

# The Impact of Build Orientation Policies on the Completion Time in Two-Dimensional Irregular Packing for Additive Manufacturing

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## ABSTRACT

The study investigates the impact of build orientation policies on the production time in additive manufacturing (AM) for mass customization business models. Two main orientation policies are considered: (1) *Laying Policy (LP)* that focuses on reducing the height of parts; and (2) *Standing Policy (SP)* that aims to minimize the projection base plane of parts to reduce the number of jobs. While LP minimizes the build time per job since parts have low height, it could increase the total completion time as the number of parts increases. On the other hand, SP takes longer build time per job due to the high height of parts, where it could lead to a fewer number of jobs. Several numerical experiments have been conducted based on *Stereolithography (SLA)*. The results show that, when the number of parts is experimentally about 40, SP could be more preferred than LP for minimizing the completion time where the shape tendency of parts is likely to affect the extent of preference for the policies. When 40 parts with long and flat shape are considered, SP reduces the completion time by 15.7% over the default policy, the initial orientation of a part, while LP reduces by only 6.6%.

*Keywords:* Additive Manufacturing, Build Orientation Determination, Mass Customization, Scheduling, and 2D Packing

## 1. Introduction

While traditional manufacturing has been successful in mass production, *Additive Manufacturing (AM)*, *3D printing* [1], has offered capabilities that are mainly helpful for customization with small quantity [2]. Recently, however, *AM for mass customization* is discussed as an opportunity to extend the boundary

of AM applications [3]. The literature has started looking at the role of AM on offering a new business model based on the mass customization in which online retailers and AM-based production facilities are working together to meet customer demands [4], [5]. Individual customers order their customized parts with various sizes and geometries through the website of online retailers. AM-based production facilities, also known as *3D printing farms*, take care of hundreds or thousands of various customer orders each day, known as *3D Printing on Demand (3DPD) business models* [6], [7].

Figure 1 represents the concept of 3DPD from the viewpoint of manufacturers which consists of three phases: part arrival, grouping, and building. In Phase 1, customer demands arrive. Every part of customer demand has a different size and shape to satisfy customized and personalized orders. In Phase 2, the arrived parts are grouped as jobs and the jobs are sent to queues of AM machines. Finally, in Phase 3, the machines sequentially take care of assigned jobs in their queues. Studies on *Design for AM (DfAM)* could be applied to Phase 1. They deal with how to design parts to improve productivity and manufacturability by using topology optimization [8], part consolidation [9], and part decomposition [10]. For Phase 2, a considerable number of approaches and methods could be applied such as build orientation optimization [11], packing optimization [12], and production scheduling [4] and planning [13]. In Phase 3, process planning at the micro level [8] such as toolpath planning could be applied [15].

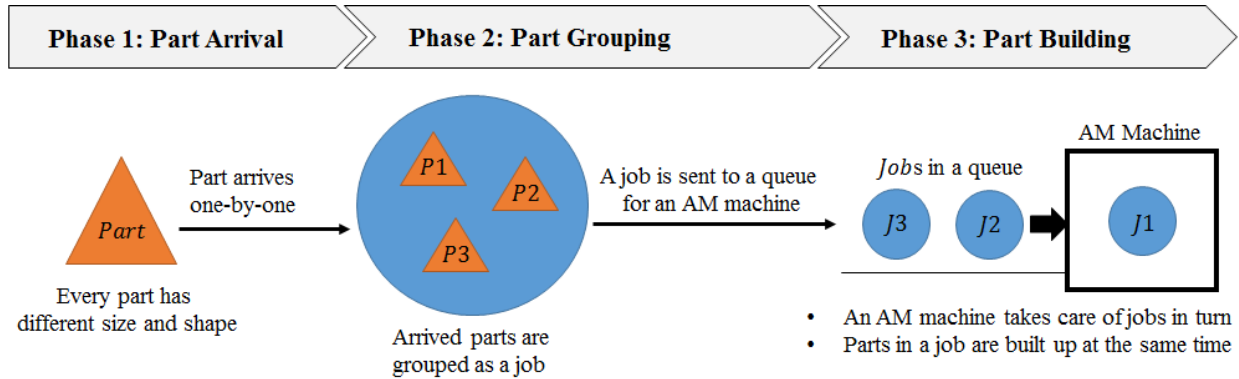


Figure 1. The concept of the 3D Printing on Demand (3DPD)

Among the above-mentioned three phases, this research mainly deals with Phase 2 by investigating how to minimize the completion time to build all jobs for one AM machine. Although this study focuses on build orientation determination to minimize completion time, it is related to packing problems since multiple parts influence each other to decide their orientations and positions on the build tray [11], [16]. We should note that, in the current research, build orientations are first decided before the part position is determined for the packing problem. According to Zhang et al. (2016) [17], there are two main tasks to determine build orientations for AM: (1) identify a set of alternative orientations from an infinite alternative build orientation space; and (2) apply multi-criteria decision making approach to determine the optimum out of the pre-identified alternatives. For the first task, two approaches are mainly considered: rule or

knowledge-based method; and the sampling method or listing method. The current study applies the listing method with the step angle defined by a user, previously developed in the literature [18]–[20]. For the second task, a build orientation is determined by the height and bottom area of a part. After build orientation determination, the part position on the build tray is decided. Since we consider multiple parts, this paper could be classified under *irregular packing problems (IPPs)* for AM. According to the four-tuple (dimensionality / objective / attributes of a container / attributes of parts) to categorize IPPs for AM proposed by Araújo et al. (2018) [21], the scope of the current research is defined as followed: (1) the two-dimensional (2D) packing; (2) the minimization of the completion time; (3) the serial production considering one container with fixed dimensions; and (4) mass customization for AM that covers the high variety of parts, the high quantity of production, and any design shape of parts. Additionally, the current study considers dynamic planning that determines the part orientation and position whenever a new part arrives to satisfy the condition of *First-In-First-Out (FIFO)*.

If the size and shape for the certain number of parts are known, build orientation and packing issues can be optimized by considering the relationship among parts such as grouping parts with similar height and packing parts with the interlocking shape as compact as possible in the workspace. However, in systems in which random parts arrive one-by-one since the size and shape of the next coming parts cannot be predicted, it is time-consuming to optimize build orientation and position for each part. Therefore, rather than finding the optimal build orientation for each part, the current research applies a consistent build orientation decision method for every part, named as a build orientation policy. For most of AM processes, part height is one of the most significant driving factors for build time minimization since it is related to the number of build layers [22], [23]. As such, this study proposes *Laying Policy (LP)* letting parts have an orientation with the lowest height by laying down on the build tray. However, LP may not have a great performance in terms of minimizing the completion time when multiple parts are considered. This is because LP causes more jobs by taking more space per part on the build tray based on 2D packing. An alternative way is to make parts stand with a small projection area onto a build tray, named as *Standing Policy (SP)*. While SP leads to a fewer number of jobs, it takes longer build time per job due to the high height of parts. In other words, laying and standing policies are preferred for lower height and a fewer number of jobs, respectively. This paper also suggests the *Default Policy (DP)*. When users create their 3D models, they should decide for the orientation of parts. DP is using the initial orientation of 3D models as a build orientation. In Section 4, DP is used to compare the results of SP and LP.

This paper identifies the effect of build orientation policies (SP and LP) depending on various conditions including the number, shape, and size of parts. Meanwhile, methods determining the preferred orientation based on height, projection area, and center of mass, measuring the shape of parts, and generating random input parts are proposed as other contributions. To present the effect of adopting a certain

policy, the non-parametric statistics is applied and a regression model is developed based on a gathered dataset to predict the future effect.

