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Technical paper

Expanding the horizons of metal additive manufacturing: A comprehensive multi-objective optimization model incorporating sustainability for SMEs

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ABSTRACT

Metal Additive Manufacturing (MAM) has seen significant growth in recent years, with sub-processes like Metal Material Extrusion (MEX) reaching industrial readiness. MEX, known for its cost-effectiveness and ease of integration, targets a distinct market segment compared to established high-end MAM processes. However, despite technological improvements, its overall integration into the industry as a viable manufacturing technology remains incomplete. This paper investigates the competitiveness of MEX, specifically its integration into the supply chain and the implications on cost and carbon emissions. Utilizing real-world data, the research develops a multi-objective optimization (MOO) model for a four-echelon supply chain including suppliers, airports, production facilities, and customers. The optimization model is combined with a previously developed cost model for MEX to optimize facility location in Norway using the NSGA-II algorithm. Employing a case study approach, the paper examines the production of an industrial part using stainless steel 17-4PH, detailing concrete process costs and system-level costs across four different production scenarios: 10, 100, 1,000, and 10,000 parts. The findings indicate MEX's potential for cost-effective production at low and diversified volumes, supporting the trend towards customization and manufacturing flexibility. However, the study also identifies significant challenges in maintaining competitiveness at higher production volumes. These challenges underline the necessity for further advancements in MEX technology and process optimization to enhance its applicability and efficiency in larger-scale production settings.

1. Introduction

Additive Manufacturing (AM) is transforming manufacturing with its rapid growth across various industries [1]. The International Organization for Standardization (ISO)/American Society for Testing and Materials (ASTM) 52900:2021 defines AM as: *"A manufacturing process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies"* [2]. This broad definition applies to all material classes, including metals, polymers, ceramics, and composites.

The classification of AM processes has been a topic of extensive discussion. Various sources classify AM based on different criteria such as material feedstock, energy source, or build volume [3]. However, the above ASTM/ISO [2] standard provides a widely accepted classification system, categorizing AM processes into seven types: Vat Photopolymerization, Material Jetting (MJ), Binder Jetting (BJ), Material Extrusion (ME), Powder Bed Fusion (PBF), Directed Energy Deposition (DED), and Sheet Lamination (SL).

Focusing on metals specifically, PBF has historically led and is by far the most adopted process [4], particularly due to its high flexibility and material selection [5]. Yet, the field is witnessing the rise of emergent technologies like DED, BJ, and Metal Material Extrusion (MEX) [6], each contributing to the diversification and expansion of MAM's applicability across various industries. Among these, MEX stands out due to its affordability (60%–80% more economical than PBF [7]) and user-friendliness, drawing parallels to Fused Deposition Modeling (FDM) in polymer manufacturing. This combination of low cost and ease of use lowers the barrier to entry and broadens the scope for practical applications across various manufacturing settings.

MEX falls under the broader classification of ME, a process widely accepted and used for polymer 3D printing. The fundamental principle of ME involves selectively dispensing material through a nozzle or orifice to build up a part layer by layer [2]. In MEX, the process begins with a feedstock of metal powders bound in a polymer matrix which acts as the binding system [8]. This feedstock is fed into a heated nozzle, where the polymer binder melts, allowing the material to be extruded layer by layer onto a build platform. As each layer is deposited, it cools and solidifies, gradually forming the part. Unlike other MAM methods that rely on high-energy sources like lasers or

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electron beams to melt metal powders or wires, MEX uses the thermal energy from the heated nozzle to melt the polymer binder, which holds the metal particles together. This results in a "green" part that is relatively fragile and requires a debinding and sintering stage similar to metal injection molding (MIM). The debinding process removes the polymer binder from the green part. Following this, the part undergoes sintering, where it is heated, causing the metal particles to fuse together and densify, resulting in a strong, final part.

The newness of MEX raises questions about its operational efficiency, economic viability, and competitive position within the broader MAM landscape. While extrusion-based techniques like FDM for polymers have been extensively explored, investigations into MEX, particularly regarding its operational efficiencies and economic viability within the metal additive space, are still unfolding [7]. This uncertainty is further compounded by mixed perspectives on MAM's overall competitiveness and cost implications. Scholarly discussions reveal a polarized view: some studies advocate MAM as a pathway to enhanced competitiveness and potential cost reductions, while others indicate the opposite [9]. Such divergent views highlight the complexities of integrating MAM and the need for process-specific analysis.

Current research primarily delves into the technological and operational dimensions of MAM [10], often overlooking the strategic and economic considerations vital for integrating new technologies like MEX. While the significant costs associated with high-cost processes like PBF, attributed to equipment and raw materials, are well-acknowledged [11,12], the economic landscape for lower-cost processes such as MEX remains less understood. Moreover, several studies highlight the need for an improved understanding of the environmental performance of MAM compared to conventional manufacturing [13–15]. For instance, Kokare et al. [16] clearly state the need to further investigate the environmental, economic, and social impacts of lesser-studied AM technologies, particularly as new AM materials, novel AM processes, and their applications are being developed. This underscores the need for a holistic assessment to fully appreciate MEX's potential within the wider manufacturing ecosystem, particularly in regions where traditional manufacturing challenges are compounded by unique geographical and logistical factors.

Addressing this gap, our research zeros in on the economic, environmental, and operational feasibility of MEX, with a special emphasis on production and supply chain-related costs. This includes examining the specific context of Northern Norway, a region characterized by its sparse population, long distances between potential customers, and a predominance of small and medium-sized enterprises (SMEs). These regional characteristics present a compelling case for the viability of lower-cost MAM processes like MEX, which could offer more flexible and economically viable solutions in areas where traditional manufacturing faces significant logistical hurdles. By incorporating Northern Norway as a case study, our analysis not only addresses a notable gap in the literature but also provides insights into how MEX can be optimally integrated into manufacturing systems facing similar geographical and logistical challenges.

Herein, in this paper, we propose a multi-objective optimization (MOO) model to identify optimal locations of MEX facilities taking into account a selection of factors including market demand, logistics, production costs, and environmental impacts. This model builds upon the theoretical and methodological groundwork established in our preceding research [17]. Our aim is to conduct a thorough analysis of both production and supply chain-related costs providing an in-depth exploration of the economic and operational implications of deploying MEX technology. Thereby enhancing and broadening the scope of our initial model with a focus on providing a nuanced understanding essential for the effective implementation of MEX. We can summarize the main contributions of the paper as the following:

- Proposed a MOO model specifically tailored to MEX.
- The proposed MOO model has a dual objective, focusing on both costs and environmental emissions.
- Provides key insights into remote and sparsely populated regions through a zone-based logistical model tailored to the remote regions of Northern Norway.
- Conducts an in-depth cost analysis of MEX, taking into account both production and supply chain-related expenses.
- Gives practical insight through the evaluation of a case study, providing concrete insight into the feasibility of MEX compared to CNC machining.

The rest of this paper is structured as follows: Section 2 offers a literature review, first exploring existing work on MAM supply chains, then specifically focusing on supply chain optimization for MAM. This section highlights similar work and clearly distinguishes how our research contributes novel insights to the existing body of knowledge. Section 3 details the development of our mathematical model for the MOO model. In Section 4, we demonstrate this model using a real industrial case, presenting the optimization process, Section 5 presents the results and Section 5 discusses these findings and their implications. Finally, Section 6 concludes the paper, summarizing our key insights and suggesting directions for future research.

2. Literature

2.1. MAM supply chains

The growing use of MAM has intensified the focus on its impact on supply chain management. MAM goes far beyond pure manufacturing efficiency, and could positively affect the entire product life cycle and supply chains [18]. Numerous researchers have discussed AM's implication on supply chain structure with both qualitative, exploitative, and quantitative studies [19]. Several studies [9,10,18,20–22] have specifically reviewed AM and supply chain for expanding the understanding of this domain and also providing research agendas towards improving adoption of AM. For instance, Franco et al. [9] examined the existing literature on AM adoption within operations and SCM. They identified a range of inconclusive findings, including competitiveness and costs. The literature is divided, with studies showing AM as both enhancing and diminishing competitiveness. Similarly, costs associated with AM adoption are debated, with contradictory views on whether AM leads to increased or decreased costs. Maximilian et al. [10] analyzed the benefits and diverse applications of AM in different sectors, emphasizing its significant role in transforming supply chain management. Their study pointed out crucial areas in need of further research to optimize the use of AM. One such area is the need for comprehensive studies on cost optimization and economic trade-offs in AM, focusing on an in-depth understanding of production expenses and the wider implications for supply chain costs. Furthermore, Asma et al. [22] focused on the application of AM specifically for spare parts supply chain management. Their work highlights the opportunities and challenges associated with adopting AM for spare parts, including both quantitative and qualitative models used in industry analyses. The review underscores the emerging nature of AM technology. Notably, they identified most existing studies rely on qualitative, analytical, and optimization analysis. However, quantitative models lack complexity in terms of SC design instances to produce optimal solutions and call for more details here, particularly due to the lack of real data and practical numerical examples from real-world case studies as highlighted by Li et al. [23].

