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Abstract

Additive manufacturing (AM) presents a unique set of manufacturability constraints, among the most important of which are the smallest producible feature size and the maximum overhang angle before support structures are required. In this work, an approach is presented which includes both a parameterization strategy for small features, and a subsequent iterative experiment for realizing minimum feature size design rules as functions of feature shape and orientation. This approach was designed to be applicable to a wide variety of AM processes, and was applied to an example machine in the material extrusion AM process category for demonstration purposes. This case study involved a thorough experimental evaluation to explore the tradeoffs between the number of oriented shapes evaluated and the predictive quality of the resulting design rules, and the results produced found that minimum feature size can vary by as much as 10x over the set of considered oriented shapes for the AM system studied. Compared to existing design rules in the literature, using the proposed approach made it possible to increase the design space for the AM system considered by providing lower minimum feature sizes when possible, by incorporating more accurate overhang angle constraints into the minimum feature size definition, and by detecting un-manufacturable features that existing design rules would have incorrectly allowed.

Keywords	Additive Manufacturing Benchmarking; Minimum Feature Size; Overhang Angle; Design Rules

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Towards a General Method for Constructing Manufacturability Design Rules for an Additive Manufacturing Process

Abstract

Additive manufacturing (AM) presents a unique set of manufacturability constraints, among the most important of which are the smallest producible feature size and the maximum overhang angle before support structures are required. In this work, an approach is presented which includes both a parameterization strategy for small features, and a subsequent iterative experiment for realizing minimum feature size design rules as functions of feature shape and orientation. This approach was designed to be applicable to a wide variety of AM processes, and was applied to an example machine in the material extrusion AM process category for demonstration purposes. This case study involved a thorough experimental evaluation to explore the tradeoffs between the number of oriented shapes evaluated and the predictive quality of the resulting design rules, and the results produced found that minimum feature size can vary by as much as 10x over the set of considered oriented shapes for the AM system studied. Compared to existing design rules in the literature, using the proposed approach made it possible to increase the design space for the AM system considered by providing lower minimum feature sizes when possible, by incorporating more accurate overhang angle constraints into the minimum feature size definition, and by detecting un-manufacturable features that existing design rules would have incorrectly allowed.

Keywords: Additive Manufacturing Benchmarking, Minimum Feature Size, Overhang Angle, Design Rules

1. Introduction

Additive manufacturing (AM) is an increasingly popular technology with numerous applications ranging from conceptual visualization to production level manufacturing [1]. Among the key advantages of AM is its independence from the design and manufacturability constraints associated with other more "conventional" means of making physical objects, such as casting, molding and machining [2]. For example, the design freedoms offered by AM processes are enabling designers to realize complex geometries which are nearly impossible to manufacture by conventional means, including the organic shapes produced via topology optimization algorithms. However, it is important to recognize that AM comes with its own unique set of manufacturability constraints as emphasized in numerous recent studies (e.g. [3], [4], and [5]), and the AM community has consistently looked for ways to better understand these constraints and mitigate their effects.

1.1. Typical AM Manufacturing Constraints

Two of the most studied AM design constraints are "minimum feature size," which quantifies the dimensions of the smallest element of a design which can be realized by a particular AM process or machine, and "overhang angle," which represents the shallowest downward-facing surface which can be produced by an AM machine (or process) without structural support. Typically a set of minimum feature sizes for various structures (such as walls, holes, etc.), and a single overhang angle (measured in degrees of offset from the build axis) are used to characterize the manufacturing capabilities of a particular process/material combination. These quantities can be obtained either directly from an AM machine manufacturer (e.g. [6]), via published research focused on a particular AM process of interest [7], or simply by manufacturing and analyzing a carefully designed test artifact [8].

These design constraints are often communicated as simple design rules (e.g. a specified maximum overhang angle) to help designers using AM systems, but the true behavior of many AM processes is quite complex and through trial-and-error experienced designers learn when they can break the rules. For example, the typical design rule for plastic material extrusion systems is to not print structures at angles shallower 45^{o} from the build surface without structural support, but this guideline can be violated deliberately by experienced AM practitioners when a desired flat element is supported at both end through a technique known as "bridging" (see Fig. 1). This reality highlights the limitations associated with typical AM design rules and suggests an opportunity for flexible and data driven approaches for accurately quantifying the capability of AM processes, and as such better understanding the true capability limitations of AM systems is an active area of research in the AM community.

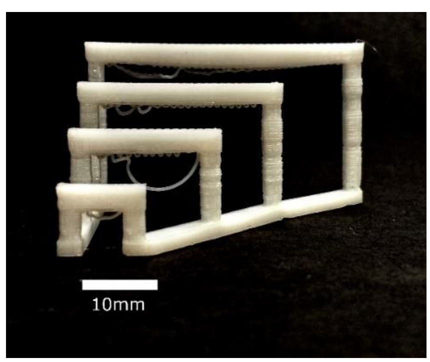


Figure 1: Image of PLA part printed on a material extrusion system that exhibits successful 'bridging' in violation of the simple 'maximum overhang angle' manufacturability constraint.

Many AM design rules rely on a combination of expert knowledge and test artifacts (e.g. [8]), which characterize the ability of a process to produce features of a given size. The use of test artifacts is advantageous because it evaluates the entire system by characterizing a specific combination of materials, mechanics, physics of deposition/fusion, software, and process settings. Unfortunately, the wide variety of AM processes available make it difficult to design a single general-purpose test artifact that is universally applicable. Also, assessment of results derived from a manufactured test artifact is made tedious due to the anisotropy of the underlying AM processes, which often requires test artifacts to be manufactured in multiple orientations to fully characterize each type of feature, and further manufacturing iterations are required if information on the statistical variation of the process is desired.

Several researchers have used test artifacts to characterize minimum feature size, generally by manufacturing a test artifact with a series of so-called "pass/fail" features of successively smaller characteristic dimensions which are then inspected (usually visually) to determine the smallest feature that can be produced "acceptably." The minimum feature size producible by a specific machine or process can vary with the type, shape and orientation of the feature, making a single design rule difficult to obtain with confidence, as explored by various researchers (e.g. [9], [10], [11] and [12]). Positive (boss) features and negative (hole) features have different minimum feature sizes because they depend on different characteristics of the process. Minimum feature size for positive features is restricted by the deposition/fusion size and layer height, whereas negative features depend on the deposition/solidification accuracy of the machine. In both cases, the material, process parameters, and underlying physics have significant effects. Small positive features might be larger than the bead size and the layer height but still be unable to support their own weight after manufacturing, resulting in warping or breakage. Additionally, small negative features can be blocked by material over-deposition in surrounding geometry, and difficulty in removing uncured build material (in powder and liquid feedstock processes) can both be far more significant than the machine's positioning resolution.

The maximum overhang angle that a machine is capable of producing is also generally evaluated using a test artifact. To obtain an overhang angle design rule a test artifact is produced that includes a specific geometry manufactured at various orientations (i.e. overhang angles), and once manufactured the features are evaluated (again usually visually) to set the design rule. Overhang angle is relatively straightforward to assess, but has received comparatively little attention from the AM research community due to the perceived simplicity of this design constraint. However, overhang angle has also been shown to be a critical factor in metal additive manufacturing processes where heat transfer and cooling effects cause overhanging features to perform poorly. Both Castillo [13] and Yasa et al. [14] addressed overhang features in metal AM utilizing an "open book" structure with sheets of material extending away from the build axis at different angles, and Mertens et al. [15] optimized machine parameters for down-facing structures in a metal powder bed fusion process and concluded that an overhang angle of 45° can be tolerated. Furthermore, overhang angle clearly remains an important limitation for material extrusion printers as well, as evidenced by recent work by Johnson et al. [16] who included overhanging features in a test artifact designed for a material extrusion AM process and reported that 45° is manufacturable while 50° from the build axis shows significant deformation.

