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RESEARCH ARTICLE

Scheduling of distributed additive manufacturing machines considering carbon emissions

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ABSTRACT

Additive manufacturing is a rapidly growing technology shaping the future of manufacturing. In an increasingly competitive economy, additive manufacturing can help businesses to remain agile, innovative, and sustainable. This paper introduces the multi-site additive manufacturing (AM) machine scheduling problem considering carbon emissions caused by production and transportation. A mixed-integer linear programming model is developed aiming to optimise two separate objectives addressing economic and environmental sustainability in a multiple unrelated AM machine environment. The former is the total cost caused by production, transportation, set-up and tardiness penalty and the latter is the total amount of carbon emissions caused by production and transportation. The model is coded in Python and solved by Gurobi Optimizer. A numerical example is provided to represent the basic characteristics of the problem and show the necessity of the proposed framework. A comprehensive computational study is conducted under 600s and 1800s time limits for two main scenarios and the results have been elaborated. This article introduces the concept of considering both economic and environmental sustainability caused by production and transportation, proposing the first mathematical model and measuring its performance through a comprehensive experimental study.

1. Introduction

Additive manufacturing (AM) has a wide range of application areas from automotive to aeronautics and healthcare. Several AM techniques have been developed based on the idea that the parts are 3D modelled and fabricated layer-by-layer based on the cross sections of the computer-aided design model. Thus, it is also referred to as 3D printing. Compared to the traditional subtractive manufacturing methods, AM technologies utilise production by additively releasing materials [1].

AM has a significant role in today's competitive economy for several reasons. Firstly, it enables the production of complex geometries which otherwise difficult or even impossible via traditional methods. That also helps integrate multiple parts into a single component, reducing assembly processes and increasing product strength and durability [2]. The geometry flexibility that AM provides allows a higher degree of customization without incurring additional costs. This has been particularly useful in sectors like medical devices, where patient-specific products can be produced. Secondly, companies can print products on-demand rather than mass-producing and storing them in inventory, which saves storage space and costs, and reduces the risk of products becoming obsolete. Another cost advantage is gained by eliminating expensive moulds, tools and machine setups.

Thirdly, rapid prototyping is possible with additive manufacturing which significantly reduces the time to market. Moreover, the nature of the production that AM utilises results in significantly less waste compared to subtractive methods, which carve out parts from larger blocks of material. Also, the carbon footprint associated with the transport of goods can be reduced thanks to locally printed parts. Hence, all these advantages are related to the environment as well as the economic benefits and flexibility.

The recent pandemic has also highlighted the importance of the resilience of supply chains and the vulnerability of global supply chains. With additive manufacturing, companies can manufacture parts in-house or domestically, decreasing dependence on international suppliers, and increasing resilience [3, 4].

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Efficient planning and scheduling of AM machines can lead to significant improvements in productivity, cost-efficiency, quality, and customer satisfaction. This is achieved through more effective resource use, reduced waste, improved delivery times, and enhanced flexibility and responsiveness to change. This paper addresses the AM machine scheduling problem where unrelated AM machines are dispersively located at different factory plants. The AM technology considered in this paper is selective laser melting (SLM) which uses a high-power laser beam to fuse fine metallic powders to create a high-density part with complex geometries. As a unique contribution to the field, a multi-objective mathematical model is developed to minimise total cost as well as total amount of carbon emissions (TCE), both caused by production and transportation.

The rest of the manuscript is organised as follows. Section 2 reviews the literature on the AM machine scheduling problem. Section 3 describes the main characteristics of the problem and presents the mathematical model developed. The results of the experimental study are provided in Section 4 and the paper is concluded in Section 5.

2. Related work

AM is an emerging field that attracts both academics and practitioners. The literature on the AM technology addressed in this paper, i.e. SLM, is rather extensive. Recently, a thorough examination and analysis of the key parameters affecting the SLM manufacturing process of difficult-to-cut alloys has been conducted based on an extensive review of the existing literature by Pimenov et al. [5]. Li et al. [6] proposed a new design method to concurrently achieve lightweight and self-sustaining design for SLM processes. However, the number of studies on the efficient planning and scheduling of these SLM machines is still limited.

As pioneering works on planning and scheduling of AM machines, Kucukkoc et al. [7] aimed to maximise the utilisation of AM machines, and Li et al. [2] focused on the minimisation of average cost by proposing a mathematical model as well as two constructive heuristics. Several researchers have followed these works, as will be summarised hereafter.

Chergui et al. [8] simultaneously addressed the scheduling and nesting problems in AM and proposed a heuristic algorithm to satisfy due dates. Kucukkoc et al. [9] proposed a genetic algorithm (GA) approach to minimise maximum lateness in a multiple heterogenous AM machine environment. Kucukkoc [1] aimed to minimise makespan in single, parallel identical and parallel unrelated AM machine scheduling problems through a MILP model developed. Li et al. [10] combined the order acceptance problem with the scheduling problem of SLM machines and proposed a dynamic and strategy-based decision-making approach. Kapadia et al. [11] have also studied the order acceptance and scheduling problem under such a condition that orders can be accepted fully or partially and proposed a GA to maximise profit. Zhang et al. [12] integrated the irregular packing constraints into the AM machine scheduling problem and proposed an improved evolutionary algorithm. Kucukkoc [13] showed the necessity of considering nesting and scheduling problems together to get applicable as well as better scheduling solutions.

Altekin and Bukchin [14] showed the necessity of considering cost and makespan objectives simultaneously and proposed a multi-objective optimisation approach to investigate the trade-off in between. Kucukkoc et al. [15] aimed to minimise the total tardiness in a parallel unrelated AM machine environment and proposed a GA-based approach. Alicastro et al. [16] aimed to minimise makespan via a reinforcement learning iterated local search algorithm in a multiple identical/non-identical AM machine environment. Another study addressing the makespan as well as total tardiness is conducted by Rohaninejad et al. [17], who developed a hybrid non-dominated sorting GA-based metaheuristic in addition to a bi-objective model. Arık [18] combined the AM machine scheduling problem with the planning of post-processing assembly operations and proposed a MILP model as well as a local search heuristic.

Hu et al. [19] solved the AM machine scheduling problem using MILP and an adaptive large neighbourhood search algorithm considering two-dimensional nesting and unequal part release times. Wu et al. [20] addressed the cloud-based 3D printing problem and proposed a heuristic algorithm for the scheduling of orders received through the cloud-based platform. Oh et al. [21] presented a taxonomy and comprehensive review of the nesting and scheduling problem in AM.

