Heterogeneous Material Order Job Scheduling Problem in Additive Manufacturing

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Abstract. To enhance the efficiency of additive manufacturing production, this paper establishes a Mixed Integer Linear Programming (MILP) model with the objective of minimizing the maximum completion time in an equivalent parallel additive manufacturing machine environment. The problem is tackled using a particle swarm algorithm, and the results are compared with those obtained from a solver to validate the superiority of the algorithm.

Keywords: Additive manufacturing；Production planning；Scheduling；Particle swarm optimization

1 Introduction

Additive Manufacturing (AM), also known as 3D printing technology, has garnered widespread attention and research in recent years. Unlike traditional subtractive manufacturing methods, AM constructs objects layer by layer through the addition of materials, fundamentally altering traditional production approaches. This paper will specifically focus on Selective Laser Melting (SLM) technology within the PBF framework. The principle of the SLM process is as follows: Initially, a scraper evenly distributes a layer of powder onto the build platform. Subsequently, a laser selectively melts the powder layer in specified areas to construct the part's structure. Finally, the build platform descends, and a new powder layer is applied.

AM scheduling primarily involves two interconnected sequential processes: part grouping and job scheduling. Part grouping aggregates parts into a cohesive job, while job scheduling arranges these jobs on AM machines. Given the high cost and processing time associated with SLM machines, effective planning and scheduling are critical for maximizing their utilization. Scheduling for SLM systems includes: (i) assigning ordered parts to SLM machines, (ii) grouping parts into jobs, and (iii) scheduling jobs on relevant machines in an optimal manner.

In summary, the study of AM scheduling issues holds significant importance for enhancing enterprise competitiveness and driving the development and progression of the entire AM domain.

J. Liao et al. (eds.), *Proceedings of the 2024 2nd International Conference on Digital Economy and Management Science (CDEMS 2024)*, Advances in Economics, Business and Management Research 292,
https://doi.org/10.2991/978-94-6463-488-4_49

2 Literature Review

Although research on production planning and scheduling in additive manufacturing (AM) plays a crucial role in optimizing the operation of this revolutionary technology, it is still in its early stages of development. Li et al. (2017)[1] mentioned that prior to their work, no research had been conducted to address production planning issues in additive manufacturing technology. The authors introduced and defined the production planning problem for additive manufacturing machines.

It wasn't until 2015 that a paper first combined scheduling with AM nesting methods[2]. From 2016 onwards, the number of papers related to scheduling has increased dramatically. Lee et al.[3] proposed a two-stage metaheuristic algorithm to minimize the maximum completion time. Kucukkoc (2019)[4] presented an MILP formulation for minimizing completion time objectives while considering various machine configurations, such as single machines, parallel identical machines, and parallel non-identical machines. Griffiths et al.[5] solved the combination problem of finding the optimal build orientation and packing of irregularly shaped parts across the same SLM machines, using total build cost as the objective function. Chergui et al. (2018)[6] aimed to complete different orders before their due dates while minimizing total tardiness and maximizing machine utilization using a custom heuristic based on the earliest due date (EDD) rule. Altekin and Bukchin (2021)[7] proposed a dual-objective MILP for minimizing cost and manufacturing lead time based on DMLS, analyzing the trade-offs between objectives.

Overall, research on the scheduling problem of additive manufacturing is still in its infancy, and it is a complex and challenging area of research that is critical to the field.

3 Problem Definition

3.1 Model Establishment

In the context of this problem, a manufacturer needs to use a set of identical additive manufacturing machines to produce parts for orders from multiple customers. Each order specifies the order ID, due date, and part requirements. The part requirements include various types of parts, each with corresponding specifications and dimensions, including height(h_i), area(a_i), volume(v_i), and material type(t_i).The set of all parts is denoted by I. Parts must be manufactured using specified materials, and the set of materials is denoted by K. There are parallel machines denoted by M, each with the same manufacturing platform parameters, namely height(MH) and area(MA). Due to the characteristics of additive manufacturing machines, multiple parts can be printed simultaneously in one production run, so the number of jobs formed in the end is less than or equal to the number of parts in the order.