2.2. MAM and supply chain optimization

The adoption of quantitative modeling in MAM supply chains is crucial for enhancing their operational efficiency and effectiveness. Quantitative models, which are becoming increasingly integral in companies' decision-making processes utilizing AM [24], can be broadly categorized into optimization and simulation methodologies [22].

Asma et al. [22] illustrate various methodologies applied in AM supply chain analysis, highlighting that the predominant focus of optimization strategies in this domain has been cost minimization, as evidenced by several detailed studies [25–29]. Additionally, a few studies have concentrated on reducing delivery times [30] and minimizing makespan time [31], indicating the diverse range of optimization goals in AM supply chains. Furthermore, various simulation methods, including System Dynamics (SD) [23,32], Discrete Event Simulation [33–36], and Monte Carlo Simulation [37–39] have been employed, each offering unique insights into the complex dynamics of AM supply chains.

The most relevant literature related to our research is those optimizations focusing on location logistics and resource allocation within AM supply chains, crucial for minimizing costs and emissions. This focus is pertinent as it directly impacts transportation logistics and efficient use of AM capabilities–core to our MOO model for facility location. Table 1 summarizes these studies.

The study by Bonin et al. [40] explores the economic viability of decentralized versus centralized manufacturing within the context of AM, particularly for the aviation industry. They employ a combination of a Process-Based Cost Model (PBCM) and an uncapacitated facility location optimization model. Their research focuses on the cost trade-offs between production, transportation, and inventory for manufacturing sites. The scenarios modeled reflect different stages of AM technology development, suggesting that centralized manufacturing remains cost-effective for most scenarios except for non-critical components and at significant production volumes — tens of thousands of units or more per year. Suggesting that the trend towards regionalization in AM may not materialize in industries characterized by low production volumes or where products have stringent specifications.

This finding bears particular relevance to our study, especially when considering the unique industrial landscape of Northern Norway. The region does not align with the high-volume demand threshold identified as a prerequisite for the economic feasibility of decentralized manufacturing. Consequently, our research adopts a centralized manufacturing perspective, recognizing the limitations imposed by the regional demand volume in Northern Norway. This approach aligns with the economic realities and underscores the importance of adapting AM strategies to specific regional capacities and demand profiles.

Saterbo et al.'s [17] initial study ventured into MAM optimization for SMEs, presenting a nascent model that mapped out facility locations against cost and lead times. However, this early model was characterized by a rudimentary description, omitting crucial elements like sustainability considerations, zone-based transportation, and a competitive analysis framework. Essentially, it crafted the basic outline of an optimization model without delving into the depth required for a comprehensive understanding of MAM's strategic implications. This foundational work, while pioneering, left significant room for elaboration, particularly in integrating environmental sustainability and detailed logistical strategies, which are addressed and substantially expanded upon in the current research.

Brito's research [25] examines the strategic positioning of 3D printers within supply chains for enhanced spare parts production, employing p-median location–allocation modeling with mixed-integer linear programming to optimize the additive manufacturing resource distribution. While the study seeks efficient supply chain network optimization, it also acknowledges the need for developing optimization models that cater to more complex design instances of AM supply chains. This points towards exploring heuristic approaches for high-demand scenarios, suggesting an area ripe for further research that our study intends to address.

He [30] examines the integration of production and transportation scheduling within the spare parts supply chain, combining 3D printing with JiT delivery systems. The model developed seeks to minimize a combination of delivery times and transportation costs through a branch-and-price methodology.

Yilmaz [31] study focuses on optimizing job and vehicle scheduling in a two-stage supply chain through AM, specifically aiming to minimize makespan using a heuristic-based approach and employing SLM/DMLS techniques. While providing valuable insights into operational optimization and emphasizing the capacity utilization of AM machines for efficiency improvements, the study also highlights areas for expansion. Yilmaz suggests the investigation of different AM methods to broaden the applicability of their findings and advocates for the exploration of alternative algorithms that cater to scenarios involving multiple manufacturers and customers, indicating potential directions for further research.

Chowdhury et al. [41] specifically develops an optimization model for the design and management of an AM supply chain network. The authors focus on creating a two-stage stochastic programming model which is used to make strategic decisions about facility location and capacity selection in the first stage, and operational decisions regarding production, post-processing, procurement, storage, and transportation in the second stage after customer demand information is revealed. Overall they aim to optimize the overall network by considering interdependencies in flow networks, resource constraints, and both process and system-level costs.

2.2.1. Research gaps

Despite the available quantitative models for MAM supply chains, there is a notable gap in terms of incorporating the intricacies of the specific AM processes [22]. While recent advancements have led to developments in facility location optimization and cost minimization strategies [25,40], there remains a critical need for more comprehensive models that fully integrate the specificity of AM processes. Although studies by researchers such as Chowdhury [41] have made some strides in unifying optimization models to consider both process-and-system level costs along with operational optimizations, these investigations often focus on prevalent AM technologies like PBF. This leaves a gap in the exploration of MEX technology, especially in contexts characterized by unique operational and cost dynamics, lower demand volumes, or specific regional requirements. Moreover, the dual objectives of cost minimization and environmental sustainability in AM supply chains are not fully addressed in current literature. The balance between economic efficiency and reducing environmental impact, including carbon emissions across the entire supply chain from raw material procurement to final product distribution, remains underexplored.

To summarize, the research gaps can be described as follows:

- To the authors' knowledge, this is the first study analyzing the supply chain network optimization of MEX, considering both production and supply chain-related costs. Unlike the prevalent focus on PBF techniques, our research delves into the operational and cost dynamics of MEX. This not only enriches the academic literature on AM but also aligns with the need for practical applications in industrial settings, addressing the lack of real-world data utilization highlighted by Asma et al. [22].
- Most existing quantitative models for AM fail to address the intricacies necessary for optimal supply chain design, resulting in oversimplified parameters that do not align with real-world scenarios [22]. For instance, Asma et al. [22] suggest that heuristic approaches should be adopted to analyze larger demand scenarios. Furthermore, Chowdhury et al. [41] highlighted the need for analyzing batch optimization for AM. Our study answers these calls by tailoring the model to the non-linear operational policies of MEX, incorporating batch optimization for MEX, and adopting a heuristic approach for analyzing various demand scenarios.
- Current literature often overlooks the integration of sustainability objectives. Our research addresses this gap by simultaneously examining economic efficiency and environmental sustainability, providing a balanced approach to reducing costs and carbon emissions across the entire supply chain.

Table 1
Summary of selected papers on AM supply chain optimization.

Ref.	Method	Goals	Objectives	Process	Gaps Mentioned
[40]	PCBM & MILP	Identify optimal location and number of facilities, and analyze trade-offs between production, transportation, and inventory.	Cost minimization	DMLS	–
[25]	MILP	Optimizing the deployment of 3D printers across the SC to minimize total costs.	Cost minimization	Polymer printing (FDM)	Optimization model development for complex AM SC instances, with heuristic approaches for high demand scenarios.
[30]	MILP	Optimizing production and transport schedules for 3D-printed spare parts to minimize delivery times and costs.	Delivery lead time minimization	Not specified	–
[31]	Heuristics	Develops an optimization model to integrate job and vehicle scheduling in a two-stage supply chain to minimize makespan and enhance capacity utilization.	Makespan time minimization	SLM/DMLS	Explore various AM methods and employ alternative algorithms for multi-manufacturer and customer scenarios.
[41]	Two-stage stochastic programming model	Optimize supply chain network design for AM by making informed decisions on facility location and capacity, accounting for uncertain customer demand.	Cost minimization	DMLS	Lack of focus on batch production efficiencies.
[17]	NSGA-II	Initial exploration of MAM optimization for SMEs, focusing on facility location, cost, and lead times.	Cost and lead time minimization	MEX	Model expansion to include environmental sustainability and supplier logistics.

3. Mathematical model

The primary focus of this study lies in the enhancement of our previously developed multi-objective optimization model for MAM [17]. Our initial model aimed to balance cost and lead time, guiding the strategic investments of SMEs. However, the evolving business landscape now demands a deeper emphasis on sustainability, an aspect somewhat overlooked in the prior model. This paper introduces an enhanced model to address this gap. We incorporate carbon emissions as a pivotal metric, aligning with cost. This section outlines our methodological approach, highlighting the optimization techniques employed.

3.1. Notations

The sets, parameters, and decision variables used in the mathematical formula are given in the Table 2.

3.2. Objective function

The decision variables are u_j, y_{im}, $X1_{ijm}$, and $X2_{jkp}$. Here, u_j is a binary decision variable. u_j indicates if facility j is open (1) or closed (0). Another decision variable is y_{im} relating to the choice of suppliers. On the continuous side, $X1_{ijm}$ represents the quantity of material m transported from supplier i to facility j, capturing the flow of materials. $X2_{jkp}$ denotes the quantity of product p shipped from facility j to customer k, ensuring that customer demands are met while respecting facility capacities. The optimization problem aims to minimize cost denoted $C(x)$ and carbon emission, denoted by $E(x)$. They are formulated as Eqs. (1) and (18). Here, x is the vector component of decision variables. Through this framework, we aim to balance economic and environmental considerations in the supply chain.

