in detail. Yi et al. (2021) presented a similar work for various AM techniques (including LPBF), yet did not consider a complete AM workflow and production planning issues. On the other hand, Mounsey et al. (2016) have used simulation to investigate some planning decisions – such as staffing levels, shift patterns, and build duration – but did not include pre-processing, post-processing, and quality control procedures in LPBF. Stittgen and Schleifenbaum (2020; 2021) also used simulation to study key performance indicators of the LPBF station, such as its utilization, throughput rate, and work in progress (WIP), but considered only the printing step and did not provide cost-based evaluations.

Prior work is therefore limited in that it either addresses a complete process workflow, investigates production planning questions, or examines time-cost tradeoffs. Yet, no model addresses each of these aspects. To progress, industry needs more capable and practical tools for techno-economic assessment of AM production system configurations that integrate process-specific workflows and cost information.

To address the gap, our work combines hybrid simulation, activity-based costing, and automated model generation in one framework for simulating LPBF-based factories. Section 2 of this paper provides background overview for the mentioned disciplines, acknowledging their importance to close the gap. Section 3 describes the proposed simulation framework. Section 4 demonstrates its use case. Section 5 summarizes our contribution and identifies some limitations of the research.

2 FACTORY SIMULATION MODELING

The usefulness of a model can be defined by three qualities: accuracy, resolution, and causal relationship (Hazelrigg 1999). The most useful model should output accurate evaluations, distinctly represent different states, and demonstrate the effects of parameter variations on system performance. With these principles in mind, we identify, four distinct research directions for techno-economic evaluations of AM-based manufacturing systems:

1. Development of the LPBF-specific cost models by analyzing the nature of the process and creating its conceptual models.
2. Development of comprehensive factory simulation tools including costs tracking for joint economic and productivity analysis.
3. Development of hybrid simulation models, providing more thorough behavior representation within the same and between multiple problem scopes.
4. Development of automated factory modeling approaches, reducing the burden of simulation projects and enabling exhaustive exploration of the factory design space.

So far, AM cost models – i.e., the first direction – has brought many insights at the process level but still quite limited in the system-level analysis. The other three directions, however, have contributed extensively at the system-level. Especially, a combination of cost tracking and simulation methods has a great potential to put AM cost models to another level of maturity. Section 2.1 summarizes prior research on combining those methods, and Sections 2.2-2.3 succinctly describe the value of hybrid simulation and automated factory modeling.

2.1 From Activity-Based Costing to Simulation-Based Costing

An accurate method for expenditures measurement is Activity-Based Costing (ABC). Comparing to a preceding approach, ABC provides higher granularity by allocating the costs at the activity level instead of the product level (Cooper and Kaplan 1991). Before ABC, methods have distributed the costs according to parts' production volumes and experts guesses on their cost contributions. This procedure has been acceptable when direct labor and material costs almost fully made up the total cost. With new production technologies and automation, it has become necessary to pay more attention to overhead costs, such as equipment maintenance and logistics (Cooper and Kaplan 1988a).

According to ABC, it is necessary to distinguish the factory operating expenses at four levels: unit, batch, product-sustaining, and facility-sustaining levels (Cooper and Kaplan 1991). The resources consumed at one level, e.g., the batch level expenses for setup, do not vary because of another level, e.g., material and labor expenses per unit. This critical distinction allows one to accurately granularize various cost contributing activities and then analyze their linkages to retained earnings generation and resource consumption. As a result, ABC quantitatively exposes business performance based on the influence of the current product line, machinery selection, and production planning.

ABC strongly emphasizes a proper identification of the cost drivers that affect a given cost category. Spedding and Sun (1999) suggest considering three types of cost drivers based on transaction, duration, and intensity. The *transaction* drivers scale costs with the number of activity occurrences. The *duration* drivers scale costs with the time taken by the activity. And the *intensity* drivers consider the varying amount of resources taken during the activity.

