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PRODUCTION PLANNING FOR MASS CUSTOMIZATION IN ADDITIVE MANUFACTURING: BUILD ORIENTATION DETERMINATION, 2D PACKING AND SCHEDULING

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ABSTRACT
The efficient production planning of Additively Manufactured (AM) parts is a key point for industry-scale adoption of AM. This study develops an AM-based production plan for the case of manufacturing a significant number of parts with different shapes and sizes by multiple machines with the ultimate purpose of reducing the cycle time. The proposed AM-based production planning includes three main steps: (1) determination of build orientation; (2) 2D packing of parts within the limited workspace of AM machines; and (3) scheduling parts on multiple AM machines. For making decision about build orientation, two main policies are considered: (1) laying policy in which the focus is on reducing the height of parts; and (2) standing policy which aims at minimizing the projection area on the tray to reduce the number of jobs. A heuristic algorithm is suggested to solve 2D packing and scheduling problems. A numerical example is conducted to identify which policy is more preferred in terms of cycle time. As a result, the standing policy is more preferred than the laying policy as the number of parts increases. In the case of testing 3,000 parts, the cycle time of standing policy is about 6% shorter than laying policy.

Keywords: build orientation determination, mass customization, scheduling, and 2D packing

1. INTRODUCTION
Over the past decade, *Additive Manufacturing (AM)*, also known as *3D printing*, has largely affected production planning within supply chain context [1], [2]. Existing literature has started looking at the role of AM on offering new business models [3], [4] in which online retailers, AM-based production facilities, and distribution centers are working together to meet the market demand [1], [5]. AM-based production facilities take care of hundreds or thousands different parts each day by using multiple machines [6]. Recently, different software packages and cloud-based services are offered to support the management and monitoring of different AM machines [7], [8]. This movement in industry shows the needs for an efficient production plan considering a considerable number of different parts and several AM machines.

Although production planning considering multiple parts and AM machines has recently received some attention in the literature [5], [9], it still requires more studies in terms of *mass customization*. AM-based production planning (or process planning [8]) includes various decision-making ranging from the micro level such as toolpath planning [11] to the macro level such as supply chain management [12], [13].

In this paper, three decisions within AM-based production planning are investigated: (1) *two-dimensional (2D) packing planning*, (2) *scheduling*, and (3) *build orientation determination*. The 2D packing planning addresses how to place multiple parts with different shapes and sizes onto the build tray while avoiding overlap among parts. The 2D packing is often preferable to 3D packing since it prevents surface damage caused by support structure among parts [14]. The scheduling for AM addresses how to assign parts to AM machines with different workspace sizes. This problem is known as *part-to-printer assignment* [5]. In the current study, a heuristic algorithm developed titled *2D packing and scheduling algorithm (PSA)*.

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Finally, determining the build orientation is another decision addressed in this study. Although optimization methods could be used to determine build orientations [15], this paper simplifies the issue by selecting among a *laying and a standing policy*. The laying policy is to let parts have an orientation with low height by laying down on the build tray. A number of studies that deal with build orientation decisions have concentrated on lowering height to save the build time [16], [17]. However, when a significant number of parts are manufactured, the laying policy may have lower performance in terms of the total cycle time including both build time and setup time since it generates more jobs by taking more space per part on the build tray. An alternative way is to make parts stand with small projection area onto a build tray, named as the standing policy. While the standing policy leads to a fewer number of jobs, it takes longer build time per job due to the higher height of parts. In short, laying and standing policies are preferred for lower height and a fewer number of jobs, respectively.

Based on the number of parts, this paper focuses on identifying the most preferred orientation policy (among standing and laying). To conduct the analysis, thousands of parts with different shapes and geometries are considered as inputs and multiple AM machines with different workspace sizes are considered as constraints. The cycle time including build time and setup time is employed as an evaluation criterion.

The paper is organized as follows. Section 2 describes the review of build orientation, packing and scheduling studies. Section 3 explains the problem statement on mass production planning. Section 4 shows the proposed heuristic algorithm consisting of two phases. Section 5 describes a numerical experiment, and finally, Section 6 summarizes the findings and future work.