3.2.1. Cost objective

$$\begin{aligned}\text{minimize}\, C = &\sum_{j\in J} \vec{F}_j \cdot u_j + \sum_{j\in J}\sum_{p\in P} \vec{V}_{jp} \sum_{k\in K} X2_{jkp} \\ &+ \sum_{i\in I}\sum_{m\in M} PC_{im} \sum_{j\in J} X1_{ijm} \\ &+ \sum_{i\in I}\sum_{j\in J} C1_{ij}\cdot X1_{ij} + \sum_{j\in J}\sum_{k\in K} C2_{jk}\cdot X2_{jk}\end{aligned} \tag{1}$$

The objective function (1) minimizes the total costs. The first three components are related to the production including the fixed facility costs, variable cost of production, and purchase costs from suppliers. The second part is related to the transportation, including the inbound transportation from the supplier to the production facility, and the outbound from the production facility to the customers. The fixed facility cost $\vec{F}_j$ are those costs that occur when starting the facility including, facility rental, salaries, utilities, and equipment depreciation such as the 3D printer itself, and associated equipment (e.g., sintering furnace, and wash for debinding). The purchase costs PC_{im} is given by Eq. (2)

$$\sum_{i\in I}\sum_{m\in M} PC_{im} \sum_{j\in J} X1_{ijm} = \sum_{i\in I}\sum_{m\in M} vm_m \cdot cm_{im} \sum_{j\in J} X1_{ijm} \tag{2}$$

Furthermore, an important facet of this work comes from the definition of the variable cost related to the 3D printing facilities, which captures the intricacies and non-linearities of the novel metal material extrusion production process. The variable production costs $\vec{V}_{jp}$ of the printing product include costs such as, labor costs C_l, energy costs C_e, and maintenance costs C_{mt}, which are based on previous developed cost model by Saterbo et al. [42]. Tailoring this to a mathematical model for 3D printing we can reformulate, $\sum_{j\in J}\sum_{p\in P}\vec{V}_{jp}\sum_{k\in K} X2_{jkp}$ taking into account each cost components from Saterbos et al. [42] cost model. Eqs. (3)–(16) showcases each cost components into the optimization model, before being compiled into Eq. (17).

$$C_l = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \left\lceil \frac{X2_{jkp}}{Q_{jp}^{print}} \right\rceil \cdot t_{batch} \cdot c_{labor} \tag{3}$$

$$C_c = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \left\lceil \frac{X2_{jkp}}{Q_{jp}^{print}} \right\rceil \cdot c_{consum} \tag{4}$$

$$C_{\text{Print,energy}} = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} T_o^p(X2_{jkp}) \cdot P_{print} \cdot c_0 \tag{5}$$

$$C_{\text{Energy,sintering}} = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} T_o^s(X2_{jkp}) \cdot P_{sinter} \cdot c_0 \tag{6}$$

$$C_{\text{Energy,wash}} = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} T_o^w(X2_{jkp}) \cdot P_{wash} \cdot c_0 \tag{7}$$

$T_o(X2_{jkp})$ is the operational time, defined as:

$$T_o^p(X2_{jkp}) = \begin{cases} (n\cdot T_{full}^p) + T_{X2_{jkp}-(Q_{jp}^{print}\cdot n)} & \text{if } X2_{jkp} > Q_{jp}^{print} \\ T_{X2_{jkp}} & \text{if } X2_{jkp} \le Q_{jp}^{print} \end{cases} \tag{8}$$

Table 2
Notations and their explanations.

Sets	
I	Set of suppliers indexed by i
J	Set of manufacturing facilities, indexed by j
K	Set of customer location, indexed by k
P	Set of products, indexed by p
M	Set of materials, indexed by m
Parameters	
$\vec{F}_j$	Fixed cost for opening a factory j
$\vec{V}_{jp}$	Variable unit cost for producing a product p at facility j
$\vec{P}C_{im}$	Purchase cost for material m from supplier i
$C1_{ij}$	Inbound transportation cost of one unit from supplier i to facility j
$C2_{jk}$	Outbound transportation cost of one unit from facility j to customer k
$E1_m$	Unit carbon emission for material m
$E2_{ij}$	Carbon emission for transportation one unit material between link i and j
$E3_{jk}$	Carbon emission for transportation one unit product between link j and k
$E4_{pj}$	Carbon emission for producing product p at facility j
D_k	Demand of each customer
Cap_j	Capacity of facility j
r_{jp},	Amount of raw material required to produce one unit of the product p at facility j
M	Large constants
vm_m	Unit volume for material m
cm_{mi}	Unit cost of material m from supplier i
$Q^{\text{print}}_{jp}, Q^{\text{Wash}}_{jp}, Q^{\text{Sinter}}_{jp}$	Maximum number of parts of product p that can be processed simultaneously by printers, wash stations, and sintering machines, respectively, at facility j
t_{batch}	Worker time for setup and post-batch processing
c_{labor}	Hourly labor cost for batch processing
c_{consum}	Unit costs for consumables required for each batch
c_0	Unit cost for electricity per kWh
c_w	Cost per unit of fluid used in washing
c_{gas}	Cost per unit of gas consumed during sintering
v_w	Unit volume of washing fluid
v_{gas}	Unit volume of gas used in sintering
PP_j	Printer purchase price at facility j
$MC_{\%j}$	Machine utilization percentage
$P_{\text{print}}, P_{\text{wash}}, P_{\text{sinter}}$	Unit power consumption for printer, wash, and sintering operation.
E^e_m	Extraction emission
E^r_m	Refining emission
$w_{metal,m}$	weight of raw metals in the alloy m
Em_{metal}	Emission factor for the metal
CF_i	Carbon footprint coefficient for energy source used at supplier i
En_m	Energy consumed during powder atomization for a material m
Decision variables	
u_j	Binary decision variable determining if the manufacturing facilities j are open
y_{im}	Binary decision variable determining whether supplier im is chosen
XI_{ijm}	Decision variable for materials shipped from supplier i to facility j
$X2_{jkp}$	Decision variable for products shipped from facility j to customer k
Auxiliary variables	
$T^p_o(X2_{jkp}), T^w_o(X2_{jkp})$ $T^p_o(X2_{jkp})$	Auxiliary variable for the printing, sintering, or washing for product p.

$$T^w_o(X2_{jkp}) = \begin{cases} (n_w \cdot T^w_{full}) + T_{X2_{jkp}-(Q^{wash}_{jp} \cdot n_w)} & \text{if } X2_{jkp} > Q^{wash}_{jp} \\ T_{X2_{jkp}} & \text{if } X2_{jkp} \leq Q^{wash}_{jp} \end{cases} \tag{9}$$

$$T^s_o(X2_{jkp}) = \begin{cases} (n_s \cdot T^s_{full}) + T_{X2_{jkp}-(Q^{sinter}_{jp} \cdot n_s)} & \text{if } X2_{jkp} > Q^{sinter}_{jp} \\ T_{X2_{jkp}} & \text{if } X2_{jkp} \leq Q^{sinter}_{jp} \end{cases} \tag{10}$$

$$n_p = \left\lfloor \frac{X2_{jkp}}{Q^{print}_{jp}} \right\rfloor \tag{11}$$

$$n_w = \left\lfloor \frac{X2_{jkp}}{Q^{wash}_{jp}} \right\rfloor \tag{12}$$

$$n_S = \left\lfloor \frac{X2_{jkp}}{Q^{sinter}_{jp}} \right\rfloor \tag{13}$$

$$C_w = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \left\lceil \frac{X2_{jkp}}{Q^{wash}_{jp}} \right\rceil \cdot (v_w \cdot c_w) \tag{14}$$

$$C_s = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \left\lceil \frac{X2_{jkp}}{Q^{sinter}_{jp}} \right\rceil \cdot (v_{\text{gas}} \cdot c_{\text{gas}}) \tag{15}$$

$$C_{mt} = \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \frac{PP_j \cdot MC_{\%j}}{Effective\ Operating\ Hours_j} \cdot T^p_o(X2_{jkp}) \tag{16}$$

This gives:

$$\begin{aligned} &\sum_{j\in J}\sum_{p\in P}\vec{V}_{jp}\sum_{k\in K} X2_{jkp} = \\ &\sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \lceil \frac{X2_{jkp}}{Q^{print}_{jp}} \rceil \cdot t_{batch} \cdot c_{labor} \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \lceil \frac{X2_{jkp}}{Q^{print}_{jp}} \rceil \cdot c_{consum} \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} T^p_o(X2_{jkp}) \cdot P_{print} \cdot c_0 \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} T^s_o(X2_{jkp}) \cdot P_{sinter} \cdot c_0 \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} T^w_o(X2_{jkp}) \cdot P_{wash} \cdot c_0 \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \left\lceil \frac{X2_{jkp}}{Q^{wash}_{jp}} \right\rceil \cdot (v_w \cdot c_w) \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \left\lceil \frac{X2_{jkp}}{Q^{sinter}_{jp}} \right\rceil \cdot (v_{\text{gas}} \cdot c_{\text{gas}}) \\ &+ \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \frac{PP_j \cdot MC_{\%j}}{Effective\ Operating\ Hours_j} \cdot T^p_o(X2_{jkp}) \end{aligned} \tag{17}$$

The cost model for the 3D printing operation is designed to account for variable costs, which are influenced by factors such as part size, geometry, quantity, and printer space utilization. A key variable in this model is $X2_{jkp}$, which denotes the number of parts to be shipped from facility j to customer k, comprising product p. The model incorporates multiple cost components, each reflective of the distinct facets of the manufacturing process. Among these components, the operational time (T_o) is crucial, as detailed in Eqs. (8), (9), and (10) representing the duration the equipment is in use.

