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RESEARCH PAPER

Evaluating the optimal facility location for additive manufacturing technology

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ABSTRACT

Goal: This research identifies the optimal location for additive manufacturing (AM) facilities within the spare parts supply chain, addressing a critical yet underexplored dimension in the literature on strategic facility location for AM technology deployment.

Design / Methodology / Approach: The study integrates agent-based discrete event simulation with scenario analysis to evaluate four facility locations for four distinct spare parts. The model aims to reduce order fulfillment losses and opportunity costs by supporting evidence-based location decisions.

Results: The findings indicate that the Thane location is the most suitable for establishing an AM facility, offering a balanced trade-off between supply reliability and economic efficiency.

Limitations of the investigation: The scope is confined to a specific case involving four locations and four spare parts, which may limit generalizability. The study's scenario-based approach also relies on assumptions that warrant further validation.

Practical implications: The results offer actionable insights for firms adopting AM in spare parts management. Strategic facility placement enhances service responsiveness, reduces downtime, and supports cost-effective fulfillment strategies.

Originality / Value: This research provides an incremental empirical contribution by proposing and demonstrating a simulation-based AM facility location selection framework, supported by real-world case data. It addresses a less explored strategic decision of AM facility placement, considering dynamic operational uncertainties, thereby extending the existing literature on AM supply chain design.

Keyword: Discrete event simulation; Spare Parts; Facility Location; Scenario Analysis; Additive Manufacturing.

INTRODUCTION

After-sales services provide a reliable revenue stream for manufacturing industries. However, choosing the optimal manufacturing technology and supply chain for spare parts remains a complex challenge for these industries (Sgarbossa *et al.*, 2021; Ghuge and Akarte, 2024b; Ghuge, Akarte and Raut, 2024). Developing an efficient spare parts supply chain is a crucial decision for manufacturing industries. This involves complex analyses of reverse engineering, procurement, and logistics to ensure economical operations (Knofius, van der Heijden and Zijm, 2019b; Frandsen *et al.*, 2020). Traditional manufacturing (TM), also called conventional manufacturing (CM) or subtractive manufacturing (SM), is a material removal process predominantly utilized for spare parts manufacturing. However, due to the constraints of the economics of scale, companies eventually end up maintaining extensive inventories with several stock-keeping units (SKUs). This results in a tie-up of high capital, and certain inventories become obsolete due to sporadic demand patterns (Ghuge, Dohale and Akarte, 2022).

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"On the other hand, additive manufacturing (AM) is a cutting-edge technology based on a layer-by-layer material addition process. It is gaining global traction due to numerous benefits, including: on-demand manufacturing, low volume, tool-less manufacturing, no economies of scale, a wide variety of parts with low cost and time, sustainable transformation, and green logistics, etc. (Sharifi *et al.*, 2021; Ghuge, Akarte and Pandey, 2022; Ghuge, Dohale and Akarte, 2022; Ghuge and Parhi, 2023; Ghuge, Akarte and Raut, 2024; Poddar *et al.*, 2024). AM is becoming prevalent in numerous industries like automotive, defence, aerospace, aviation, electric components, medicine, architecture, footwear, and is also used for frugal innovation, etc. (Dos Santos and Benneworth, 2019; Gibson *et al.*, 2021; Ghuge and Akarte, 2024a; Lemma *et al.*, 2025; WohlersReport, 2025). This diverse range of applications highlights the remarkable growth of AM, evident in the substantial double-digit market growth observed over 11 years from 2011 to 2021 (Wohlers Report, 2022). Further, according to AM Power (2024), the AM industry is expected to grow by 13.9 % per annum until 2028.

With characteristics like unforeseen demand patterns, low volume, high inventory storage, obsolescence, and a highly complex supply chain, etc. AM technology has become one of the prominent manufacturing technologies for aftermarket and legacy parts (spare parts) (Knofius, van der Heijden and Zijm, 2016; Chaudhuri *et al.*, 2021; Foshammer *et al.*, 2022; Ghuge, Dohale and Akarte, 2022). This clearly demonstrates that AM is the best option to overcome the challenges in spare parts supply chains.

Numerous research studies are ongoing in the areas of AM and supply chain and operations management, such as the identification of spare parts produced through AM (Chaudhuri *et al.*, 2021; Foshammer *et al.*, 2022; Ghuge, Dohale and Akarte, 2022; Cardeal, Leite and Ribeiro, 2023), AM process selection (Wang, Blache and Xu, 2017; Jamwal *et al.*, 2021), selection of optimal sourcing strategies among CM, AM, or hybrid (Cestana *et al.*, 2019; Knofius *et al.*, 2021; Sgarbossa *et al.*, 2021), decision of stock, 3D print or expedite (Westerweel *et al.*, 2021) and centralized vs decentralized supply chain configuration (Fu *et al.*, 2014; H. Khajavi, Holmström and Partanen, 2018; Montero *et al.*, 2020).

While prior research has begun to explore supply chain configurations for AM, there is a relative scarcity of empirical, data-driven studies that quantitatively evaluate optimal AM facility placement under dynamic, real-world operational constraints. This study aims to address this gap by proposing a simulation-based approach that captures stochastic factors like machine failures and replenishment delays, which are central to spare parts management. To address this gap, our study investigates the following research question:

What is the optimal facility location for deploying additive manufacturing to minimize opportunity costs and order fulfillment losses in the spare parts supply chain?