1.2. AM Manufacturability Approaches

Many of the AM manufacturability studies reported in the literature (such as those discussed in the previous subsubsection for minimum feature size and overhang angle) are typically done for one of two reasons, either: a) to compare the capabilities of different AM processes, or b) to study a single AM system in order to develop a process-specific design rule.

The use of benchmark parts (or test artifacts) to compare multiple AM processes began early in the days of additive manufacturing [17], and follows from similar techniques in other manufacturing domains, for example ISO 10791-7 [18]. Most of the studies surveyed include pass/fail features as one piece of a larger test artifact designed to measure dimensional accuracy, geometric accuracy, surface finish and/or other machine characteristics. Xu et al. [19] and Mahesh et al. [20] each published results from different test parts manufactured on four different AM platforms which included a small series of pass/fail features. They visually inspected each part after manufacturing and classified features as “successful” or “unsuccessful”. Byun and Lee [21] used an algorithm to lay out features of differing shapes in a test matrix and included 4 sets of pins and holes (both rectangular and circular), as well as walls in pass/fail feature tests on four printers. In 2005, Kruth et al. evaluated the ability of several powder bed fusion processes to produce fine features using a series of circular holes, cylinders, and walls in a test part also designed to evaluate surface finish, dimensional accuracy, and mechanical properties [22]. Later, Yasa et al. built on Kruth’s test artifact, introducing additional pass/fail features as well as fins at various angles from the build plane [14]. Moylan et al., with the US National Institute of Standards and Technology (NIST), surveyed existing test artifacts and proposed one of their own design for standardization [8]. It includes vertically-oriented circular cylinders/holes as well as fins/slots which are evaluated by optical microscope. Figure 2 shows this section of the NIST part in both digital and manufactured form, and this figure is provided for reference purposes as an example of a currently accepted general test artifact for characterizing AM processes.

(a) (b)

Figure 2: NIST Test Artifact: (a) CAD model, and (b) as manufactured using a material extrusion system.

Alternatively, restricting the study of the capability of AM to a single process (and often a single machine) generates process knowledge more suitable for use in parameter optimization and in the generation of design guidelines. Some researchers have combined experimental evaluation with process models. For example, Ponche et al. used multi-physics modeling of the additive laser melting process combined with experimental evaluation of a test artifact to generate both quantitative predictions of minimum wall thickness and qualitative relationships between certain geometries and defects which are used as input to a topology optimization process [5].

Another advantage of focusing manufacturability research on a single process is the flexibility to explore both the material and process parameter spaces. An approach published by Meisel and Williams explored the minimum sizes of small positive and negative circular and rectangular features on the PolyJet process, characterizing the effect of different materials and process parameters [4]. Despite the PolyJet process's theoretical accuracy of 42 µm, their experiments indicate that the minimum feature size is anywhere between 372 µm and 897 µm, depending on feature geometry, material, and process settings. They recommend using 897 µm (21 times the X/Y accuracy) as a design rule that works in the worst case, unless care is taken to control material and other parameters. This study is also among a very small number of studies to consider the statistical variation of pass/fail features, which is an area that needs further study due to the inherent variability in any physical process.

A few researchers have performed thorough assessments of polyamide powder bed fusion machines utilizing plastic powder feedstocks (e.g. [10], [11] and [23]). In each study, 5 or more test artifacts, each containing as many as 150 features, were manufactured in different orientations to explore a variety of fine features and functional components, reporting both build success and (in some cases) dimensional variation for each feature in order to help create a detailed design guide for various features. Seepersad et al. [10] and Govett et al. [23] both utilized a "red-yellow-green" traffic light scale for reporting printing success. The large number of parts to be manufactured and features to be evaluated make these studies very expensive and time consuming but provide value to readers by surveying a much wider set of features with a high level of detail. The large number of different features surveyed also means the cost of producing multiple copies in order to estimate process variability is generally prohibitive. An open question not addressed in these works is how many levels of each feature parameter (variations in diameter or length, for example) must be included to provide predictive design rules.

Evaluation of the smallest manufacturable size or the maximum overhang angle of a feature of arbitrary shape and orientation using any of the approaches discussed above requires the manufacture of a potentially prohibitively large number of test artifacts in order identify the process limit of interest, all of which contain pass/fail features of several possible sizes and/or orientations (e.g. [12], [4]). As a result, most designers utilize a small set of simple guidelines (or rules-of-thumb), which include a significant factor of safety over the process's real lower limits to account for variables not captured in the experimental evaluation.

The manufacturability constraints associated with AM systems is obviously of interest to the producers of commercial AM systems, but the raw results of any manufacturer-driven research are rarely disclosed. AM manufactures instead frequently publish simple design guidelines for their products including "rule-of-thumb" values for wall thickness, detail size, and sometimes minimum feature size, in addition to a wide variety of suggestions for changes which make designs more manufacturable on the company's equipment (e.g. [24] and [25]). As pointed out in the bridging example provided in Fig. 1, these types of simplistic design rules can unnecessarily gloss over the true (and often more complex) capabilities of an AM system.

1.3. Objectives and Scope of the Proposed Approach

As evidenced in the previous sections, the AM community is interested in better understanding the capabilities and limitations of AM systems in order to help designers better use AM effectively. That being said, the approaches currently reported in the literature all have inherent weaknesses, given that they are either a) focused on a specific AM process and thus lack general applicability, b) are limited in terms of the types of features considered and thus incapable of producing effective design rules that capture the true performance of an AM system over a wide variety of application, or c) are of limited use in understanding the complex capabilities of an AM system with any statistical significance.

In previous work, the authors reported on an initial study quantifying the minimum feature size for a powder bed fusion process using polyamide powder, finding that feature shape and orientation could change the minimum manufacturable size by an order of magnitude, especially for negative features [12]. With this prior work as a starting point, this paper provides a general framework for determining the minimum feature size capability of an AM system as a function of shape and orientation on minimum feature size. This new approach can be applied to any AM process of interest, and furthermore is capable of generating datasets suitable for the development of general design rules that capture the true complex behavior of the system or process of interest. The proposed approach has been applied to an example AM processes from the material extrusion category, and results of that study are reported and discussed in this paper. It is important to note here that this approach is general enough to be applied to any AM machine of interest and should not be considered only applicable to material extrusion printers. Specific contributions of the approach proposed in this paper include the following:

a. The proposed approach combines minimum feature size and overhang angle constraints into a single, richer design ruleset based on the minimum manufacturable scale for features of various shapes and orientations.
b. The proposed cross-platform approach is adaptive and iterative, making it possible to obtain high quality minimum feature size estimates with a measure of statistical confidence for any AM process or machine of interest.
c. The approach is implemented with an underlying designed experiment, the size of which can be adjusted based on the user-desired level of expense and machine time, and the tradeoff between experiment size and predictive accuracy of the design rules has been explored for the considered AM processes presented in this paper.

The rest of the paper is laid out as follows. Section 2 contains the details of the proposed general experimental procedure for determining the minimum feature size for a given printer. Implementation details for the specific experiments performed are provided in Section 3. Results from the experiment performed are shown in Section 4. Section 5 presents an application AM example, fabricated using the proposed approach. Finally, Section 6 provides some concluding remarks.

