A discrete event approach to the simulation of selective laser sintering 3D printing large scale production

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Abstract

Various industries, especially construction and building renovation, need custom components in quantities that traditional 3D printing methods are unable to supply. This article addresses the challenge of expanding the Additive Manufacturing (AM) production scale, emphasizing careful consideration in scaling strategies. In particular, it provides insights for optimizing AM factory productivity through discrete event simulation. The article models the setup and processing times for a selective laser sintering case study, examining the variability in machine and operator numbers for cost reduction and increased daily production, in two scenarios.

The first scenario is the reference for comparison with the one proposed in this paper. The working hours and days, and the type of machines in the production line are the same in both scenarios. In the proposed scenario, the effect of the number of operators and machines was studied by FlexSim software and compared with the referenced scenario in terms of the cost, daily production count, and average waiting time. It offers a practical roadmap for successful AM production scaling.

Keywords

Additive Manufacturing, 3D Printing, Selective Laser Sintering Machine, Discrete Event Simulation, Layout Guidelines, Cost Reduction

1. Introduction

Additive Manufacturing (AM) and digital fabrication are frequently used in the construction industry and other manufacturing domains to achieve a variety of objectives, including waste reduction, cost and time savings, and architectural freedom [1]. However, because the industry is distinct and conservative, digital technologies have been gradually adopted as auxiliary tools for conventional, well-established processes. Through improvements in mechanical, physical, and chemical qualities as well as dimensional precision, AM technologies are transforming the manufacture of components [2].

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Even though AM has historically been good at creating complex geometries[3], a typical drawback is that it only deposits one material at a time, which results in geometry-dependent performance outcomes. The dynamic manufacturing landscape is changing dramatically due to the impact of sophisticated technology, making small-scale production more affordable and resource efficient. The emergence of AM as a direct production technique forces businesses to reevaluate existing manufacturing strategies' locations and approaches [4].

A variety of goals have been the focus of earlier research on AM production planning, including decreasing production costs [5], delays [6], and processing times [7], as well as maximizing profit and resource use [8]. Technology must be included in production planning and control procedures for AM to become industrialized. This will increase output, reduce costs, and improve product quality [12].

Using a variety of techniques from production planning and scheduling optimization in conventional manufacturing could help address these issues. Computer simulation and other optimization methods have shown to be quite beneficial for conventional manufacturing systems in terms of both design and operation. A significant breakthrough in dynamic system modeling was the advent of Discrete Event Simulation (DES) modeling, which made it possible to incorporate real-world unpredictability for production scheduling [9]. With successful applications in bottleneck identification and manual assembly [10], where it was combined with operational management to address lot size issues and lower production costs, DES has demonstrated a high degree of effectiveness in simulating and resolving complicated queuing problems. Owing to its effectiveness, DES offers a viable way to analyze and improve AM process planning.

DES has several benefits, but it cannot automatically carry out iterative optimization on its own. As such, it requires the incorporation of appropriate optimization techniques to attain more improvements. The advantages of combining DES with optimization tools to address complicated production difficulties have been shown in conventional manufacturing environments [11]. Building on this achievement, FlexSim, a DES software, has the potential to improve AM production system design and planning. It is feasible to create AM production planning techniques that are more reliable and effective by combining the advantages of both approaches, eventually improving the capabilities of additive manufacturing systems [12].

With a particular focus on the Selective Laser Sintering (SLS) process, this research presents a simulation-optimization approach to handle scheduling and bottleneck identification challenges in additive manufacturing. Through the application of productivity increase strategies from conventional production to additive manufacturing, this study highlights the value of integrating FlexSim with DES. Using this method can help make well-informed decisions about the configurations of the equipment, which will ultimately save costs.

The paper is structured as follows: The problem statement in the context of SLS processing is fully described in Section 2, where it will be thoroughly examined and then improved. In Section 3, the research methodology is explained in detail along with how it relates to the findings in Section 4. Section 4 explores the ramifications of these findings. Section 5 concludes the analysis and makes recommendations for further research.