Operational time depends on whether $X2_{jkp}$ surpasses the combined processing capacity of the machine, denoted by Q^{print}_{jp}, Q^{wash}_{jp}, and Q^{sinter}_{jp}. This cumulative capacity is the total count of parts that all machines can manage in a single run. For instance, with each printer having a capacity for 6 parts and two printers in service, the total capacity per operation is 12 parts. When $X2_{jkp}$ exceeds the capacity Q^{print}_{jp}, the operational time is the sum of the full-capacity runs' time (full batch time times the number of full batches, n_p, n_w, n_s) and the time required for any additional parts. The number of full batches for printing (n_p), washing (n_w), and sintering (n_s) are calculated using the floor function, $\lfloor \cdot \rfloor$, which rounds down to the nearest integer to denote complete batches. If $X2_{jkp}$ is at or below the printers' capacity, operational time is directly proportional to the time needed to produce that particular batch. The decision to include both full and partial batches in the operational time calculation acknowledges the non-linear nature of the 3D printing process. This means that processing less than a full batch could take disproportionately more or less time than a full batch. The model's adaptability to handle varying production volumes within the same batch significantly enhances its practicality and accuracy.

For other aspects of the model, such as labor and consumables where both complete and partial batches are relevant, the ceiling function, $\lceil\cdot\rceil$, is used. This function rounds up to the nearest integer, ensuring that even a single part requires a full batch's worth of resources.

3.2.2. Environmental objective

The second objective function, as represented in Eq. (18), is geared towards minimizing the overall carbon emissions. This function comprises three distinct components:

1. Emissions stemming from the acquisition of raw materials at the supplier end.
2. Emissions related to transportation.
3. Emissions associated with the production process at the factory.

The carbon emissions are quantified in terms of carbon dioxide equivalents (CO_2e)

$$\text{minimize } E = \sum_{m\in M} E1_m \sum_{i\in I}\sum_{j\in J} X1_{ijm} + \sum_{i\in I}\sum_{j\in J} E2_{ij} \sum_{m\in M} X1_{ijm} + \sum_{j\in J}\sum_{k\in K} E3_{jk} \sum_{p\in P} X2_{jkp} + \sum_{j\in J}\sum_{p\in P} E4_{jp} \sum_{k\in K} X2_{jkp} \tag{18}$$

At the supplier level, two contributors to carbon emissions are the extraction and refining of raw metals, and the energy demand for the powder atomization and production of powder for the MAM process as depicted in Eq. (19). Here, $e1_m$ is the emission attributed to the extraction and refining of material m, and $e2_m$ is the energy consumption for powder production of the same material.

$$E1_m = e1_m + e2_m \tag{19}$$

Eq. (20) details the energy consumption for the powder atomization process. Here, En_m stands for the energy consumed during powder atomization for material m, while CF_i is the carbon footprint coefficient at supplier i tied to the specific energy source.

$$e2_m = \sum_{i\in I}\sum_{j\in J} X1_{ijm} \cdot En_m \cdot CF_i \tag{20}$$

Eq. (21) consolidates the emissions, which together constitute the supplier's carbon emissions.

$$\sum_{m\in M} E1_m \sum_{i\in I}\sum_{j\in J} X1_{ijm} = \sum_{m\in M} (e1_m + En_m \cdot CF) \sum_{i\in I}\sum_{j\in J} X1_{ijm} \tag{21}$$

The carbon emissions associated with the production phase are detailed in Eq. (22). This equation incorporates the AM process, the debinding process, and the sintering process. An additional factor, CE, represents the carbon emission coefficient corresponding to the energy source in use.

$$\sum_{j\in J}\sum_{k\in K}\sum_{p\in P} CE \cdot \big(T_o^p(X2_{jkp}) \cdot P_{wash} + T_o^w(X2_{jkp}) \cdot P_{sinter} + T_o^s(X2_{jkp}) \cdot P_{print}\big) \tag{22}$$

The final objective function, as showcased in Eq. (23), represents a combination of the emissions from the supplier, AM production facility, and transportation processes.

$$\text{minimize } E = \sum_{m\in M} (e1_m + En_m \cdot CF) \sum_{i\in I}\sum_{j\in J} X1_{ijm} + \sum_{i\in I}\sum_{j\in J} E2_{ij} \sum_{m\in M} X1_{ijm} + \sum_{j\in J}\sum_{k\in K} E3_{jk} \sum_{p\in P} X2_{jkp} + \sum_{j\in J}\sum_{k\in K}\sum_{p\in P} CE \cdot (T_o^p(X2_{jkp}) \cdot P_{wash} + T_o^w(X2_{jkp}) \cdot P_{sinter} + T_o^s(X2_{jkp}) \cdot P_{print}) \tag{23}$$

3.3. Constraints

The model is subject to several constraints ensuring feasibility and satisfaction of the demand requirements. These constraints are defined as follows:

- **Demand Satisfaction Constraint**: Constraint (24) ensures the total number of parts sent to a customer meets that customer's demand.

$$\sum_{j\in J} X2_{jkp} = D_k, \quad \forall k \in K, p \in P \tag{24}$$

- **Facility Capacity Constraint**: Constraint (25) ensures that the total amount of parts produced by a facility does not exceed its capacity,

$$\sum_{p\in P}\sum_{k\in K} X2_{jkp} \le \mathrm{Cap}_j \cdot u_j, \quad \forall j \in J \tag{25}$$

- **Material Availability and Consistency of Shipments**: Constraint (26) ensures that materials transported to facility j satisfy the necessary conditions.

$$\sum_{i\in I}\sum_{m\in M} X1_{ijm} = \sum_{k\in K}\sum_{m\in M} r_{mp} \cdot X2_{jkp}, \quad \forall j \in J, p \in P \tag{26}$$

- **Supplier selection constraint:** To determine which suppliers to engage with, the decision variable y_{im} is introduced. Constraint: (27) guarantees that if supplier i is not chosen ($y_{im} = 0$), no materials m can be procured from supplier i. Conversely, if supplier i is chosen ($y_{im} = 1$), then materials can be procured. M is a large number representing the maximum possible quantity.

$$X_{ijm} \le M \cdot y_{im}, \quad \forall m \in M, i \in I, j \in J \tag{27}$$

- **Non-negativity and Binary Constraints**: The decision variables in the model should satisfy the non-negativity and binary restrictions, given by:

$$u_j, y_{im} \in 0,1, X1_{ijm}, X2_{jkp} \ge 0, \quad \forall i \in I, j \in J, K \in K, p \in P, m \in M \tag{28}$$

4. Demonstration

Following the development of our mathematical model, we will conduct a practical test using a specific use case. This use case, drawn from a previous study [42], focuses on the application of MAM, particularly MEX. The part in question, as illustrated in Fig. 1, was constructed from stainless steel (17-4 PH). It had printed dimensions of 44 mm × 111 mm × 78 mm. The Metal X printer, along with its requisite post-processing equipment, was employed to realize this component. In the debinding operation, the trigger was submerged in the Opteon SF-79 washing fluid and later sintered using two types of gases, argon gas, and 3,0 mol-% Hydrogen gas.

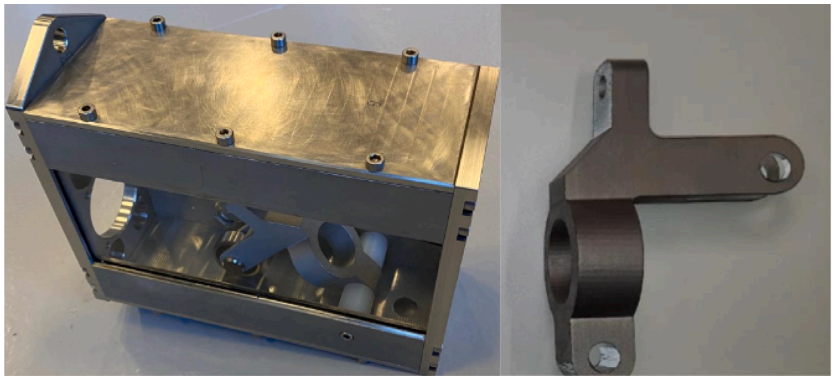

Fig. 1. 3D printed 17-4 PH stainless steel part, fabricated through Metal X for our case study.