Different from the common approach caused by the nature of the AM machine scheduling problem, Kim and Kim [22] addressed the problem by considering the maximum processing time of parts when calculating the processing time of a batch. They proposed three meta-heuristics to minimise makespan considering sequence-dependent set-up times.

Che et al. [23] introduced the part orientation problem into the AM machine scheduling and proposed a MILP model as well as a simulated annealing algorithm for solving it. Oh and Cho [24] addressed the AM machine scheduling problem within a flow-shop environment considering both the build and post processes simultaneously. A mixed-integer programme was also proposed to minimise makespan for different scheduling policies. Ying et al. [25] proposed an adjusted iterated greedy search algorithm to solve the single AM machine scheduling problem. Zipfel et al. [26] proposed an iterated local search algorithm for customer order scheduling in additive manufacturing focusing on the total weighted tardiness of orders. Kucukkoc [27] considered the batch delivery of parts belonging to several customers when solving the multiple AM machine scheduling problem. Ying and Lin [28] attempted to minimise makespan in parallel AM machine scheduling problem with a two-stage assembly process. Lee and Kim [29] focused on the 3D rotation of parts and aimed to minimise makespan in parallel AM machine scheduling problem with 2D nesting constraints.

Dwivedi et al. [30] introduced the simultaneous production and transportation problem where the route of a mobile AM-installed vehicle is optimised considering the delivery due dates of customer orders. Exact and heuristic solution approaches were developed and their effectiveness has been tested through computational tests. Zehetner and Gansterer [31] addressed the multi-site AM machine scheduling problem to minimise the total cost accumulated by production, inventory, setup and transportation.

Although production scheduling and transportation problems have been integrated into other domains of scheduling literature [32-34], it has not been handled properly in the AM machine scheduling field. As seen from the survey given above, there is only one study which addresses the multi-site AM machine scheduling problem, by Zehetner and Gansterer [31]. However, Zehetner and Gansterer [31] only focused on the cost including transportation. In our work, we address the multi-site AM machine scheduling problem and employ a new objective function related to the sum of carbon emissions caused by production and transportation. Therefore, this study contributes to the literature by introducing the multi-site AM machine scheduling problem considering carbon emissions and proposing a MILP model for solving it. AM machines are unrelated (having different processing speed-, cost- and emission-related parameters) and orders received from geographically dispersed customers have certain tardiness penalty costs.

3. Problem definition

Part orders ($i \in I$) received from customers ($u \in U$) are assigned to machines ($m \in M$) located at geographically dispersed factory plants ($p \in P$) and allocated to batches ($j \in J$) to be produced sequentially. They are shipped to customers after production, in such a concept of on-demand production. The schematic representation of the addressed problem is given in Figure 1. Note that the numbers of plants, customers, part orders and machines provided in the figure are just for illustration purposes and they may vary in the practical applications.

Each part has a volume (v_i), area (a_i), height (h_i), due date (dd_i) and tardiness penalty cost (dc_i). Each machine's build platform has a maximum supported area (A_m) and height (H_m). Machines require different times to set-up (set_m), release per unit volume of material (vt_m) and powder-layering (rt_m). As the machines have different specifications, they cause different amounts of CO_2 equivalent emissions during production.

Batches are constituted of different combinations of parts seeking the main objective of the problem. As already done in the literature, the total volume and the maximum height of the parts are used to calculate the processing time of a batch in this paper as well. Hence, grouping parts with similar heights together may reduce the processing time. That yields reduced production costs and production emissions. However, as introduced in this paper, if there is more than one plant at which the machines are utilised, this approach might ignore additional costs and carbon emissions caused by transportation. That is because the solution that minimises the processing time-related measures (i.e. makespan or cost) does not necessarily minimise the delivery-related metrics such as transportation cost and transportation emissions. Therefore, a more sophisticated holistic approach is required to deal with all these considerations effectively. For this aim, a mixed-integer mathematical model is developed with two different objectives considering economic aspects and environmental sustainability.

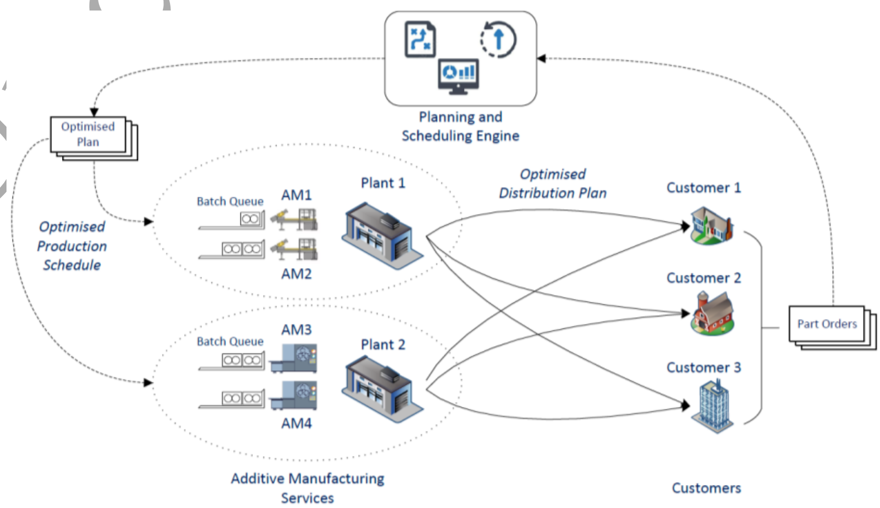

Figure 1. The schematic representation of the addressed problem

It was justified by Kucukkoc [1] that scheduling parallel AM machines to minimise makespan is strongly NP-hard, having additional complexities over classical batch scheduling problems. This is because the processing time of a batch is calculated via a function [1, 2]. Moreover, this paper focuses on total cost (instead of makespan) integrating the transportation problem in terms of both total cost and emission aspects, which increases the complexity of the problem even more.

The following subsection presents the model developed, followed by a numerical example.

3.1. Mathematical model

The mathematical model is developed over the work by Li et al. [2] and Kucukkoc [1]. It has two objectives, such that f_1 aims to minimise the total cost and f_2 aims to minimise the total amount of carbon emissions, i.e. TCE. The notation, parameters and decision variables are given below, followed by the model.