2. Problem Statement

The main goal of this study is to present a method for increasing production rate by adjusting layout and parameters. To achieve this, the production system described in [13] is examined, and the potential applications of a specific mathematical technique are explored to optimize workstation layouts for the integration of additive manufacturing technologies, specifically SLS and SLM (Selective Laser Melting). The project comprised designing a prototype design based on selected 3D printing techniques and a hypothetical production scenario.

Because 3D printing can create products with intricate patterns and greater production runs, investor interest in the technology is predicted to increase. Furthermore, the construction of enterprises focused mostly on 3D printing machinery. As such, it is imperative to establish clear rules and norms for designing layouts conducive to the seamless operation of additive manufacturing devices. According to the material in reference[13], SLS technology is the primary focus of this endeavor.

A hypothetical production schedule was created for the computational study, with an emphasis on the use of 3D printing equipment to manufacture a certain product type, with a special emphasis on SLS-produced goods.

3. Methodology

3.1. Reference model

Before making any modifications, FlexSim should first simulate the reference model. The production plan called for producing 20,000 units of the product a year, according to work [13], Other presumptions include:

1. The SLS machines' simultaneous printing capacity is eight units.
2. There are 250 working days in a year.
3. There are two production shifts.
4. Working day utilization factor (0.9375), considering work breaks (assumed to be from 12:00 PM to 12:30 PM).

The recommended number of machines, together with their setup and processing time, are displayed in Table 1 along with the number of machines that were found to be required using a particular formula. Additionally, in Fig. 1 the factory's structure is outlined.

The layout plan was meticulously designed to optimize the workstation layout's efficacy; the plot form allows for product receipt on one side of the production hall and material supply on the other. This configuration was purposefully designed to allow materials to flow continuously, increasing overall operational efficiency. The goal of this design is to create a productive and well-organized work environment that will help to increase the overall performance and productivity of the manufacturing plant.

A method for representing business processes that understandably incorporate formal characteristics is the Business Process Represent and Notation Diagram (BPMN). Its visual approach helps identify issues such as infinite loops, for preserving correctness and coherence in process descriptions [14]. The preceding layout's description of the SLS production process is visually shown in Fig. 2, which facilitates comprehension and improves clarity.

Table 1
Recommended Machinery from ref [13]

Machine Names	Quantity	Setup Time (min)	Process Time (min)
Powder Mixing	2	10	15
Sifter	1	10	5
SLS Device	4	30	320
Cabin Sandblaster	1	10	5
Grinder	2	15	8
Varnishing	1	10	5
Packing Station	2	10	7

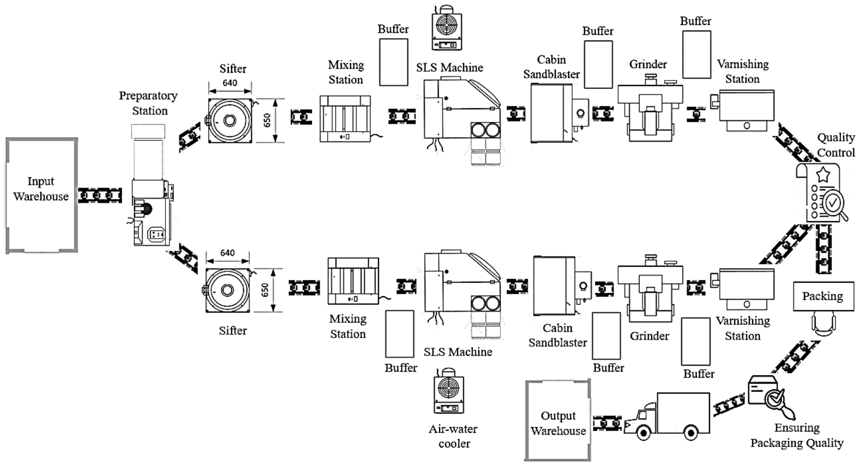

Figure 1: Exemplary Layout Plan for 3D Printing machines and devices, modified from [13].

The production simulation task consists of three basic phases, as follows (Fig. 2).