4.1. Simplifications and assumptions

Our model incorporates several assumptions to simplify the problem and enhance its manageability:

- **Single Material and Product:** The model is focused on a single product and material and support material.
- **Demand Estimation:** Demand for the products within Northern Norway was estimated by analyzing industrial activity through employer statistics provided by Statistisk sentralbyrå (SSB). Recognizing the correlation between the number of employers and economic vibrancy, demand was proportionally distributed across selected cities with a threshold of more than 100 employers to concentrate on areas with significant economic activity. This allowed for the creation of demand scenarios.
- **Production Limitations:** The production capacity of each facility is defined by the number and capacity of available printers, denoted as cap_j in the model.
- **Carbon Emission Estimations:** Carbon emissions are approximated based on existing literature and studies. This estimation encompasses the product, from raw material sourcing to production and delivery.
- **Geographical Limitations:** The optimization is tailored to the unique conditions and logistical challenges inherent to Northern Norway.
- **Facility Location:** Our model generates random facility locations with a consideration for existing road infrastructure. We implement a maximum snapping distance of 50 km to ensure proximity to the nearest road. However, it is possible for some generated locations to be impractical (for instance, in the middle of the sea). To address this issue, we employ a repair function that verifies the feasibility of each facility location. If a location is deemed infeasible, the model generates a new random location.
- **Material cost:** The material cost is derived from known expenses for supplies obtained from the USA. For materials sourced from China, where exact cost data is not available, we employ a conservative estimate. This estimate assumes a slightly lower cost, reflecting the general market observation that materials from China tend to be cheaper compared to those from the USA.

4.2. Supply chain optimization model

The optimization functions are designed based on two criteria: cost estimation and carbon emission estimation.

4.2.1. Cost estimation

Cost estimation is a pivotal component of our optimization model, covering a comprehensive analysis of the supply chain and production processes. Material costs are determined by the supplier location and volume as described in the assumption section. Furthermore, in line with the methodology of the previous study [42], we recorded data throughout the printing process. This data, which includes the same values used previously for production cost estimation, forms the backbone of our analysis. We supplemented these findings with external data sources, encompassing energy prices, labor rates, and the costs associated with machinery. The cost associated with the production process includes machine, labor, consumables, maintenance, and post-processing. These are further adjusted to take into account volume-dependent variables. (Cost is not linear, and is based on the capacity of the printers, the product printed, and the volume of the printed products as described in the cost model chapter).

Initially, we calculated truck transportation costs based on distance and a standard freight rate. However, to accurately capture the intricacies of transportation costs, we leveraged data from expedited courier services. Unlike traditional models that assume transportation costs increase linearly with distance, our approach acknowledges the complexity of real-world logistics by incorporating cost variations across different zones. We analyzed both inbound (supplier to production) and outbound (production to customer) logistics, employing air and truck freight. For domestic truck freight within Norway, we used the Norwegian postal system's cost calculations based on postal codes. This method allows for precise cost determination between any two postal addresses, significantly enhancing the realism of our shipping cost estimates. It accounts for variations in costs associated with domestic courier services, which can fluctuate based on factors such as distance, parcel size, and weight within specific "Posten" zones. To accurately apply this system to our logistics model, we conducted reverse geocoding to ascertain the postal code of the factory. This process involved using a detailed table of all Norwegian postal codes to map the factory's physical location to its corresponding postal code. For international shipping, we opted for air freight and turned to the FedEx air freight calculator, a tool that estimates transportation costs based on weight, volume, and distance between airport locations. This tool allowed us to calculate the costs associated with moving goods from international suppliers to selected airports in Norway.

4.2.2. Carbon emission estimations

The carbon emissions consist of supplier-related emissions, transportation, and production. For each potential facility location, we compute the driving distances to all customers and the nearest airport to estimate carbon emissions related to transportation. Given the continuous nature of our optimization problem, these distances need to be calculated each time a new factory location is proposed. To address this, we employ OpenRouteService [43], a customizable tool for calculating driving distances. We host an OpenRouteService server on our laptop, enabling continuous access to updated driving distances between customers and the airport.

Furthermore, we estimate the emission at the supplier. The emission related to the extraction and refining of the stainless steel 17-4 PH

Table 3
Estimated CO2 emissions of powder fabrication [46,47].

Country	GWP per kWh (kg CO2 eq/kWh	Emission per kg powder
China	0.534	11.214
USA	0.39	8.19

alloy are estimated based on Global Warming Potential (GWP). Norgate [44], indicate a GWP of 6.8 kg CO2 equivalent per kilogram of stainless steel. Moreover, for the production of metal powder for 3D printing, we consider the energy requirements and carbon emissions associated with its production, taking into account the energy mix of the producing country. According to Kruzanov [45] they estimated the energy consumption for the fabrication of stainless steel powder to be 2.1 kWh per kg powder. Furthermore, by taking into account the energy sources in China and USA respectively, we can calculate the emission per kg powder as depicted in Table 3.

4.3. A two-phased optimization method

The optimization process focuses on Northern Norway, seeking the optimal longitude and latitude for the factory. We use a continuous search approach, factoring in the choice of four airports and two suppliers.

The multi-objective problem necessitates a two-phased optimization approach. The first phase employs heuristic methods, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to explore the solution space and identify potential solutions. The second phase verifies these solutions, applying weights to the optimization problem to derive a single, optimal solution (see Fig. 2).

4.3.1. Phase I: Optimization

In this paper, NSGA-II, a metaheuristic method is utilized due to the continuous location problem. This algorithm efficiently manages trade-offs between conflicting objectives, including cost and carbon emissions. Our mathematical model, covering operational, financial, and environmental aspects, forms the basis of this optimization. This evaluation focuses on the macro-level optimization of the supply chain. Determining the number of printers, facility locations, supplier selection, and transportation routes.

4.3.2. Phase II: Ranking and evaluation

The second phase involves refining the solutions from NSGA-II. Here, we prioritize and score each solution to identify the optimal facility location. This phase ensures the feasibility and optimality of the solutions, refining the heuristic findings into a definitive outcome. This outcome is then used in the evaluation of the feasibility of producing through MAM expanding on the Sæterbos et al. [42] research, by not only taking into account production cost but also supply chain cost, while giving vital information about carbon emission.

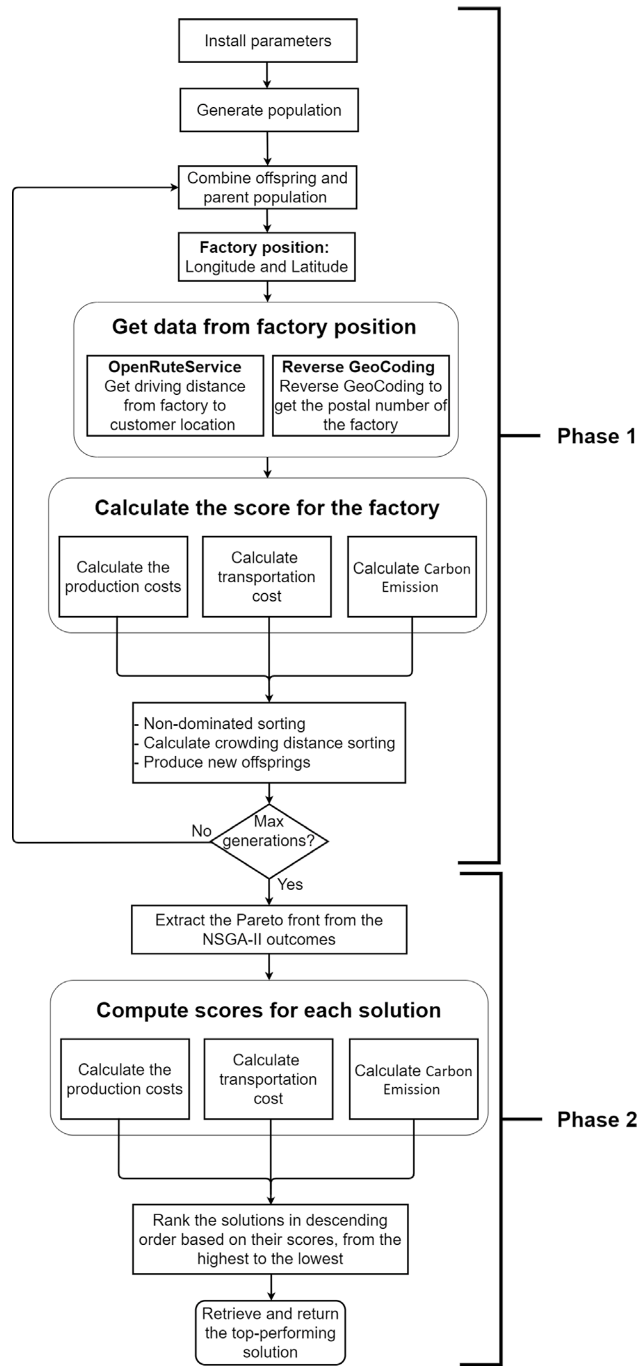

Fig. 2. Flowchart of the optimization system.