To advance further from the outdated accounting principles and enhance an ABC-based practice, researchers have proposed costing methods relying on simulation. In a seminal panel, Kleindorfer, Nordgren, Moore, Phillips and Zuk have drawn multiple arguments on the need to combine the strengths of Discrete-Event Simulation (DES) and ABC (Zuk et al. 1990). Two of the most compelling reasons to employ DES are: (1) its ability to provide a complete summary of production activity, and (2) to support ABC's granularity. It is because the events of DES and the activities of ABC represent an absolute match and refer to the same process segments. This way, a DES-ABC blend enables combined performance and economic analysis that can handle high system complexity and be "fast-forwarded into the future to obtain realistic projections of further running costs and expenditure" (Spedding and Sun 1999). For AM, accessing comprehensive studies of modernized production systems will bolster its industrialization.

Later, Labitzke et al. (2009) introduce a fair distinction between the costing methods relying on simulation. If the cost estimation happens after the simulation run using the data produced by the latter, such an approach shall be called more generally as "*simulation-based costing*." E.g., see the work of Takakuwa (1997). If the costs are calculated throughout the simulation, i.e., the chosen estimation technique is integrated into the same model, then it is a "*cost simulation*" approach. Spedding and Sun (1999) provide one of the earliest instances of cost simulation and outline the steps necessary to implement ABC in simulation. The method selection would depend on the capability to account for the costs during the simulation run. For example, Moore discusses the difficulty in allocating the "leftover" costs that are not associated with one single activity, i.e., overhead, and therefore names them as "unallocatable" (Zuk et al. 1990). Moore notes that idle machines, idle labor, or unused facility space entail such costs, and it is easier to account for them after the simulation than along it. Cooper and Kaplan (1988b) suggested that an accounting system shall treat such costs separately from the product costs, e.g., as "a cost of the period."

Nevertheless, despite the high utility of simulation-enabled costing tools, their application in industry has been limited (Calvi et al. 2019). Presumably, it is because of high effort demands associated with model development and data collection. As highlighted in Section 1, and in the review by Kadir et al. (2020), known AM cost models still do not leverage the benefits of simulations.

2.2 Hybrid Simulation

Hybrid simulation is a way to model, simulate, and analyze multi-level decision-making by combining either of three simulation techniques: System Dynamics (SD), Discrete-Event Simulation (DES), and Agent-Based Simulation (ABS). Borshchev and Filippov (2004) compare each paradigm, highlighting the differences in level of abstraction and process mechanics: SD allows to represent continuous processes at a high abstraction level; DES is a top-down approach with centralized behavior definition, representing the system as a sequence of "passive" discrete events at a necessary level of detail; and ABS is a "bottom-up" approach defining the behavior of individual model components (agents) and their discrete actions, allowing for a wide range of granularity and eventually leading to emergence of "decentralized" system behavior. Hybrid simulation has been used to capture one or multiple scopes of operations.

In single-scope, different paradigms are applied to model different operations within the same system level (e.g., a factory.) For example, Buth et al. (2017) used a hybrid approach to simulate a flexible manufacturing system. The authors illustrated how DES-focused modeling tools allow the introduction of ABS capabilities via built in functionality (e.g., by embedding custom object-oriented programs). Dubiel and Tsimhoni (2005) used a hybrid DES-ABS approach to enhance decision-making at the individual human level and thus simulate theme-park operations without pre-defined paths.

In multi-scope, modelers usually use one of SD, DES, or ABS to model different levels of a system, where the method is chosen depending on the level studied. For example, Jain et al. (2013) applied SD and DES to model the complexity of supply chains and evaluate energy consumption. They used SD for high-level modeling of a seven-node supply chain, and DES to model a certain node in the chain (a brake manufacturing system). Barbosa et al. (2021) combined all three methods to study supply chain sustainability using ABS, in which different agents' behavior was defined through SD and DES.