To answer this, we develop an agent-based discrete event simulation model that evaluates various scenarios involving four facility locations and four spare parts, drawing on real-world data from a machine manufacturing company. This strategic lens on AM facility placement fills a vital gap in the literature and offers actionable insights for practitioners.

The rest of this article is organized as follows. Section 2 comprises the development of a simulation-based AM spare parts supply chain model by considering the situation as an AM facility located almost equidistant from all four supply locations. Explicitly, in Section 2.1, the model overview demonstrates how authors have assessed the different scenarios of each facility location, considering the uncertainty in the models. The case study is illustrated in Section 3. Section 4 describes the outcome of a case study. This offers initial insights that printing at an optimal location is a sensational approach to accommodate all the facilities' demands. The theoretical and managerial implications have been explicitly demonstrated in Section 5. In the end, Section 6 discusses the research's conclusions, discussion, and future research avenues.

Theoretical Framework and Literature Review

This section covers AM for the spare parts supply chain, Facility location, and AM initiation and justification for the simulation-based Methodology. Finally, Key research gaps are highlighted.

Prior research on AM for spare parts has largely advanced three complementary threads. First, studies on AM parts and process selection emphasize when AM is economically and technically viable relative to conventional sourcing, including implications for inventory and responsiveness (Wang, Zhong and Xu, 2018; Foshammer *et al.*, 2022; Ghuge, Dohale and Akarte, 2022). Second, work on network configuration and decentralization investigates hub-and-spoke vs. distributed AM footprints and hybrid AM-CM sourcing, highlighting how digital production and shortened lead times alter traditional supply-chain design trade-offs (Durão *et al.*, 2017; Knofius, van der Heijden and Zijm, 2019a; Montero *et al.*, 2020; Sgarbossa *et al.*, 2021). Third, the facility-location literature provides a broad toolkit (discrete/continuous FLP, hub-location, and stochastic/robust models) for siting service capacity under demand uncertainty and service-level constraints (Knofius, van der

Heijden and Zijm, 2019a; Montero *et al.*, 2020; Friedrich, Lange and Elbert, 2022, 2023).

Research Gaps and Methodology Justification

While previous studies address AM part identification and process selection, AM-CM sourcing, and centralized versus decentralized supply-chain designs, but largely at the network level. It rarely tackles the granular, operational decision of siting a single facility within an existing multi-plant network to curb real-time downtime costs. Empirical studies typically rely on deterministic or steady-state assumptions, overlooking the dynamic interplay of stochastic part failures, inventory depletion, and production delays that shape spare-parts supply chains. We extend this stream by proposing an agent-based, discrete-event simulation framework with scenario analysis (Varum and Melo, 2010; Jha and Mohan, 2023; Ortiz-Barrios *et al.*, 2023) to evaluate facility-location alternatives under uncertainty, validated on industrial data, and designed to capture operational complexities. Our contribution is threefold: (i) an empirical, uncertainty-aware assessment of AM facility location, (ii) a real-world validated model using industrial data, and (iii) methodological rigor that captures operational complexity.

METHODOLOGY

Building on the theoretical grounding outlined in the literature review section, this study adopts an agent-based discrete event simulation model to evaluate the optimal location for additive manufacturing (AM) facilities. To achieve this, we developed an agent-based discrete event simulation (DES) model using AnyLogic®. This approach is suitable for capturing the complex, stochastic behavior of spare part failures and replenishment dynamics (Jha and Mohan, 2023; Ortiz-Barrios *et al.*, 2023). Further, scenario analysis is used to model uncertainty in demand and supply disruptions (Varum and Melo, 2010). The stepwise modeling process was validated through expert consultations with industry professionals and academic researchers to ensure practical relevance and credibility. The overall research steps, illustrated below, serve as a guide for evaluating different facility location scenarios under given operational constraints.

Research steps

1. *Overall Objective:* Identify a suitable AM facility location for spare parts supply.
2. *Problem Identification:* Literature review and expert consultation revealed a gap in AM facility location modeling under real-world constraints.
3. *Part selection:* Based on the segmentation approach (Ghuge, Dohale and Akarte, 2022) and company experts, four AM-suitable parts were shortlisted.
4. *Data collection:* Conducted through structured interviews with operations managers, maintenance engineers, and spare part planners. Historical data were gathered on failure rates, lead times, replenishment cycles, printing times, and cost of downtime.
5. *Model Design:* An agent-based DES model was developed using AnyLogic© to simulate machine failures, inventory depletion, and AM-based replenishment. Four location scenarios were created, each with part-specific supply-demand dynamics based on the real-life case example of Ferro Oil Tech (I) Pvt. Ltd.
6. *Simulation Execution:* The simulation was run for 500 operational days, with multiple replications for robustness. Metrics such as order fulfillment rate, spare part losses, and aggregate downtime costs were recorded.
7. *Scenario Analysis and Evaluation:* Scenarios were evaluated based on total loss due to downtime and unavailability. The optimal facility location was identified by comparing outcomes across locations.
8. *Model Validation:* Face validation was conducted with domain experts. Further sensitivity analysis and Monte Carlo simulations were used to test robustness.