2. Proposed Approach

In this section the details of the proposed approach are presented. The set of small features considered in this study is a parameterized set of small fins (positive features) and an identical complementary analysis of slots (negative features). The parameterization selected includes three factors, including Length/Thickness (r_l), Thickness/Width ("r_w", where $r_w = 1$ corresponds to a bar) and angle from the vertical ("ϕ", where $\phi = 0$ indicates a feature whose axis is parallel with the build direction). Fins are assumed rectangular, and the angle of the fin about the feature axis is fixed (i.e. the extreme edge of each fin is parallel to the build plate), see Fig. 3a. The parameter space considered for positive features is presented graphically in Fig. 3(b) for visualization purposes and a similar figure for negative features could also be produced.

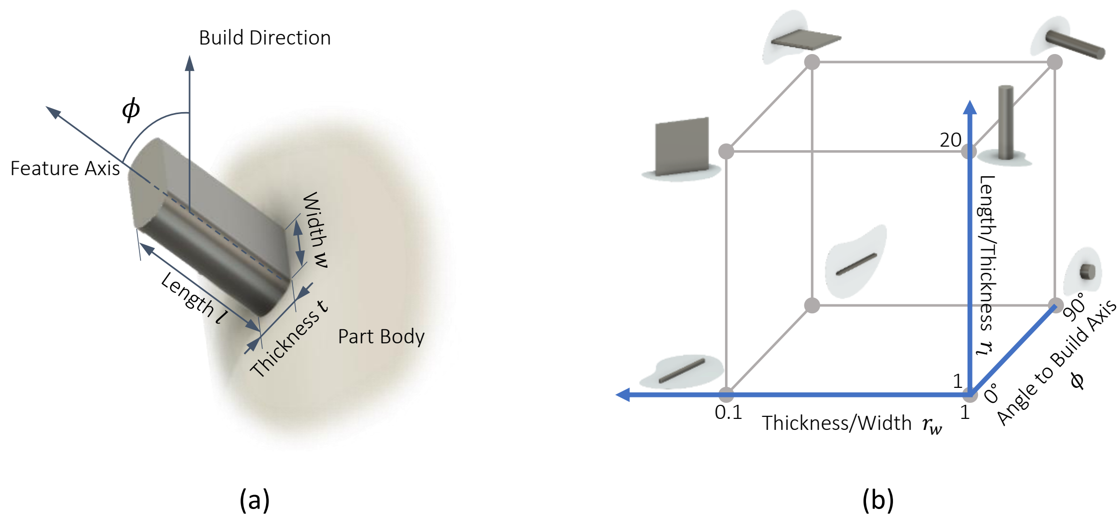


Figure 3: Parameter space of features considered in this study.

Figure 4 depicts the overall structure of the proposed cross-platform approach for determining the minimum feature size of an AM process. In Fig. 4(a), a high-level design of experiments process is carried out in the *Experiment Design* phase (Subsection 3.2), which selects points in the parameter space of small features to evaluate for minimum feature size (a simplified, two-parameter space is used in the figure). Each point selected in the high-level experiment defines a particular shape and orientation of a feature (Fig. 4(b)), and the goal is to determine the smallest scale (i.e. the smallest thickness t) at which the feature can be consistently manufactured. To do this, the feature is replicated six times at different scales on a test artifact in the *Artifact Definition and Generation* phase (Subsection 3.3) using initial guesses for the minimum and maximum thickness derived from manufacturer specifications or user judgement (Fig. 4(c)). This test artifact is then fabricated in the *Manufacture and Evaluation* phase (Fig.

4(d) and Subsection 3.4), and the user codes each feature as successful (✓) or unsuccessful (✗). Based on the results, in the subsequent *Iteration* phase (Subsection 3.5) a new set of minimum and maximum scales is specified, and a new artifact is defined. This occurs a set number of times (the question of how many times it should occur is addressed later in this work), after which all collected data for the current oriented shape is combined and used to estimate a minimum feature size based the probability of a feature being successfully manufactured (shown in Fig. 4(e)). The minimum feature size values for each individual oriented shape sampled are combined in the *Design Rule Definition* phase (Subsection 3.6), in which a function is fit to the data creating a predictive design rule.

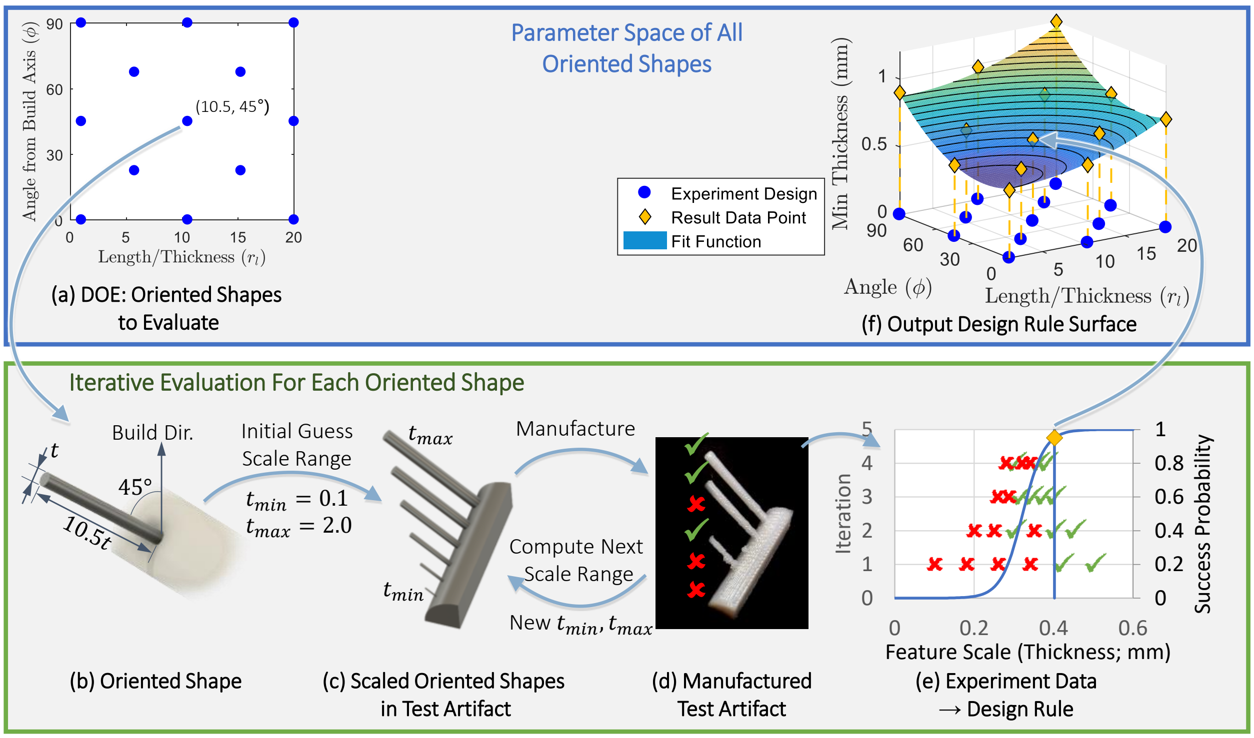


Figure 4: Overview of the (simplified) experimental procedure followed. Top box (frames (a) and (f)) indicate steps associated with the high-level experiment over a wide range of orientations and shapes. Bottom box (b-e) shows a low-level procedure for evaluating each individual sample of the higher-level experiment.