2. LITERATURE REVIEW

Build orientation determination and packing issues

The build orientation decision influences a variety of manufacturing performance measures such as build time, surface roughness, the amount of support, shrinkage, curling, distortion, and resin flow [18]. Traditionally, the determination of build orientation has been studied for a single part [19], [20]. In the case of multiple parts, the build orientation decision problems have addressed packing issues as well [17], [21]. The packing problems address the best way to optimally place multiple parts (with same or different shapes) into a specified build space (3D) or onto the build tray (2D) based on a set of user-defined objectives [14]. To name a few studies, Gogate and Pande (2008) developed a 3D packing system for optimizing the multi-parts placement in AM [22]. In their study, build orientations for each part have been optimized according to user-defined criteria and further, the packing heuristic based on placement rules was modified to fit the 3D packing problem. Freens et al. (2015) investigated *stereolithography apparatus (SLA)*-based 3D packing problem modified from the classical bin packing problem by using *integer linear programming (ILP)* [23]. Zhang et al. (2016) also suggested the 2D placement optimization in which two optimization processes are conducted sequentially: (1) AM feature-based orientation optimization, which decides on the best build orientation for each part to guarantee the production quality; and (2) parallel nesting optimization, which aims to maximize the compactness of placements by using the projection profiles of parts. The study discusses that, in 3D packing, the surface of parts could be damaged by support structure since parts are placed over others. From this viewpoint, choosing 2D or 3D packing depends on AM technologies. 3D packing could be proper for *selective laser sintering (SLS)* that does not need support structures. On the other hand, 2D packing could be appropriate for other technologies generating support structure such as SLA and *fused deposition modeling (FDM)*.

However, most of the above-mentioned studies have focused on handling only one single job. If a large number of parts are fed into the system, then they would require a series of 2D or 3D packing decisions. In this case, multiple jobs for packing are needed. Additionally, considering multiple AM machines with different workspace sizes is also a critical issue since the workspace size affects build orientation determination and/or packing planning.

Scheduling for AM

In this paper, scheduling refers to properly distributing a group of parts to multiple AM machines. Recently, the scheduling in AM environment has been highlighted in the literature. For instance, Li et al. (2017) proposed a concept for production planning in which a number of parts come into a parallel production system with multiple AM machines [9]. The study addressed the way that multiple parts should be grouped together as jobs and assigned to multiple AM machines in order to minimize production costs. Their study highlights the point that, as the number of parts and machines increases, it is challenging to find the global optimum. Therefore, they have suggested a heuristic algorithm to find local optimums. However, the study did not consider build orientation and packing issues that are important in practice. Ransikarbum et al. (2017) also suggested a multi-objective optimization method for part-to-printer assignment for 3D printer scheduling [5]. They have modeled the problem as *a mixed integer linear programming (MILP)*. Based on FDM, their model considers operating cost, load balance among 3D printers, total tardiness, and the total number of unprinted parts as objectives. Fera et al. (2018) proposed a scheduling method for a single AM machine based on SLM [24]. In their method, the schedule that meets due dates with small production cost is optimized based on a *genetic algorithm (GA)*. However, the study limited the number of machines to a single one and assumed that build orientations are given. Griffiths et al. (2018) addressed build orientation determination, 2D packing, and scheduling issues in their publication [21]. However, they assumed that the size of workspace is identical for all AM machines and focused on small volume production that is less than 50 parts.

3. PROBLEM STATEMENT

3.1 Production systems with multiple AM machines

Figure 1 shows the concept of AM-based production system proposed in this paper. A set of parts with different shapes and sizes are considered as inputs. Parts are grouped as jobs and the jobs are assigned to a specific machine. In the production system, there are multiple AM machines with different workspace sizes. A machine simultaneously builds multiple parts, grouped as a job, on the build tray. With parallel production, multiple machines take care of assigned jobs. After finishing a job, a machine requires a setup process to prepare the next job. For each job, parts are placed on a rectangular build tray. The width and length of a build tray are the same as the workspace size of its assigned machine. Note that input parts are replaced with bounding boxes as elements for packing and the bounding boxes are placed by 2D packing, meaning that the elements are not placed over each other and are sequentially placed one by one. Given the above-mentioned statement, a decision-making approach for AM production planning including build orientation determination, 2D packing, and scheduling is established with the aim of minimizing the total cycle time.