## 2. Literature Review

Since the current research is classified under *irregular packing problems (IPPs)* for AM, this section highlights the scope of the current study according to the four-tuple (dimensionality / objective / attributes of a container / attributes of parts) to categorize IPPs for AM proposed by Araújo et al. (2018) [21]. In addition, in terms of production planning and scheduling, the concept of the planning horizon is explained to specify the research scope.

### 2.1 Dimensionality

Irregular packing problems for AM are distinguished into two types depending on the dimension to place multiple parts into a specified build space (3D) or onto a build tray (2D) [12]. To maximize space utilization, the 3D packing has often used in AM [21], [24]–[26]. However, the 2D packing is sometimes preferred to prevent surface damage caused by support structure among parts in *Stereolithography (SLA)* [19], *Fused Deposition Modeling (FDM)* [12] and *Selective Laser Melting (SLM)* [16]. As SLA is mainly used in this paper, the current study is based on the 2D packing.

### 2.2 Objective

IPPs for AM are categorized into four objectives: (1) output maximization; (2) single input minimization; (3) cost minimization; and (4) time minimization [21]. In the classic IPPs, the output maximization is a classical knapsack problem. It finds a subset of demanding parts that maximize the total volume (or profits) of packed parts [19]. The single input minimization, also known as a strip packing problem [27], determines a configuration of all demanding parts that minimizes the width or length of a container. The minimization dimension is the width for 2D packing [28] or the height for 3D packing [24]. The single input minimization for 2D packing can be applied to continuous 3D printing [28] using a conveyor belt. The cost minimization is similar to the classic bin packing of IPPs to find a configuration of all demanding parts that minimizes the number of bins [29]. However, unlike the classic bin packing problems, problems of the cost minimization for AM are more focused on minimizing the total cost rather than minimizing the number of bins [16], named as jobs in this paper. Unlike other objectives based on theoretical methods of IPPs, the time minimization is more practical. For AM, considering time minimization is a new objective compared with other objectives considered in classical packing problems. This type of problems can be combined with scheduling problems considering the makespan [30], the total tardiness, or the earliness [4]. The current study focuses on the time minimization considering completion time (makespan or total build time) that is equivalent to the sum of build time for all jobs.

### 2.3 Attributes of a container

This paper uses the term, a *container*, referring to a space to build parts in an AM machine although other terms can be used such as build chamber, workspace, bin or build tray. Depending on the number of AM machines, there are two types of production: single- and multi-machine production. In the case of the single-machine production, one container of a single AM machine has fixed dimensions or open dimension of Z-height or X-width [21]. For the fixed dimensions, if only one job is allowed for a container, it becomes the output maximization problem described in Section 2.2. However, if multiple jobs are allowed for the same container, it becomes the cost or time minimization problem, which is the serial production for a single AM machine [31]. For the open dimension, one job is usually considered rather than multiple jobs, which becomes the single input minimization problem. While Z-height is usually opened if 3D packing is considered, X-width is opened if 2D packing is considered. The 2D packing with the open dimension of X-width is an issue of the continuous production for AM [28].

For another case, in multi-machine production (parallel production), multiple containers of different AM machines can be identical or heterogeneous in build volume specification [21]. Unlike the single-machine production, multi-machine production has another extra issue that grouped parts should be assigned to a certain machine [13]. In multi-machine production, studies for heterogeneous containers [4], [30] might be more complicated than just dealing with identical containers [32]. The current research focuses on single machine production to take care of multiple jobs, which is the serial production considering one container with fixed dimensions.

### 2.4 Attributes of parts

The manufacturing parts can be categorized in terms of three different criteria: the variety of parts, the quantity of production, and the design complexity of parts. The variety of parts refers to the number of different types of parts. The quantity of production considers the number of items including all types of parts, known as production volume. The design complexity refers to the extent of the complication of part geometry. Similarly, Conner et al. (2014) suggested three metrics for manufacturing parts (customization, production volume, and complexity) [33] and Araujo et al (2018) showed two criteria (demand variation and mean complexity) [21]. In traditional manufacturing, even though the variety of parts is limited and the design complexity of parts is low, the quantity of production could be large. On the other hand, whereas AM can take care of various parts with complex shapes, the production volume is relatively low [3], [34]. The current study considers an extremely high variety of parts that every part has different shape and size and covers a wide range of design complexity that is from simple to complex shape. For the quantity of production, 40 parts with different sizes and shapes are considered in Section 4 for the numerical experiments. Although 40 parts is not a high number, the conclusion of experiments could be applied to the high production volume since as the number of parts increases, the result of the experiments is converging

to a certain level before the threshold of 40 parts in Figure 10. Consequently, this research targets the mass customization that requires considering the high variety of parts, the high quantity of production, and any design shapes.

## 2.5 Planning horizon

Planning horizon refers to the length of time required for the decision-making on packing and scheduling. In this study, it is assumed that each customer demand has only one part and demands arrive sequentially. In the case that customer demands are coming throughout a certain period of time, a manufacturer needs to decide about the timing of planning for packing and scheduling. Herein, there are two options: static and dynamic planning. In static planning, the manufacturer waits until a certain number of orders is collected or a certain time period is passed and then makes a plan based on build orientation determinations, packing, and scheduling.

In dynamic planning, a manufacturer determines the part position whenever a part arrives. This is one of the ways to satisfy the condition of the FIFO rule. While a set of parts are considered for packing at the same time in the static planning, in the dynamic planning, parts are considered sequentially. Although most of the studies on IPPs have used static planning [4], [12], [16], the current research focuses on the dynamic planning with the use of FIFO policy.

## 3. Approach

Given the five conditions described in Section 2, this section details Phase 2, grouping arrival parts as illustrated in Figure 1. Phase 1 of part arrival is an uncontrollable input factor and Phase 3 is the outcome of how Phase 2 is handled. To obtain a better result in Phase 3, this section shows which issues should be considered in Phase 2 and how to address them. Additionally, a method for numerically measuring the shape of parts is proposed in which the impact of shape on minimizing the completion time is quantitatively investigated. Note that, in this research, PreForm [35], a commercial slicing software, is used to generate support structure for a part and place parts based on 2D packing.

### 3.1 Grouping arrival parts as jobs

Figure 2 specifies part grouping, Phase 2 in Figure 1. Grouping parts as jobs includes determining build orientations and placing parts onto a container based on 2D packing [12]. Once a new part arrives, its build orientation is determined based on a certain policy. Support structure for Part  $p$  is generated based on its build orientation. Then, the feasibility of an available job,  $J_{Avl}$ , is checked whether Part  $p$  can be put in the container that may already include other parts. If  $J_{Avl}$  is feasible, Part  $p$  is placed onto the container of  $J_{Avl}$  and the job is used for the next incoming part once again. Otherwise,  $J_{Avl}$  becomes a full job,  $J_{full}$ , and it is sent to the queue of an AM machine for building up. In this case, a newly available job,  $J_{Avl}$ , is created

with an empty container and Part  $p$  is first placed. In short, an available job,  $J_{Avl}$ , accepts parts until it is infeasible.

Figure 3 shows the processes that  $J_{Avl}$  becomes infeasible. When  $p_1$  gets placed, the status of  $J_{Avl}$  has been changed from  $J_{Avl}^{(1)}$  to  $J_{Avl}^{(2)}$  and  $J_{Avl}^{(2)}$  is still feasible. However, after including  $p_2$ , the job,  $J_{Avl}^{(3)}$ , becomes infeasible. In  $J_{Avl}^{(3)}$ , red parts are not buildable since they are partially outside of the container. In this case, since  $J_{Avl}^{(3)}$  is infeasible to include  $p_2$ , the previous status of the job,  $J_{Avl}^{(2)}$ , is sent to the queue as a full job,  $J_{full}$ , and then  $p_2$  is placed in an empty container of a new job. If a part does not come any more, the current job,  $J_{Avl}$ , becomes  $J_{full}$  without the feasibility check for a new part and then it is sent to the queue. With the above procedure, parts within the same container are grouped as a job and FIFO is satisfied by building up parts of the same job at the same time. An AM machine sequentially takes care of jobs in the queue and the completion time,  $T$ , is the sum of build time for every job as shown in Equation (1).