Altogether, the literature shows great value in employing a hybrid simulation approach to improve model accuracy, resolution, and the definition of causal relationships. Given the sophisticated, multi-physical nature of the AM process and entailed quality uncertainty along printing and post-processing steps, it is especially important to apply hybrid simulation for accurate bottom-up definition of system behavior.

2.3 Automated Generation of Simulation Models

Creating a simulation model is a complex endeavor involving problem- and simulation-specific knowledge, typically leading to weeks or months long cooperative effort between several experts (Popovics et al. 2016; Thiers et al. 2016). Such projects usually have five intertwined scopes of work, with the second and third taking about 60% of total effort: (1) problem definition, (2) data collection and management, (3) model conceptualization and refinement, (4) experimentation and analysis, and (5) verification and validation (Popovics et al. 2016; Milde and Reinhart 2019; Bangsow 2020). Furthermore, project complexity also affects the use of the simulation in practice, when the user needs to update the model, e.g., for alternative configurations of the system (Thiers et al. 2016).

Aiming to improve accessibility and applicability of factory simulations, researchers have focused on automating the model creation process. Skoogh et al. (2012) tackled data collection and management and achieved a drastic time reduction compared to a manual approach. Thiers et al. (2016) automated the transition from a concrete front-end system definition to an abstract back-end structure, resulting in a substantial improvement in the model's utility. Popovics et al. (2016) demonstrated another example by structuring input data and encapsulating simulation-specific knowledge in a predefined environment. Reinhardt et al. (2019), in their review of related work, conclude that industrializing the automated approach requires overcoming challenges in data collection and its transformation into reliable models, especially in the context of dynamic data sources. Nevertheless, automated model generation promises significant impact, and new simulation tools have to leverage its advances.

Building upon the progress presented in Section 2, this work acknowledges the value of each research direction, and recognizes even greater value in their integration that is lacking in current body of work. We believe that enriching AM cost models with comprehensive simulation will enable more robust analysis and promote AM adoption. We present such a simulation framework in Section 3.

3 MATERIALS AND METHODS

Our method for simulating AM production facilities combines four research directions discussed in Sections 1-2. Specifically, we rely on hybrid Discrete-Event (DES) and Agent-Based Simulation (ABS), augment it with Activity-Based Costing (ABC) for granular cost tracking, and provide the automatic model generation capability to efficiently study the design space. The result is a more comprehensive analysis of LPBF-based manufacturing systems. The simulation framework covers an end-to-end LPBF workflow, from build preparation to quality control. It was implemented in Tecnomatix Plant Simulation version 2201.0005. Figure 1 summarizes the scope of the proposed approach.