1. **Preprocessing:** Precise handling and control of powders for additive manufacturing are critical in the field of powder management. To maintain uniformity and quality, handling, preparation, and storage are required. Several machineries are crucial to the production process in the model setup. The input warehouse serves as the starting point, receiving and holding raw materials needed to create parts in accordance with orders from customers. The Powder Selection station is responsible for carefully evaluating and choosing only flawless powders so that only materials of the highest quality move on to the next phase. After that, the Powder Mixing station, also known as a powder blender or mixer, is essential for blending dry powders uniformly and preserving product quality during the manufacturing process. The Sifter is an additional crucial station that is accountable for eliminating

foreign objects, confirming the size of the powder grains, and enabling ongoing quality inspections. It guarantees maximum utilization for the manufacturing process, breaks up product lumps, and separates coarse materials.

2. **Processing:** This section focuses on the SLS procedure. SLS Instrument: The SLS Device is a key part of the manufacturing process. It is designed to work smoothly with Industry 4.0 environments, making it a production platform that looks forward. The SLS technique, developed by Desktop Manufacturing Corporation [15], uses a laser beam to solidify powdered materials layer by layer. A 3D CAD model is loaded, converted to STL format, and then sliced into layers [15]. Before laser sintering, plastic powder is placed and heated, causing the powder to fuse selectively by the cross-section of the model. The product is cleaned and may go through finishing procedures like varnishing and sandblasting after printing [16]. The use of 3D printing equipment, such as the EOS GmbH FORMIGA P 110 and related support equipment, at a recently built facility is the basis of this essay. The SLS technique is used by these gadgets to operate [17].

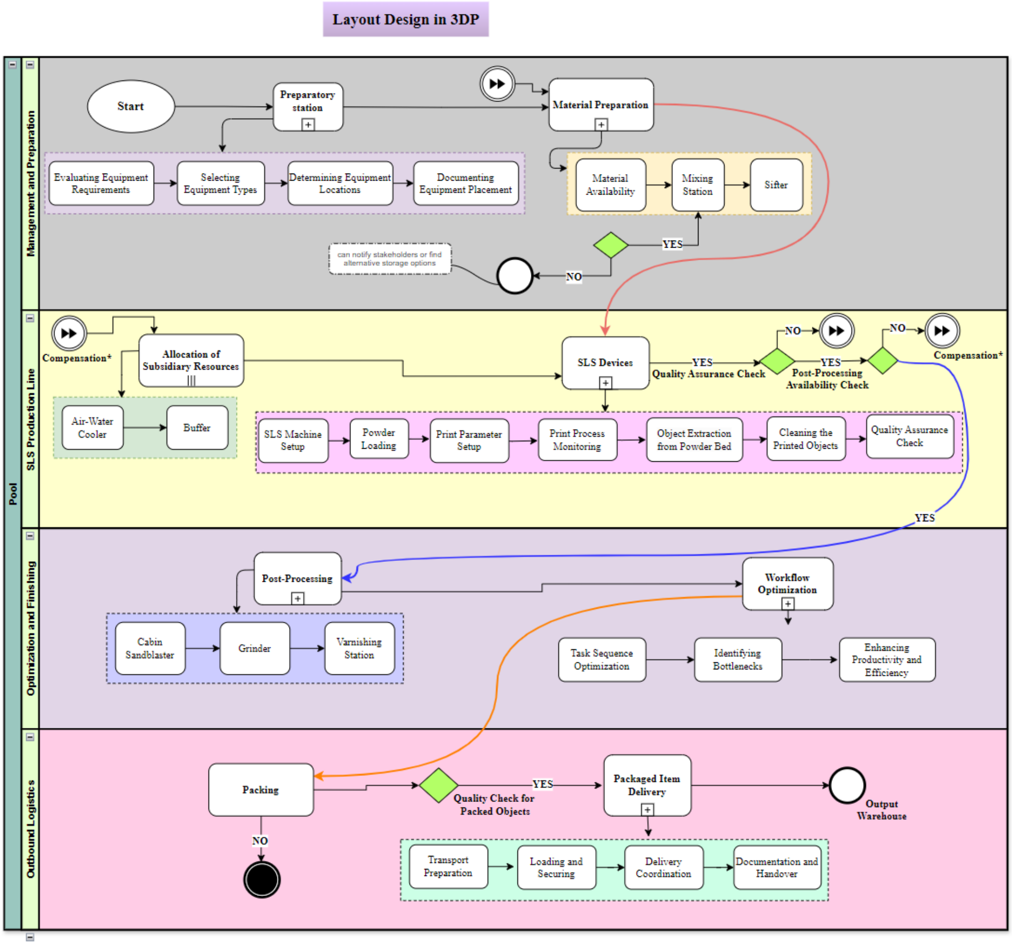

Figure 2: BPMN Diagram of the SLS Workflow

3. **Post-processing:** The equipment used at this stage is essential for the manufactured parts' packing, protection, and refinement. Abrasive materials are propelled at high