2.1. Focusing Assumptions

In developing this proposed approach, several focusing assumptions are explicitly made in the experimental setup to reduce noise and improve tractability. Under these assumptions, the approach shown in Fig. 4 is described in detail in the following subsections.

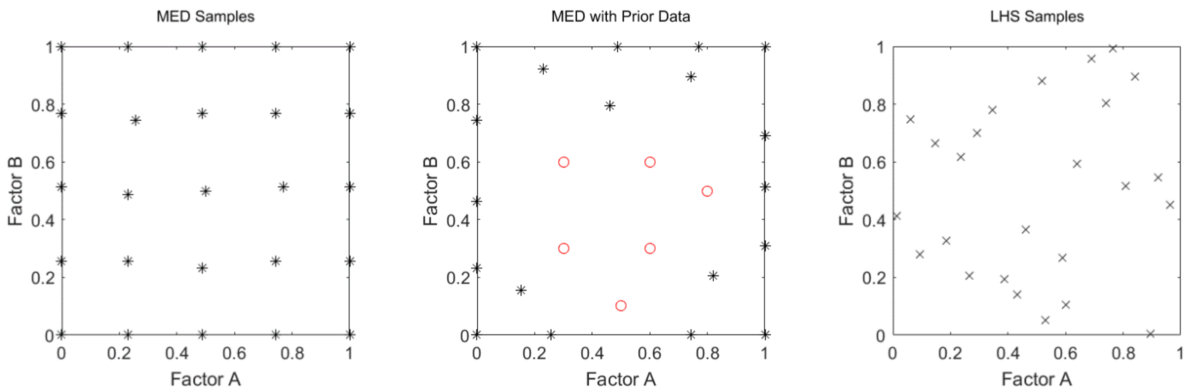
a. To keep the size of the parameter space of small features manageable, only straight, small cylindrical and rectangular features are considered, and rectangular features are assumed to be "level" with the build plate (no rotation about the feature axis).
b. It is assumed that as the scale of a feature increases, it is more likely to be manufactured successfully, and that this relationship can be modeled with a logistic ("S"-shaped) function. This approach will struggle when the AM process allows random failures for features of any size, or if the bending stress in long features during post processing rises faster than the increased strength from larger base thicknesses can overcome it.
c. The experiments are performed on only one machine (per process), with consistent settings, operating procedures, or post-processing regimens.
d. Because the determination of which features are "successful" is made by a human user, assessment is done by a single individual in each case to avoid differences in interpretation.
e. Features which are entirely in the build plane (i.e. the feature axis is horizontal) are supported at both ends so as to realize the "bridging" effect shown in Fig. 1.
f. Finally, neither strength nor geometric accuracy of the resulting features is considered when scoring, only the visual similarity between the design and the manufactured product.

2.2. Experimental Design

A design of experiment (DOE) process is used to select which coordinates (data points) in the parameter space described in Fig. 3 should be evaluated. Two types of data points are desired, "training" points which are used to define the design rule functions, and "test" data points at different locations which will be used to evaluate the predictive ability of the design rules at different points.

The training points are selected using the Maximum Entropy Design (MED) method, which is a design of experiments (DOE) technique that generates an ordered list of points, with each new point placed in the sample space such that the coverage of the space is maximized considering all previously placed points [26]. If some data (e.g. prior conducted experiments) is already known, the MED approach can use this information as a prior, providing additional data points to sample in light of the preexisting information (see Fig. 5(b)). The experiment presented here consists of 76 MED data points.

The "test" sample locations, which are used to evaluate the quality of the design rule functions at points not included in the training dataset, is constructed using the popular Latin Hypercube design method [27]. The Latin Hypercube design evenly and randomly distributes the sample points across the design space, maximizing the distribution uniformity when collapsed to each coordinate axis (see Fig. 5(c) for an example). This experiment uses 32 Latin Hypercube data points for testing.



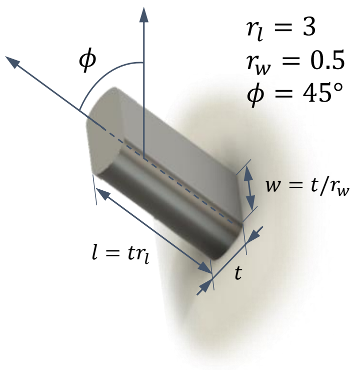
(a) (b) (c)

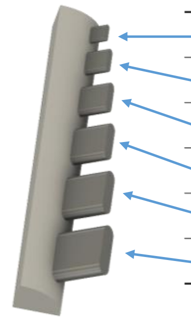
Figure 5: Examples of experiment designs. Numbers indicate order of the data points. (a) MED experiment with no prior data. (b) MED experiment ("*" symbols) with prior data ("o" symbols). (c) Latin Hypercube experiment design

2.3. Artifact Definition and Generation

Each of the data points selected in the training and test data sets must have its minimum feature size evaluated using the process laid out in Fig. 4(b)-(e). The experiment is carried out for both positive and negative features, so in addition to the positive (bar) features shown in Fig. 4, a similar experiment evaluates holes of the same shape and orientation. Note that the minimum and maximum thicknesses for the positive and negative features vary independently.

The scale for each feature is controlled by varying the thickness, t (see Fig. 6). For each oriented shape being evaluated, the aspect ratios of length and width to thickness (i.e. the r_l and r_w) as well as the orientation (overhang angle ϕ) are fixed (since these define a single oriented shape in the parameter space), and the size (scale) of each individual feature is set by selecting an appropriate thickness. A series of six scales of the oriented shape are included on the test artifact which linearly interpolate between a minimum and maximum scale (defined by thicknesses t_{min} and t_{max}). The maximum and minimum scale will be adjusted after each time the artifact is manufactured and evaluated, as described in the Subsection 3.5.





t (mm)	w (mm)	l (mm)
1	2	3
1.4	2.8	4.2
1.8	3.6	5.4
2.2	4.4	6.6
2.6	5.2	7.8
3	6	9

(a) (b)

Figure 6: Illustration of thickness as the parameter which controls scale. (a) An example feature (which specifies aspect ratios and overhang angle, but not scale), and (b) the same oriented feature manifested in several scales by varying thickness t. Note that all numeric dimensions are for illustration only; actual dimensions vary in successive iterations of the test artifact.

For efficiency, instead of manufacturing a single test artifact for each oriented shape (as shown in Fig. 4(c) and in Fig. 6(b) for simplicity), 5-7 oriented shapes are grouped into artifacts which can evaluate them all at once. Recall that each oriented shape is replicated multiple times at different scales, so each test artifact contains between 30 and 42 individual features. Figure 7 shows an example of four test artifacts containing a variety of features in both positive and negative form.