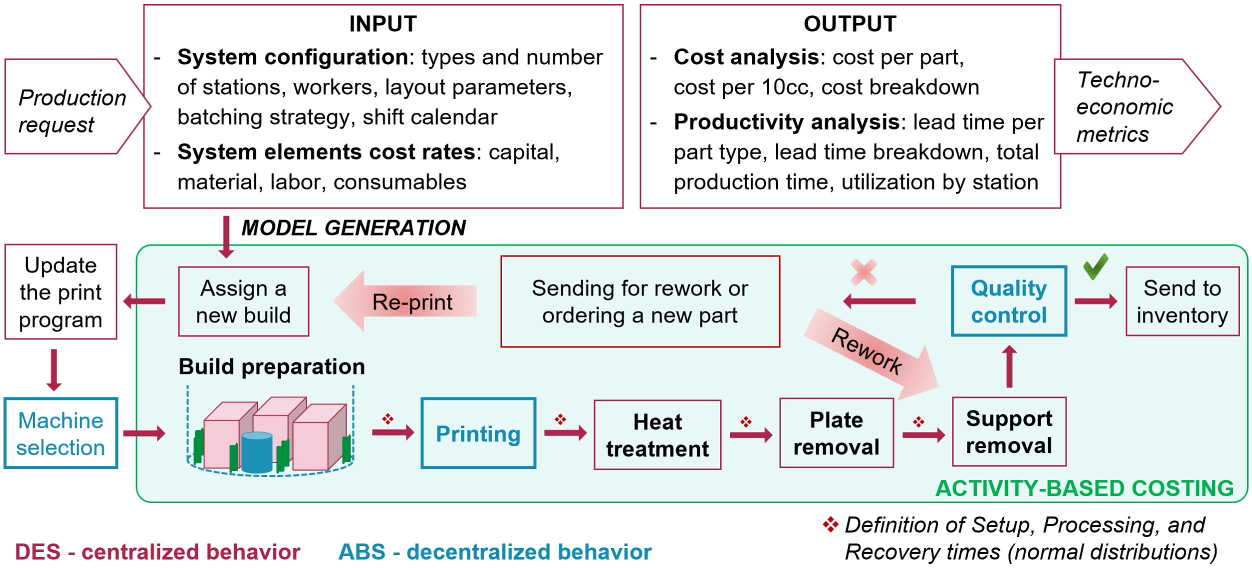

Figure 1: Overview of the simulation framework developed for this study.

In a chosen hybrid simulation approach, the default material and information flows are centralized and governed by DES, whereas some objects' individual behaviors are decentralized and governed by ABS. Thus, DES defines the workflow sequence, from build preparation to quality control. ABS defines the active behavior of selected steps: e.g., the 3D printers, before setup, may request the refill of powder feed hoppers and require a longer setup time, or quality control would define part quality and either send it to inventory as a successfully produced good, or send to additional post-processing, or discard as a defect. The combination of approaches provides better model accuracy, resolution, and the definition of causal relationships. Importantly, such architecture ensures higher flexibility for future framework extension, when new agent classes will be introduced to represent manufacturing processes and decisions not covered in this work. ABS-based behavior at the station level plays a key role in enabling high granularity through bottom-up emergence of system behavior, as opposed to its top-down definition based solely on DES.

The first step is model definition via standardized input spreadsheets specifying product and factory configuration details. At the product side, we define the parts we need to produce in a given time frame, including the information on their dimensional, material, and quality requirements. At the factory side, we define the system configuration and the operational regimes, such as the number of stations of each type, number of employees, the shift pattern, equipment layout parameters, and the batching strategy. The detailed description of model constructs is presented in pp. 93-116 of Shakirov (2021).

Based on the input, the framework proceeds with layout generation. It derives and positions the model objects for stations, buffers, and storage elements – one-by-one, along the aisles – in compliance with the user-specified layout parameters. In doing so, the model first removes the objects of the previous simulation, then creates new objects adjusting their dimensions, and assigns their attributes according to user specifications. The method starts with positioning the build preparation (BP) stations (engineers' workstations for creating the print instruction files). Next, the AM machines and their buffers are placed next to the BPs, being limited by the maximum length and width of one division. With the same restrictions, the method continues creating and arranging the rest of the stations (e.g., furnaces) and system buffers.

Next, the framework simulates the production operations. It considers four major stages in LPBF-based AM of metal parts: pre-processing (build preparation), printing, post-processing (heat treatment, part removal from the build plate, and support removal), and inspection. At each step, we consider possible station setup, processing, recovery, and failure events (activities). The build preparation (BP) step formulates the list of parts that will compose the build according to one of three batching strategies reported in Shakirov et al. (2020). In this work, we use only the *max fill* strategy, which puts a maximum quantity of parts of the same type in one build and is typical of production orders within industry.