speeds by the Cabin Sandblaster to clean and prepare surfaces. To attain desired forms and finishes, surface grinders are essential tools for refining SLS-printed objects. Protective coatings are applied through vanishing to prevent environmental damage. Careful packaging is required during packing to simplify storage and guarantee product safety throughout transit. Before being distributed, completed goods are centralized and stored in the output warehouse. The goal of these post-processing sub-processes is to improve the final product's quality and appearance by smoothing out surface flaws, applying protective coatings, and improving the surface finish on printed parts.

3.2. Modelling in FlexSim software

The reference production line's layout plan, created to satisfy FlexSim software's processing requirements, is the main topic of this article. 21 processors, 4 temporary storage spaces, 1 pallet temporary storage zone, and 1 input and output warehouse are needed to build the model. The production line's FlexSim simulation model is shown in Fig. 3. Building the model and precisely adjusting its parameters are essential to the simulation's success.

Materials in FlexSim are routed to the powder selection buffer from the input warehouse. The powder is fed into the powder mixing machines and blended after they have finished setting up. Following the processing time, the mixture is moved to a sifter machine, which separates the larger grains from the smaller ones. The mixture is then transported to a buffer because, in this work, the SLS machines have 320 minutes to prepare 8 parts at once. This is accommodated by putting a buffer before the SLS machine and using FlexSim's "Round Robin if Available" setting in the buffer's output. Once the parts are ready from the SLS machines, another combiner is added. To guarantee that eight parts enter the machine, are created, and exit at the same time, the combiner is configured in "batch" mode in this phase. Then, another combiner machine is set up, but this time, the options section has the "pack" option chosen. To finish, distinct separator machines are placed next to each SLS machine and configured for "unpacking." Because of software constraints, the combiner cannot directly pick batch mode, and the separator cannot unpack, so this layout design is required. To accomplish the packing before the separator starts the unpacking process, an additional combiner is placed in between them.

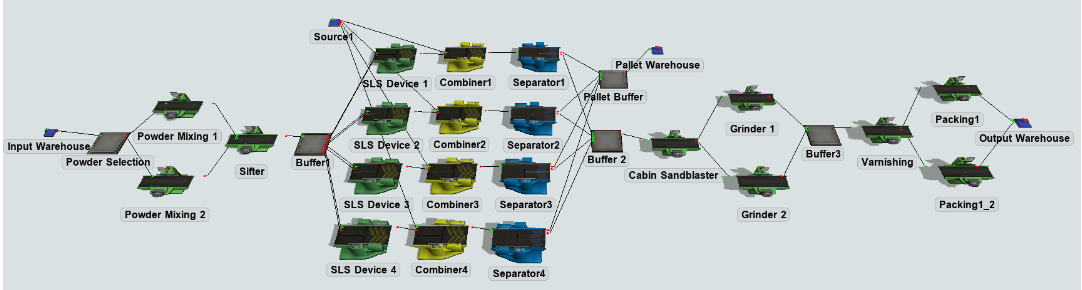

Figure 3: Simulation Model of SLS production line in FlexSim.

Next, two buffers are added to FlexSim: one for gathering the pallets and the other to collect the assembled components. After that, these pallets are sent to the warehouse so they can be used again on a production line. After that, the components move to the cabin sandblaster, where they go through a procedure using highly accelerated abrasive compounds. This stage improves the pieces' overall finish by smoothing down uneven surfaces and removing surface defects. The parts are moved to the grinder station once they are finished. Here, the SLS pieces' surface polish is improved, any lingering support structures or build platform attachments are eliminated, and any dimensional errors that might have happened during printing are fixed. Before proceeding to the next level, this careful procedure makes sure that the parts fulfill the requirements and quality standards.