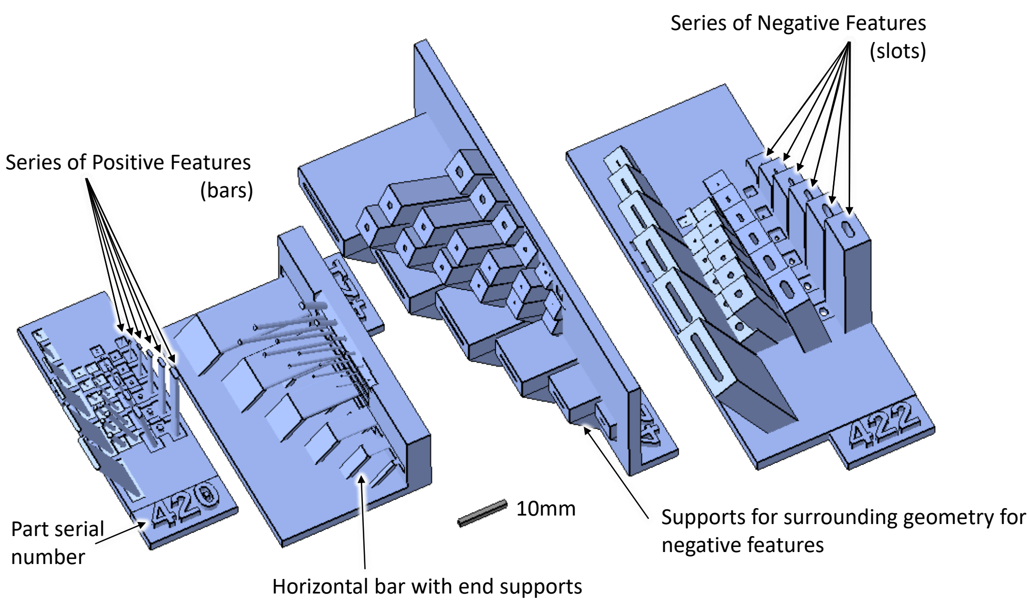


Figure 7: An example group of test artifacts.

Initially, the range of scales for all positive features is set using an initial guess for t_{min} and t_{max}, with negative scales selected at a different initial range, based on the best judgement of the operator. The definition of the artifact geometry is performed using a parametric model built in OpenSCAD [28], which generates an STL definition of the solid. Negative features are realized as through-holes surrounded by a fixed amount of geometry, and the model also defines a base plate to adhere to the build plane and supports for bridging positive features. Serial numbering is included to aid in experiment organization.

2.4. Manufacture and Evaluation

Each test artifact is manufactured on the target process. In most cases the artifact should be producible without generating additional supports. After manufacturing and selected post-processing (such as removal from the build plate or cleaning), each feature is visually assessed and scored according to its reproduction of the original design. “Acceptable” or “Pass” features are defined as ones in which material fills the original feature in the intended shape. The exact characteristics of an acceptable feature are left to the user to determine as the procedure provided here does not require a particular definition of passing or failing. For example, this approach could be extended to consider a feature’s deviation from a dimensional tolerance as a pass/fail metric.

2.5. Iteration

After the first manufacturing run, the scores of the individual features are recorded and used to determine the next range of feature scales to use. In subsequent iterations, all of the data for a particular shape and orientation coordinate is combined to select the next range of features.

When sufficient data is present, regression is used to fit a logistic function to the features, providing a continuous estimate for the probability of feature success over the range of scales (see the bottom row of Fig. 8). When a logistic fit is possible, the next range of scales to investigate is selected as the range between 5% probability and 95% probability. When a reasonable logistic fit is not possible, either because too little data has been collected or because the passing and failed features are completely separated, a simple heuristic is used (see the top row of Fig. 8) to first try and center the pass/failure transition point in the range of sampled features, then zooms in on the transition in order to more accurately estimate the transition point in an effort to produce a good logistic fit with additional data. Complete separation in the context of logistic regression refers to the case where the “passing” and “failing” data points can be divided perfectly by picking an appropriate threshold (even allowing one or more “pass” and “fail” data points exactly on the threshold). In this case the steepness of the transition becomes unbounded.

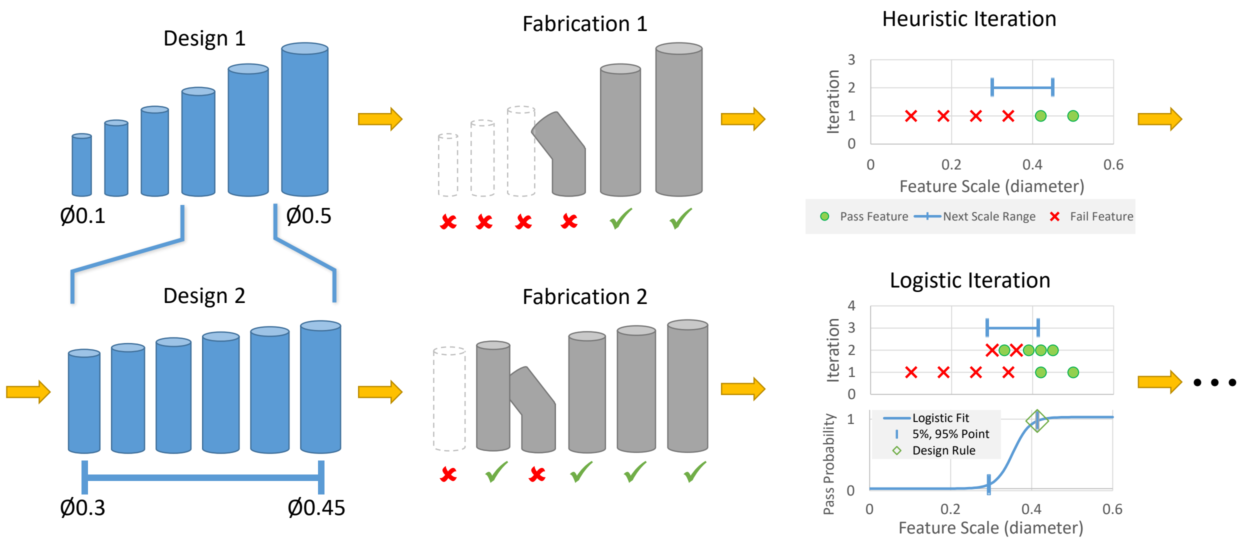


Figure 8: The Iteration Process. When insufficient data or complete separation between the passing and failed features sampled is present, a heuristic approach is taken to determine the next set of scales to evaluate. When a logistic fit is possible, the next range of scales is selected as the 5%-95% probability range.

2.6. Design Rule Definition

After a set number of iterations, the data for each shape and orientation coordinate is combined using logistic regression to a single minimum feature scale, the scale at which features have a 95% probability of successful manufacture (see diamond in plot on the bottom right of Fig. 8). If a reasonable logistic fit is still not possible, a heuristic is used to determine the minimum feature scale by collecting more data through further experiments. Thus, a single minimum feature scale (thickness) for each oriented shape specified in the original DOE is produced through the iterative manufacturing and evaluation of the feature at dozens of scales using the procedure described above. In this specific experiment, 6 iterations of 6 scales each were used, producing 36 total manufactured features per data point.

The processed data now consists of a single minimum feature size for each coordinate in the experiment designs. These data are separated back into training and test datasets, and the training data (which consists of independent parameter coordinates and dependent minimum feature sizes) is used to fit a polynomial function over the experiment space, producing a continuous design rule function for minimum feature thickness over all shape and orientation parameters. The predictive quality of the design rule function is checked by comparing its predictions with the measured data in the test dataset.

By measuring minimum feature size at various overhang angles, it is expected that the maximum overhang angle design constraint will be automatically captured by correspondingly large minimum feature sizes for features with greater degrees of overhang; details of the actual behavior are presented in a subsequent section.

3. Implementation Case Study

As previously stated, the approach detailed in Section 3 was implemented on a machine from the material extrusion AM process category for demonstration purposes. Unlike with the powder bed fusion process studied previously in Weiss, et al. [12], overhang angle is a significant concern for material extrusion printers (along with other processes like vat photopolymerization), and the parameterization used for the proposed approach can consider both the minimum feature size and overhang angle constraints simultaneously.