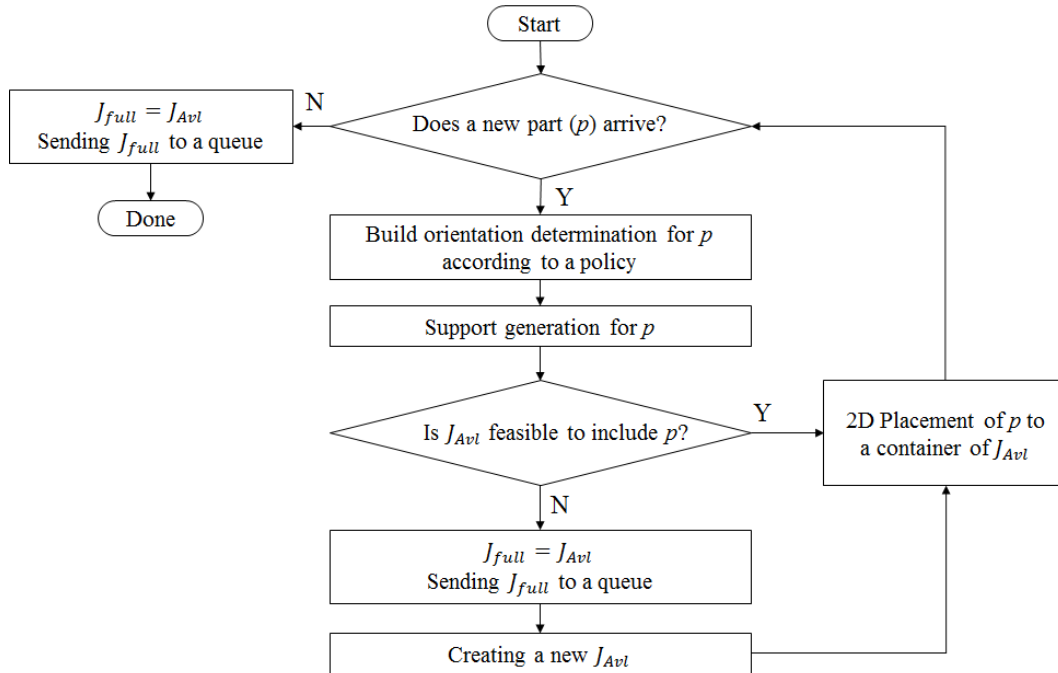


Figure 2. The determination procedure of build orientations, 2D packing, and jobs

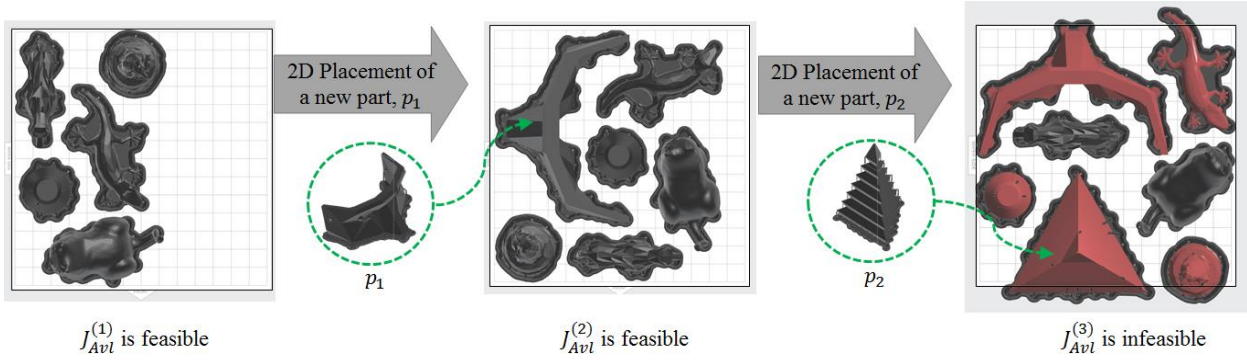


Figure 3. Feasible and infeasible jobs

$$T = \sum_{j \in J} t_j \quad (1)$$

, where  $t_j$  is the build time of Job  $j$  and  $J$  is a set of jobs.

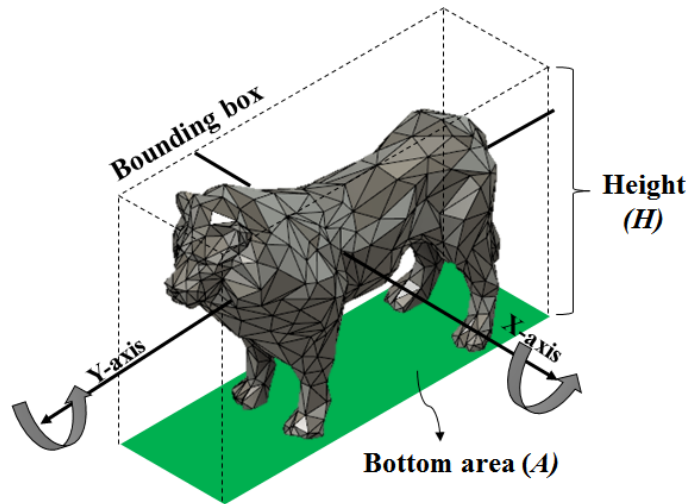
To obtain build orientation candidates, the step angle decided by a user is used. In this method, if the user provides a smaller value of the step angle, a better solution is expected since it explores a bigger solution space. However, this could increase the computational efforts. The current study adopts this approach to allow users to control the computation time by using the proper step angle. With a certain step angle, a part is rotated according to X- and Y-axis. Rotating with Z-axis is considered in the process of 2D packing. Figure 4 represents an example of the lion model and its orientation candidates. In this example, since a step angle is set as 15 degrees, 24 candidates for each axis are considered. As a combination of candidates for X- and Y-axis, 576 orientation candidates ( $24 \times 24$ ) for the lion model in Figure 4-(a) are plotted in Figure 4-(b). The plotting is represented by an HA graph in which X-axis shows the rectangular bottom area,  $A$ , of the bounding box of a part and Y-axis represents the height,  $H$ , of a part. To have an identical unit for area and height, the square root of the area is used in X-axis. The values of  $H$  and  $A$  depend on build orientations of a part. Figure 4-(a) shows  $H$  and  $A$  of the lion model with the initial orientation that is rotating 0 degree for X- and Y-axis. Sometimes, some orientation candidates may have the same  $H$  and  $A$ . In that case, the candidates are plotted in the same spot in an HA graph. Therefore, Figure 4-(b) seems fewer than the 576 points.