Subsequently, the parts are queued to prevent the creation of bottlenecks. After that, they proceed to the varnishing station to receive a layer of ornamental or protective varnish. The items are cleaned and, if desired, prepped before coating to ensure an even application. Before the pieces are packaged for storage or additional processing, thorough quality inspections are carried out after drying or curing. The components then head to the packing station. They are packaged here in compliance with standardizing procedures. They are delivered to the output warehouse for distribution after being confirmed.

3.3. Improving the process of the reference model

As stated before, the primary goal is to determine the optimal machine count by examining various scenarios to increase production. The purpose of these scenarios is to determine how many SLS, sifter, cabin, varnishing, and packing machines are needed to reach output levels that are at least as high as the reference [13].

Before describing the scenarios, it is crucial to determine the feasibility of adjusting the number of SLS machines. To this aim, the reference layout design is used as the basis for evaluating the SLS machines' performance. A low machine usage rate raises the potential for a reduction in the total number of SLS machines. The ideal number of SLS machines found from this assessment is then used to define the scenarios.

Procedures for handling bottlenecks and equipment configurations are important aspects of manufacturing processes that have a big impact on production efficiency. To increase production line productivity, remove bottlenecks, and maximize equipment utilization rates, it is crucial to examine variables including equipment processing time, blocking time, and idle time [18]. The finished system model seeks to enhance equipment use while minimizing idle rates. The crucial step in determining the production line's operating state involves assessing the number of SLS machines in operation.

The number of machines in the first test was configured according to the guidelines provided in the article, focusing on output computation using four SLS machines over 250 days. In the second test, all machine quantities remained consistent with the article's specifications, except for the SLS machines, which were reduced to three, to determine the output within the same 250-day period. Similarly, in the third iteration, the number of SLS machines was reduced to two, while still adhering to the article's specified machine quantities.

Four parameters—the sifter, cabin sandblaster, varnishing, and packing machines—are used to evaluate the number of other machines in the FlexSim model. For these parameters, both lower and upper limits have been established to evaluate various scenarios within the flexible framework of FlexSim. Specifically, the lower and upper bounds for these machines are as follows: cabin sandblaster machines range from 1 to 3, sifter machines range from 1 to 2, varnishing machines range from 1 to 3, and packing machines range from 1 to 2. By acquiring the output of the best SLS, which was examined in Table 2, the optimal number of these parameters was found.

Table 2
Scenarios for Machines

Scenarios #	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Cabin Sandblaster	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2
Sifter Machine	1	1	1	1	1	1	2	2	2	2	2	2	1	1	1	1	1	1
Varnishing Machine	1	1	2	2	3	3	1	1	2	2	3	3	1	1	2	2	3	3
Packing Station	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Scenarios #	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
Cabin Sandblaster	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3
Sifter Machine	2	2	2	2	2	2	1	1	1	1	1	1	2	2	2	2	2	2
Varnishing Machine	1	1	2	2	3	3	1	1	2	2	3	3	1	1	2	2	3	3
Packing Station	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2

Furthermore, an analysis was carried out by considering the impact of utilizing a distribution function on the deterministic processing time values found in Table 2. It was assumed that the distribution was normal, with the mean values matching those in the reference and a standard deviation set at 20% of the mean (std = mean * 0.2).

4. Results

The production rate that resulted from building the model using the reference model's data was identical to that of the reference model. After that, the validation was confirmed.

4.1. System Simulation Analysis for SLS machine

Table 3 presents the outcomes of these experiments. It illustrates how, after 250 days, employing 4 SLS machines yields a total production of 23,438 pieces. However, according to FlexSim, the equipment utilization graphical representation in Fig. 4(a) shows that the processing times for SLS machines 1, 2, 3, and 4 are, respectively, 58%, 57.97%, 57.96%, and 57.96%. Furthermore, these machines' collection percentages are 33.86%, 32.68%, 33.90%, and 32.68%, respectively.

A total of 23,309 objects are produced, according to a probability distribution analysis performed on four SLS machines. SLS machines 1, 2, 3, and 4 have collection percentages of 33.15%, 33.44%, 33.87%, and 33.09%, and processing speeds of 58.04%, 57.79%, 57.37%, and 58.14%, respectively, as shown in Figure 4(b).