In addition, machines have production parameters: VT^K is the time required for creating material type k per volume unit. HT is the time required for spreading powder per height. The setup between two consecutive jobs processed on the same machine may involve a change in material, necessitating consideration of sequence-dependent material changeover time. This refers to the time required for a complete powder change when switching from material(k) to material(k'), denoted as $SET^{kk'}$. Note that this changeover time includes the base setup time, i.e., the time required for initialization and cleaning before/after each job when no material change is performed. Additionally, there is preparation time(Pre^k) based on the material of the job when the machine is idle and the first job is assigned.

3.2 MILP Model

X_{mji}, Y_{mj}^k are binary variables. If part i is assigned to job j on machine m, then X_{mji} equals 1; otherwise, it is 0. If job j on machine m is manufactured using material k, then Y_{mj}^k equals 1; otherwise, it is 0. A job is considered to be utilized if at least one part is assigned to it. The number of job batches is less than or equal to the number of parts.

The maximum completion time is denoted by $C_{max} = \max\{CT_{mj}\}$ and the objective is to minimize the maximum completion time, which is represented by equation (1):

$$minZ = \max_{j \in J}\{CT_{mj}\} \tag{1}$$

Equation (2) ensures that each part is assigned to a job on a machine:

$$\sum_{m \in M} \sum_{j \in J} X_{mji} = 1, \forall i \in I \tag{2}$$

In this paper, the two-dimensional nesting problem is reduced to a one-dimensional boxing problem, where the basic idea is that the sum of the areas of the parts does not exceed the floor space capacity of the machine platform, i.e. equation (3):

$$\sum_{i \in I} X_{mji} a_i \le MA, \forall j \in J, m \in M \tag{3}$$

Equation (4) implies that jobs must be formed consecutively, ensuring that parts cannot be allocated to unused batches and that batch j+1 can only be processed if batch j is processed first:

$$\sum_{i \in I} X_{m(j+1)i} \le G * \sum_{i \in I} X_{mji}, \forall m \in M, j \in J \tag{4}$$

Equation (5) (6) ensure that parts belonging to the same material are all assigned to the same lot:

$$Y_{mj}^k * G \ge \sum_{\forall i \in I | t_i = k} X_{mji}, \forall j \in J, m \in M, k \in K \tag{5}$$

$$Y_{mj}^k \le \sum_{i \in I} X_{mji}, \forall m \in M, k \in K, j \in J \tag{6}$$

The equation (7) ensures that each formed job has at most one material type:

$$\sum_{k \in K} Y_{mj}^k \le 1, \forall m \in M, j \in J \tag{7}$$

Equation (8) prevents parts with different types of materials from being assigned to the same job:

$$\sum_{\forall i' \in I | t_{i'} \neq k} X_{mji'} \leq G * \left(1 - X_{mji}\right), \forall j \in J, m \in M, k \in K, i \in I | t_i = k \quad (8)$$

Equation (9) is used to compute the production time of a job (j ∈ J) on a machine m:

$$PT_{mj} \geq VT^k \sum_{i \in I} v_i X_{mji} + HT \max_{i \in I}\{h_i X_{mji}\} \quad (9)$$

As shown in the equation, it consists of two parts: 1. material forming time based on the total volume of the part, and 2. powder layering time based on the maximum height of the part.

The completion time of the first job on machine m can be expressed as equation (10)

$$CT_{m1} \geq PT_{m1} + Pre^k - G * (1 - Y_{m1}^k) \forall m \in M, j = 1, k, \in K \quad (10)$$

The completion time of operations on machine m other than the first one can be expressed by equation (11):

$$CT_{mj} \geq CT_{mj-1} + PT_{mj} + SET^{kk'} + G * \left(Y_{mj-1}^{k'} + Y_{mj}^k - 2\right) \forall m \in M, j \in J \backslash \{1\}, k, k' \in K \quad (11)$$

The completion time of the part is equal to the completion time of the job to which the part is assigned, shown as equation (12):

$$C_i \geq CT_{mj} - G * \left(X_{mji} - 1\right), \forall m \in M, j \in J, i \in I \quad (12)$$

Also the completion time of the order is equal to the completion time of the largest part in the order. The variable definition fields are as equation (13):

$$X_{mji}, Y_{mj}^k \in \{0,1\}, CT_{mj}, PT_{mj} \geq 0 \quad (13)$$

3.3 Algorithm Solving

Particle Swarm Optimization (PSO) is a population intelligence based optimization algorithm where each particle has a position and velocity. The particles find the best solution in the solution space by updating their position and velocity.