Notation:

i	: part index, where $i \in I$
j	: batch index, where $j \in J$
m	: machine index, where $m \in M$
u	: customer index, where $u \in U$
p	: factory plant index, where $p \in P$

Parameters:

dis_{pu}	: distance between factory plant p and customer u
P_p^M	: the set of machines available at factory plant p
U_u^I	: the set of parts belonging to customer u
h_i	: the height of part i
a_i	: the area of part i
v_i	: the volume of part i
dd_i	: the due date of part i
dc_i	: unit tardiness penalty cost for part i
A_m	: the area of machine m's build platform
H_m	: the maximum height of a part that can be built on machine m
vt_m	: the time required to form per unit volume of material on machine m
rt_m	: the unit recoating (powder-layering) time on machine m, *(the layer height unit is assumed to be the same with that used for the part height)*
set_m	: the time needed to set-up machine m
τ_m	: unit time cost for machine m
ψ	: a large enough positive number
$unit^{TC}$	: unit transportation cost
hc	: unit time cost for human work
ε^{Tr}	: unit carbon emissions amount released to transport per volume of part per km
ε_m^{Pr}	: unit carbon emissions amount released by machine m per unit time

Decision variables:

X_{ijm}	: 1, if part i is allocated to batch j on machine m; 0, otherwise
Y_{jm}	: 1, if batch j on machine m is utilised; 0, otherwise
PC_{jm}	: production cost for batch j on machine m
SC_{jm}	: set-up cost for batch j on machine m
He_{jm}	: the maximum height of the parts allocated to batch j on machine m
vol_{jm}	: the total volume of the parts assigned to batch j on machine m
TC_u	: total transportation cost for customer u
TV_{pu}	: total volume transported from factory plant p to customer u
ct_i	: completion time of part i
tt_i	: tardiness of part i
s_{jm}	: starting time of batch j on machine m
p_{jm}	: processing time of batch j on machine m
c_{jm}	: completion time of batch j on machine m
TE_{pu}	: carbon emissions caused by transportation from factory plant p to customer u
PE_m	: carbon emissons caused by production on machine m

Objective functions:

$$Min\ f_1 = \sum_{j \in J} \sum_{m \in M} \left(PC_{jm} + SC_{jm}\right) + \sum_{u \in U} TC_u + \sum_{i \in I} dc_i tt_i \tag{1}$$

$$Min\ f_2 = \sum_{p \in P} \sum_{u \in U} TE_{pu} + \sum_{m \in M} PE_m \tag{2}$$

Subject to:

$$\sum_{j \in J} \sum_{m \in M} X_{ijm} = 1 \quad \forall i \in I \tag{3}$$

$$\sum_{i \in I} X_{ijm} \leq \psi Y_{jm} \quad \forall j \in J, m \in M \tag{4}$$

$$Y_{jm} \leq \sum_{i \in I} X_{ijm} \quad \forall j \in J, m \in M \tag{5}$$

$$\sum_{i \in I} a_i X_{ijm} \leq A_m \quad \forall j \in J, m \in M \tag{6}$$

$$PC_{jm} \geq vt_m \tau_m vol_{jm} + rt_m \tau_m He_{jm} \quad \forall j \in J, m \in M \tag{7}$$

$$SC_{jm} \geq set_m Y_{jm} hc \quad \forall j \in J, m \in M \tag{8}$$

$$He_{jm} \geq h_i X_{ijm} \quad \forall i \in I, j \in J, m \in M \tag{9}$$

$$TC_u \geq unit^{TC} \sum_{p \in P} dis_{pu} TV_{pu} \quad \forall u \in U \tag{10}$$

$$TV_{pu} \geq \sum_{i \in U_u^I} \sum_{j \in J} \sum_{m \in P_p^M} v_i X_{ijm} \quad \forall p \in P, u \in U \tag{11}$$

$$tt_i \geq ct_i - dd_i \quad \forall i \in I \tag{12}$$

$$ct_i \geq c_{jm} + \psi(X_{ijm} - 1) \quad \forall i \in I, j \in J, m \in M \tag{13}$$

$$ct_i \leq c_{jm} + \psi(1 - X_{ijm}) \quad \forall i \in I, j \in J, m \in M \tag{14}$$

$$c_{jm} \geq s_{jm} + p_{jm} \quad \forall j \in J, m \in M \tag{15}$$

$$s_{jm} \geq c_{j-1,m} + set_m Y_{jm} \quad \forall j \in J \; and \; j > 1, m \in M \tag{16}$$

$$s_{jm} \geq set_m Y_{jm} \quad \forall j \in J \; and \; j = 1, m \in M \tag{17}$$

$$s_{jm} \leq \varphi Y_{jm} \quad \forall j \in J, m \in M \tag{18}$$

$$p_{jm} \geq vt_m vol_{jm} + rt_m He_{jm} \quad \forall j \in J, m \in M \tag{19}$$

$$vol_{jm} \geq \sum_{i \in I} v_i X_{ijm} \quad \forall j \in J, m \in M \tag{20}$$

$$vol_{jm} \leq \psi \sum_{i \in I} X_{ijm} \quad \forall j \in J, m \in M \tag{21}$$

$$TE_{pu} \geq \varepsilon^{Tr} dis_{pu} TV_{pu} \quad \forall p \in P, u \in U \tag{22}$$

$$PE_m \geq \varepsilon_m^{Pr} \sum_{j \in J} p_{jm} \quad \forall m \in M \tag{23}$$

$$X_{ijm} \in \{0,1\} \quad \forall i \in I, j \in J, m \in M \text{ and } Y_{jm} \in \{0,1\} \quad j \in J, m \in M \tag{24}$$

$$PC_{jm}, SC_{jm}, He_{jm}, s_{jm}, p_{jm}, c_{jm}, vol_{jm} \geq 0 \quad \forall j \in J, m \in M \tag{25}$$