4.4. Scenario analysis

To evaluate the competitiveness of MAM on different supply chain network designs, a scenario analysis is performed and critically discussed. Four scenarios are presented showcasing the impact of varying demand levels (i.e., production volume). Specifically, we executed four distinct optimizations, each corresponding to a different demand scenario for the manufactured part: 10, 100, 1000, and 10,000 units. This range of demand scenarios was selected to provide a broad spectrum of insights into how volume variations affect the competitive landscape of MAM. The demand scenarios were chosen to reflect a realistic and varied market demand spectrum for products manufactured via MAM, from very low to very high volumes:

- 10 Parts Demand: Simulates a niche, highly customized product scenario or a preliminary market test phase.
- 100 Parts Demand: Represents a low to moderate demand, typical for specialized industrial components or limited series production
- 1000 Parts Demand: Corresponds to a growing market acceptance and wider application of the parts, indicating a mature but specialized market segment.
- 10,000 Parts Demand: Reflects mass production scenarios, where MAM is fully competitive with traditional manufacturing processes in terms of both cost and volume.

For each scenario, we detail the overall cost and emissions associated with the procurement, production, and distribution of raw materials and finished products. A key aspect of our analysis is the calculation of unit costs. Our calculation of unit costs takes into account

Table 4
Ranked solutions for demand of 10 parts based on weighted sum.

Rank	Supplier	Airport	Costs (NOK)	CO2 (kg CO2)	Coordinates (lat,long)
1	USA	Tromsø	67 021.4	22 602.8	(69.6817, 18.9366)
2	USA	Evenes	67 181.4	22 551.3	(68.5406, 17.4482)
3	China	Tromsø	63 231.4	43 621.3	(69.6839, 18.9366)
4	China	Evenes	63 391.4	43 569.4	(68.5406, 17.4482)

Table 5
Ranked solutions for demand of 100 parts based on weighted sum.

Rank	Supplier	Airport	Costs (NOK)	CO2 (kg CO2)	Coordinates (lat,long)
1	USA	Bodø	332 443.17	150 805.23	(67.2158, 15.4780)
2	USA	Tromsø	332 442.17	150 876.49	(69.4982, 18.9205)
3	USA	Evenes	333 236.17	150 230.60	(68.5493, 17.5552)
4	China	Bodø	306 813.17	289 440.50	(67.2602, 15.3387)
5	China	Tromsø	306 812.17	289 662.03	(69.6765, 17.5558)

Table 6
Ranked solutions for demand of 1000 parts based on weighted sum.

Rank	Supplier	Airport	Costs (NOK)	CO2 (kg CO2)	Coordinates (lat,long)
1	USA	Bodø	3 057 498.19	1 450 589.96	(67.2581, 15.2947)
2	USA	Evenes	3 060 776.19	1 447 046.19	(68.5502, 17.5491)
3	China	Bodø	2 810 568.19	2 783 673.05	(67.2876, 15.4780)
4	China	Evenes	2 813 846.19	2 779 872.16	(68.5502, 17.5462)

Table 7
Ranked solutions for demand of 10,000 parts based on weighted sum.

Rank	Supplier	Airport	Costs (NOK)	CO2 (kg CO2)	Coordinates (lat,long)
1	USA	Bodø	30 425 243	14 451 981	(67.3063, 15.3952)
2	USA	Tromsø	30 425 235	14 480 191	(69.5507, 18.8975)
3	USA	Evenes	30 454 223	14 412 714	(68.5461, 17.5549)
4	China	Bodø	27 965 643	27 724 610	(67.3064, 15.3328)
5	China	Tromsø	27 965 635	27 752 804	(69.5072, 18.9076)

the actual materials used and the specific logistics costs associated with each part. We estimate material costs based on the proportion of materials consumed for production, ensuring that our cost analysis reflects only the resources directly utilized. For inbound logistics, costs are allocated based on the percentage of material volume used, providing a precise estimate of transportation expenses on a per-unit basis. Outbound logistics costs are evenly distributed across the produced units, simplifying our analysis due to variable customer locations. Furthermore, We approach production cost estimation from two perspectives: the actual cost of producing the demanded quantity and an optimized cost considering the maximum capacity of our printers. This dual analysis allows us to understand the cost implications of different production scales, offering insights into the potential for cost reduction through increased efficiency.

5. Results

This section presents the results of a comprehensive analysis across four distinct demand scenarios for MAM, ranging from low-volume, niche products to mass production scales. Each scenario was evaluated using the NSGA-II algorithm across 100 iterations, with a population of 100 and offspring of 80. In the second phase, we ranked the solutions based on a weighted sum of cost (weight = 0.8) and emission (weight = 0.2). The outcomes highlight the operational configurations, cost implications, and environmental impacts of MAM under varying market demands. While the methodology remained consistent across scenarios, this section focuses on the unique findings and insights derived from each.

5.1. NSGA-II optimization results

The NSGA-II optimization provides initial supply chain designs including facility location, transportation flows, and the selection of suppliers and airports for four demand scenarios: 10, 100, 1000, and 10,000 units. The top-ranking solutions from these optimizations are presented in Tables 4, 5, 6, and 7. These tables detail the chosen supplier locations, airports, facility coordinates, and the corresponding costs and emissions for each scenario. Additionally, Figs. 3, 4, 5, and 6 demonstrate the geographic placements of the facilities within Northern Norway's logistical network, as plotted via the Openrouteservice API. These map illustrations, show the road structures, customer location as well as facility location for the four demand scenarios.

5.2. Unit cost analysis

Following the optimization phase, a meticulous unit cost analysis was undertaken to evaluate the economic and environmental efficiency of each product. This analysis considered the actual consumption of materials and logistics costs–both inbound and outbound transportation–tailored to each production scale. Presented in Table 8, this detailed breakdown elucidates the cost and emissions for each component, offering a comparative perspective on the financial and environmental costs per unit. Assumptions were made regarding the production facility operating at full capacity, allowing for the allocation of fixed costs over an increased production volume, thus enhancing cost efficiency.

Table 8
Unit cost and emissions breakdown across four demand scenarios, detailing cost, emissions, and supply chain configurations including airport and supplier selection.

Demand	10	100	1000	10 000
Supplier	USA	USA	USA	USA
Airport	Tromsø	Bodø	Bodø	Bodø
Printers	1	3	25	250
Material spools	4	32	314	3131
Support material spools	1	1	3	26
Total costs (Optimal printer utilization)	3421.5	3115.9	3054.1	3042.4
Production (Optimal printer utilization)	2206.6	2206.6	2198.9	2198.7
Material	409.5	409.5	409.5	409.5
Air freight	422.97	422.97	422.97	422.97
Inbound truck freight	32.63	9.31	3.79	3.65
Outbound truck freight	349.7	67.42	18.747	7.5303
Total emission	2260.26	1508.0	1450.62	1445.18
Supplier emission	8.99	7.19	7.1	7.04
Production emission	2.2	2.41	2.41	2.41
Air emission	2212.5	1460.25	1402.72	1396.97
Truck inbound	0.23	3.298	2.44	3
Truck outbound	36.34	34.85	35.95	35.76

5.3. Cost breakdown across demand variations

Table 8 and Fig. 8 collectively illustrate how production, material, and transportation costs fluctuate across different production scales. Notably, while the cost of materials remains unchanged across scenarios, reflecting consistent unit consumption, transportation costs exhibit a decline, benefitting from economies of scale. This trend, however, does not extend to production costs, which remain relatively constant across different scales of operation. This constancy underscores a fundamental challenge in MAM: the absence of traditional economies of scale, which significantly impacts the cost-efficiency of production, especially at higher volumes.

The production costs emerge as a primary bottleneck, preventing cost reductions that could be achieved through economies of scale prevalent in conventional manufacturing processes. This bottleneck is exacerbated by the significant costs associated with air freight, which, despite being lower than production costs, still constitute a substantial portion of the overall transportation expenses. Fig. 7 reveals that air freight accounts for a considerable percentage of transportation costs, especially at larger production volumes.

Fig. 3. Map of Northern Norway showing facility and customer locations for the 10-unit demand scenario generated from Openrouteservice.

Fig. 4. Map of Northern Norway showing facility and customer locations for the 100-unit demand scenario generated from Openrouteservice.

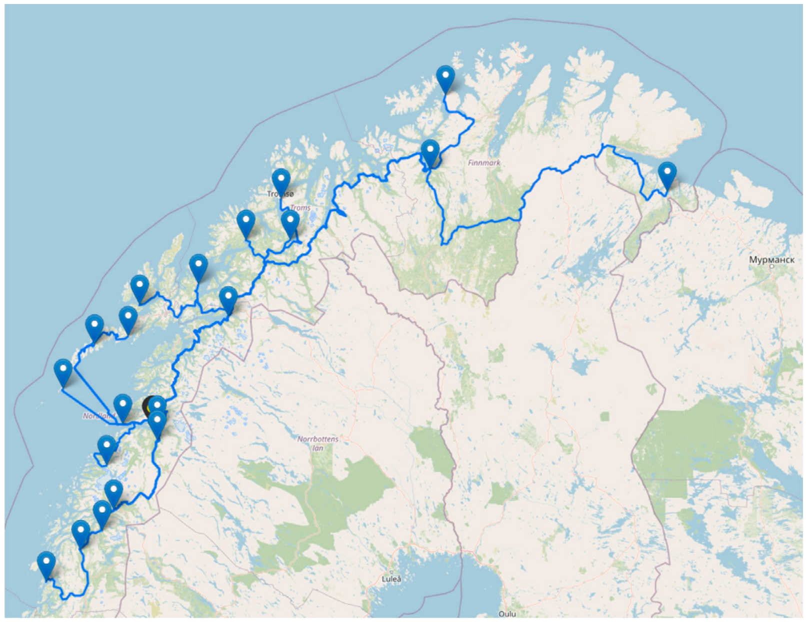

Fig. 5. Map of Northern Norway showing facility and customer locations for the 1000-unit demand scenario generated from Openrouteservice.