When the instruction file arrives at the printer, the model defines the processing times, i.e., setup time, printing time, and the recovery time. First, it updates the table tracking the operational information on each printer, such as the amount of powder left in the powder feed hoppers. If the amount of powder is sufficient for an upcoming build, then the setup time accounts only the build plate installation time with assumed mean value of 20 minutes. If not, the setup operation would also include the hopper refill step taking 25 minutes (i.e., the setup time mean would be 45 minutes). The printing time is defined as the sum of times spent on machine warm-up, inerting, and printing itself (i.e., layer-by-layer powder melting). The first summand is a machine-specific argument defined with the input data; the second summand is a sum of a pure powder melting time and the overall recoating time. The recovery time includes machine-specific cool-down time and the time for build plate removal (taken as 15 minutes). Additionally, we assume machine cleaning after each third build job (lasting 30 minutes) and preventive weekly maintenance (lasting three hours). After the machine cools down, the operator is called to uninstall the build and carry it to the buffer.

Before the parts exit, the framework accounts associated expenditures; and the same applies to BP and other LPBF steps. We use Activity-Based Costing (ABC), allowing to systematically identify all workflow activities at four levels (unit, batch, product, facility), across four cost categories (material, capital, labor, consumables), and scaling with three cost driver types (transaction, duration, intensity). E.g., for a batch-level activity – such as printing one build or build storage between consequent operations – we calculate four cost categories with corresponding scaling rules. They are then allocated among part types proportionally, e.g., the printing cost scales with the part volume and the storage cost with the part's bounding box volume. Currently, the model does not consider any product-level activities, such as assembly or functional inspection. Building on the two options of DES and ABC integration mentioned in Section 2.1, this work employs a mixed approach for accounting unallocatable costs. The system will define the allocatable costs during the simulation run and the unallocatable costs after it. This allows evaluation of idle costs and to adjust final costs by accurately accounting for resulting machine utilization, compared to costing models not based on simulation and using a fixed uptime rate.

The material cost is the sum of the material required for each part, support material, and the wasted material. Powder waste is inevitable, as in-process effects (e.g., spatter) denature the powder morphology and make it unsuitable for recycling (Mounsey et al. 2016). This work uses the powder waste rate of 9.5% reported by Walachowicz et al. (2017), which is applied to the mass of unmelted powder in the build. The cost of wasted material is then distributed among different part types proportionally to their cumulative masses. "Raft" support material is distributed among the part types proportionate to their cumulative footprint on the build plate. Finally, the cost of material spent on parts and non-raft supports is added for each part type.

The capital cost of printing is associated with the machine purchase cost and based on an hourly cost of ownership per machine (Gee et al. 2022). The cost per build is then assigned fractionally to each part type according to the part's mass; here, mass is used as a proxy for a part's contribution to the overall build time. The labor cost of printing is calculated according to variable full-time equivalents (FTEs) for operator's work during print supervision and setup. In setup, i.e., build exchange and cleaning operations, the FTE equals 100%, and in supervision it is taken as 15%.

The cost of consumables has several contributors which scale differently. Gas consumption scales directly with build time, as the model assumes a constant volumetric flow rate (L/hr) to a machine during printing and cool down. The same method applies to warm-up and purging but with a higher flow rate. Cost is assigned according to the cost per L of gas. The cost of electricity is accounted based on machine's hourly power consumption and the cost per kWh. Since mass is used as a proxy for the overall build time, the costs of gas and electricity per part type are scaled with its mass. The other consumable costs scale transactionally with the number of builds, i.e., irrespective of their duration. This is because some components are replaced either wholly, e.g., filtration units, or fractionally per-build; e.g., the substrate is surfaced between each build and discarded after a certain number of builds. (The model assumes 10 builds per substrate.)

Additionally, the exit method assigns probabilistic as-printed and as-inspected values on the tracked internal quality (IQ) parameters for each part in the build. The assumption here is that the printer has optical or infrared sensing/imaging instruments allowing identification of critical flaws, that have been correlated with historical ex situ testing data. If the as-inspected value is less than the lower limit, then the corresponding part is marked as defect and re-ordered for rework. The overall scrap rate, including after post-processing, is taken as 5%.