Research Design and Procedure

This research follows a single embedded case study approach based on a real-world Indian machine manufacturing company with four production plants located at Thane, Nashik, Bhusawal, and Khatwad, which serve as the candidate locations for installing the AM facility. The case company was selected using purposive sampling, based on its maturity in AM adoption, geographical coverage, and availability of expert inputs.

Data Collection and Inputs

The study utilizes a combination of primary and secondary data:

- Primary Data: Structured interviews with operations managers, AM engineers, and maintenance experts at the case company were conducted to understand part criticality, failure behavior, replenishment cycles, and cost implications. A structured expert interview protocol and company database queries were used. Parameters such as part printing time, lead time, failure probability, and downtime cost were recorded and triangulated.
- Secondary Data: Internal records were used to extract historical failure rates, printing times, success probabilities, replenishment delays, and downtime costs

The key parameters used in the model include:

- Part failure rates (modeled as exponential distributions),
- Printing times and success probabilities (location-dependent),
- Replenishment lead times and delay/cancellation probabilities,
- Downtime cost per part per day,
- Initial base stock inventory of one unit per part per location.

These inputs were triangulated across sources and validated by domain experts.

Sample and Unit of Analysis

The unit of analysis is the AM facility location decision across four potential sites. The company has over 200 active spare parts; four were selected (A05, A13, A17, and a Height Sensor) for this study based on expert validation using criteria such as AM suitability, high downtime impact, and functional compatibility. All parts are fabricated using MS1 material and the EOS DMLS system due to its proven industrial use and compatibility with all four chosen parts. Discrete event simulation outputs were analyzed to compute aggregate opportunity cost losses at each location under various scenarios. Monte Carlo analysis tested robustness.

This structured approach ensures transparency and replicability in AM facility location decision-making using simulation.

Modelling and Simulation Steps

The simulation model was developed in AnyLogic®, using an agent-based DES paradigm to mimic real-time spare part failure and replenishment dynamics. The modeling was structured as follows:

Step 1: Initialization

Each spare part is represented as an agent possessing key attributes, namely failure rate, printing time, success probability, and downtime cost. All facilities commence with a base inventory of one unit per spare part. To account for the randomness inherent in failure events, the demand process is modeled using a Poisson distribution, enabling the simulation of stochastic spare part requirements.

Step 2: Demand Trigger and Fulfillment

In the event of a spare part failure, the inventory is reviewed. If the required part is unavailable, an additive manufacturing (AM) production request is issued to the designated facility. After successful fabrication, delivery is attempted, taking into account the facility's characteristic probabilities of delay, cancellation, and successful fulfillment.

Step 3: AM Facility Configuration

The study initially considers the AM facility to be centrally located, maintaining equal distance from all plants. Subsequent simulations explore scenarios where the facility is repositioned to each of the four designated candidate sites. The model operates under the assumption of unlimited fabrication capacity, as all spare parts are composed of the identical material composition and can be printed simultaneously within a single printer bed setup.

Step 4: Performance Metrics and Loss Calculation

Simulation output includes part-level and location-level data on:

- Demand occurrences,
- Inventory availability,
- Fulfilled and unfulfilled requests,
- Downtime losses.

Downtime loss is calculated as:

$$Loss_L^{(r)} = \sum_\beta \left(Unfulfilled_{i,L}^{(r)} \times \ Downtime\ Cost_\beta\right)$$

where β denotes the spare part, and L denotes the facility, r denotes replication
Step 5: Simulation Horizon
Each facility location scenario was simulated for 500 operational days, with 100 replications per scenario to address stochastic variability.

MODEL INFORMATION

Assumptions

To streamline the simulation and focus on evaluating facility location decisions, several assumptions were made. First, the initial simulation assumes that the AM facility is equidistant from all four plants. Second, the fabrication capacity is considered infinite due to the uniformity of material, maraging steel (MS1), and simultaneous printing capability on a single printer bed. Third, all spare parts follow a fixed reorder point policy with one unit of inventory, as per expert recommendations. Lastly, printing success rates and part failure distributions are treated as location-specific but constant throughout the simulation. These assumptions enable simplification without compromising the relevance of the core facility location analysis.

Authors contemplate multi-item spare parts with a single-echelon supply chain, as demonstrated in Figure 1. The motivation of the research lies in selecting the most suitable facility location for the AM technology by maximizing the machine availability and minimizing the lead time and cost of spare parts. Machine availability is gauged as the ability to perform predefined tasks like drilling, milling, etc., without interruptions like breakdowns. It is expressed as uptime over total time, which is the sum of downtime and uptime.

Authors consider the four spares $\beta = \{\beta_1, \beta_2, \beta_3, \beta_4\}$, these are mission-critical spares for the particular machines suggested by the case company experts. Further, the spare parts have already been fabricated using additive manufacturing to satisfy the machines' functional and other essential requirements. The case company has four manufacturing plants, and the plant has an ample amount of space to install the facility in-house to fulfil the demand for all four spares. After an extensive discussion with company experts, the authors consider the on-demand manufacturing approach, and the company carries only one qty of inventory due to high spare parts costs. Thus, whenever the spare part is consumed from inventory, the requirement for the spare part is manufactured using AM technology. Initially, the company has located one AM facility equidistant from all four locations and would like to install it at one of the four locations to reduce the economic losses due to the unavailability of spare parts.