Fig. 6. Map of Northern Norway showing facility and customer locations for the 10 000-unit demand scenario generated from Openrouteservice.

Fig. 9 breaks down the costs for production, particularly sintering costs and machinery depreciation are identified as the predominant contributors to the overall cost. Sintering costs, driven by gas expenditures, and depreciation, a direct outcome of machinery usage rates, place a heavy financial burden on the manufacturing process. The slow production speeds of MAM technologies, even under optimal operational conditions, significantly inflate production costs. The detailed process analysis highlights that printing alone can occupy up to 90 h for a complete batch, with post-processing adding approximately 75 h, potentially reducible to 45 h with enhanced sintering capacity. This indicates that to achieve cost reductions at larger scales, a significant enhancement in printing speed is imperative.

5.4. MAM competitiveness versus CNC machining

To evaluate the cost-effectiveness of MEX relative to conventional CNC machining, a detailed comparative analysis was carried out for demand scenarios of 10, 100, 1000, and 10,000 units. This comparison utilized the total unit costs derived from each scenario for MEX and quotations obtained from CNC machining companies online for CNC machining costs. Fig. 10 illustrates the unit costs for CNC machining and MEX production across these four demand scenarios. In this figure, the red line represents the unit cost of MEX where the production process is optimized for throughput efficiency, accounting only for the material used and transported on a proportional basis. Conversely, the blue line depicts scenarios for MEX without process optimization,

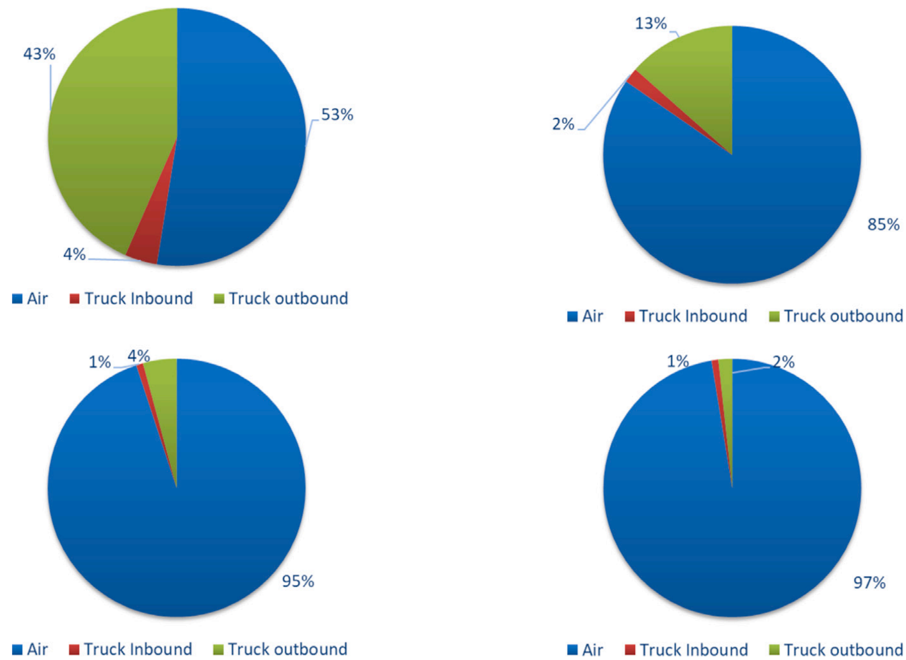

Fig. 7. Comparison of transportation costs across demand levels: top left–10, top right–100, bottom left–1000, bottom right–10,000.

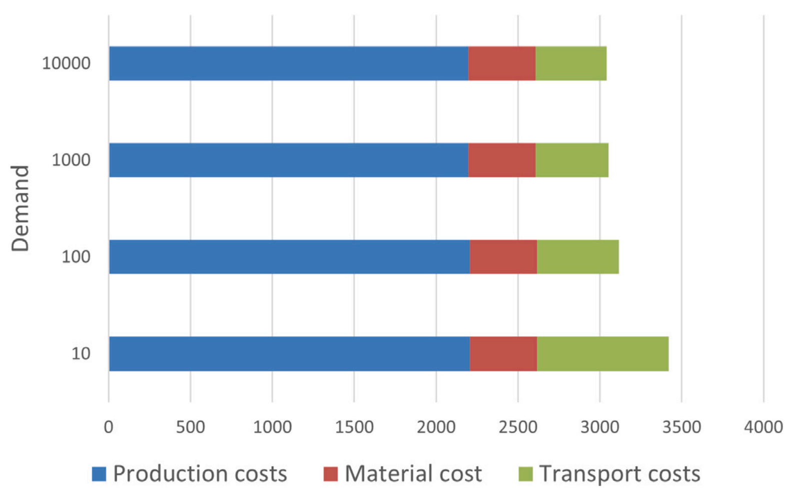

Fig. 8. Visualization of cost trends across demand variations.

where production accounts for the entire cost of material spools required and the transportation for all these spools, irrespective of the actual percentage used (e.g., for a demand of 1 unit, the full cost of the spool is considered rather than just the 20% utilized). Similarly, it includes full transportation expenses. The green line, meanwhile, delineates the CNC machining costs for producing and transporting 1, 10, 100, and 1000 parts. While quotations for 10,000 parts were not obtainable, it is anticipated that the cost would continue to decrease, aligning with economies of scale, and thus be lower than that for 1000 parts.

6. Discussion

This study examines the competitiveness of MEX within the MAM landscape, expanding the analysis beyond process-level costs to encompass system-level implications, including supply chain logistics and carbon emissions. This broader perspective is crucial for understanding MEX's role in manufacturing practices, a significant contribution given the current literature's focus on technological aspects and process efficiency.

6.1. Geographical consideration

A key dimension of our study explored the viability of MAM in remote areas, specifically focusing on Northern Norway, where the vast distances between potential customers present unique challenges. Unlike most existing studies for MAM optimization that rely on distance to estimate transportation costs, our methodology employed a zone-based system. This system accurately determined costs between postal addresses across the region, an approach particularly suited to the geographical nuances of Northern Norway. The significance of this method lies in its ability to navigate the challenges posed by significant uninhabited or sparsely populated areas, which might be incorrectly favored in distance-based models.

The zone-based approach proves effective in remote settings by prioritizing population centers within the zoning system. This ensures that potential facility locations are strategically chosen, aligning with areas of higher population density rather than arbitrary points in vast, unpopulated regions. Such a methodology not only enhances the accuracy of cost estimations but also aligns facility placement

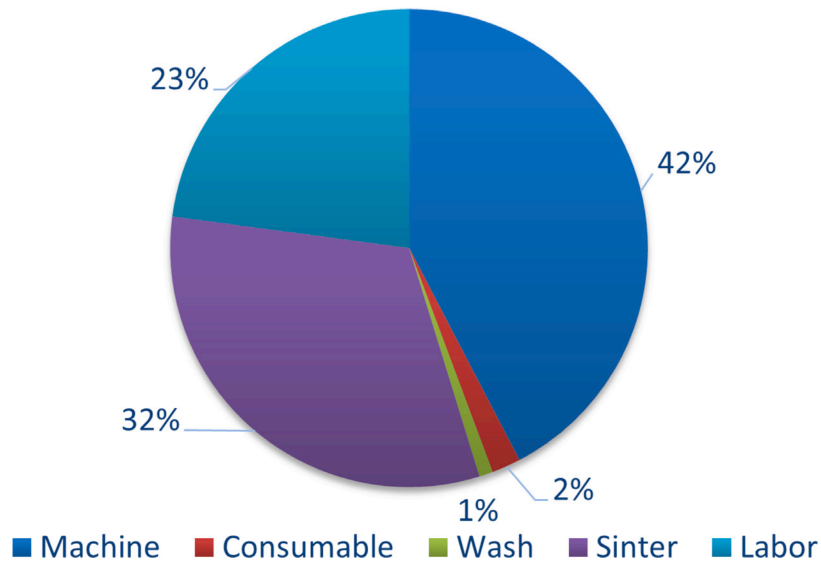

Fig. 9. Breakdown of production costs uniform across all demand scenarios.