Material extrusion machines force heated polymer through a small nozzle, drawing out a layer of the desired part in the build space. A maximum overhang angle of 45^{o} for the material extrusion process is often suggested in the literature (e.g. [16] and [29]). Several sources of part failure are possible when fabricating small features via material extrusion. Small features can fail due to drooping, which describes the situation where a lack of structure underneath the newly extruded material causes it to deform downward before solidification occurs. Additionally, small positive features can fail mechanically (e.g. break) due to the material being unable to support its own weight throughout the manufacturing process in the presence of machine vibrations. Negative features can fail due to an over-extrusion of material in the surrounding solid regions causing blockage, especially near the start or the end of the feature where extra-dense “floor” and “roof” structures are produced. In addition, the manufacturer-supplied preparation software for the printer may choose to eliminate some small features as un-manufacturable, or instead instruct the machine to place a single line of solid material even though a thin feature is smaller than the line width of the deposition process, further adding to potential error sources. By assessing the entire process end-to-end, all sources of potential errors are accounted for, providing a “real-world” estimate of manufacturing success.

The experimental design for this study consisted of 55 training data points selected using the Maximum Entropy Design (MED) technique (as previously discussed), considering all three feature parameters as design factors (r_l, r_w, and ϕ). An additional 21 data points were selected (again using MED) along the “Bar” face ($r_w = 1$) of the parameter cube (see Fig. 3(b)) for two reasons: 1) because of significant practical design interest in structures involving bars, and 2) to produce a two-dimensional subset of data for visualization purposes. This resulted in a total training dataset size of 76 feature parameter coordinates. The test dataset chosen consisted of an additional 20 points selected from the full range of three design factors, this time using the Latin Hypercube design technique.

Each test artifact, sampling 5-7 oriented shapes, was generated and manufactured once per iteration, and the full experiment consisted of six total iterations. For the material extrusion process study, parts were manufactured on a FlashForge Finder using white PLA filament as the feedstock, an extrusion temperature of 220°C, a layer height of 0.183 mm, and with all support settings disabled. After manufacture, these parts were removed from the build plate and analyzed without any further post-processing. When assessing the resulting parts for successful manufacture, the primary criterion considered was the presence of stable features which accurately reflected the overall length and shape of the designed feature. Small amounts of warping and drooping were permitted so long as the mechanical integrity and general shape of the feature remained intact. Holes were required to be visibly clear. It is important to note here that the assessment did not measure the geometric or dimensional accuracy of the produced features, as this study was focused on minimum printable feature exclusively rather than also focusing on feature accuracy. Other studies have suggested that inaccuracies in these quantities are prevalent near the minimum feature size of AM processes due to compensations used in the preparation software and mechanical accuracy of the AM platform (e.g. [4] and [10]). Quantifying these deviations is beyond the scope of the present work.

In order to produce general design rules using the obtained data, after manufacturing and evaluation of the test artifacts was complete linear, quadratic, and cubic polynomial functions ($\hat{s}_1$, $\hat{s}_2$, and $\hat{s}_3$ respectively) were fit to the training datasets as candidate continuous design rule functions. The linear relationship can be stated as:

$$\hat{s}_1(r_w, r_l, \phi) = a_1 r_w + a_2 r_l + a_3 \phi + a_4 \tag{1}$$

with r_w the thickness/width ratio, r_l the length/thickness ratio, and ϕ the angle between the feature axis and the build direction and $a_1, \dots, a_4$ fitting parameters to be determined using least squares regression. The second order and third order polynomials are,

$$\begin{aligned}\hat{s}_2(r_w, r_l, \phi) = {} & a_1 r_w^2 + a_2 r_l^2 + a_3 \phi^2 + a_4 r_w r_l \phi + a_5 r_w r_l + a_6 r_l \phi + a_7 r_w \phi \\ & + a_8 r_w + a_9 r_l + a_{10} \phi + a_{11}\end{aligned} \tag{2}$$

$$\begin{aligned}\hat{s}_3(r_w, r_l, \phi) = {} & a_1 r_w^3 + a_2 r_l^3 + a_3 \phi^3 + a_4 r_w^2 r_l + a_5 r_w r_l^2 + a_6 r_l^2 \phi + a_7 r_l \phi^2 \\ & + a_8 r_w^2 \phi + a_9 r_w \phi^2 + a_{10} r_w r_l \phi + a_{11} r_w^2 + a_{12} r_l^2 + a_{13} \phi^2 \\ & + a_{14} r_w r_l + a_{15} r_w \phi + a_{16} r_l \phi + a_{17} r_w + a_{18} r_l + a_{19} \phi + a_{20}\end{aligned} \tag{3}$$

Because polynomial regression attempts to minimize the overall error between the function and the input data points, the results sometimes include regions of the $\hat{s}$ functions which are significantly lower than any sampled data point, a case unlikely to occur in practice for sufficiently large samples. To remedy this, the polynomial fits are further adjusted to always be no smaller than the smallest data point sampled using the following transform:

$$\begin{aligned} &\tilde{s}_i(r_w, r_l, \phi) = \max(\hat{s}_i, t_{lower}) \\ &t_{lower} = \text{mean}(t_1, t_2, t_3) \\ &\text{with} \quad t_1 < t_2 < t_3 < \cdots < t_n \end{aligned} \tag{4}$$

where t_{lower} is a lower limit on the minimum feature thickness constructed by averaging the three smallest minimum thicknesses observed in the current sample. This “min clamping” helps ensure that predicted feature sizes are manufacturable by ensuring they are at least as large as some feature in the current data set which has been manufactured successfully.

4. Case Study Results

A summary of the results obtained from the material extrusion experiment as described in Section 3 are shown in Table 1, and as shown around 90% of the oriented shapes showed enough stochastic behavior to create a reasonable logistic fit. A more detailed presentation of these results along with an analysis of the key takeaways for each study based on these results are presented in the following subsections.

Table 1: Summary Case Study Results

		Positive	**Negative**
Iterations/artifact		6*	
Feature types with logistic fit		90%	91%
Min. Feature Size (Thickness) Estimates (mm)	**Smallest**	0.18	0.307
	Largest	1.583	1.249
	Mean	0.596	0.773

*A limited set of features were allowed significantly more scale iterations in order to test convergence limits for the approach, as discussed later in this section.

The results from this case study will be presented and discussed in three different contexts. First, the effectiveness of the iteration-based approach to fit a logistic regression to each parameterized feature studied is evaluated as a building block for subsequent analyses. Next, the subset of the experiment that includes on the cylindrical “bar” features (points with $r_w = 1$) is presented both to visualize the results produced by the proposed approach and to also compare the expected and observed behavior for the material extrusion process evaluated. Finally, the results from the full (3 factor) experiment are presented, showing the performance of a series of polynomial fits to the full sample space of feature size data, providing sample design rule functions for the material extrusion process.

4.1. Evaluation of the Logistic Regression Fit

The validity of the design rule functions produced by this approach depends greatly on the quality of the individual estimates of minimum feature size for the parameter combinations tested. These estimates depend on the number of iterations of the experiment performed, which for this approach correspond directly to how many copies of each feature at varying scales were manufactured. Most references surveyed in the Background section include 4-10 copies of individual pass/fail features in a particular orientation when comparing processes, and while several exhaustive studies include hundreds of individual features, they are organized into similar shapes manufactured at between 10 and 21 different sizes ([11], [23]). No surveyed work addresses the question of how many features should be included in such a study, and only Meisel and Williams [4] have given attention to the stochastic behavior of the process near the minimum feature size limit.