In this research, three types of build orientation policies are considered: DP, LP, and SP. DP is using the initial orientation of a 3D model. If DP is adopted, the initial orientation of parts is used without any other orientation decision process. In Section 4, DP is employed as a base level to show how much other policies can reduce the completion time. LP aims to reduce the height of parts, which usually results in lower build time per job. On the contrary, SP focuses on minimizing the bottom area of the bounding box of a part, which results in a smaller number of jobs. Figure 5 represents an example of the lion model for

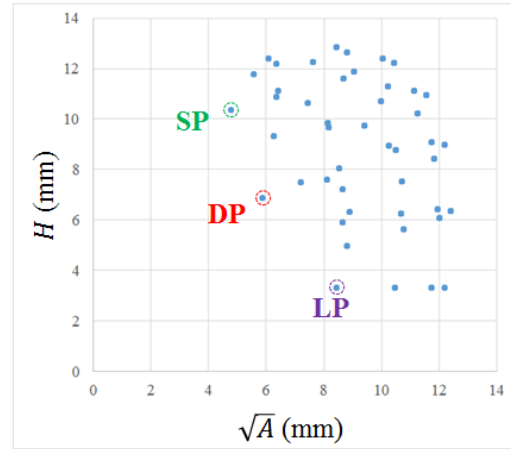
the three policies with a generated support structure. Depending on a certain policy, one of the build orientation candidates is chosen. Selection processes of candidates for each policy are as follows:

- Orientation decision steps for LP
  - Step 1: Choose candidates with the lowest height.
  - Step 2: If more than two candidates are selected in Step 1, choose candidates with the smallest area among them.
  - Step 3: If more than two candidates are selected in Step 2, choose candidates with the lowest center height of mass among them.
- Orientation decision steps for SP
  - Step 1: Choose candidates with the smallest area.
  - Step 2: If more than two candidates are selected in Step 1, choose candidates with the lowest height among them.
  - Step 3: If more than two candidates are selected in Step 2, choose candidates with the lowest center height of mass among them.

According to the above processes, plots of SP and LP in Figure 4-(b) are obtained.



(a) Rotation of Lion for X- and Y-axis



(b) An HA graph (H: the height of a bounding box; and A: the bottom area of a bounding box)

Figure 4. Rotation of Lion: (a) a lion model; and (b) an HA graph for the lion model

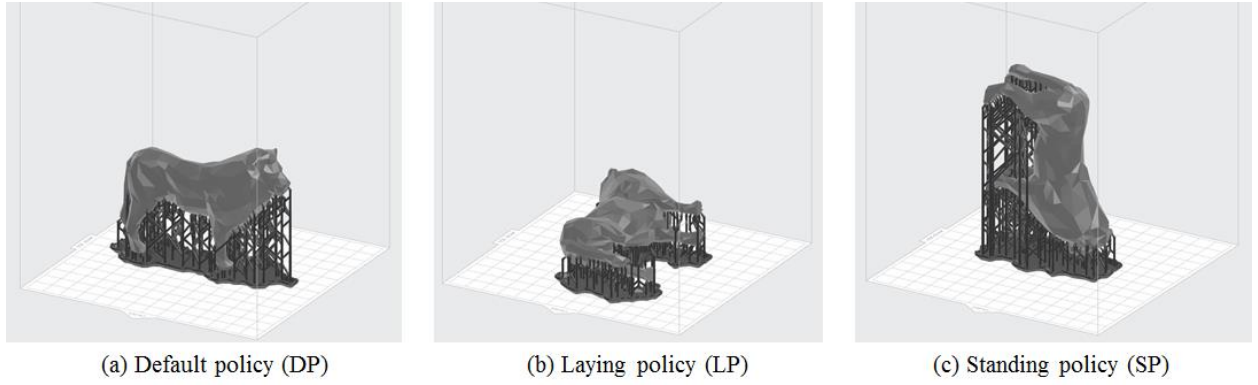


Figure 5. Three orientations depending on different policies: default, laying and standing policies

Some orientation candidates need more support structure than other candidates, which leads to wasting material and increasing build time. To simply exclude those from a set of orientation candidates, the center of mass is used. Sometimes, although the values of  $H$  and  $A$  are the same, certain orientations make difference in terms of build time due to the amount of support structure. Figure 6 presents an example of this case. In Figure 6, the bolt has the same values of  $H$  and  $A$  in (a) and (b) even though two cases have different build orientations. In terms of computation time, it might be time-consuming to accurately check out the amount of support structure for orientation candidates of every part by generating support structure through a toolpath. As such, the center of mass of a part is used to simply exclude candidates causing much support structure. The focus of this paper is how to apply the center of mass regardless of how it is obtained. There are efficient methods [36] and software [37] in the literature that can help us with identifying the center of mass for an object. When a candidate with the high position of the center of mass is selected, it is likely that the amount of mass is highly placed, which requires more support structure. Therefore, in this case, a candidate with the lowest position of the center of mass is chosen as shown in Figure 6-(a).

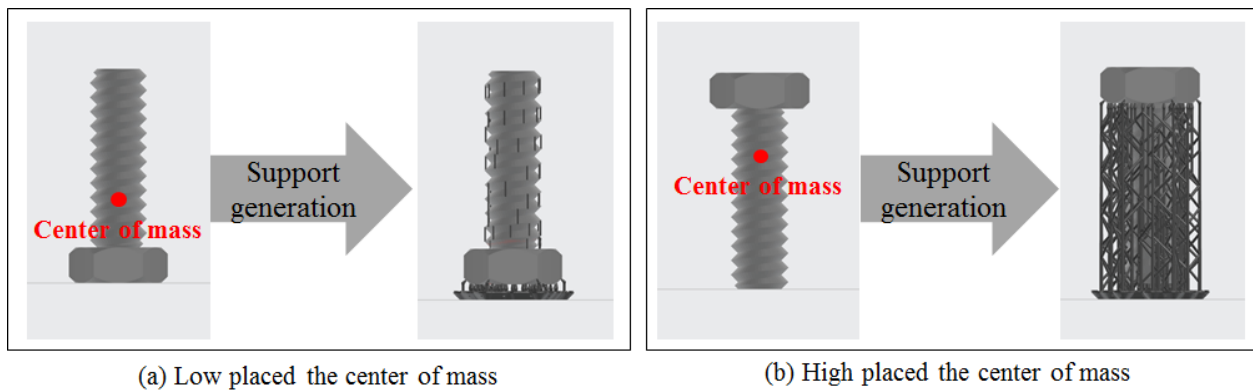


Figure 6. The effect of the center of mass on deciding build orientations to reduce support quantity

In this research, a certain orientation policy is applied to every incoming part due to the condition of the dynamic planning with FIFO explained in Section 2.5. Without the condition, a set of parts can be

simultaneously considered to determine build orientations. This means that the build orientation of a certain part can be determined with the consideration of other parts including shape, size, orientation, and position within a container. In this case, it is likely to get closer to obtain the optimum orientation for every part. However, those conditions force to decide of the build orientation part-by-part sequentially. In the dynamic planning, the build orientation of a part should be decided without the information (shape and size) of the next incoming parts since random parts will arrive. In addition, a current part cannot even be inserted in the previous job since the job has already been sent to the queue of the AM machine to keep the condition of FIFO. In brief, in the middle of decision processes, it is hard to expect which orientation is better. In this situation, practical guidelines could be to minimize the height of parts (by LP) and the number of jobs (by SP). As the first step studying this kind of circumstances, the research aims to apply LP or SP to every part and to investigate the effect of the two policies.

### 3.2 Measuring the shape of parts

In this paper, we quantitatively measure part shape to analyze the effect of orientation policies based on the part geometry. However, any measurement methods that quantify part geometry as a number can be applied instead of the proposed method in the paper. There is a wide range of methods in the literature for measuring the shape of parts such as design complexity [38], [39]. However, using our measurement method could be efficient to compare SP and LP since the processes of finding SP and LP for a certain part include a process identifying part shape by using an HA graph.