$$TV_{pu}, TE_{pu} \geq 0 \quad \forall p \in P, u \in U \tag{26}$$

$$TC_u \geq 0 \quad \forall u \in U \tag{27}$$

$$PE_m \geq 0 \quad \forall m \in M \tag{28}$$

$$tt_i, ct_i \geq 0 \quad \forall i \in I \tag{29}$$

The objective given in Eq. (1) aims to minimise the total cost accumulated from production, set-up, transportation and tardiness. The aim of the other objective given in Eq. (2) is to minimise the TCE calculated considering (i) the transportation of parts from plants to customers and (ii) their production on the machines. Note that the time consumed when setting up the machine is not included in this calculation. Eq. (3) ensures that every part is assigned to exactly one batch and machine. Eq. (4) prevents assigning a part to a batch if the batch is not utilised. Eq. (5) relates the two decision variables (Y_{jm} and X_{ijm}) to each other. Eq. (6) satisfies the area capacity of the building platform based on the specifications of the AM machines. Eq. (7) calculates the production cost of each batch using the total volume and the maximum height of the parts allocated to that batch. Eq. (8) is to calculate the set-up cost of each batch utilised. Eq. (9) gets the maximum height of the parts in the batch. Eq. (10) calculates the transportation cost for each customer based on the total volume of the parts shipped to that customer, which is calculated by Eq. (11). Tardiness of each part is calculated by Eq. (12), using its completion time (ct_i) calculated through Eq. (13) and Eq. (14). Note that these two constraints are specially formed to avoid non-linearity as the completion time of the part is gathered from the completion time of the batch that the part is allocated into. The completion time of a batch is obtained from Eq. (15). The start time of a batch is calculated by Eq. (16) and Eq. (17) taking the set-up time of the batch and completion time of the previous batch on the same machine (if any) into account. Eq. (18) sets the start time of the batch to zero if the batch is not utilised. Eq. (19) calculates the processing time of each batch based on its total volume (from Eq. (20)) and maximum height (by Eq. (9)). Similar to Eq. (18), Eq. (21) sets vol_{jm} to zero if there is no part in the batch. Carbon emissions are obtained through Eq. (22) and Eq. (23). In Eq. (22), the total volume shipped from each plant to each customer is multiplied by the unit transportation amount and distance to get the carbon emissions caused by transportation. In Eq. (23), carbon emissions by production in each batch is summed to get the TCE caused by production. Domain constraints are provided in Eqs. (24)-(29).

3.2. Numerical example

Here we consider a numerical example consisting of two factory plants, each of which has two AM machines (i.e. M1 and M2 at plant 1 and M3 and M4 at plant 2) to fabricate a total of 16 parts received from four customers. The complete data, including the specifications of parts and machines (generated based on the test data available by [1, 2]) and the distances between factory plants and customers, are provided in Appendices.

The problem is solved under two scenarios: (i) total cost is minimised using f_1 and (ii) TCE is minimised using f_2. When the model is run to optimise f_1, the optimal solution is obtained within 53.4s. The detailed production schedule and distribution plan based on the optimal solution are reported in Table 1 and Table 2, respectively. As seen from Table 1, five batches are utilised in total (four at plant 1 and one at plant 2).

Table 1. The production schedule based on the optimal solution considering the first objective function (f_1)

Plant	Mach.	Batch	Assigned Parts	PC_{jm}	SC_{jm}	vol_{jm}	He_{jm}	s_{jm}	p_{jm}	c_{jm}
1	M1	1	1,12,16	2525.38	40	1050.73	6.90	2.00	42.0897	44.0897
		2	11,14	8447.83	40	3990.77	12.59	46.0897	140.7970	186.8870
		3	9	3107.30	40	1142.25	11.81	188.887	51.7884	240.6750
	M2	1	8,10,15	14552.10	40	6869.78	21.79	2.00	242.535	244.5350
2	M3	1	2,3,4,5,6,7,13	11982.70	20	4025.19	36.50	1.00	149.783	150.7830

Table 2. The distribution plan based on the optimal solution considering the first objective function (f_1)

From Plant	To Customer	Shipped Parts	TV_{pu}	TE_{pu}
1	1	1	826.08	3097.80
	3	8,9,10,11,12	8453.26	47549.60
	4	14,15,16	3774.19	28306.40
2	1	2,3,4	1727.59	3239.23
	2	5,6,7	1982.60	1858.69
	4	13	315.00	1476.56

While there are three batches planned to be executed on M1, no batch is planned for M4. That is based on the optimal solution obtained by the model to minimise the total cost. The model determines the best combination of parts to be grouped and allocates them to the best machine and plant considering all the capacity constraints as well as the costs caused by production, set-up, transportation, and tardiness. For example, the batch that part 9 is allocated is scheduled on M1 after batch 2 (instead of after batch 1 on M2 at the same plant) as it can start to set-up at 186.887 (rather than 244.535).

When the problem is solved with an ultimate goal to minimise f_2 (scenario 2), the optimal solution is achieved within 7.15s (much shorter than that for scenario 1). The production schedules for machines and the distribution plan to customers are respectively provided in Table 3 and Table 4. A total of five batches have been utilised again but with a different combination of batches and tasks as clearly seen in the tables. This time both machines on both plants are employed to minimise the TCE majorly caused by transportation. As expected, parts belonging to Customer 3 are allocated to the machines at Plant 1 to minimise transportation emissions. For the same reason, other parts are scheduled for production at machines located at Plant 2. However, transportation is not the single factor causing carbon emissions. The model has the ability to minimise production emissions as well. For this aim, parts by different customers may be grouped into the same batch. For example, as seen in Table 3, parts 2, 5, 6, 7 and 15 belonging to three different customers are grouped to be produced in the same batch considering the capacity limits of the machines and height similarity of the parts.

The objective function values and their components are reported in Table 5, comparatively, for both scenarios. For the first scenario which aims to minimise the total cost (f_1), f_1 is obtained as 43895.9 and the TCE for this solution is calculated as $f_2 = 89327.7$. When the objective is altered to minimise the TCE, f_2 is obtained as 77216.4 and the total cost for this solution is acquired as $f_1 = 46463.5$. This clearly shows how the two objective functions act. In scenario 2, while the production emissions increase (from 3799.4 to 3851.9), the model reduces the transportation emissions with a significant amount (from 85528.3 to 73364.5) to minimise the TCE, i.e. 77216.4.

Table 3. The production schedule based on the optimal solution considering the second objective function (f_2)

Plant	Mach.	Batch	Assigned Parts	PC_{jm}	SC_{jm}	vol_{jm}	He_{jm}	s_{jm}	p_{jm}	c_{jm}
1	1	1	8,10	11061.40	40	4984.78	21.79	2.00	184.3560	186.3560
		2	11	5139.77	40	2204.41	12.59	188.356	85.6629	274.0190
	2	1	9,12	3332.90	40	1264.07	11.81	2.00	55.5483	57.5483
2	3	1	1,3,4,13,14,16	10354.90	20	3805.26	17.13	1.00	129.4370	130.6050
	4	1	2,5,6,7,15	13945.70	20	4820.20	36.50	1.00	174.3210	175.3210

Table 4. The distribution plan based on the optimal solution considering the second objective function (f_2)

From Plant	To Customer	Shipped Parts	TV_{pu}	TE_{pu}
1	3	8,9,10,11,12	8453.26	47549.60
2	1	1,2,3,4	2553.67	4788.13
	2	5,6,7	1982.60	1858.69
	4	13,14,15,16	4089.19	19168.10

Table 5. The comparison of the objective terms for the two optimal solutions

Objective	*Min* f_1	*Min* f_2
Total Cost (*GBP*)	43895.9	46463.5
$\sum_{j\in J}\sum_{m\in M}(PC_{jm}+SC_{jm})$	*40795.3*	*43994.6*
$\sum_{u\in U}TC_u$	*2280.7*	*1956.4*
$\sum_{i\in I}dc_i tt_i$	*819.9*	*512.5*
Total Emission (*gr* CO_2 *eq.*)	89327.7	77216.4
$\sum_{p\in P}\sum_{u\in U}TE_{pu}$	*85528.3*	*73364.5*
$\sum_{m\in M}PE_m$	*3799.4*	*3851.9*

3.3. Alternative scenarios

Additional scenarios have been constituted here to observe the behaviour of the model under different conditions with no time limit. Brief information on each scenario is as follows:

A-1: The objective is to minimise f_1 where the upper limit for f_2 is restricted to 80 kg.