To address this question, four of the test artifacts in the material extrusion process experiment, containing a total of 12 positive and 12 negative feature types, were allowed to iterate for an additional 11 iterations (for a total of 17). After each iteration, the minimum feature thickness, which value would be returned if the experiment was to be stopped at this point, is compared with the final design rule after all 17 iterations have completed. Significant variations in the design rule are seen in the first few iterations, as the pass/fail threshold is located, and the range of feature scales focuses in on this transition. If the design rule determined after 17 iterations is taken to be fully converged, the variation and convergence behavior in the design rule value at prior iterations is visualized in Fig. 9.

For both positive and negative features, after four iterations, only about half of the features are within 10% of the final value. After six iterations, all but two of the 12 feature types have converged to within 10%. This suggests that six iterations is the minimum required to provide reasonably accurate design rules for this process. Six iterations at six scales per iteration corresponds to 36 copies of each feature, significantly more than used by other researchers. Also, unlike existing studies, the iterative approach used here reduces the dependence of the minimum feature size on the accuracy of the guess used to set the initial range of feature scales, as successive iterations adapt to the results of previous ones.

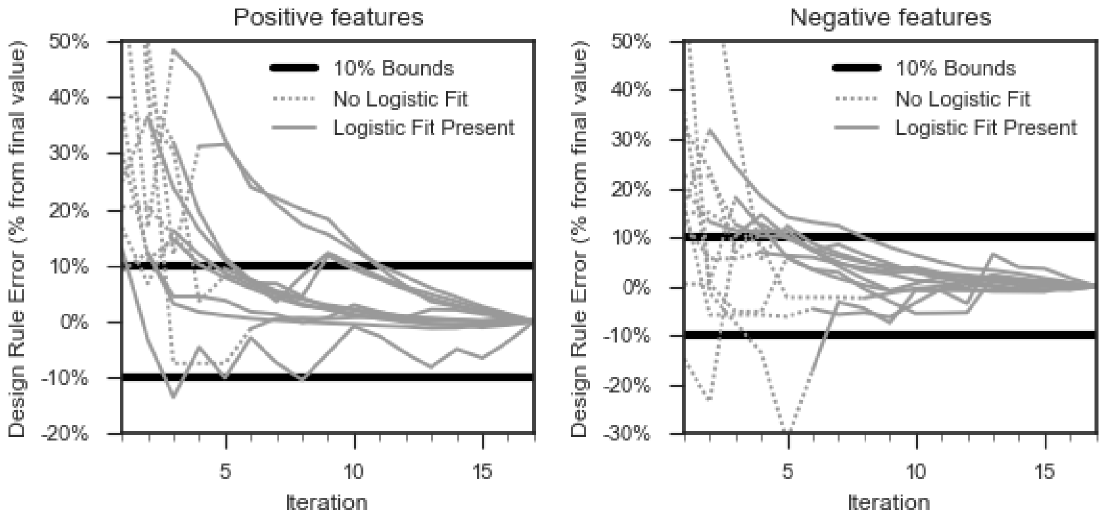


Figure 9: Value of the minimum feature thickness t for each iteration for 12 positive and 12 negative features, as a percentage of the final value (after 17th iteration).

Stochastic variations in the processes was also seen across all the oriented shapes. As the iterations progress, the heuristic algorithm used zooms in on the pass/fail transition, and at some scale the stochasticity of the process begins to be seen in variations in results between features of similar scale or between manufacturing runs. Once this variation is present, logistic regression is used to map a probability function to the data. In order to adjust for this stochasticity, the minimum feature size reported corresponds to a 95% pass probability, which for the positive material extrusion data represents an average increase of 0.149 mm over the smallest successfully manufactured feature, but only a 0.040 mm increase over the largest failed feature. These results represent a significant fraction of the mean minimum feature size over the dataset, suggesting that using a single series of features on one manufacturing run to assess minimum manufacturable feature size is not a reliable way to produce robust design rules.

Another assumption in the proposed approach is the suitability of logistic regression as a tool for modeling the underlying success probability function. The statistics literature suggests a minimum sample size of 50 data points is required to employ logistic regression with confidence [31]. For the 24 features on the artifacts allowed to iterate 17 times, a total of 96 data points are present, and the binned data visually match the progression of a logistic curve; for example see Fig. 10. For the remainder of the data, after six iterations only 36 data points are collected, which is too few to confidently apply logistic regression techniques, making the results not yet statistically significant. As a result, controls in the iteration process were applied to keep incorrect or unreasonable logistic fits from being utilized. Logistic regressions are rejected if the fit is less than 50% probable, or if the spread of the probability distribution is more than twice the spread of the data collected so far. In these cases the heuristic approach is used instead. Six iterations (corresponding to 36 data points per feature type), was determined to be the minimum appropriate amount of data to collect, and for stronger statistical confidence in the result, eight or more iterations are suggested, resulting in 48+ data points, enough to satisfy the best practices of the literature.

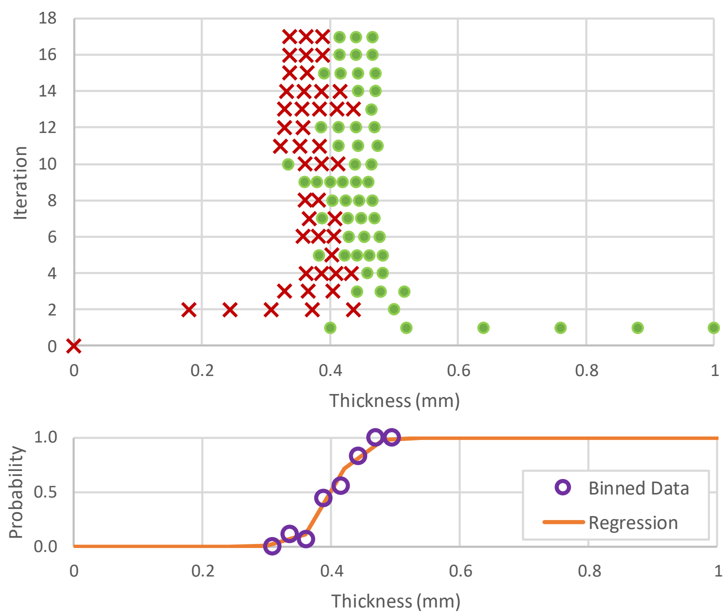
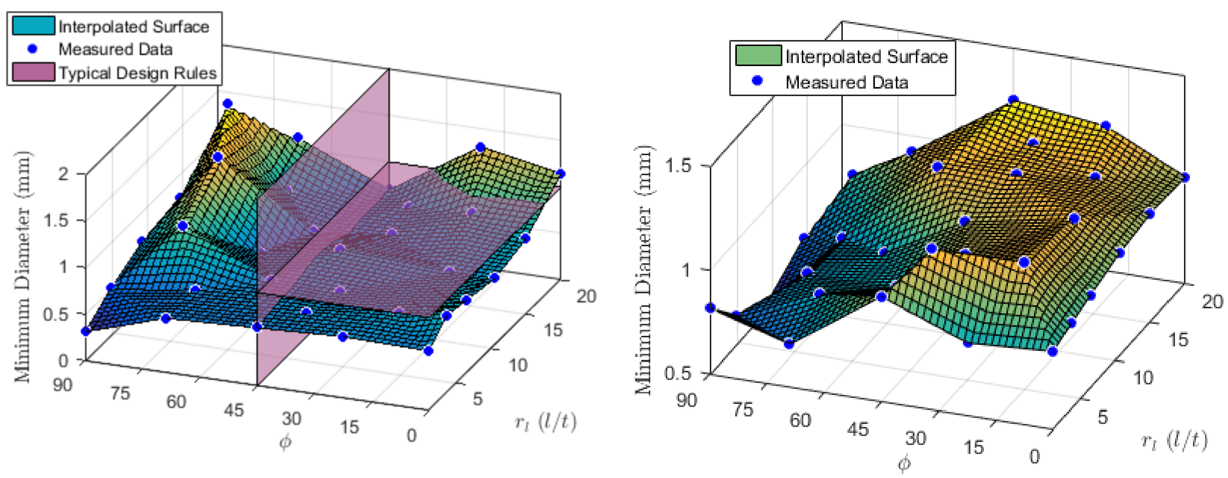


Figure 10: The scored features by iteration and grouped by bin above the corresponding logistic regression curve for a single feature type.