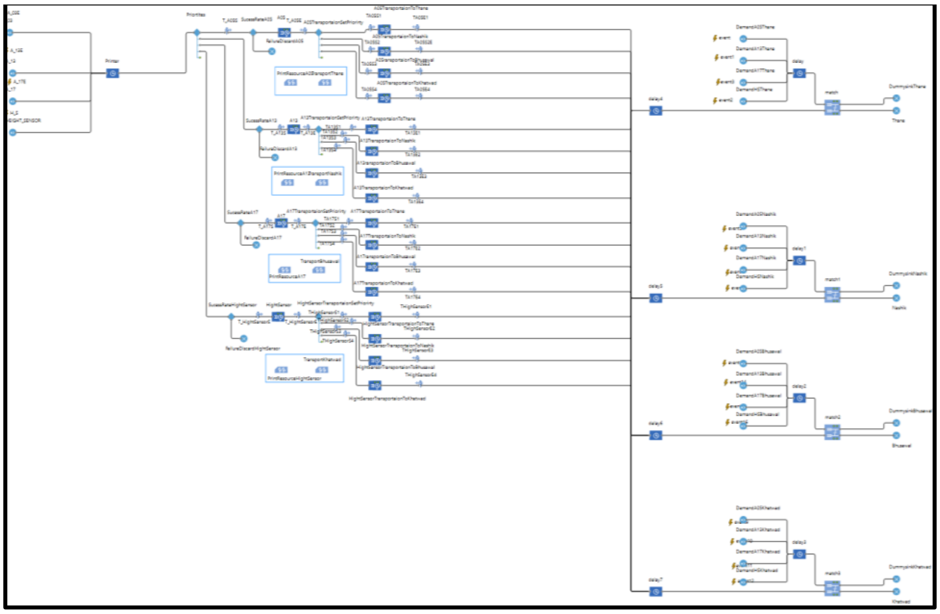

Figure 1 - Simulation model for each spare part and location
Source: Prepared by the author

The authors analyze a system consisting of four machines deployed at four distinct locations, each reliant on a specific type of mission-critical spare part. The failure of these spare parts is modeled using an exponential distribution, capturing the randomness and independence of such events. Although both Additive Manufacturing (AM) and Traditional Manufacturing (TM) spares are assumed to exhibit identical failure rates, the use of superior material properties in AM supports this equivalence.

Focusing exclusively on AM-produced spares, the model aims to determine an appropriate facility location for sourcing and delivering these spares to all four demand points $L = \{l_1, l_2, l_3, l_4\}$. It seeks to determine an optimal facility location for sourcing and fulfilling spare part demand across all sites. Despite the mission-critical nature of these spares, their high procurement cost has led the company to maintain a minimal inventory—only one unit per spare part. Consequently, the (S, S–1) inventory policy is employed, wherein a new order is placed only when the existing unit is consumed (Knofius *et al.*, 2021). According to this policy, a replenishment order is initiated only when the existing unit is consumed. The AM facility is assumed to be equidistant from all four locations, and the supply of spares occurs directly from this central facility. The model further assumes infinite fabrication capacity, as all spares are made from the same material and can be co-produced on a single printing bed.

Demand for spares is triggered only when inventory is depleted, and machine failure necessitates replacement. Upon such demand, spares are dispatched to the required location $[L\,\epsilon(l-1)]$ to the specified location from the AM facility $(L-1)$. Failure of the spare parts β_n are assumed to follow the exponential distributions with parameters δ_β and these failures are assumed to be mutually independent. The model also assumes periodic and scheduled replenishment of inventory.

Calculation

Authors adopted the scenarios analysis tool, which is very commonly employed to deal with uncertainties (Varum and Melo, 2010). The same type of metal 3D printer is utilized with MS1 material for all the spares. Further, discrete event simulation, which is the most widely adopted tool for decision-making in operations and supply chain management, is employed to illustrate various simulation scenarios (Abideen and Mohamad, 2021; Al-Hawari *et al.*, 2022; Jha and Mohan, 2023; Ortiz-Barrios *et al.*, 2023).

Montecarlo Simulation

To quantify the impact of input uncertainty on the location decision, we implemented a Monte Carlo experiment around the baseline agent-based DES model in AnyLogic®. Each Monte Carlo replication generates a perturbed, but plausible, instance of the system and re-evaluates all four location scenarios under the same random conditions.

Uncertain inputs and distributions. Three empirically uncertain inputs were varied around their validated base values:

- Part failure rates (λ_i) for each spare $\beta\,\epsilon\{\beta_1, \beta_2, \beta_3, \beta_4\}$, sampled from a triangular distribution with support $\left[0.85_\beta^{(0)}, 1.15_\beta^{(0)}\right]$ *and mode* $\lambda_\beta^{(0)}(\pm 15\%)$
- Printing success probability at each location $P_L^{(0)}$: triangular $\left[0.90\, P_L^{(0)}, \min\left(1{,}1.10P_L^{(0)}\right)\right]$ *and mode* $\mathrm{P}_L^{(0)}(\pm 10\%)$.
- Delay/cancellation probability at each location $Q_L^{(0)}$: triangular $\left[max\left(0, 0.95\, Q_L^{(0)}\right), \min\left(1{,}1.05Q_L^{(0)}\right)\right]$ *and mode* $\mathrm{Q}_L^{(0)}(\pm 5\%)$.

(Base values $\lambda^{(0)}, \mathrm{P}^{(0)}, \mathrm{Q}^{(0)}$) are those elicited and validated with the company and listed in the case data tables.)