A-2: The objective is to minimise f_2 where the upper limit for f_1 is restricted to 45000 GBP.

A-3: Lexicographically minimise both objectives, where the primary objective is to minimise f_1 and the secondary objective is to minimise f_2

A-4: Lexicographically minimise both objectives, where the primary objective is to minimise f_2 and the secondary objective is to minimise f_1

The problem has been solved under four different scenarios detailed above and the results have been summarised in Figure 2.

Table 6. Design of the test problems

Problem #	nbPlants	nbCustomers	nbParts	nbMachines	Machines at Plants
P1	2	2	10	2	[M1], [M2]
P2			10	2	[M2], [M1]
P3			14	2	[M1], [M2]
P4			14	2	[M2], [M1]
P5	2	3	12	2	[M1], [M2]
P6			12	2	[M2], [M1]
P7			16	3	[M1, M1], [M2]
P8			16	3	[M1], [M2, M2]
P9	2	4	18	2	[M1], [M2]
P10			18	2	[M2], [M1]
P11			20	3	[M1, M1], [M2]
P12			20	3	[M1], [M2, M2]
P13	2	5	20	3	[M1, M1], [M2]
P14			20	3	[M1], [M2, M2]
P15			22	4	[M1, M1], [M2, M2]
P16			22	4	[M1, M2], [M1, M2]
P17	3	3	14	3	[M1], [M1], [M2]
P18			14	3	[M2], [M2], [M1]
P19			16	4	[M1], [M2, M2], [M1]
P20			16	4	[M1, M2], [M1], [M2]
P21			20	4	[M2], [M1, M2], [M1]
P22	3	4	16	4	[M2], [M1, M1], [M2]
P23			20	4	[M1], [M2, M2], [M1]
P24			20	4	[M1, M2], [M1], [M2]
P25			28	4	[M2], [M1, M2], [M1]
P26			28	4	[M1], [M1], [M2, M2]
P27	3	5	30	4	[M2], [M1, M1], [M2]
P28			36	4	[M1], [M2, M2], [M1]
P29			36	4	[M1, M2], [M1], [M2]
P30			44	4	[M2], [M1, M2], [M1]
P31			44	4	[M1], [M1], [M2, M2]
P32	3	6	40	5	[M2, M2], [M1], [M1, M2]
P33			44	5	[M1, M1], [M2, M2], [M1]
P34			44	5	[M1, M2], [M1, M2], [M2]
P35			46	5	[M2], [M1, M1], [M2, M2]
P36			46	5	[M2], [M1, M2], [M1, M2]

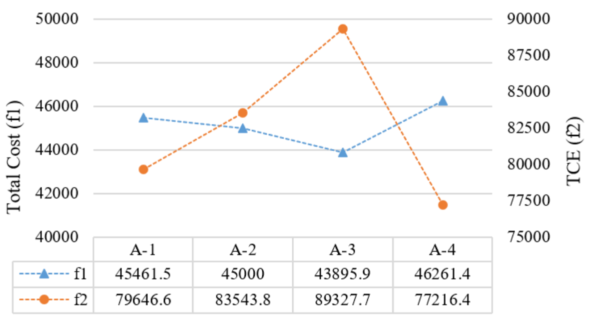

Figure 2. The comparison of the objective values belonging to the optimal solutions obtained under different scenarios

As seen in Figure 2, the minimum value for the total cost has been observed for A-3 where $f_1 = 43895.9$ and $f_2 = 89327.7$. The minimum value for the TCE has been observed for A-4 where $f_1 = 46261.4$ and $f_2 = 77216.4$. These results are in line with the expectations since f_1 is minimised primarily in A-3 while f_2 is minimised primarily in A-4.

In A-2, the TCE could be reduced to 83543.8 when the total cost was constrained with an upper limit of 45000. With regard to A-1, a solution has been obtained with $f_1 = 45461.5$ and $f_2 = 79646.6$ due to the conflicting objectives ensuring that the TCE was limited to a maximum value of 80 kg. As seen in these results, total cost increases in order to reduce the TCE to satisfy the constraint.

To sum up, this numerical example clearly shows the relationship between the conflicting objectives and the effectiveness of the proposed mathematical model.

4. Experimental study

A comprehensive computational study has been conducted to observe the performance of the mathematical model proposed. For this aim, a total of 36 test problems [35] have been generated and solved under different scenarios using a PC equipped with Intel(R) Core(TM) i7-1165G7 2.80GHz with 20 GB Ram. Descriptive information on the test problems is given in Table 6. The second, third, fourth and fifth columns in the table denote the number of plants, the number of customers, the number of parts and the total number of machines utilised at plants, respectively. The machine park at each plant is provided in the last column indicating their types. If we consider P8, the test problem has two plants with a total of three machines, to produce a total of 16 parts received from three customers. There is only one machine of type M1 at plant 1 and there are two machines of type M2 at plant 2.

The model has been coded in Python 3.11.4 and executed by Gurobi Optimizer 10.0.2. Each problem has been solved under two different scenarios, i.e. (i) total cost is minimised ($Min(f_1)$) and (ii) TCE is minimised ($Min(f_2)$). Two different time limits have been applied, i.e. 600s and 1800s, to better observe the model's performance and compare the results obtained under different conditions.

The values of the unit transportation cost ($unit^{TC}$), unit carbon emission amount caused by transportation (ε^{Tr}) and hourly human cost (hc) have been kept the same with the numerical example (as already provided in the Appendices).

Table 7 reports the results obtained by Gurobi Optimizer under the 600s time limit. First, each problem has been solved to minimise the total cost ($Min(f_1)$). The objective value of the solution is reported (second column) together with the optimality status of the model (third column) and the time consumed by the solver (fourth column). If the optimal solution is not achieved, the optimality gap of the best solution is given instead. The fifth column gives the TCE for the solution obtained when minimising total cost.