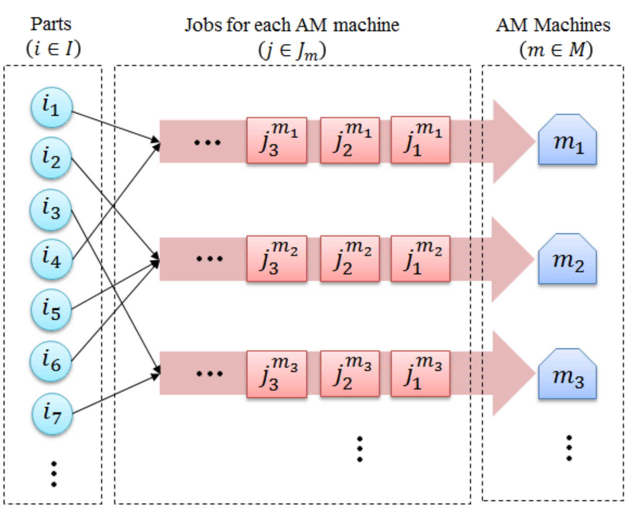


Figure 1. Concept model for AM-based production systems (modified from [9])

3.2 Cycle time model

Equation (1) shows the cycle time, T, for multiple machines, M, in the case of parallel production. In parallel production, a machine with the longest cycle time reflects the cycle time of the entire system.

In Equation (2), each machine has its own cycle time, T_m, consisting of the total build time and the total setup time. The total build time is the sum of build time for each job, t_j^{bld}. The total setup time is the multiplication of the setup time, ST, with the number of jobs, $|J_m|$. To simplify the build time calculation, build time is estimated based on the part geometry rather than a toolpath generated by a slicer software. In addition, the time to generate support structure is not considered. Equation (3)-(5) are modified from the models in [24] and [25]. In Equation (3), based on SLA, t_j^{bld} is composed of scanning time to draw parts within Job j, t_j^{scan}, and transition time between layers within Job j, t_j^{trn}. Equation (4) and (5) represent the ways t_j^{scan} and t_j^{trn} are computed, respectively. In Equation (4), V_j, l, s and d denote job volume that is the sum of part volume within a job, layer thickness, scan speed, and scan distance. In Equation (5), t^{rec} and H_j denote recoating time of new layer and the job height which is the height of highest part within a job.

$$T = \max_{m \in M}(T_m) \tag{1}$$

$$T_m = \sum_{j \in J_m} t_j^{\text{bld}} + t^{\text{set}}|J_m|, \quad \text{for } \forall m \in M \tag{2}$$

$$t_j^{\text{bld}} = t_j^{\text{scan}} + t_j^{\text{trn}}, \quad \text{for } \forall j \in J \tag{3}$$

$$t_j^{\text{scan}} = \frac{V_j}{l \cdot s \cdot d}, \quad \text{for } \forall j \in J \tag{4}$$

$$t_j^{\text{trn}} = \frac{t^{\text{rec}} \cdot H_j}{l}, \quad \text{for } \forall j \in J \tag{5}$$

4. THE PROPOSED HEURISTIC APPROACH

Figure 2 shows the overall proposed procedure for production planning in AM. The procedure is composed of two phases. In the first phase, build orientations of input parts are determined. Then, based on the orientations of parts, 2D packing and scheduling are decided in Phase 2.

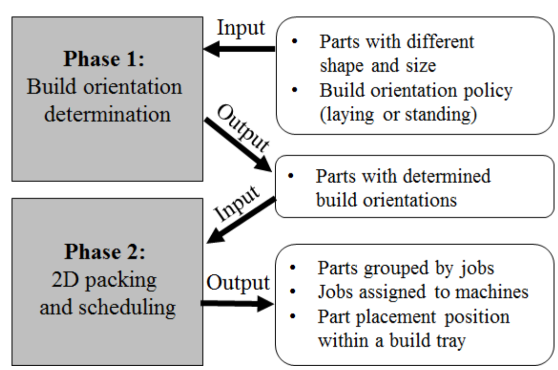


Figure 2. A procedure of production planning for AM

4.1. Phase 1: Build orientation determination

To simplify the build orientation determination problem, two general policies are considered: (1) laying policy and (2) standing policy. The laying policy focuses on reducing the height of parts, which generally results in lower build time per job. On the contrary, the standing policy concentrates on minimizing the bottom area of the bounding box of a part, which results in the smaller number of batches. Figure 3 represents an example of a gear for both laying and standing policies. In this paper, the width, length, and height of a bounding box are dimensions for X-, Y- and Z-axes, respectively.

The Phase 1 algorithm takes as inputs a set of parts and a certain policy (laying or standing), and outputs a build orientation for each part. To search for the best build orientation candidates, a part is rotated to a certain degree (a rotation step) in each axis. If a rotation step is too small, the computation time is longer since it requires searching a bigger space. In the case of laying policy, rotations on X- and Y-axes are searched first to find the minimum height for the part. Note that the rotation on Z-axis is not considered here since it does not affect the height of the part. After deciding the rotation degrees for X- and Y axes, rotation on Z-axis is searched to find the smallest bottom area of the bounding box of a part. In the case of standing policy, all rotation degrees for X-, Y-, and Z-axes are searched at the same time to find the smallest bottom area.