The post-processing stage includes heat treatment (HT), cool down (CD), wire Electrical Discharge Machining (EDM) for build plate separation (BS), and manual supports removal (denoted as PP). HT is assumed to process only one build at a time. HT and EDM parameters specified based on the material (see Section 4 for regimes used in this work). Support removal rate is taken as 30 cc/hr for any material. To account for variation in geometric complexity, the model includes the *post-processing complexity* factor, reducing the rate proportionally to factor's value. Similarly to printing, the framework sets duration values for post-processing steps and tracks their costs.

Quality control (QC) is the final stage devoted to parts visual inspection and optical metrology for dimensional and surface defects. QC assumed to take 10 minutes for any part. Its exit control method assigns as-inspected values for the tracked parameters following the normal distribution law, which mean value equals the as-produced value. Then, it compares this "measured" value with lower and upper specified limits (LSL and USL), differently for shaft- and hole-type dimensions. E.g., if the hole-type dimension is lower than the LSL, i.e., the part needs additional material removal, and there are no other defects identified, then the part is tagged as "rework" and sent to additional post-processing upon method completion. If the hole parameter value is higher than the USL, the part is tagged as "defect" with regard to this QC parameter. Such parts move to the specified defects isolator and re-ordered.

Upon completion of the simulation series, the framework outputs statistics on the considered techno-economic indicators, such as cost per cc, system throughput per time period, average lead time per part, WIP storage cost, Taguchi quality loss cost (Taguchi 2004), and more. The following section verifies the fulfillment of these functional requirements. Due to the novelty of this work, it has not yet been empirically validated in case study; further validation studies are planned for the future.

4 MODEL CASE STUDY

This section presents the use of the framework for techno-economic evaluation of the LPBF-based factory producing two part types shown in Figure 2: an acetabular hip implant (AHI) cup and an impeller. Their relevant specifications are given in Table 1. For comparability, both parts are assumed to be made of Ti-6Al-4V ELI powder, at $200 US/kg. We consider the following heat treatment (HT) routine for this material: annealing at 900°C for two hours, annealing at 700°C for one hour, and cool down (CD) at a constant cooling rate of 10°C/min (Kasperovich and Hausmann 2015). After HT, we assume having residual cool down step lasting one hour for each build. In build separation (BS), the EDM table feed rate for this material is taken as 8 mm/min. The cost of countermeasure for Taguchi "nominal-the-best" quality loss function was taken as an arbitrary value of $70 US for both AHI cup and impeller.

The objective of the study is to choose a primary LPBF printer type for a hypothetical high-volume production facility – having a limit of $25 million US in capital investment – by simulating its 60 days of operation in a three-shift mode providing 24-hour coverage 7 days a week. We consider three alternative LPBF machines: S-m400, S-m400-4, and S-m400-12. The first two correspond to the specifications of commercial EOS M400 and M400-4 machines with one and four lasers, and the last one is a hypothetical architecture with 12 lasers. Their assumed (installed) purchase costs are $1 million US, $1.76 million US, and $3 million US, correspondingly. To promote commensurate investment in different configurations, this study allows to add a less expensive printer if the budget allows. We also account for capital investment in heat treatment furnaces ($30 thousand US) and EDM machines ($200 thousand US) per station.

To simplify the study, this work considers a constant build rate per laser, being 30 cc/hr for Ti-6Al-4V (Gee et al. 2022). Thus, we assume the build rates of 30 cc/hr for S-m400, 120 cc/hr for S-m400-4, and 360 cc/hr for S-m400-12. The non-mentioned cost rates, such as volumetric cost of inert gas, hourly wages, build plate cost, follow the work of Gee et al. (2022b).

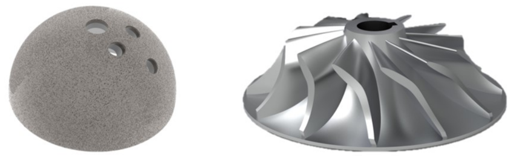

Figure 2: CAD models of the analyzed parts. Left – acetabular cup (2012); right – impeller (2021).