The sixth column corresponds to the objective value of the best solution when minimising TCE ($Min(f_2)$). The optimality status (and/or gap) and the consumed time are given in the seventh and eighth columns, respectively. The total cost (f_1) of the solution obtained when minimising TCE (f_2) is also provided in the last column.

As seen from Table 7, an optimal solution has been found for 13 out of 36 test problems when minimising f_1, i.e. P1-P8, P17-P18 and P20-P22. As for the remaining problems, the optimal solution was not verified within the time limit given (600s). Due to the complexity of the model, the time required to get the optimal solution increases with the increase in the number of parts, machines, plants and customers. For example, P1 and P2 have been solved optimally with around 1s running time while P22 required over 300s to get the optimal solution and verify it. Even, P9-P16 were unable to be solved within 600s time limit optimality, for which the optimality gap ranged between 1.18% and 4.27%. The optimality gap also tends to increase with the increased problem complexity and reaches as high as 14.94% for P35.

With regard to minimising TCE ($Min(f_2)$), Gurobi was able to retrieve the optimal solutions in 25 out of 36 test problems (as seen in Table 7). This time, the performance of the solver was higher in comparison to the above scenario. The reason lying behind could be the complexity of the total cost calculation, in comparison to the calculation of TCE. The optimality gap of the solutions was not high, with a maximum of 0.67 for P35.

Table 7. Results obtained under 600s time limit

Problem	$Min(f_1)$ / 600s				$Min(f_2)$ / 600s			
	f_1	Opt/Gap%	Time (s)	f_2	f_2	Opt/Gap%	Time (s)	f_1
P1	20289.39	Opt	0.92	21035.8	12389.50	Opt	0.06	22551.3
P2	20220.76	Opt	1.12	18462.2	12655.63	Opt	0.31	20576.7
P3	47200.17	Opt	12.24	37967.8	25914.56	Opt	2.02	51962.7
P4	47447.75	Opt	18.15	47252.1	42811.26	Opt	2.03	49050.2
P5	47902.08	Opt	4.81	104059.0	95392.25	Opt	0.17	51516.2
P6	47251.24	Opt	5.30	79652.1	70837.72	Opt	0.26	48358.7
P7	52509.16	Opt	293.34	118567.0	104784.77	Opt	0.73	7.50537e+07
P8	53425.41	Opt	439.24	115085.0	104784.77	Opt	2.06	56960.7
P9	56349.66	1.47	600	124532.0	108666.76	Opt	2.07	6.0064e+07
P10	55497.35	2.12	600	87588.1	84126.98	Opt	5.91	57011.8
P11	56195.39	2.09	600	130371.0	110672.94	Opt	3.71	67642
P12	57271.33	3.42	600	124984.0	110672.94	Opt	44.72	67464.5
P13	56265.97	1.18	600	133937.0	116906.02	Opt	5.20	63070.6
P14	57359.01	3.31	600	129050.0	116906.02	Opt	27.32	67043.8
P15	59224.73	3.86	600	144023.0	126371.48	Opt	133.49	64851.1
P16	58472.57	4.27	600	135850.0	101615.67	Opt	8.95	6.00628e+07
P17	48145.79	Opt	38.52	86458.4	80678.96	Opt	1.97	51049.9
P18	48172.25	Opt	26.77	81036.6	70257.92	Opt	0.20	50832.7
P19	52520.97	0.51	600	117055.0	104784.77	Opt	1.95	60258.7
P20	51807.17	Opt	218.52	90064.2	80194.22	Opt	3.37	1.0505e+08
P21	51777.71	Opt	178.09	88959.4	79928.09	Opt	0.55	56401.5
P22	51769.16	Opt	328.50	87811.8	80790.83	Opt	51.51	7.00524e+07
P23	56113.41	2.73	600	126655.0	110672.94	Opt	20.51	66408.5
P24	55469.07	3.32	600	100769.0	86129.99	Opt	18.01	8.75553e+07
P25	67381.39	8.98	600	75797.2	67843.31	Opt	288.12	1.40072e+08
P26	67340.38	8.30	600	87420.8	80114.86	0.3	600	72800.3
P27	73685.83	10.39	600	120263.0	103579.80	0.48	600	76800.2
P28	83390.44	10.78	600	139193.0	122773.54	0.11	600	93856
P29	83572.60	10.67	600	153428.0	135783.21	0.37	600	93922.8
P30	99175.03	14.03	600	158087.0	139492.17	0.14	600	124806
P31	99189.24	13.42	600	166476.0	152290.35	0.55	600	115397
P32	92832.03	12.51	600	166237.0	146158.08	0.59	600	2.62585e+08
P33	97749.64	12.51	600	180140.0	142728.23	0.21	600	1.45105e+08
P34	98855.99	13.99	600	174022.0	142605.50	0.16	600	135230
P35	104208.04	14.94	600	266096.0	162757.17	0.67	600	109776
P36	103919.76	14.55	600	169917.0	149400.53	0.16	600	129297

Table 8 reports the results obtained when the time limit was set to 1800s. As seen from the table, the number of optimal solutions has increased to 17 in comparison to 13 obtained under the 600s time limit when minimising f_1. For the remaining instances, the optimality of the solutions was not verified. However, it was observed that the optimality gap has reduced slightly, except for P10 (for which it was reduced from 2.2% to 0.55%).

As also observed for the 600s time limit, Gurobi was able to obtain and verify 25 optimal solutions in total under the 1800s time limit. However, the average of the optimality gap has been reduced from 0.34% to 0.325% for the remaining 11 test problems. For P30, increasing the time limit from 600s to 1800s has not contributed to the capability of the model as the same solutions with the same gap have been attained under both conditions. For some cases (such as P32), the increased time limit helped prune the lower bound further and reduced the gap (e.g. from 0.59% to 0.53%).

5. Conclusions and future work

This paper addressed the scheduling of parallel unrelated AM machines located at geographically dispersed factory plants. Due to the increasing environmental concerns and the requirements for the sustainable use of resources, the TCE (released during production and transportation of parts -from plants to customers) has been minimised through a separate objective function.