Common random numbers (paired comparison). For each replication r, we draw one vector of uncertain inputs $\theta^{(r)} = \lambda^{(r)}, \mathrm{P}^{(r)}, \mathrm{Q}^{(r)}$. We then evaluate all four location scenarios (AM at Thane/Nashik/Bhusawal/Khatwad) using the same $\theta^{(r)}$ and identical random seeds for event streams (failures, processing, transport). This “common random numbers” design yields fair, low-variance paired comparisons across locations.

Replication, horizon, and responses. We ran 100 replications $(r = 1, 2, \ldots, 100)$; each replication simulates 500 operational days per location scenario. For each location L and replication r we record:

- Total downtime loss $Loss_L^{(r)} = \sum_\beta\left(Unfulfilled_{\beta,L}^{(r)} \times\ Downtime\ Cost_\beta\right)$
- order-fulfillment rate, and
- stockout counts.

The decision rule in replication $r\ is\ L^*(r) = \arg min_L\, Loss_L^{(r)}$. We summarize robustness with:
Selection frequency $Pro(L\ is\ optimal) = \frac{1}{100}\sum_r 1\{L^*(r) = L\}$,
Loss distribution per location (mean, standard deviation, and 95% CI of $Loss_L^{(r)}$), and
Ranking stability (how often the full ranking of locations matches the baseline).

Case Example

To demonstrate the developed model, the authors consider a case company in the machine manufacturing business with four plants at various locations, namely, Thane, Nashik, Bhusawal, and Khatwad, for potential printing facility locations. These sites form the candidate locations for potential AM facility installation.

A total of seven domain experts from the case company were engaged during model development and validation. These include:

- Two operations managers (one from the central planning team, one from the Thane plant),
- Two AM engineers (responsible for technology validation and machine configuration),
- One supply chain manager,
- Two maintenance heads (from Nashik and Bhusawal facilities).

The experts were chosen based on their role relevance, operational experience, and exposure to AM integration projects within the company. These experts contributed across three rounds of interviews, workshops, and model walkthroughs, ensuring that input parameters and model behavior reflected realistic operational dynamics.

The data used for the case model—such as printing times, downtime cost per day, failure probabilities, replenishment lead times, and cancellation probabilities—was sourced from:

- Internal enterprise maintenance records (spare consumption logs, downtime tracking systems),
- Expert-provided cost approximations and failure statistics, validated against SAP-based historical reports, and
- The company's AM deployment feasibility documents.

A total of four spare parts were selected based on their downtime impact, demand sporadicity, and technical feasibility for AM using MS1 material on an EOS DMLS machine. These parts are A05, A13, A17, and a Height Sensor. Chart 2 presents their attributes—printing time, cost of downtime per day, failure probability, and scheduled replenishment interval—as provided and validated by the expert panel.

The model initially assumes an AM facility centrally located (equidistant) from all four sites and simulates 3D printing and distribution to each plant based on on-demand inventory logic. The facility then gets virtually reallocated to each of the four sites to test loss minimization.

The demand and fulfillment scenario for each location is illustrated in Figure 4 and Charts 4–7. These show how inventory shortfalls, delays, and printing constraints affect aggregate loss per location, forming the basis for identifying the optimal AM facility location.

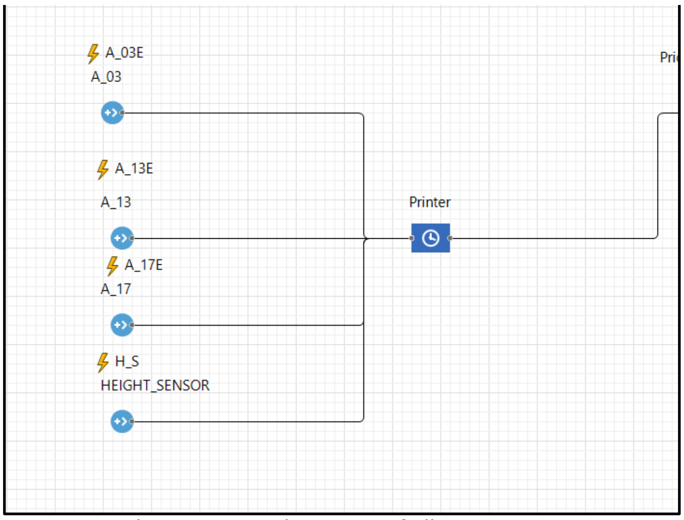

Figure 2 - Initial Printing of all spare parts
Source: Prepared by the author

The details of each spare part are demonstrated in Chart 2. For instance, the Height sensor can print within 12 hrs and has a 154000 INR loss due to failure in order fulfillment (Cost)/ day (24 hrs). The lead time of the Height sensor with TM is 55 days, with a scheduled replenishment of 195 days. The failure probability of AM parts is 0.02 or 2% for the Height sensor, and the scheduled replenishment values for each location and for each part are given in the A_03E, A_13E, A_17E, and H_S in Figure 2.