To obtain SP and LP, we need to check possible orientation candidates of a certain part and to identify which candidates correspond to SP and LP. Once candidates for SP and LP are obtained, the shape of part can be easily measured by using the Euclidean distance. In Equation (2), the design index,  $D$ , is the Euclidean distance between the two dots of SP and LP on an HA graph. The index shows how long and flat of a part to investigate the effect of SP and LP. This is related to the Sphericity of a part.

$$D = \sqrt{(x^{DP} - x^{SP})^2 + (y^{DP} - y^{SP})^2} = \sqrt{(\sqrt{A^{DP}} - \sqrt{A^{SP}})^2 + (H^{DP} - H^{SP})^2} \quad (2)$$

where,  $(x^{DP}, y^{DP})$  and  $(x^{SP}, y^{SP})$  are the coordinates of DP and SP in an HA graph.  $D$  represents how close the shape of the part to a sphere. When  $D$  gets closer to 0, the part shape gets closer to a sphere. On the contrary, when  $D$  gets larger, the part shape gets long or flat. In Figure 7, four models are represented to show how  $D$  is different depending on the shape of parts. As shown in the figures, while the part shape is close to a sphere or a cubic when  $D$  is small, the shape is long or flat when  $D$  is relatively large.

Figure 8 represents how to interpret the shape and size of parts depending on the positions of two dots of SP and LP on an HA graph. If the two dots are close to the origin, a corresponding part is small. Otherwise, the part is large. If the distance between the two dots is large, the shape of a corresponding part is prone to be long or flat. As  $H$  and  $A$  are minimized, the probability of having the small process time

increases, which means that dots being close to the origin in an HA graph become prime candidates. On the other hand, dots being far from the origin are less important as candidates. Usually, dots of DP, LP and SP are relatively close to the origin compared to other dots as shown in Figure 4-(b).

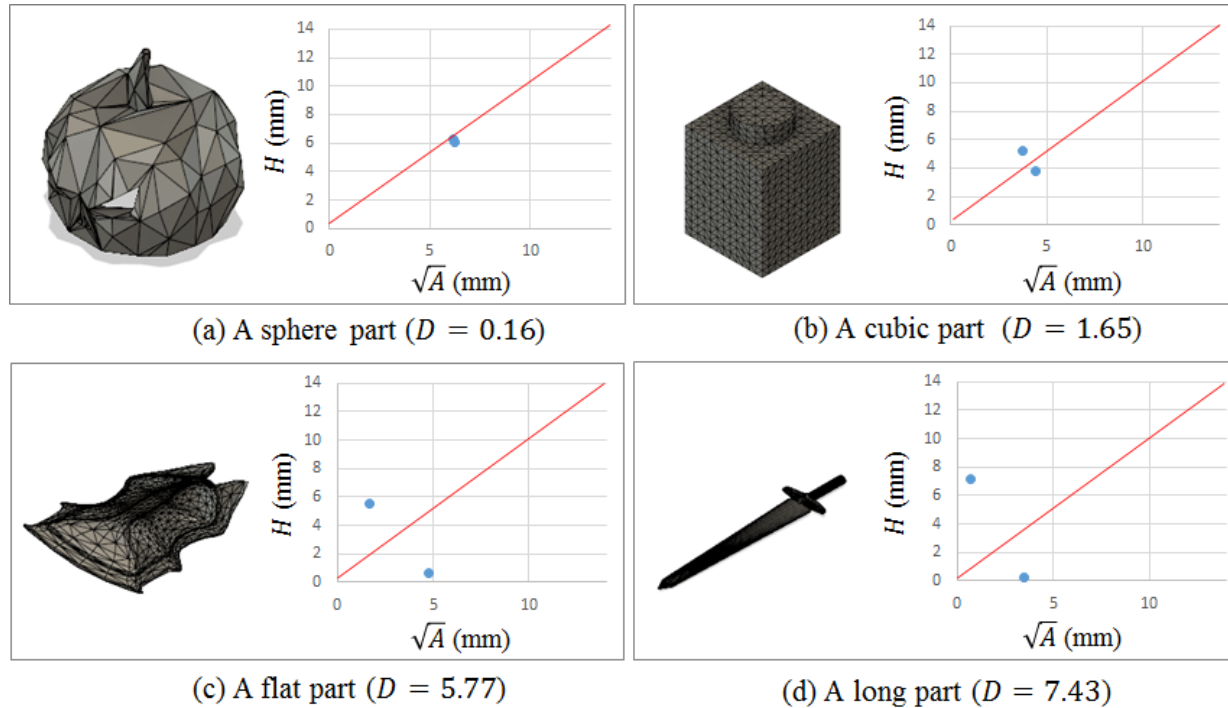


Figure 7. Examples representing the design index,  $D$ , depending on the shape of parts

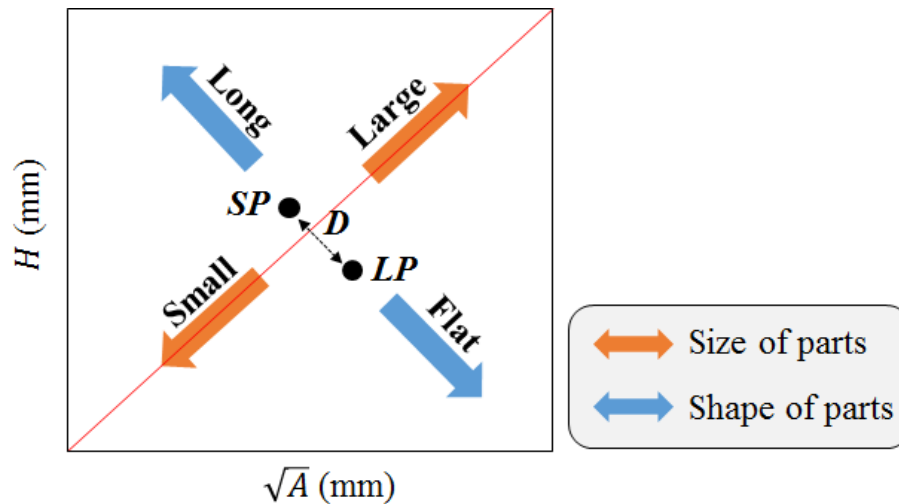


Figure 8. Interpretation of an HA plot with two plots of LP and SP

#### 4. Numerical experiment

In this section, some numerical experiments are conducted with various cases to understand the effect of build orientation policies by changing the number, size, and shape of incoming parts. What we want to know throughout the experiments is as follows:

- Does applying a certain orientation policy affect the minimization of the completion time?
- If yes, which policy is more preferred when many parts are considered?
- Do the size and shape of parts affect the decision on policy preference?

For the experiments, all three phases in Figure 1 should be prepared to simulate 3DPD. Section 4.1 shows how to simulate incoming random parts for Phase 1, the part arrival. For Phases 2 and 3, PreForm, a commercial slicing software, is used to place parts based on 2D packing, generate support structure, and estimate build time for each job. In PreForm [35], Formlabs Form2 that is an SLA printer is chosen as a 3D printer for the experiments. The type of material is Black V3 (FLGPK03), the size of the container is  $145 \times 145 \times 175$  mm and layer thickness is 0.1 mm. Parts are built up on a raft generated by supports and the raft thickness is 2.0 mm. The shortest distance between the part and the raft is 5.0 mm.

##### 4.1 Random part generation and build orientation determination

Incoming parts are randomly generated and their build orientations are determined by using the CAD platform of Autodesk Fusion 360 [37]. To generate random input parts, 100 geometries are chosen from Thingiverse.com [40] that is an online community to share 3D models. The number of facets of chosen geometries is less than 10,000 to reduce the computation time for re-scaling part size and changing orientations. The size of the chosen 100 geometries is normalized by re-scaling the maximum dimension (width, length, or height) of a bounding box into 10 mm. As such, although the maximum size of a bounding box is consistent as 10 mm for all seed parts, they have different shapes.