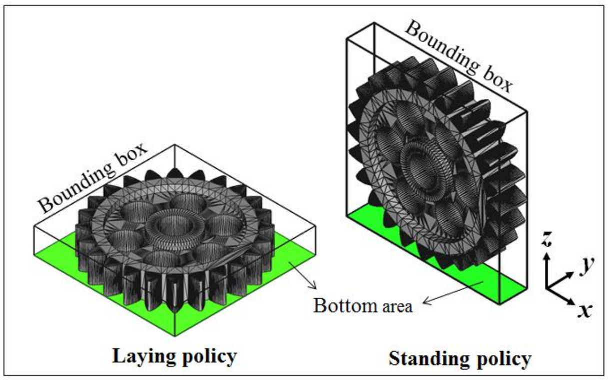


Figure 3. Bounding boxes for laying and standing policies

4.2. Phase 2: 2D packing and scheduling

Figure 4 shows the overall procedure of PSA. First, a set of not scheduled parts, I^{NSch}, is initialized. I^{NSch} includes all input parts with their build orientations that are determined in Phase 1. Each part in I^{NSch} is going through a feasibility check to look for feasible machines, M_i^{fsb}. Each part has different feasible machines since machines have a variety of workspace sizes. Even for the same part, feasible machines could be different depending on the build orientations. This is why the build orientations of parts are determined in advance in Phase 1. The algorithm is run until I^{NSch} is empty, meaning that all parts are scheduled. To place a part, the tallest part is selected from I^{NSch} with the aim of minimizing wasted time caused by the height gap between parts.

Figure 5 clarifies the concept of height gap. It represents two different cases of assigning four parts (p_1, p_2, p_3 and p_4) into two AM machines. In Case 1, p_1 and p_3 should wait until manufacturing p_2 and p_4 are finished due to the height gap. On the other hand, in Case 2, there is no wait time, since parts with similar height are grouped as the same job. Therefore, Machine 1 can finish the job sooner than Machine 2 and move on to the next job without any idle time. Therefore, by grouping parts with similar height, the height gap can be minimized. In PSA, by placing parts according to their heights, parts with similar height are grouped.

The next step is to choose a machine for assigning Part i. Each machine has their own cycle time. When a part is assigned to a machine, the cycle time of the machine is updated. Note that the longest cycle time decides the overall cycle time of the system. Therefore, it is important to maximize the machine utilization and balance the cycle time among multiple machines in order to reduce the overall cycle time. To balance the cycle time of machines as much as possible, whenever a part should be assigned to a machine, a machine with the shortest cycle time in M_i^{fsb} is selected.

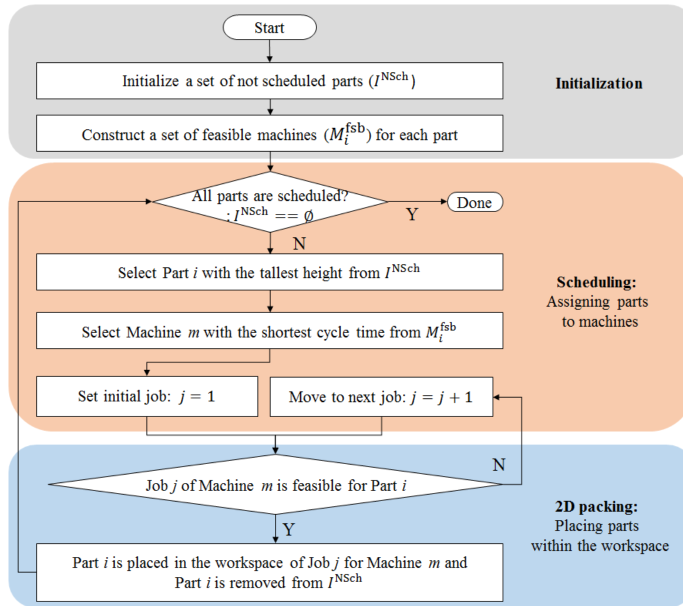
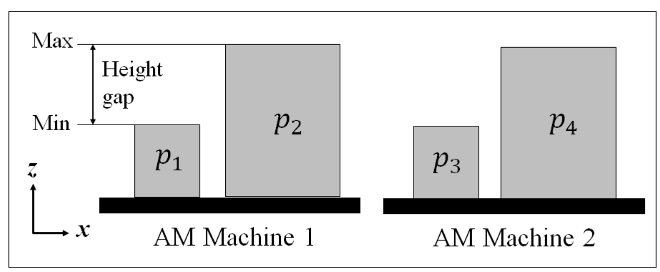
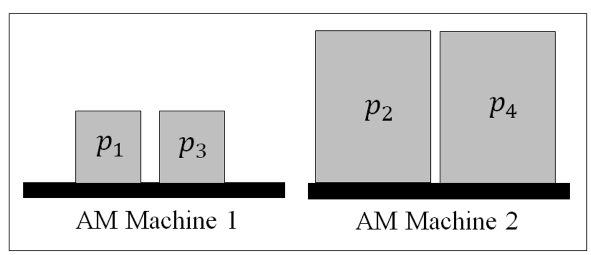