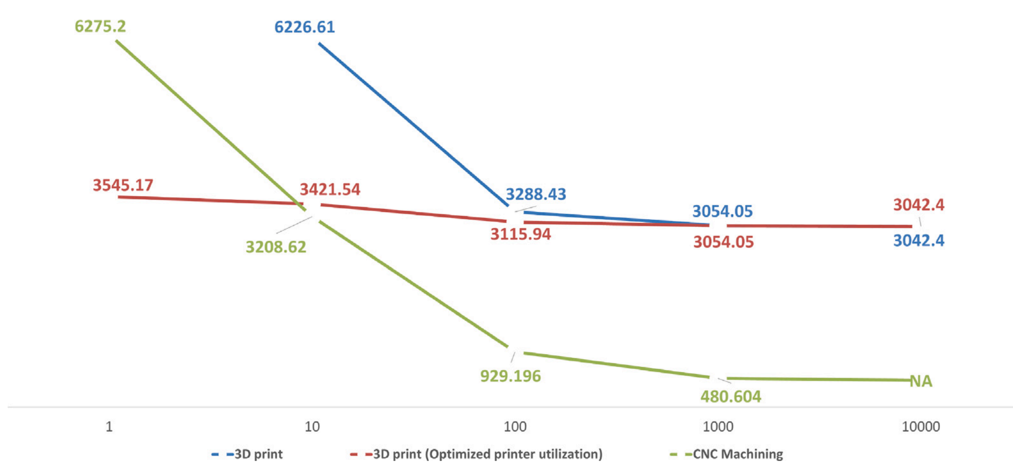

Fig. 10. Unit cost comparison of MEX (optimized in red, non-optimized in blue) versus CNC machining (green) across four demand scenarios, highlighting scale-based cost-effectiveness. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

with logistical practicality, thereby supporting the potential adoption of MAM in regions like Northern Norway where traditional logistic models may falter. Our results predominantly feature potential facility locations near larger cities or key logistical hubs, demonstrating the effectiveness of this approach. However, it is important to note that the nature of the zoning system and the extensive search space mean the solutions suggest general location areas rather than exact points. For pinpoint precision in facility siting, optimization parameters would require adjustment, necessitating a larger population and extended runtime for the analysis. While our model adopts a zone-based system for accurate cost estimations, it importantly still accounts for distance in assessing carbon emissions. This approach provides a balanced analysis, emphasizing both economic efficiency and environmental sustainability. By integrating distance-based emission insights with zone-focused cost calculations, our study offers a comprehensive framework for evaluating MAM adoption in remote areas, addressing both logistical and ecological considerations.

6.2. Operational insight

MEX is often regarded as a cost-effective and user-friendly entry point into the realm of MAM, offering significant advantages for newcomers by lowering the barriers to entry. Our analysis across four production scenarios, 10, 100, 1000, and 10,000 units, sheds light on MEX's competitiveness and supports the aforementioned statement. To a certain degree... Specifically, our findings indicate that MEX remains cost-effective and operationally efficient for producing up to 10 units as described in Fig. 10. Beyond this point, the comparative cost advantages over traditional manufacturing methods, such as CNC machining, start to diminish, corroborating the prevailing view that MAM, including MEX, is less competitive at higher production volumes. This efficiency, however, hinges on optimal production operations. A pivotal insight from our study is the balancing act required to maximize 3D printer utilization: the production volume must be large enough to prevent equipment from remaining idle, yet diversified enough to cater to specific manufacturing needs. For example, our operational model suggests that one printer, coupled with a washer and sintering furnace, can handle up to 40 parts a month. Nonetheless, producing and delivering more than 10 parts of the same type becomes economically unviable when compared to CNC machining, due to diminishing cost benefits with increased volume.

Further exploration identified critical challenges impacting MEX's broader application, particularly the low production throughput that escalates machine-related costs. Additionally, sintering emerges as a notable expense in the MEX process. Alternative sintering techniques, such as transitioning to continuous furnaces for higher volume runs instead of the batch furnaces employed in our study, could significantly reduce these costs. Implementing such changes could enhance MEX's feasibility for larger production scales, addressing one of its main limitations.

From the transportation perspective, our findings indicate that while truck transportation locally incurs relatively minor expenses, air freight represents the predominant cost factor. This observation underscores the critical importance of not only fostering local production but also pursuing local sourcing strategies or more cost-effective alternatives, such as sea freight, as opposed to air freight. However, it is important to acknowledge that sea freight, while financially more viable, introduces significant delays. Given the on-demand nature and potential need for swift production capabilities in MAM, the extended lead times associated with sea freight may not align with the operational requirements of businesses relying on MAM technologies. This aspect of our analysis highlights the complex trade-offs that companies must navigate when integrating MAM into their production and supply chain strategies. While local production and sourcing can substantially reduce transportation costs, the choice of shipping method must be carefully balanced against the need for timely delivery and responsiveness to market demands. This strategic consideration requires detailed analysis and thoughtful planning by each company seeking to leverage MAM for competitive advantage.

6.3. Challenges and opportunities for scaling MEX production

Enhancing MEX to compete at larger volumes requires more than just increasing production speed; significant improvements are needed across several areas. The prolonged production times of machines represent a major bottleneck that must be addressed to enhance viability. Additionally, the gas consumption associated with the sintering process needs to be significantly reduced, possibly through adopting continuous operations. Material costs and transportation expenses, particularly those related to air freight which are a significant cost driver at larger volumes, must also be lowered. Collectively, these adjustments could position MEX as a competitive option for larger-scale production. However, in its current state, MEX is best suited for low-volume production. This study has demonstrated MEX's feasibility within the Norwegian supply chain, marking it as a viable option for specific uses, especially in the spare parts supply chain, where the lower population and industrial activity align with MEX's capabilities. Nevertheless, a comprehensive market analysis and efficient use of machinery are crucial, as inefficient operation can quickly escalate costs and diminish returns on investment.

Despite these challenges, MEX's role in the MAM landscape remains vital, particularly for applications requiring high customization and low volume. The technology's capacity for detailed and flexible manufacturing processes aligns well with industries seeking to respond quickly to niche market demands or specialized component needs. However, the transition to larger-scale production necessitates advancements in MEX technology and process optimization, including faster production speeds, more efficient sintering methods, lower material costs, and sourcing from local suppliers.

7. Conclusion

This study has provided an in-depth exploration of the feasibility and competitiveness of MEX within the broader MAM landscape, with a special focus on its integration into the supply chain and implications on cost and carbon emissions. Our MOO model, which incorporates real-world data, offers critical insights into the operational and economic dimensions of MEX, particularly within the unique geographical context of Northern Norway. Key findings indicate that while MEX shows significant potential for cost-effective production at low volumes, its competitiveness diminishes as production scales increase. This aligns with the current understanding that MAM, including MEX, is most advantageous for applications requiring high customization and low production volumes. Our analysis demonstrates that MEX remains economically viable for producing up to 10 parts, with cost advantages decreasing substantially for higher volumes when compared to traditional manufacturing methods such as CNC machining.

The study highlights several critical challenges that need addressing to enhance the scalability of MEX. These include the low production throughput of MEX machines, high sintering costs, and significant air freight expenses. Addressing these challenges through technological advancements and process optimizations – such as faster production speeds, continuous sintering operations, and local sourcing – could improve the cost-efficiency of MEX at larger production scales. Furthermore, our innovative zone-based logistical model for Northern Norway offers a practical approach to understanding and mitigating transportation costs, which are particularly significant in remote areas with sparse populations. This model ensures that potential facility locations are aligned with population centers, enhancing logistical feasibility and cost-effectiveness.

Lastly, MEX requires significant advancements to compete effectively at higher scales. Our findings underscore the importance of continuous research and development in MEX technology and process optimization to expand its applicability and efficiency. This study enhances the broader understanding of MAM's economic and environmental impacts, offering specific insights and strategies that can be applied to similar regions facing geographical and logistical challenges. By addressing these challenges, MEX can become a more viable option for diverse manufacturing needs, supporting both economic and sustainable development.

The novelty of our research can be summarized as follows:

- **Comprehensive Multi-Objective Optimization Model**: Developed a model that incorporates cost and environmental impacts for MEX.
- **Geographical Focus**: Provided insights specifically tailored to the unique logistical challenges of Northern Norway.
- **Zone-Based Logistical Approach**: Employed a novel method for accurately estimating transportation costs based on zones rather than just distance.
- **Scenario Analysis**: Evaluated MEX's competitiveness across various production volumes (10, 100, 1000, and 10,000 units), highlighting its cost-effectiveness at low volumes.
- **Production and Transportation Cost Breakdown**: Detailed analysis of production costs, highlighting the major contributors and potential areas for cost reduction.
- **Environmental Impact Assessment**: Quantified carbon emissions across the supply chain, emphasizing the importance of sustainable practices.
- **Strategic Insights for MEX Improvement**: Identified key areas for technological advancements and process optimizations necessary for scaling MEX production efficiently.

For future research, expanding the scope of products and materials analyzed would offer deeper insights into the versatility and adaptability of MEX in various manufacturing scenarios. This could involve exploring different product geometries and materials to further validate the model's applicability across diverse industrial contexts. Furthermore, comparing the costs and emissions of MME against other MAM processes, rather than only traditional manufacturing methods like CNC machining, for various volumes and products, is an interesting and valuable direction for future research.

CRediT authorship contribution statement

Mathias Sæterbø: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Halldor Arnarson:** Writing – review & editing, Writing

– original draft, Software. **Hao Yu:** Writing – review & editing, Software, Methodology. **Wei Deng Solvang:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used the AI language model ChatGPT by OpenAI in order to improve language and correct errors in writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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