In this paper, one-dimensional coding is used. Each particle dimension is equal to the number of parts, where the order of the size of the elements is the corresponding part number. Suppose there are 10 parts, the area of the machine building platform is 900, the corresponding material is [1,2,1,1,1,1,2,2,2,2,1,2,1], and the area is [100,300,500,350,250,600,550,450,300,350]. The particle generated by random numbers is [0.93 0.17 0.79 0.32 0.54 0.01 0.84 0.55 0.25 0.17], and after decoding the part number is obtained as [10, 2, 8, 5, 6, 1, 9, 7, 4, 3]. Next the material constraints and area constraints group the parts in indexed order to form jobs. Firstly, job 1 is formed and part 10 is assigned to this job. Since the material type of part 2 is different from that of part 10, part 2 is not scheduled; since part 8 is of the same material as that of part 10 and the sum of the areas of the two is 450+350=800<900, part 8 is assigned to job 1. The same judgment is made for the following parts, and there is no part that can satisfy the constraints, so job 1 is assigned. Assignment is complete, remove part 8 and part 10 from the parts list. create a successor and do the same until all parts have been assigned. The resulting jobs are: Job 1: parts 10 and 8; Job 2: 2, 6; Job 3: 5,1,4; Job 4: 9,7; Job 5: 3.

4 Tests and Results

For the test instances, eight configurations are given in this paper as shown **Table 1.** Design of problem instances, which are designed according to four classifications: the number of orders(O), the number of parts contained in each order(P), the number of machines(M), and the number of materials(K). The part data is from the open dataset in the literature, and the machine data is randomly generated based on reasonable realistic data. For each configuration, five test files are randomly generated under it to verify the effectiveness of the algorithm by comparing the computational results of the solver and the algorithm.

Table 1. Design of problem instances

	Config1	Config2	Config3	Config4	Config5	Config6	Config7	Config8
O	5	5	10	10	15	15	15	20
P	4	5	4	5	4	5	6	6
M	2	2	2	2	2	2	5	5
K	2	2	2	2	2	2	3	3

The MILP model and algorithm were implemented in the gurobi solver and Pycharm respectively, and all experiments were done on a 2.40GHz Intel Core i5-9300H CPU with the MILP runtime set to 3600s, and a comparison of the test results is shown in the table 2 below. It is worth noting that of all the test instances, only configuration 1 had 4 files MILP solved for the optimal solution, and the rest of the instances ran until the end of the time as of. In terms of running time, the algorithms all took significantly less time to solve than the solver did. In terms of solution results, the performance of the algorithms is compared by calculating gap = $(C_{pso} - C_{gurobi})/C_{gurobi}$, where and represent the objective function values obtained by the algorithm and the solver solution, respectively, with smaller values of gap indicating better algorithmic solutions. From the results, for the solution of this problem, the use of particle swarm algorithm has good results.

Table 2. Results of the computational study

configurations	gap	PSO time/s
Config1	8%	3
Config2	2%	3
Config3	2%	5
Config4	6%	8

Config5	2%	11
Config6	3%	14
Config7	-6%	17
Config8	-1%	25

5 Conclusions

In this paper, based on extensive reading of the literature of previous years, with the objective of minimizing the maximum completion time, an additive manufacturing environment consisting of parallel SLM machines is considered, and a particle swarm algorithm is used to solve the production scheduling problem where there are multiple print materials for the ordered parts, and good results are obtained in the comparison of the solvers. In the subsequent research should be more in-depth, improve the algorithm to get better results, at the same time, for large-scale problems need to use multiple algorithms to solve and compare.

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