Table 8. Results obtained under 1800s time limit

Problem	$Min(f_1)$ / 1800s				$Min(f_2)$ / 1800s			
	f_1	Opt/Gap%	Time (s)	f_2	f_2	Opt/Gap%	Time (s)	f_1
P1	20289.39	Opt	0.88	21035.8	12389.50	Opt	0.06	22551.3
P2	20220.76	Opt	1.22	18462.2	12655.63	Opt	0.29	20576.7
P3	47200.17	Opt	11.18	37967.8	25914.56	Opt	1.88	51962.7
P4	47447.75	Opt	14.60	47252.1	42811.26	Opt	2.07	49050.2
P5	47902.08	Opt	3.87	104059.0	95392.25	Opt	0.17	51516.2
P6	47251.24	Opt	4.66	79652.1	70837.72	Opt	0.25	48358.7
P7	52509.16	Opt	283.43	118567.0	104784.77	Opt	0.65	7.50537e+07
P8	53425.41	Opt	439.22	115085.0	104784.77	Opt	2.07	56960.7
P9	56349.66	Opt	1037.79	124532.0	108666.76	Opt	2.11	6.0064e+07
P10	55497.35	0.55	1800	87588.1	84126.98	Opt	5.89	57011.8
P11	56195.39	Opt	1614.39	130371.0	110672.94	Opt	3.68	67642
P12	57188.60	2.60	1800	124116.0	110672.94	Opt	41.02	67464.5
P13	56265.97	Opt	808.61	133937.0	116906.02	Opt	4.72	63070.6
P14	57359.01	2.63	1800	129050.0	116906.02	Opt	25.88	67043.8
P15	59224.73	2.66	1800	144023.0	126371.48	Opt	118.60	64851.1
P16	58472.57	3.17	1800	135850.0	101615.67	Opt	8.14	6.00628e+07
P17	48145.79	Opt	38.84	86458.4	80678.96	Opt	1.85	51049.9
P18	48172.25	Opt	26.79	81036.6	70257.92	Opt	0.19	50832.7
P19	52520.97	Opt	701.57	117055.0	104784.77	Opt	1.80	60258.7
P20	51807.17	Opt	219.98	90064.2	80194.22	Opt	3.12	1.0505e+08
P21	51777.71	Opt	178.13	88959.4	79928.09	Opt	0.54	56401.5
P22	51769.16	Opt	329.59	87811.8	80790.83	Opt	47.23	7.00524e+07
P23	56113.41	1.47	1800	126655.0	110672.94	Opt	19.25	66408.5
P24	55424.50	1.74	1800	99097.5	86129.99	Opt	16.14	8.75553e+07
P25	67213.99	8.44	1800	82364.3	67843.31	Opt	267.75	1.40072e+08
P26	67340.38	6.93	1800	87420.8	80114.86	0.19	1800	72800.3
P27	73679.17	10.39	1800	120393.0	103579.80	0.41	1800	76800.2
P28	83346.94	10.17	1800	139193.0	122773.54	0.10	1800	93856
P29	83539.95	10.26	1800	151289.0	135783.21	0.35	1800	93922.8
P30	99175.03	13.45	1800	158087.0	139492.17	0.14	1800	124806
P31	98982.84	13.13	1800	171216.0	152267.39	0.53	1800	117297
P32	92825.93	12.30	1800	166235.0	146158.08	0.53	1800	2.62585e+08
P33	97748.12	11.69	1800	180517.0	142717.12	0.20	1800	1.77619e+08
P34	98855.99	13.34	1800	174022.0	142594.35	0.15	1800	7.01354e+07
P35	104130.56	14.41	1800	176594.0	162755.40	0.65	1800	109346
P36	103307.96	13.74	1800	167487.0	149387.44	0.14	1800	132740

A MILP model is proposed for the first time in literature, and a numerical example is presented to show the applicability and practicality of both the method and the addressed problem. Some practical scenarios have been constituted to show the applicability of the model and further elaborate results. A comprehensive computational study has also been conducted to test the performance of the model and it was observed that the number of instances solved optimally has increased when the time limit was increased from 600s to 1800s, as expected. The results of the computational tests indicate that the model is capable of producing practical results within a short amount of computation time. The methods proposed in this work can easily be adapted to solve real-world problems and increase the use of shareable resources environmentally friendly while minimising total cost. While the problem size may increase in real-life applications due to the enormous number of orders, parts and machines; the proposed models can still produce efficient solutions under certain time limits. They can also be integrated into existing decision support systems together with complex heuristic techniques to get quality solutions timely manner.

Future studies may consider implementing a heuristic and/or metaheuristic algorithm to quickly solve large-size problems especially. One can also develop lower bounds for the problem studied here for comparison purposes. It is also possible to further extend the MILP model proposed in this work with new industry-oriented constraints and/or energy considerations.

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Appendices

Table A1. Data on parts used for the numerical example

u	i	h_i	a_i	v_i	dd_i	dc_i
1	1	6.9	209.06	826.08	120	1
	2	26.04	550.11	952.6	120	1
	3	15.97	23.63	71.91	120	1
	4	17.04	99.53	703.08	120	1
2	5	27.94	56.85	272.92	155	2.5
	6	36.5	742.97	1583.98	155	2.5
	7	17.38	50.02	125.7	155	2.5
3	8	18.46	300.66	3144.39	180	2
	9	11.81	435.66	1142.25	180	2
	10	21.79	131.88	1840.39	180	2
	11	12.59	349.83	2204.41	180	2
	12	2.67	84.97	121.82	180	2
4	13	17.13	48.27	315	320	3
	14	12.53	269.66	1786.36	160	3
	15	18.09	175.77	1885	160	3
	16	4.27	122.62	102.83	160	3

Table A2. Data on machines used for the numerical example

m	A_m	H_m	VT_m	RT_m	SET_m	τ_m	ε_m^{Pr}
1	625	32.5	0.030864	1.4	2	60	6
2	625	32.5	0.030864	1.4	2	60	6
3	1600	40	0.030864	0.7	1	80	6.25
4	1600	40	0.030864	0.7	1	80	6.25

Table A3. Parameter values for the numerical example

Parameter	Value
hc	20 GBP/hr
$unit^{TC}$	0.001 $GBP/(km * cm^3)$
ε^{Tr}	0.0375 $gr/(km * cm^3)$

Table A4. Distances between plants and customers (in *km*) used for the numerical example

Plant/Customer	1	2	3	4
1	100	75	150	200
2	50	25	225	125

References

[1] Kucukkoc, I., *MILP models to minimise makespan in additive manufacturing machine scheduling problems.* Computers & Operations Research, 2019. 105: p. 58-67.

[2] Li, Q., I. Kucukkoc, and D.Z. Zhang, *Production planning in additive manufacturing and 3D printing.* Computers & Operations Research, 2017. 83: p. 157-172.