Chart 2 - Essential information on spare parts

Spare part	Printing time in hours	Loss due to failure in order fulfillment (Cost)/ day	Part Failure Probability	Scheduled Replenishment
A05	14.0	100000	0.04	20
A13	16.0	82000	0.06	50
A17	20.0	320000	0.09	35
Height Sensor	12.0	154000	0.02	55

Source: Prepared by the author

To introduce uncertainty in the simulation model, the authors consider the probability of cancellation/delay due to exogenous or unforeseen circumstances at each location. Furthermore, the schedule replenishment varies according to each location (see Chart 3). The probability of failure at each location is also shown to introduce more complexity in the model.

Chart 3 - Essential information about each facility

Locations	Probability of Cancellation /delay	Scheduled Replenishment	Probability of successfully printing spare parts at a particular location
Thane	0.12	35	0.90
Nashik	0.07	40	0.95
Bhusawal	0.27	60	0.82
Khatwad	0.11	42	0.85

Source: Prepared by the author.

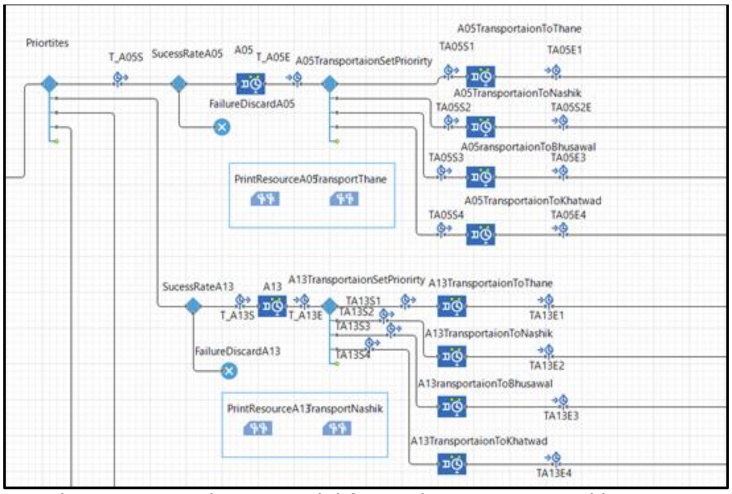

Figure 3 - Simulation model for each spare part and location
Source: Prepared by the author

The information utilized in this study was gathered from industry experts working in the case company. As given in Figure 3, the authors demonstrated the sample examples of A05 and A13 spare parts, considering the constraints in Charts 2 and 3. For instance, the 3D printer, which is equidistant from all the supply facilities, has given equal printing priority to each spare part. The success rate for all four spare parts is described as the probability of successfully printing each spare part. The transportation priority for each location is computed based on the probability of cancellation, and it is computed as,

$$Thane\ location\ success\ rate = 1 - Probability\ of\ cancellation\ or\ delay$$
$$Thane\ location\ success\ rate = 1 - 0.12$$
$$Thane\ location\ success\ rate = 0.88\ or\ 88\%$$

This information is employed in the simulation model for each part and location to develop the schematic diagram of AM facility location (see Figure 1). Each piece of information is exclusively described in Figure 1 and validated through industry experts, and the authors have consulted with the experts to run the simulation model for 500 days.

Further, the subsequent step is to supply the 3D-printed spare parts according to the demand for each location. For instance, as depicted in Figure 4, two locations are considered, namely, Thane and Nashik. For Thane, delay 4 illustrates the probability of supply cancellation, which is 1. The demand for parts A05, A13, A17, and the Height sensor is 19, 8, 10 and 7, respectively. Thus, the total spare part demand is 44, of which 3 spare parts are available in the inventory, which are A05 and A13, 2 and 1 qty, respectively. Thus, the final demand becomes 41 qty. However, the total printed parts supplied to the Thane location is 11 qty, out of which the A05, A13, A17, and height sensors are 2, 1, 4, and 5 qty. Similarly, for the Nashik location, the demand is depicted as 5, 3, 7, and 4 for the A05, A13, A17, and the Height sensor, respectively, with an available inventory of A05 in 1 qty (see Chart 5). The total printed parts provided are 11 nos., out of which A05, A13, A17, and the Height sensor are 3,2,1 and 5, respectively.

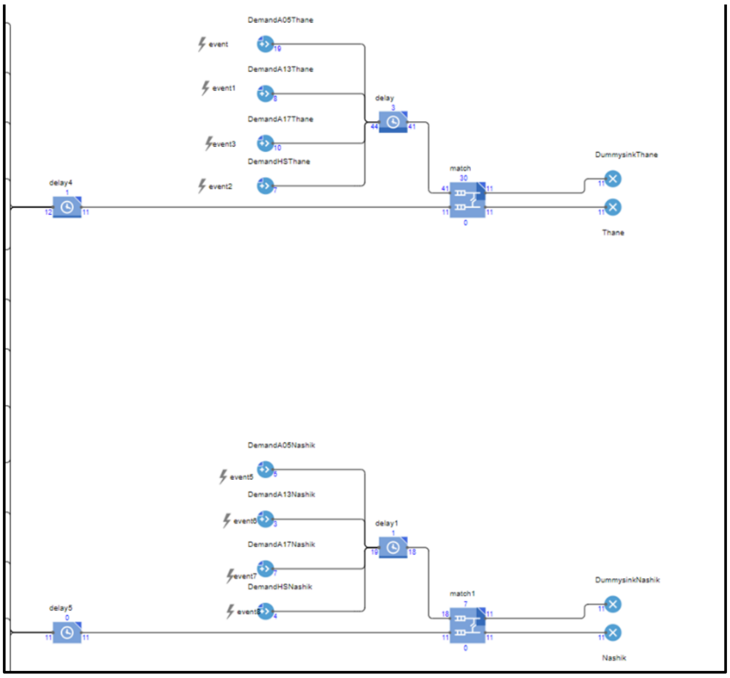

Figure 4 - Demand and supply information for Nashik and Thane facilities
Source: Prepared by the author.