Figure 4. 2D packing and scheduling algorithm (PSA)



(a) Case 1



(b) Case 2

Figure 5. Height gap between parts for multiple AM machines

Parts are grouped as jobs and a machine takes care of multiple jobs sequentially as shown in Figure 1. As such, a job is a work order assigned to a machine. In the algorithm, each part should be assigned to a job. To do this, feasible jobs are searched from the initial work order (*j=1*) of the selected machine. If a certain job is feasible for a part, it means that there is enough room to place the part on the build tray of the job. Therefore, the part will be assigned to the job. Otherwise, the search moves on to the next job. If the search cannot find any feasible parts, a new job is created and the part is assigned to the new job. In Figure 4, both cases of searching next available job and creating a new job are expressed in moving to the next job ($j = j + 1$). The reason for searching from the initial job is to place parts as compactly as possible in order to reduce the number of jobs. The more parts are packed in a job, the less space is wasted. The way to recognize feasible space in a job is based on *Left-Bottom (LB)* approach [27]. With this approach, objects are stacked from the corner of left and the bottom in a rectangular space.

A numerical example of manufacturing eight gears with different geometries and shapes is provided to show how PSA works. The parameters for estimating the cycle time are listed in Table 1, and the specification of eight given parts are summarized in Table 2. It is assumed that the build orientations are already determined. Two machines, M1 and M2, with different workspace sizes are considered as follows:

- M1: $85 \times 85 \times 120$ (mm)
- M2: $60 \times 60 \times 100$ (mm)

Table 1. Parameters for cycle time estimation [25], [28]

Layer thickness (TH): 0.05 mm	Scan distance of part (SD): 0.1 mm
Scan speed (SS): 10,000 mm/s	Setup time (ST): 300 s
Recoat time for a layer (RT): 6 s	

Table 3 represents the overall scheduling procedure for this example. Finally, Figure 6 and 7 present the result of PSA including the layout of the top view and a Gantt chart.

As seen in Table 3, parts are labeled as Pi. In Step 1, P5 is chosen since it has the highest height, 14.00 mm. Then, it is placed in the first job for M1. At this point, it does not matter which machine is selected since the cycle time of both machines is the same. Figure 6 shows that P5 is placed in the left-bottom corner of the workspace. After placing P5, the part is removed from a set of not scheduled parts, *I*, and the cycle time for each machine is updated based on Equation (2). In Step 2, P1 is selected as the highest part in *I*. Note that P2 could also be chosen instead of P1 since their height is the same. P1 is assigned to the first job, J1, of M2 since the cycle time of M2, 0s, is shorter than another. In Step 3, P2, the highest part, is chosen in *I* and then tried to be assigned to the first job, J1, of M2. However, there is no room for P2 in J1 because of P1. Therefore, P2 is placed in the new job, J2, for M2. Note that P8 is only placed in jobs for M1 since the workspace of M2 is not feasible for the part, meaning that M1 is the only feasible machine for P7. In Step 4, P8 is targeted to be placed on the right side of P5. However, the sum of their width, 86.9mm, is over the available width, 85mm, of M1. Therefore, P8 is placed at the top of P5. In Step 5, P6 is placed in J1 for M1 since the job is feasible for the part. In Step 6, P7 is placed in the new job, J2, for M1 since there is no room in J1. In Steps 7 and 8, for P3 and P4, M1 keeps being chosen since its cycle time is shorter than another one. In Step 9, there is no more part left in *I*, so the algorithm is stopped. As shown in Figure 7, since M2 has the longest cycle time, 3522.29s, it determines the cycle time of the whole system based on Equation (1).