Table 1: Parts specifications.

	Unit	Acetabular Cup	Impeller
Outer diameter (mm)	mm	48	150
Height (mm)	mm	27	43
Part volume (cc)	cc	7.5	188
Supports volume (fraction of part volume)	-	0.1	0.1
Post-processing complexity	-	1	2
Max # of parts per 400x400 mm build plate	pc	60	5

First, we use the framework to find balanced system configurations for each of the six cases. We start with calculating the number of AM stations fitting in the budget limit and then adjust the numbers of other stations not leading to bottlenecks and WIP build up. This is enabled by the automated generation capability, where we only change the number of machines and the framework generates the configuration. From simulation, we can observe the bottlenecks from station utilization statistics ("blocked" segment) and WIP build up, as shown in Figure 3 for the third configuration of the impeller example. The resulting quantities of each station type per configuration are given in Table 2.

Table 2: Simulated factory configurations.

		CapEx	S-m400	S-m400-4	S-m400-12	HT	BS	PP	QC
AHI Cup	1	$24.44M	24	0	0	8	1	6	12
	2	$24.47M	1	13	0	13	1	7	21
	3	$24.82M	0	0	8	14	2	8	23
Impeller	1	$24.32M	24	0	0	4	1	4	1
	2	$24.32M	1	13	0	8	1	8	1
	3	$24.50M	0	0	8	10	1	9	2

Then, we simulate all six experiments to output the necessary evaluations. The simulation lead time, with 10 observations per experiment was 4 hours (the experiments run in parallel on AMD Ryzen™ 7 PRO 5850U). Table 3 shows the resulting throughput estimations for each configuration, and Figure 4 shows the lead time and cost evaluations.

We can see that a system producing smaller parts is generally less productive and more expensive. In the most productive scenarios of the current study – i.e., for configurations #3 based on 12-laser printers – the resulting volumetric throughput for AHI cups was ~30% less than for impellers, and their volumetric cost was ~70% higher. The cost contribution of post-processing activities is also more significant for smaller parts at the cost per part level (and this is also true for the cost of quality loss). At the same time, longer prints of larger parts (impellers) lead to fewer post-processing stations required in the system, and therefore make it more susceptible to flow variations and more prone to WIP build up. As a result, we see higher HT and QC lead time portions, even though mean HT and QC durations are assumed equal for both part types.

Figure 3: Configuration comparison. A (top, right) - with the bottleneck between AM and HT; indicated by larger "Blocked" (yellow) and "Waiting" (gray) portions of AM stations in the resource statistics chart and WIP build up at the AM stage (circled). B (bottom, left) - a balanced configuration used in the second Impeller experiment; a residual "Blocked" fraction attributes to recovery steps. Both system states are shown after the 45th simulation day.

Table 3: Throughput evaluations.

	Vol. throughput per day (cc/day)			Total throughput in 30 days (parts)		
Configuration #	1	2	3	1	2	3
AHI Cup	113,465	192,097	209,046	45,147	83,179	76,434
Impeller	123,324	234,546	300,019	1,968	3,743	4,787