RESULTS AND DISCUSSION

The simulation results clearly demonstrate the impact of facility location on performance. This aligns with established theory that proximity to demand centers reduces lead times and costs (Farahani, SteadieSeifi and Asgari, 2010). This effect is amplified in AM due to its on-demand nature. As shown in the results for the Thane location, which incurred significantly lower aggregate down-time costs, this underscores the critical role of strategic AM facility placement in enhancing service responsiveness. The results presented in Charts 4-7 reveal stark differences in performance across locations. Thane incurred the lowest aggregate loss (INR 422,000), significantly outperforming Nashik (INR 1,948,000), Bhusawal (INR 2,744,000), and Khatwad (INR 1,050,000). This superior performance is attributed to Thane's higher printing success rate and lower probability of delay (see Chart 3), which led to better fulfillment rates, especially for the high-cost A17 spare part. The negative values for some parts (e.g., Height Sensor at Nashik) indicate instances of over-supply, but these were insufficient to offset the high losses from stockouts of other critical components.

Chart 4 - Spare parts demand, fulfilment, and loss incurred at Thane

Location:			Thane			
Part No.	**Demand**	**Spares available in inventory**	**Fulfil**	**Remain**	**Losses due to the unavailability of each part**	**Total losses of each part**
A05	19	2	2	15	100000	1500000
A13	8	1	1	6	82000	492000
A17	10	0	4	6	320000	1920000

Height Sensor	7	0	5	2	154000	308000
					Aggregate Losses	4220000

Source: Prepared by the author

Chart 5 - Spare parts demand, fulfilment, and loss incurred at Nashik

Location	**Nashik**					
Part No.	**Demand**	**Spares are available in inventory**	**Fulfil**	**Remain**	**Losses due to the unavailability of each part**	**Total losses of each part**
A05	5	1	3	1	100000	100000
A13	3	0	2	1	82000	82000
A17	7	0	1	6	320000	1920000
Height Sensor	4	0	5	-1	154000	-154000
					Aggregate Losses	1948000

Source: Prepared by the author

Chart 6 - Spare parts demand, fulfilment, and loss incurred at Bhusawal

Location	**Bhusawal**					
Part No.	**Demand**	**Spares are available in inventory**	**Fulfil**	**Remain**	**Losses due to the unavailability of each part**	**Total losses of each part**
A05	41	4	7	30	100000	3000000
A13	4	0	9	-5	82000	-410000
A17	6	1	5	0	320000	0
Height Sensor	3	0	2	1	154000	154000
					Aggregate Losses	2744000

Source: Prepared by the author

The simulation indicates that locating the AM facility in Thane is optimal. This outcome is driven by the high replenishment frequency for spare A05 and the significant losses associated with A17 stockouts. The current AM setup already satisfies a substantial portion of demand originating from Khatwad, followed by Nashik. Overall, these preliminary findings suggest that situating AM facilities near major demand centers can facilitate a rapid response to stockouts for high-value spares held in small inventories. Even under elevated replenishment delay probabilities, scenarios with facilities closer to demand hubs (e.g., Thane) achieved higher fulfillment rates. The results indicate that strategic positioning of AM capacity has the potential to improve service levels and mitigate costs associated with stockouts, which are key components of supply chain resilience. However, a comprehensive assessment of resilience would require testing against a broader set of disruption scenarios. This case study provides an initial contribution to AM facility-location research that considers multiple parts and sites.

Chart 7 - Spare parts demand, fulfilment, and loss incurred at Khatwad

Location	**Khatwad**					
Part No.	**Demand**	**Spares are available in inventory**	**Fulfil**	**Remain**	**Losses due to the unavailability of each part**	**Total losses of each part**
A05	5	1	3	1	100000	100000
A13	4	0	6	-2	82000	-164000
A17	5	0	2	3	320000	960000
Height Sensor	4	1	2	1	154000	154000

Location	Khatwad					
Part No.	Demand	Spares are available in inventory	Fulfil	Remain	Losses due to the unavailability of each part	Total losses of each part
					Aggregate Losses	1050000

Source: Prepared by the author.

Robustness Analysis

There are several ways to validate the simulation models, like comparing them with historical data, conducting face validation, conducting sensitivity analysis, comparing them with benchmarks, validating against real-world observations, etc. However, due to the popularity and model uniqueness, the authors have shortlisted the three approaches to showcase the robustness of the model.

To address the impact of parameter uncertainty on the simulation results, we conducted a robustness analysis on the following three approaches:

Face Validation

The simulation logic and agent behavior were reviewed and refined in consultation with company experts. Based on their feedback, model parameters (e.g., failure rates, replenishment intervals, printing probabilities) were refined iteratively to align the model with observed operational behavior. This approach ensured both conceptual soundness and contextual accuracy.

Behavioral Calibration

Simulated outputs such as failure frequency, stockouts, and replenishment delays were compared against historical trends to ensure realism.

Key parameters were varied to assess model robustness:

- Part failure rate ±15%,
- Printing success rate ±10%,
- Delay/cancellation probability ±5%.