[3] Bouchenine, A. and M.A.M. Abdel-Aal, *Towards supply chain resilience with additive manufacturing: A bibliometric survey.* Supply Chain Analytics, 2023. 2: p. 100014.

[4] Naghshineh, B. and H. Carvalho, *The implications of additive manufacturing technology adoption for supply chain resilience: A systematic search and review.* International Journal of Production Economics, 2022. 247: p. 108387.

[5] Pimenov, D.Y., et al., *Influence of selective laser melting process parameters on the surface integrity of difficult-to-cut alloys: comprehensive review and future prospects.* International Journal of Advanced Manufacturing Technology, 2023. 127(3-4): p. 1071-1102.

[6] Li, Z., et al., *Incorporating draw constraint in the lightweight and self-supporting optimisation process for selective laser melting.* The International Journal of Advanced Manufacturing Technology, 2018. 98(1): p. 405-412.

[7] Kucukkoc, I., Q. Li, and D.Z. Zhang. *Increasing the utilisation of additive manufacturing and 3D printing machines considering order delivery times*. in *19th International Working Seminar on Production Economics, February 22-26*. 2016. Innsbruck, Austria.

[8] Chergui, A., K. Hadj-Hamou, and F. Vignat, *Production scheduling and nesting in additive manufacturing.* Computers & Industrial Engineering, 2018. 126: p. 292-301.

[9] Kucukkoc, I., et al. *Scheduling of Multiple Additive Manufacturing and 3D Printing Machines to Minimise Maximum Lateness*. in *20th International Working Seminar on Production Economics, February 19-23*. 2018. Innsbruck, Austria.

[10] Li, Q., et al., *A dynamic order acceptance and scheduling approach for additive manufacturing on-demand production.* International Journal of Advanced Manufacturing Technology, 2019. 105(9): p. 3711-3729.

[11] Kapadia, M.S., et al., *A genetic algorithm for order acceptance and scheduling in additive manufacturing.* International Journal of Production Research, 2021: p. 1-18.

[12] Zhang, J., X. Yao, and Y. Li, *Improved evolutionary algorithm for parallel batch processing machine scheduling in additive manufacturing.* International Journal of Production Research, 2020. 58(8): p. 2263-2282.

[13] Kucukkoc, I. *Metal Additive Manufacturing: Nesting vs. Scheduling*. in *Optimization and Data Science: Trends and Applications*. 2021. Cham: Springer International Publishing.

[14] Altekin, F.T. and Y. Bukchin, *A multi-objective optimization approach for exploring the cost and makespan trade-off in additive manufacturing.* European Journal of Operational Research, 2021.

[15] Kucukkoc, I., Z. Li, and Q. Li, *2D Nesting and Scheduling in Metal Additive Manufacturing*, in *Communications in Computer and Information Science*. 2021. p. 97-112.

[16] Alicastro, M., et al., *A reinforcement learning iterated local search for makespan minimization in*

additive manufacturing machine scheduling problems. Computers and Operations Research, 2021. 131.
[17] Rohaninejad, M., et al., *A hybrid learning-based meta-heuristic algorithm for scheduling of an additive manufacturing system consisting of parallel SLM machines.* International Journal of Production Research, 2021: p. 1-21.
[18] Arık, O.A., *Additive manufacturing scheduling problem considering assembly operations of parts.* Operational Research, 2021.
[19] Hu, K., Y. Che, and Z. Zhang, *Scheduling unrelated additive manufacturing machines with practical constraints.* Computers & Operations Research, 2022. 144: p. 105847.
[20] Wu, Q., et al., *Online order scheduling of multi 3D printing tasks based on the additive manufacturing cloud platform.* Journal of Manufacturing Systems, 2022. 63: p. 23-34.
[21] Oh, Y., et al., *Nesting and scheduling problems for additive manufacturing: A taxonomy and review.* Additive Manufacturing, 2020. 36: p. 101492.
[22] Kim, Y.J. and B.S. Kim, *Part-grouping and build-scheduling with sequence-dependent setup time to minimize the makespan for non-identical parallel additive manufacturing machines.* The International Journal of Advanced Manufacturing Technology, 2022. 119(3): p. 2247-2258.
[23] Che, Y., et al., *Machine scheduling with orientation selection and two-dimensional packing for additive manufacturing.* Computers and Operations Research, 2021. 130.
[24] Oh, Y. and Y. Cho, *Scheduling of build and post processes for decomposed parts in additive manufacturing.* Additive Manufacturing, 2022. 59.
[25] Ying, K.C., et al., *Adjusted Iterated Greedy for the optimization of additive manufacturing scheduling problems.* Expert Systems with Applications, 2022. 198.
[26] Zipfel, B., J. Neufeld, and U. Buscher, *An iterated local search for customer order scheduling in additive manufacturing.* International Journal of Production Research, 2023: p. 1-21.
[27] Kucukkoc, I., *Batch Delivery Considerations in Additive Manufacturing Machine Scheduling Problem* in *Operations Research and Data Science in Public Services*, L.P. Matteo Cosmi, Alice Raffaele, Marcella Samà, Editor. 2023, Springer Cham: Switzerland.
[28] Ying, K.C. and S.W. Lin, *Minimizing makespan in two-stage assembly additive manufacturing: A reinforcement learning iterated greedy algorithm.* Applied Soft Computing, 2023. 138.
[29] Lee, S.J. and B.S. Kim, *Two-stage meta-heuristic for part-packing and build-scheduling problem in parallel additive manufacturing.* Applied Soft Computing, 2023. 136.
[30] Dwivedi, G., et al., *Simultaneous Production and Transportation Problem: A Case of Additive Manufacturing.* Transportation Science, 2023. 57(3): p. 741-755.
[31] Zehetner, D. and M. Gansterer, *The collaborative batching problem in multi-site additive manufacturing.* International Journal of Production Economics, 2022. 248: p. 108432.
[32] Cakici, E., S.J. Mason, and M.E. Kurz, *Multi-objective analysis of an integrated supply chain scheduling problem.* International Journal of Production Research, 2012. 50(10): p. 2624-2638.
[33] Low, C., C.M. Chang, and B.Y. Gao, *Integration of production scheduling and delivery in two echelon supply chain.* International Journal of Systems Science: Operations and Logistics, 2017. 4(2): p. 122-134.
[34] Aminzadegan, S., M. Tamannaei, and M. Fazeli, *An integrated production and transportation scheduling problem with order acceptance and resource allocation decisions.* Applied Soft Computing, 2021. 112.
[35] Kucukkoc, I. *Dataset used for the test problems.* 2023; Available from: https://ikucukkoc.baun.edu.tr/projects/Dataset_carbon.rar.

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