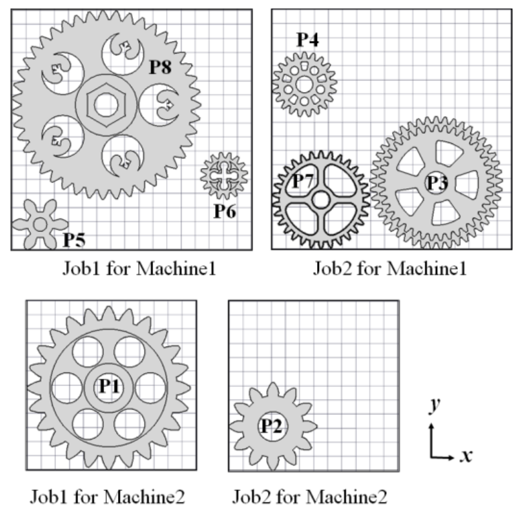


Figure 6. The result of 2D packing and scheduling: part placement for each job

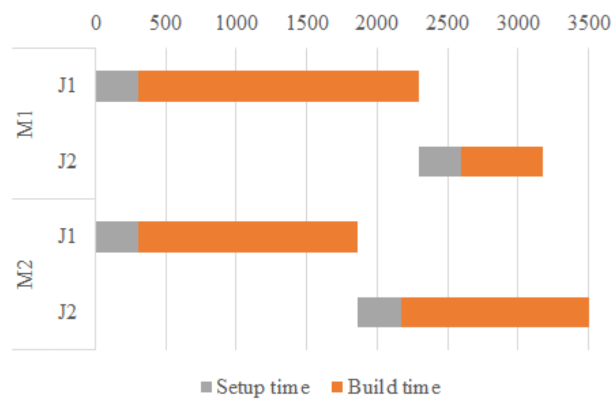


Figure 7. The result of 2D packing and scheduling: production plan for each job

Table 2. Specification of eight parts in the example

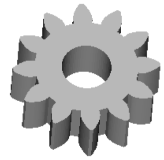
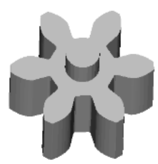
	P1	P2	P3	P4
Shape				
Bounding box (width×length×height)	$57.93 \times 57.93 \times 10.50$	$31.19 \times 31.19 \times 10.50$	$46.99 \times 46.99 \times 3.00$	$22.98 \times 22.91 \times 1.50$
Area of bounding box on the X-Y plane	3355.35	972.57	2206.89	526.47
Part volume	15240.33	4874.33	3047.97	367.14
Feasible machines (M_i)	M1, M2	M1, M2	M1, M2	M1, M2
	P5	P6	P7	P8
Shape				
Bounding box (width×length×height)	$19.97 \times 17.88 \times 14.00$	$16.68 \times 16.68 \times 6.0$	$34.80 \times 34.92 \times 4.00$	$66.93 \times 66.98 \times 9.00$
Area of bounding box on the X-Y plane	356.93	278.09	1214.94	4482.77
Part volume	1369.47	500.45	1728.56	13930.61
Feasible machines (M_i)	M1, M2	M1, M2	M1, M2	M1

Table 3. The scheduling procedure of the example

Step	Machine	Job		Cycle time (s)	Not scheduled parts: *I*
		1	2		
1	M1	N/A	N/A	**0.00**	P1, P2, P3, P4, **P5**, P6, P7, P8
	M2	N/A	N/A	0.00	
2	M1	P5	N/A	2007.39	**P1**, P2, P3, P4, P6, P7, P8
	M2	N/A	N/A	**0.00**	
3	M1	P5	N/A	2007.39	**P2**, P3, P4, P6, P7, P8
	M2	P1	N/A	**1864.81**	
4	M1	P5	N/A	**2007.39**	P3, P4, P6, P7, **P8**
	M2	P1	P2	3522.29	
5	M1	P5, P8	N/A	**2286.00**	P3, P4, **P6**, P7
	M2	P1	P2	3522.29	
6	M1	P5, P8, P6	N/A	**2296.01**	P3, P4, **P7**
	M2	P1	P2	3522.29	
7	M1	P5, P8, P6	P7	**3110.58**	**P3**, P4
	M2	P1	P2	3522.29	
8	M1	P5, P8, P6	P7, P3	**3171.54**	**P4**
	M2	P1	P2	3522.29	
9	M1	P5, P8, P6	P7, P3, P4	3178.88	
	M2	P1	P2	*3522.29	

5. COMPARISON OF TWO ORIENTATION POLICY: LAYING AND STANDING POLICIES

In this section, two orientation policies, namely laying and standing, are compared to identify which one is preferred in terms of the number of production parts. The proposed algorithm is coded using Python 2.7.8 and is run as a macro file in the CAD platform of FreeCAD 0.16.