Monte Carlo Simulation

Monte Carlo selection frequency

Across 100 Monte Carlo replications, Thane was selected as the cost-minimizing location in 89% of runs. Interpreted as a binomial proportion, the associated 95% confidence interval (Wilson) for this selection probability is approximately 0.82–0.94, indicating a high likelihood that Thane remains optimal under realistic input perturbations.

Loss distributions by location

While absolute total-loss values $Loss_L^{(r)}$ varied with the sampled inputs, Thane's mean loss remained the lowest across replications, and its dispersion overlapped minimally with the next-best site. (We report per-location mean, SD, and 95% CI of $Loss_L^{(r)}$)

Ranking stability

Using common random numbers ensured a fair, paired comparison in each replication. The relative ranking of locations was stable across runs: in the majority of replications the full ranking matched the baseline ordering, and when deviations occurred they were limited to swaps among non-optimal locations, leaving the arg min unchanged.

Interpretation

These results demonstrate that the location decision is robust to simultaneous, realistic perturbations in failure rates (±15%), printing success (±10%), and delay/cancellation (±5%). In other words, the model's policy recommendation (place the AM facility at Thane) is insensitive to moderate input uncertainty, reinforcing its credibility for managerial use.

These findings enhance the model's credibility and indicate that the current results are not highly sensitive to small to moderate parameter deviations, suggesting generalizability across similar industrial settings.

CONCLUSION

In this research, the authors evaluate four potential locations for an additive manufacturing (AM) facility to determine the optimal site for producing four specific spare parts. The authors used an agent-based simulation model, gathering data from industry experts on factors such as printing time, delivery time, inventory time, and machine downtime. The simulations assess various scenarios quantitatively and are tested with a case study involving a machine manufacturing company with four production sites.

This study contributes to the evolving literature on AM supply chain design by applying an agent-based discrete event simulation model to determine the optimal location for an AM facility. While prior research has established the strategic value of decentralized AM networks, our study provides an operational-level demonstration, using validated industrial data, of how facility placement impacts performance metrics like downtime cost and fulfillment rate under stochastic conditions. This granular, empirical analysis addresses a dimension that has received less attention in prior studies. The model considers different scenarios and integrates AM technology into the spare parts supply chain. At the outset, the model assumes one printer centrally located among the four supply sites. The study includes uncertainties like production loss, printing failure, and delays.

The findings reveal that determining the optimal facility location significantly reduces costs and machine downtime. According to the simulation results, Thane is the best location for the AM facility, followed by Bhusawal, due to high losses from spare parts' unavailability. The study also indicates that the current AM facility, centrally located, is capable of meeting the demand for the Khatwad and Nashik sites under the simulated conditions. Additionally, the case study provides initial evidence for how machine availability can impact the facility's location.

Research Implications

This research proposed a simulation-based decision-making framework for optimal AM facility location. Thus, this study is expected to have some noteworthy implications for the body of knowledge and practitioners.

Theoretical Implications

This study offers two important contributions to the literature on AM facility location. First, it applies a simulation-based framework using real operational data from a manufacturing firm, extending prior conceptual or hypothetical studies on AM network design. Second, it emphasizes location-based performance trade-offs linking machine downtime, inventory losses, and fulfillment under uncertainty, which have received limited attention in empirical AM facility studies.

Managerial implications

The proposed simulation-based AM facility location offers valuable practical implications.

- The outcome of each location can be utilized to determine the optimal facility location by gauging the aggregate cost incurred at each location.
- The practitioners could utilize the proposed framework to get a glimpse of strategic investment decisions in the AM facility by comparing the potential losses incurred at different locations.

Limitations and Future Research

This study presents a simulation-based framework for identifying optimal AM facility locations in spare parts supply chains, focusing on economic trade-offs such as order fulfillment losses and machine downtime. However, several limitations offer directions for future research. First, the model adopts a single-objective focus on cost. Future work can explore multi-objective frameworks incorporating environmental (e.g., emissions, energy use) and social (e.g., employment, equity) metrics using hybrid methods like simulation-optimization, MILP, or evolutionary algorithms.

Second, it assumes fixed replenishment and does not evaluate strategic decisions like printing on demand or emergency procurement. Stochastic and game-theoretic models could enhance realism under uncertainty. Third, several simplifying assumptions were necessary for model tractability and to isolate the core location decision. The assumption of infinite fabrication capacity is justified in this study by the uniformity of material (MS1) and the ability to print all four parts simultaneously on a single printer bed. However, this assumption limits the generalizability of the findings to scenarios with high part variety requiring different materials or specialized printers, where capacity queuing and scheduling become critical factors. Similarly, the focus on only four mission-critical spare parts was essential for a deep, case-driven analysis and model validation. While this provides rich insights for similar high-value, low-volume contexts, it restricts the direct application of the results to supply chains with a broader and more diverse spare part portfolio. Future research should relax these assumptions to include capacity constraints and a larger set of parts to enhance generalizability. Fourth, location modeling used discrete points. A map-based spatial approach using real geographies and transport data could better assess centralized vs. decentralized AM networks. Lastly, this work sets the foundation for future decision-support models comparing AM and traditional manufacturing (CM) based on urgency, complexity, and cost-benefit trade-offs, enriched by life cycle assessment and resilience metrics.

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