When an incoming part is needed, one geometry is randomly picked up from a set of the seed parts. Then, the part size is re-scaled with a uniform distribution. Based on the above-mentioned method, this research simulates parts arrival with different shapes and sizes. According to a policy, a part orientation is determined. When DP is adopted, the default orientation of arrival parts is applied instead of changing their build orientations. On the other hand, when LP or SP is adopted, orientation candidates are generated for each part by rotating 30 degrees. With a step angle of 30 degrees, 12 candidates for each axis are considered. As a combination of candidates for X- and Y-axis, 144 orientation candidates ( $12 \times 12$ ) are generated for each part since X- and Y-axis are considered for rotations. The details of how to choose the final orientation for LP or SP is described in Section 3.1.

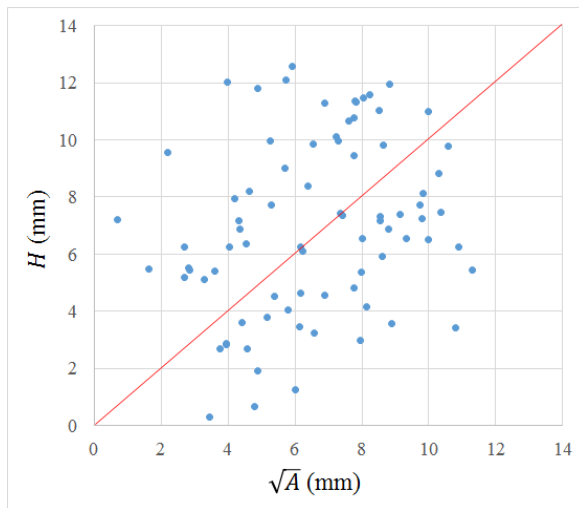
In the numerical experiments, five different cases for input arrival parts are chosen to show the effect of shape and size. Table 1 shows the five different cases depending on part size and shape: *SA*, *MA*,

$LA$ ,  $MLF1$  and  $MLF2$ . Parts for each case are randomly generated depending on its different conditions. In the 100 seeds, parts satisfying the condition of the part shape parameter are only used for part re-scaling. Herein, there are three cases for part shape:  $D > 0$  for any parts ( $A$ ),  $D > 5$  for little long or flat parts ( $LF1$ ), and  $D > 7$  for very long or flat parts ( $LF2$ ). Each case has a different design index,  $D$ . The size of parts satisfying the shape condition is re-scaled with different uniform distributions (UD): (0.5, 0.8) for small ( $S$ ), (0.5, 1.3) for medium ( $M$ ) and (1.0, 1.3) for large ( $L$ ) parts. By the combinations of the conditions for part size and shape, the experiment defines five different cases for random arrival parts as shown in Table 1.

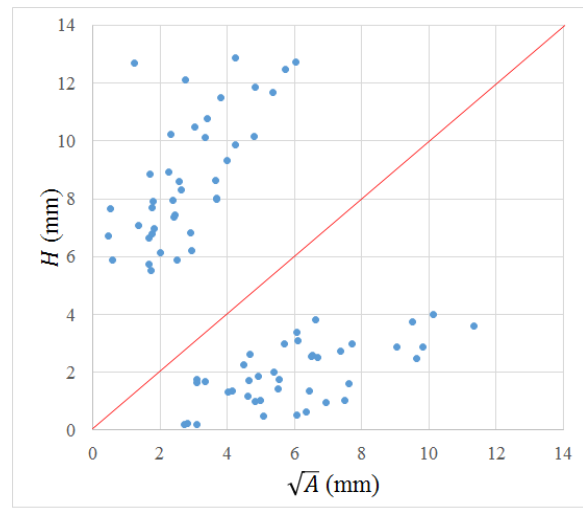
Figure 9 represents the plots of DP and SP for 40 parts in HA graphs. As explained in Section 3, the shape and size of parts can be expected by using the plots of DP and SP. The plots in Figure 9-(b) spread out from the red centerline more than the plots in Figure 9-(a), which means that Case MLF2 has more long and flat parts than Case MA. In the view of part size, the plots in Figure 9-(c) is closer to the origin than the plots in Figure 9-(d), which indicates that Case SA has smaller parts than Case LA.

Table 1. Five cases for arrival parts

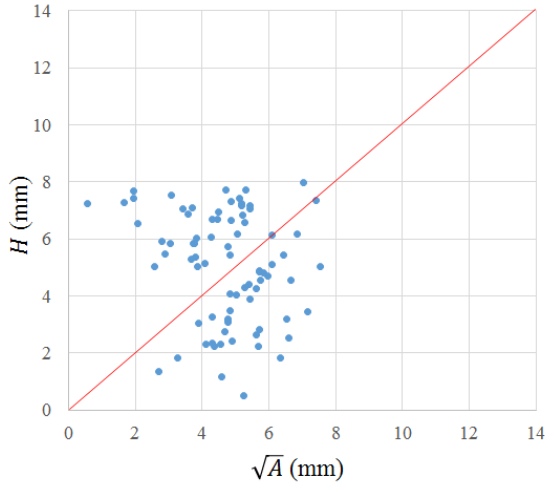
|                                                            | Part size                          |                                     |                                    |
|------------------------------------------------------------|------------------------------------|-------------------------------------|------------------------------------|
|                                                            | Small parts (S)<br>: UD~(0.5, 0.8) | Medium parts (M)<br>: UD~(0.5, 1.3) | Large parts (L)<br>: UD~(1.0, 1.3) |
| Any parts (A)<br>: $D > 0$                                 | SA                                 | MA                                  | LA                                 |
| Part shape<br>Little long or flat parts (LF1)<br>: $D > 5$ |                                    | MLF1                                |                                    |
| Very long or flat parts (LF2)<br>: $D > 7$                 |                                    | MLF2                                |                                    |



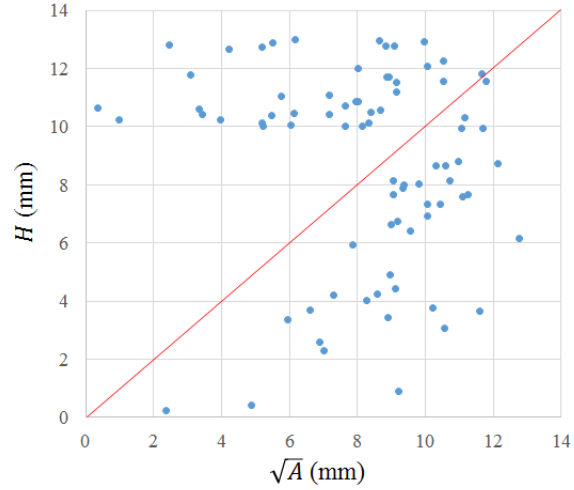
(a) Medium-sized any parts (MA)



(b) Medium-sized very long or flat parts (MLF2)



(c) Small-sized any parts (SA)



(d) Large-sized any parts (LA)

Figure 9. The plots of DP and LP for 40 parts in HA graphs

#### 4.2 The effect of increasing the number of parts

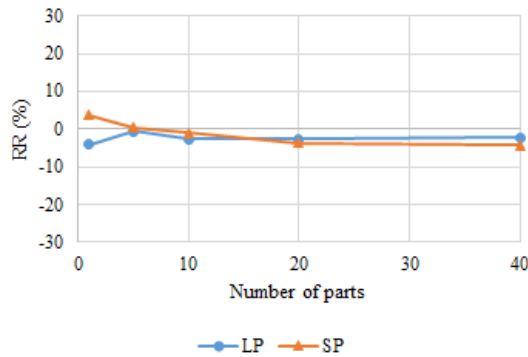
The completion time of 1, 5, 10, 20, and 40 parts are examined to show the trend of the impact of the number of parts. To reduce the variance of random part generation, all experiments are replicated 6 times. Table 2 represents the average completion time for the 6 replications and the average completion time is used for the comparison of policies. To show the extent to which LP or SP improves the completion time over DP, a *reduction rate (RR)* is suggested. The RR of LP and SP is calculated in Equations (3) and (4).  $T^{LP}$ ,  $T^{SP}$ , and  $T^{DP}$  are the completion time of LP, SP and DP, respectively. When RR goes below 0, LP or SP is more preferred than DP by having less completion time.