For case studies, we assume that all parts have various geometries. The bounding boxes of the parts are considered as inputs to the proposed algorithms. The bounding boxes are used as inputs for two main reasons: (1) to minimize the influence of support generation on build time; and (2) to minimize computation time for analyzing part geometry. Note that the build time estimation model in Equation (3) does not include the support generation time. To simulate various geometries of parts, the three dimensions of bounding boxes (width, length, and height) are randomly and independently generated using uniform distribution (1, 120) (mm).

To identify the preference for the laying and standing policies depending on the number of parts, experiments are conducted with six different conditions: 10, 50, 100, 500, 1000 and 3000 parts. 10 to 3000 parts are randomly generated and each condition is replicated five times to reduce the variability of random part generation. The unit setup time, t^{set}, is 300s. Three machines (M1, M2, and M3) with the following workspace sized are considered:

- M1: $140 \times 140 \times 160$ (mm)
- M2: $120 \times 120 \times 160$ (mm)
- M3: $100 \times 100 \times 160$ (mm)

Table 4 shows the cycle time for both policies, T^{stand} and T^{lay}, and a comparison indicator, $T^{\text{stand}}/T^{\text{lay}}$, that represents which policy is preferred. If the comparison indicator is greater than 1, then the laying policy is preferred. Otherwise, the standing policy is preferred. Figure 8-(a) is plotted by using the average value of the comparison indicators through five replications. The result shows that as the number of parts increases the standing policy is more preferred. In this case study, the threshold to change the preference is about 100 parts. With less than 100 parts, the laying policy is more preferred. However, the preference dramatically decreases for the cases with less than 100 parts. Over the 100 parts, the comparison indicator is converged to about 93%, meaning that T^{stand} is 7% smaller than T^{lay}.

As mentioned before, the job height is defined by the height of the highest part within a job. The shorter job height would be preferred in order to minimize the build time. Additionally, to minimize the total setup time, a fewer number of jobs would be preferred since fewer jobs require fewer setup processes. Basically, the laying policy focuses on the minimum job height while the standing policy concentrates on the minimum number of jobs. Figure 8-(b) and (c) illustrate this point.

In Figure 8-(d), the number of parts per job for standing policy increases until a certain level. This is due to the point that the standing policy has more chances to place parts on their smaller bottom area, which results in more packed parts in the workspace. However, as more parts enter the algorithm, it saturates jobs, which leads to the point that the number of parts per job converges to a certain level.

Usually, as the number of parts increases, the cycle time of each machine is relatively similar to others by line balancing. Figure 8-(e) and (f) represent the line balancing of two policies for two conditions of 10 and 3000 parts, respectively. As shown in Figure 8-(e), when a few parts are considered, it is challenging to keep the line balance, particularly in the laying policy. On the contrary, in Figure 8-(f), the cycle time for three machines is almost the same, meaning that the production line is well balanced.

6. CONCLUSION

This study deals with production planning of parts with different shapes and geometries for multiple AM machines. The production plan has two main phases: (1) build orientation determination; and (2) 2D packing and scheduling planning. In Phase 1, two orientation policies, including laying and standing policies, have been discussed. In Phase 2, a heuristic algorithm is proposed for solving 2D packing and scheduling problem.

The case study shows that the standing policy is more preferred to the laying policy when the number of parts increases. For example, when 10 parts are going through the algorithm, the cycle time of the laying policy is about 26% lower than the standing policy. On the other hand, the cycle time of the standing policy is about 6% lower than the laying policy when 3000 parts are tested. However, the gap converges to a certain level as the number of parts increases.

This research can be extended in several ways. The impact of the shape and size of parts on the policy preference can be studied further. In addition, the two phases of the algorithm can be integrated where the build orientation can be determined based on the packing and scheduling decisions. Furthermore, the build time estimation model can be elaborated by considering the tool path or support structure or replaced with cost models.