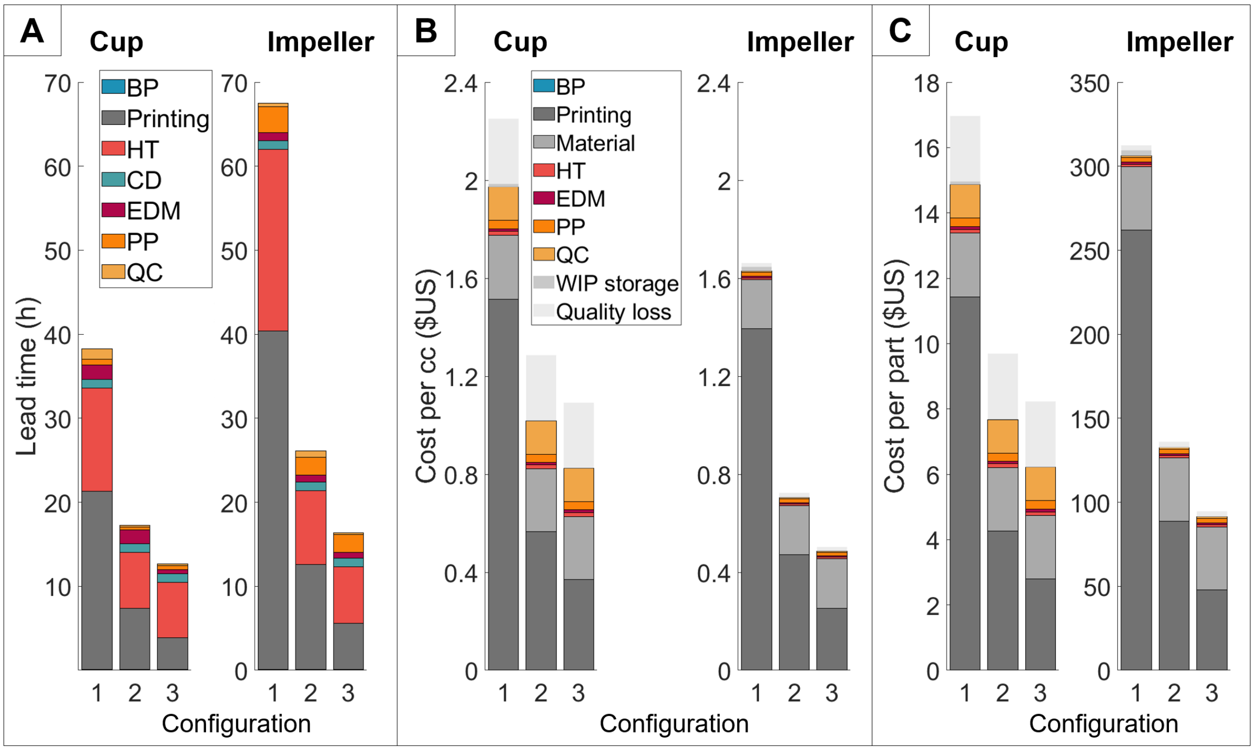

Figure 4: Cost and Lead time evaluations. A - Lead time breakdown. B - Cost per cc breakdown. C - Cost per part breakdown.

5 DISCUSSION AND CONCLUSIONS

Factory simulation demonstrates itself as a powerful approach to provide comprehensive techno-economic evaluations. In this work we present a multi-tool method combining hybrid DES-ABS simulation, activity-based costing, and automatic generation of the simulation models. Altogether, this allows to cover an end-to-end workflow of an AM-based factory with high granularity and efficiently study its design space based on major techno-economic tradeoffs, such as between cost per part, cost per cc, lead time, system throughput, station utilization, etc. (Note that the model evaluates the cost of goods sold and doesn't consider corporate overhead or selling, general, and administrative expenses.) The framework also paves the way towards more rigorous factory-level analysis of the quality control policies and their impact on the performance. In demonstration, we quantitatively illustrate the impact of machine-level productivity improvement on the overall system performance. On the part-factory design tradeoffs, we show that smaller parts are more expensive in terms of cost per volume unit and require more post-processing stations (under equal duration assumptions for different geometries). This is because the larger parts demand longer printing times, what leads to a higher ratio between the numbers of AM and HT stations for their higher utilization and absence of bottlenecks. In our future work, we aim to address the limitations in quality control and build design assumptions (e.g., consideration of test coupons), post-processing considerations (e.g., the lack of depowdering and machining steps), and to conduct a validation study.

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