$$RR^{LP} (\%) = \frac{T^{LP} - T^{DP}}{T^{DP}} \times 100 \quad (3)$$

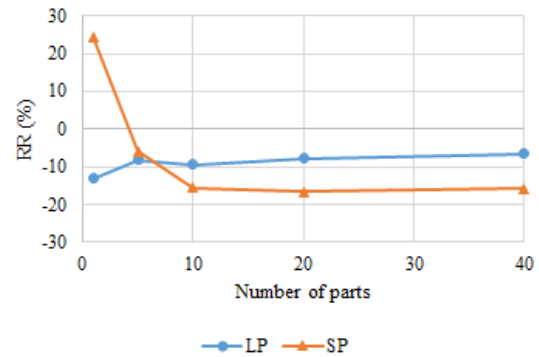
$$RR^{SP} (\%) = \frac{T^{SP} - T^{DP}}{T^{DP}} \times 100 \quad (4)$$

Figure 10 demonstrates RR of the four cases, MA, MLF2, SA and LA, according to the number of parts. As expected, for all cases, when only one part is considered, LP is more preferred than DP and SP since the only one job is considered for the single part and, in this case, the completion time is mainly affected by the build height. However, as the number of parts increases, the RR of LP and SP is getting close and even reversed for 40 parts of MA, MLF2 and SA. This indicates that SP could be more preferred than LP when a lot of parts are considered. For 40 parts of MLF2, SP reduces the completion time by 15.73% over DP while LP reduces by only 6.63%. In the experiments, the threshold of switching the preference of LP and SP is about 5 parts in most cases. This is the moment when more than 2 jobs are required to take care of multiple parts. One more important fact in Figure 10 is that RR of LP and SP is getting converged into a certain level as the number of parts increases. In this experiment, converging to a

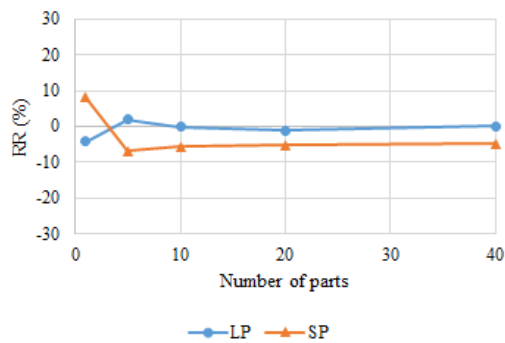
certain level is almost done before 20 parts, which means that RR of LP and SP would not be that much different even if 1000 parts are considered. This is the reason that the experiment result of the current research can be applied to a significant number of parts for mass customization.



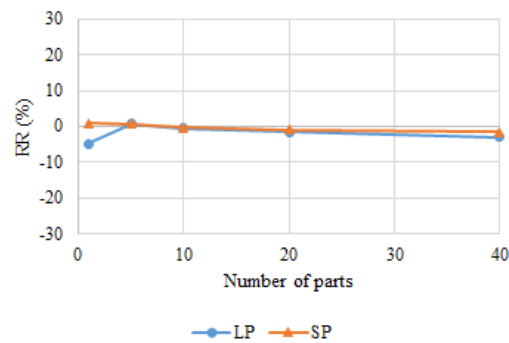
(a) Medium-sized any parts (MA)



(b) Medium-sized very long or flat parts (MLF2)



(c) Small-sized any parts (SA)



(d) Large-sized any parts (LA)

Figure 10. The reduction rate (RR) of LP and SP according to the number of incoming parts

Table 2. The average completion time for 6 replications

| # of parts | Case | DP (m) | LP (m) | SP (m) | RR <sup>LP</sup> (%) | RR <sup>SP</sup> (%) | Case | DP (m) | LP (m) | SP (m) | RR <sup>LP</sup> (%) | RR <sup>SP</sup> (%) |
|------------|------|--------|--------|--------|----------------------|----------------------|------|--------|--------|--------|----------------------|----------------------|
| 1          | MA   | 321    | 294    | 332    | -4.16                | 3.66                 | MLF2 | 625    | 599    | 648    | -13.08               | 24.35                |
| 5          |      | 1,911  | 1,965  | 1,966  | -0.51                | 0.48                 |      | 2,331  | 2,319  | 2,342  | -8.16                | -5.89                |
| 10         |      | 5,116  | 5,005  | 4,963  | -2.62                | -1.06                |      | 5,565  | 5,420  | 5,506  | -9.43                | -15.51               |
| 20         |      | 10,882 | 10,630 | 10,408 | -2.69                | -3.72                |      | 11,369 | 11,063 | 10,946 | -7.88                | -16.65               |
| 40         |      | 20,477 | 20,064 | 19,468 | -2.28                | -4.31                |      | 20,381 | 19,916 | 19,502 | -6.63                | -15.73               |
| 1          | SA   | 328    | 314    | 355    | -4.17                | 8.13                 | LA   | 919    | 873    | 926    | -4.92                | 0.82                 |
| 5          |      | 1,126  | 1,148  | 1,048  | 2.01                 | -6.87                |      | 4,589  | 4,622  | 4,624  | 0.73                 | 0.77                 |
| 10         |      | 2,036  | 2,033  | 1,919  | -0.16                | -5.75                |      | 9,162  | 9,107  | 9,126  | -0.61                | -0.39                |
| 20         |      | 3,961  | 3,914  | 3,756  | -1.19                | -5.17                |      | 17,847 | 17,575 | 17,668 | -1.53                | -1.00                |
| 40         |      | 7,466  | 7,476  | 7,097  | 0.13                 | -4.94                |      | 34,639 | 33,605 | 34,088 | -2.99                | -1.59                |

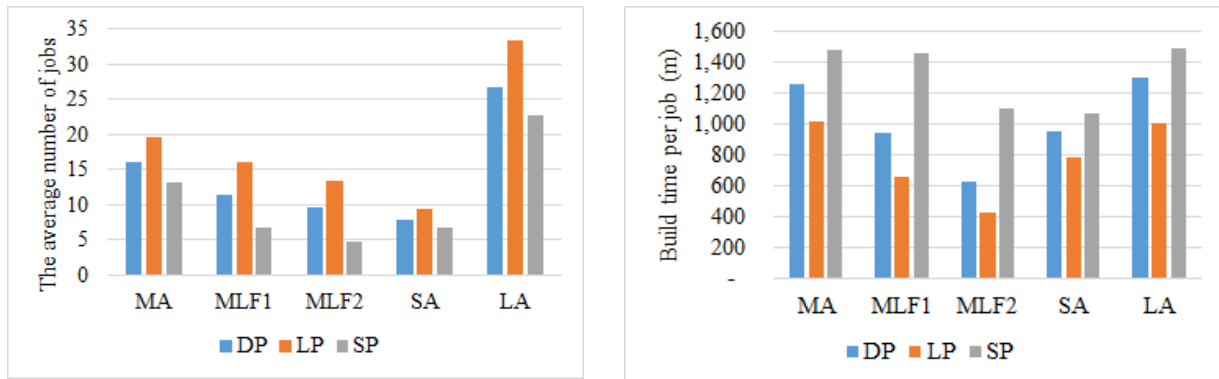
Medium-sized any parts (MA); Medium-sized very long / flat parts (MLF2); Small-sized any parts (SA); and Large-sized any parts (LA)

### 4.3 The effect of changing the shape and size of parts

This research aims to examine the mass customization situation in which a lot of different parts are produced. In Figure 10, as the number of parts increases from 1 to 40, the RR of LP and SP is converged into a certain level. As such, we assume that 40 parts are a sufficient level as many parts to investigate the characteristics of this system.