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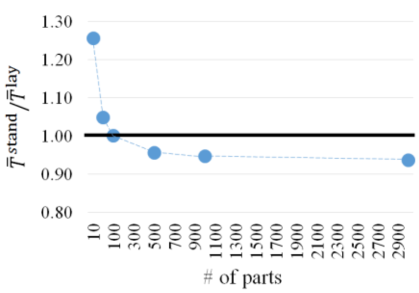
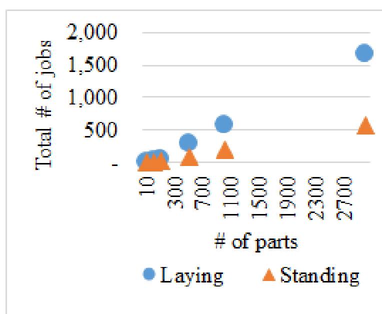
Table 4. Cycle time (s) for standing and laying policies and their comparison indicator

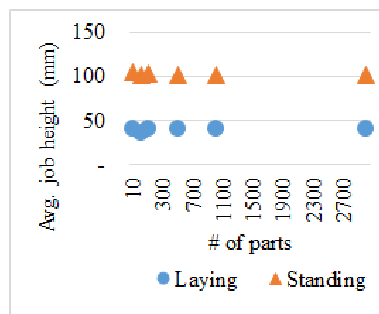
	# of parts	Replication 1	2	3	4	5	Avg.
T^{stand}	10	40,243	45,379	57,310	37,699	41,123	44,351
	50	121,504	129,988	124,797	115,238	**136,611**	125,627
	100	**264,156**	253,250	227,003	327,128	**259,759**	266,259
	500	**1,258,354**	**1,130,017**	1,145,441	**1,136,901**	**1,199,940**	1,174,131
	1000	**2,403,027**	**2,336,097**	**2,275,413**	**2,290,435**	**2,260,775**	2,313,149
	3000	**7,144,578**	**6,783,495**	**6,694,533**	**6,748,051**	**6,705,339**	6,815,199
T^{lay}	10	**35,805**	**31,536**	**40,762**	**37,519**	**31,419**	35,408
	50	**118,270**	**120,259**	**113,913**	**108,982**	138,741	120,033
	100	279,695	**248,532**	**224,521**	**320,801**	256,929	266,096
	500	1,328,073	1,184,338	**1,205,138**	1,176,750	1,246,039	1,228,068
	1000	2,522,615	2,465,209	2,409,274	2,408,385	2,399,982	2,441,093
	3000	7,646,439	7,257,360	7,126,534	7,207,393	7,174,983	7,282,542
$\frac{T^{\mathrm{stand}}}{T^{\mathrm{lay}}}$	10	1.12	1.43	1.40	1.00	1.30	1.25
	50	1.02	1.08	1.09	1.05	0.98	1.04
	100	0.94	1.01	1.01	1.01	1.01	1.00
	500	0.94	0.95	0.95	0.96	0.96	0.95
	1000	0.95	0.94	0.94	0.95	0.94	0.94
	3000	0.93	0.93	0.93	0.93	0.93	0.93



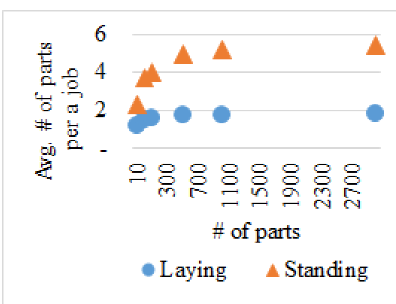
(a) A comparison indicator ($T^{\mathrm{stand}}/T^{\mathrm{lay}}$)



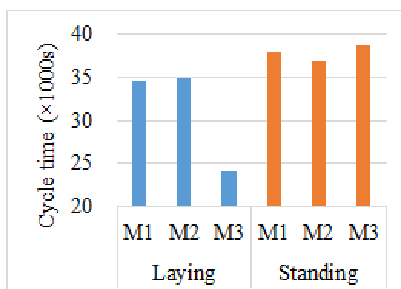
(b) Total number of jobs



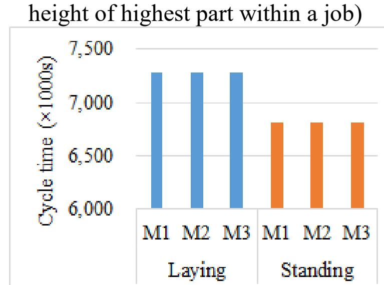
(c) Average job height (job height: the height of highest part within a job)



(d) Average number of parts per job



(e) Cycle time (# of parts = 10)



(f) Cycle time (# of parts = 3000)

Figure 8. Policy preference depending on the number of production parts

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