Following a trial that lasted 250 days, a comparable analysis using three SLS machines produced a production volume of 23,446 units. The experiment's equipment utilization rates are displayed in Figure 5(a). 13.32%, 13.34%, and 13.37% are the collection percentages, and 77.33%, 77.31%, and 77.27% are the machine processing durations that were measured.

Table 3

SLS Machine Configuration Output Comparison

Experiment Number	Number of SLS Machines	Parts Produced in 250 Day	
		Without distribution	With distribution
1	4	23,438	23,309
2	3	23,446	23,315
3	2	18,094	18,003

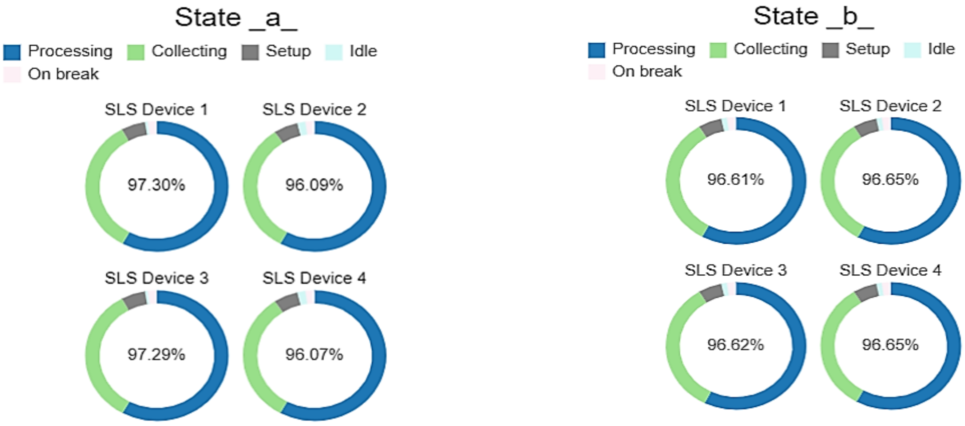

Figure 4: Production Analysis for 4 SLS Machines in 250 Days: (a) Fixed Processing Time, (b) Distribution-Based Processing Time

23,315 units were produced in a follow-up test with distribution-based processing. The experiment's equipment utilization rates are shown in Figure 5(b). The evaluations of the machine processing times are 76.76%, 76.78%, and 76.77%, and the collection percentages are 13.72%, 13.71%, and 13.71%.

When the research was expanded to include a scenario with only two SLS devices, 18,094 units were produced over 250 days. A similar normal distribution study, conducted with the same parameters, resulted in 18,003 units.

Three SLS machines are the best option, according to a thorough investigation. Regardless of distribution-based or fixed processing durations, the results roughly agree, indicating that three SLS machines make up the ideal configuration. This setup guarantees sufficient production after the 250-day term in addition to increasing daily operating efficiency. It is also more cost-effective to use three machines than four. Because it optimizes production and reduces the need for additional machinery, using a three-machine arrangement is economical.

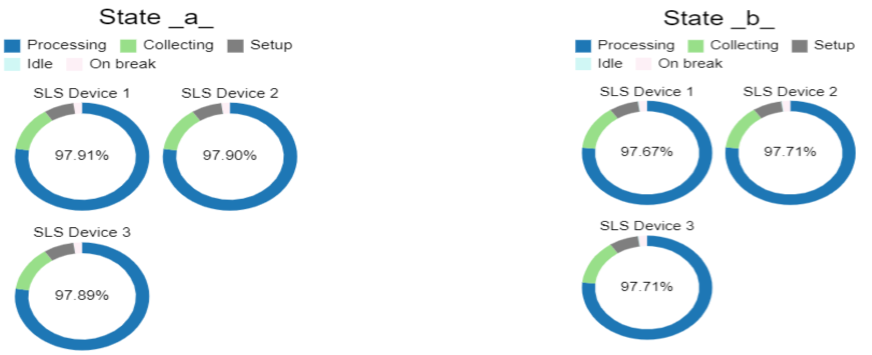

Figure 5: Production Analysis for 3 SLS Machines in 250 Days: (a) Fixed Processing Time, (b) Distribution-Based Processing Time

4.2. Comparing different scenarios

The results across several scenarios are presented in Table 4. A review of the data reveals three distinct production rate levels.