40 parts are randomly generated, grouped by several jobs and produced by AM. The build time for all jobs is summarized as the completion time. This process is replicated 6 times to reduce the variability of the random part generation. Figure 11-(a) shows the average number of jobs for 6 replications when 40 parts are considered. For policies, LP causes a large number of jobs and the shorter build time per job while SP causes a small number of jobs and the longer build time per job. This is because SP allows parts to be packed in the same job by letting them tall. On the contrary, LP causes relatively many jobs by letting parts lay down over a lot of jobs. For the size of parts, as expected, considering large parts requires more jobs since it is hard to pack large parts to the same job. In addition, for the shape of parts, the longer and more flat parts are considered, a fewer number of jobs are required. This is because it is likely that those parts are packed to the same job with less empty space.

In Figure 11-(b), the build time per job is calculated by dividing the completion time by the average number of jobs. As shown in the figure, the size of parts does not strongly affect the build time per job. In this experiment, even though large parts cause many jobs, it does not mean that build time per job for large parts is also large. Figure 11-(b) shows that build time per job of MA and LA is similar for any policies. However, when MA, MLF1, and MLF2 are compared in terms of the shape of parts, it tends to reduce build time per job as the shape is getting long and flat.



(a) The average number of jobs

(b) Build time per job

Figure 11. The average number of jobs and build time per job when 40 parts are considered;  
 $\text{build time per job} = \text{completion time} / \text{the average number of jobs}$

While MLF2 shows a relatively large difference in Figure 10-(b) when 40 parts are considered, it is hard to tell for other cases that LP or SP makes a significant completion time reduction compared to DP.

To investigate the effect of the size and shape of parts on the completion time according to policies, statistic tests are used. Since the number of replications is only six, Mann-Whitney test as non-parametric statistics is applied. In this test, we can recognize that LP or SP significantly reduce the completion time over DP.

As shown in Table 3, all cases are not significant but the test between DP and SP in MLF2 as P-value is 0.031 with 0.05 confidence level. For the tests for DP and SP, P-values are getting reduced as the shape of parts is getting longer and flatter from MA to MLF2. This means that when SP is adapted to produce a lot of long and flat parts, it is likely to reduce the completion time. The reduction rate, RR, could be getting large as more long and flat parts come to the system. On the other hand, LP is less effective to reduce the completion than SP in the same condition. Additionally, unlike the shape of incoming parts, the size of parts does not strongly affect the reduction of the completion time.

Table 3. P-values for Mann-Whitney Test (confidence level=0.05)

|           | MA    | MLF1  | MLF2         | SA    | LA    |
|-----------|-------|-------|--------------|-------|-------|
| DP and LP | 0.575 | 0.936 | 0.378        | 1.000 | 0.471 |
| DP and SP | 0.471 | 0.298 | <b>0.031</b> | 0.173 | 0.810 |

#### 4.4 Polynomial regression analysis for a design index ( $D$ ) and a reduction rate ( $RR$ ) of SP over DP

The previous section shows that SP could be more effective than LP when more than 40 parts are considered. In this section, SP is further investigated to predict the reduction rate,  $RR^{SP}$ , based on a design index,  $D$ , meaning the shape of parts.

With the fact that  $RR^{SP}$  depends on the shape of parts, the prediction model can be provided based on the dataset obtained in the previous sections. Since the five cases of SP are replicated 6 times, 30 pairs of  $D$  and  $RR^{SP}$  are obtained. These pairs are plotted to draw a fitting curve. Minitab 18 [41] is used for fitting. A fitted curve is drawn based on a quadratic regression model as shown in Figure 12. As a result, a regression equation in Equation (5) is suggested for the prediction model with 70.18 % of  $R^2$ . Therefore, with considering more than 40 parts in the same experiment conditions including the size of a container and the type of SLA printer,  $RR^{SP}$  that describes how much SP can reduce the completion time can be predicted based on Equation (5).

$$RR^{SP} = -26.32 + 10.42D - 1.167D^2 \quad (5)$$

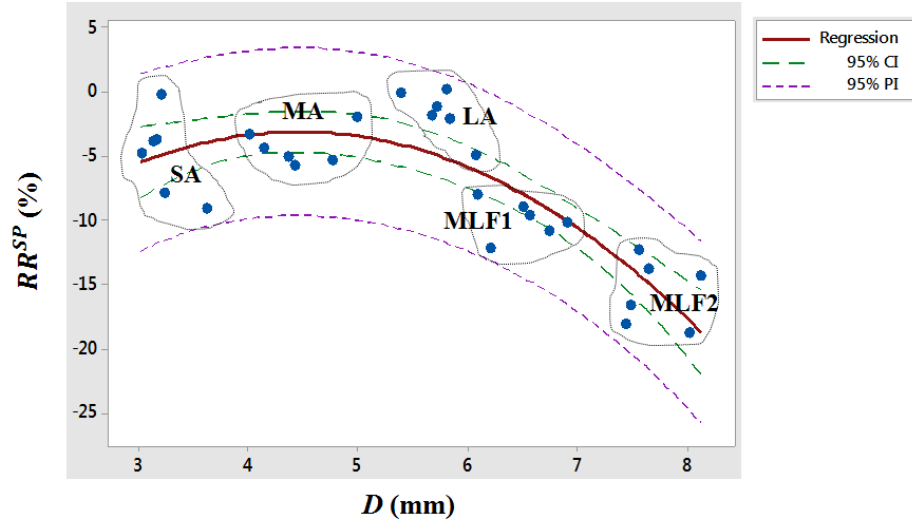


Figure 12. A fitted curve based on a quadratic regression model

## 5. Conclusion and Future Work

The objective of the paper is to discuss the concept of *3D Printing on Demand (3DPD) business model* in which the focus is on mass customization. In such business models, a number of parts with different sizes and geometries arrive where they are grouped for build processes and are placed on a container based on 2D irregular packing. In this paper, the following research question has been addressed: which build orientation policy (Laying or Standing Policy) results in lower completion time under certain conditions?

In the case of 2D irregular packing problems, this paper investigates the effect of two orientation policies on minimizing the completion time. Several numerical experiments are conducted. The outcomes of the experiments suggest that, while LP is preferred in the small number of parts (less than 5 parts), SP could be preferred when a large number of parts are considered. Additionally, the shape of parts affects the extent to which SP reduces the completion time over DP. The current paper contributes to extending the boundary of IPPs in AM by considering scheduling issues such as dynamic planning and FIFO.

This research can be extended in several ways. The effectiveness tendency of orientation policies can be investigated further by running experiments in different conditions. For instance, although this research only focused on a certain SLA machine, the experiments can be conducted based on other machines and other AM processes such as SLM. Furthermore, the problem can be extended to consider multiple AM machines as parallel production. In this case, other scheduling techniques such as assigning jobs to AM machines should be studied. In addition, the manufacturing analysis of parts such as stress analysis or

analyzing the mechanical properties of assemblies, materials, the AM technology, and the surface quality could be considered since those factors impact the completion time and the orientation policies. Also, the simulation results can be compared to actual results for validation. For example, the regression equation can be validated by identifying that the predicted RR is how close to the actual RR.

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