Table 4

Production Rate Comparison

Scenario #	Production		Scenario #	Production	
	*	(Mean, std) **		*	(Mean, std) **
1	20688	(20562.93, 9.96)	19	20691	(20567.03, 9.98)
2	**23446**	**(23312.16, 9.96)**	20	23450	(23452.21, 9.10)
3	20688	(20686.57, 10.27)	21	20691	(20682.39, 10.19)
4	23446	(23313.64, 9.90)	22	27135	(27126.44, 99.00)
5	20688	(20688.14, 10.36)	23	20691	(20684.56, 10.31)
6	23446	(23313.70, 9.98)	24	27135	(27126.34, 99.06)
7	20691	(20566.93, 9.99)	25	20688	(20563.07, 10.00)
8	23450	(23440.57, 8.80)	26	23446	(23313.53, 10.27)
9	20691	(20691.17, 10.30)	27	20688	(20664.27, 10.05)
10	23450	(23451.51, 10.50)	28	23463	(23321.06, 10.96)
11	20691	(20692.76, 10.37)	29	20688	(20667.24, 10.31)
12	23450	(23451.47, 10.50)	30	23463	(23320.96, 10.96)
13	20688	(20563.03, 10.02)	31	20691	(20567.03, 9.98)
14	23446	(23313.46, 10.32)	32	23450	(23452.26, 9.07)
15	20688	(20664.77, 10.48)	33	20691	(20682.36, 10.18)
16	23463	(23320.99, 10.89)	34	27135	(27126.29, 98.96)
17	20688	(20667.29, 10.03)	35	20691	(20684.67, 10.16)
18	23463	(23320.97, 10.93)	36	27135	(27126.37, 98.91)

* With deterministic processing time

** Normal distribution for the processing time

The target output rate of 20,000 units within the allotted 250 days is shown in the first row. The desired results are achieved in Scenarios 1, 3, 7, and 13. These scenarios are distinguished by having the highest production rates while using the fewest machines compared to the others. The reason scenario 1 is the best of them all is that it uses the fewest equipment to create this much. As an alternative, scenario 2 appears to be the best option and the second tier indicates a production potential of 23,000 units. But, at a production rate approaching 28,000 units, the third-tier deviates considerably from our goal. Besides, reaching this rate would require an increased number of machines, which would be against our objectives. The same data was examined under different circumstances in which a normal distribution was used to define the processing time. The output rates of both techniques are rather close to one another, as Table 4 illustrates.

The ideal situation is shown by the results for both scenarios as follows. The investigation shows that the 20,000 unit production benchmark specified in the article may be met with three SLS machines and four machines in the sections that were evaluated. But as scenario 2 illustrates, to reach a greater output, a production rate of 23,000 units can be reached thanks to the cooperation of three SLS units and five machines located in the researched stations.

Two important considerations must be made before making the final choice. First, if selling 20,000 units at the lowest possible cost is our top goal, then scenario 1 is the greatest option. However, since using five machines yields the highest production, scenario 2 is the greatest choice if our objective is to ensure steady costs for all analyzed stations (packing machines, varnishing, sifter, and cabin sandblaster). Determining which parameters are most essential to us is what thus makes a difference.

5. Conclusions

This study has addressed the complexities of scaling up AM production, emphasizing the necessity of meticulous planning and strategy in expansion efforts. The benefits and challenges of applying AM technology can be very large and include the construction industry, particularly the field of cultural heritage rehabilitation. By leveraging discrete event simulation through FlexSim software, the intricacies of optimizing AM factory productivity, focusing on a selective laser sintering case study have been explored. Key findings from the study include the impact of operator and machine variability, a clear roadmap for reducing costs and increasing output, enhanced efficiency through strategic workforce and machine adjustments, the reduction in waiting times, and streamlining production. Finally, the paper has proved the importance of using advanced simulation tools to predict and mitigate potential bottlenecks and inefficiencies, ensuring smooth transitions during AM production scale-up.

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