4.2. Visualization and Evaluation of Results Obtained

To visualize the type of results obtained by this approach, and to compare the results obtained using the proposed approach to other traditional design rules, a subset of the dataset produced was considered. This subset of data included the main experiment data points with $r_w = 1$, and the 21 additional MED data points produced by holding r_w fixed at 1 and only allowing the other two parameters (r_l and ϕ) to vary. The additional MED data points were selected with the main experiment data specified as prior information, making the resulting combined dataset have good coverage over the space while reusing the experimental results from the larger experiment. The minimum feature size determined with a 95% confidence via the logistic regression, expressed as the diameter of the cylinder, was used as the dependent variable (z-axis) for each assessed oriented shape in this analysis. Results for both positives and negative features are shown with interpolating surfaces, are presented in Fig. 11.

As can be seen in Fig. 11(a), bar (positive) features with high angles of overhang require comparatively larger minimum feature sizes for long bars, where r_l is large, caused by drooping, which was expected. Long, nearly-vertical cylinders also see a large minimum feature diameter, resulting from comparatively small in-plane cross-sectional area and loads on the printed structure induced by the motion of the print head. Long features near 45° have more cross-sectional area in each plane and can therefore be manufactured more reliably at smaller diameters. The bridging effect allows very slender cylinders in the horizontal direction, so long as both ends are supported. Short features (with $r_l < 5$) show relatively little dependence on angle, so long as the parent body remains below/beside the small features meaning some source of support is present.



(a) (b)

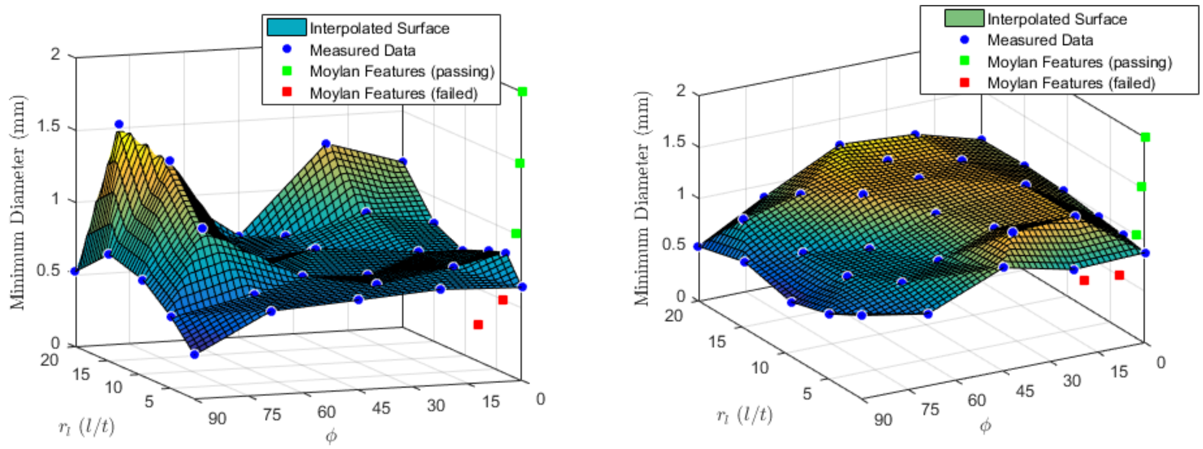
Figure 11: Interpolated visualization of the cylinder data, parameterized by the length/diameter ratio r_l and the overhang angle ϕ. Design rules from industry best practices are shown as translucent planes. (a) Positive features (b) Negative features.

Figure 11(a) also presents the industrially-generated design rules from i.materialse [29], by plotting the specified 1.0 mm wall thickness and 45° maximum overhang angle as shaded planes. It is evident from the figure that the existing suggestions work reasonably well for the bulk of positive design cases. The typical overhang angle for positive features in this process (visualized with the vertical plane in Fig. 11(a)) avoids the regions of drooping, which correspond to the higher minimum feature sizes. However, this strict maximum overhang angle excludes the possibility of including smaller features at any angle, so long as the lower edge of the feature remains supported. In fact, the strict maximum overhang angle criteria excludes approximately 43 % of the design space studied for which the minimum feature size is less than 1 mm. No industrial guidelines were identified which provide general design guideline for the minimum hole diameter in the material extrusion process studied.

Holes in the material extrusion process studied (see Fig. 11(b)) performed best in the horizontal configuration, where very small holes are easy to create by not depositing material for one or two layers. Vertical holes can be smaller in diameter than angled holes because the clean alignment between layers reduces the likelihood the hole will be fully blocked by over-extrusion. Since the failure modes for holes are generally not dependent on depth, little variation is seen in the r_l direction.

Depending on the method used to select a minimum feature size design rule, different problems arise. A conservative estimate for the positive features of the material extrusion process studied would place the minimum feature size at the worst-case value, which in the present study was 1.25 mm (excluding features below the overhang angle). With this estimate, all features above the overhang cutoff should be manufacturable, but a significant portion of the design space is restricted (i.e. features much smaller than the design rule are producible in shorter lengths). In addition, it requires a fairly thorough survey of the space to accurately locate the feature type which sets this conservative design rule, so generally a few sample points and a generous safety factor is used instead. On average, a conservative design rule of 1.25 mm diameter over-estimates the true minimum by 0.49 mm over the interpolated design space of cylinders with $\phi < 45°$.

In the existing literature, a design rule is typically selected based on a single sample, generally placed at $\phi = 0°$ and $1 \leq r_l \leq 10$. For example, the NIST part [8] includes a series of five cylinders, all 2mm tall, with diameters [0.25, 0.5, 1.0, 1.5, 2.0] mm for this purpose. To show the comparison between the proposed approach and the NIST artifact approach, these points are visualized in Fig. 12 with red square. As can be seen in the figure, based on this case study a design rule based on the smallest manufactured feature size is accurate for most positive features below the overhang angle cutoff. However, for long features, especially not quite vertical ones, the actual minimum feature size is underestimated by the NIST artifact by as much as 0.25 mm (25%), and a designer utilizing this optimistic design rule will very likely obtain an unsatisfactory product. For negative features (Fig. 12(b)), the NIST artifact's results are also optimistic, as the variation in minimum hole diameter with hole angle is significant over much of the domain.



(a) (b)

Figure 12: The interpolated sampled data, with the data points from the NIST test artifact [8] overlaid on the ϕ=0 plane with red square, for both: (a) Positive features, and (b) Negative features.

4.3. Analysis of Developed Polynomial Design Rules

As discussed previously the literature approaches the problem of assessing feature size for various feature shapes either by assigning a single minimum feature size constraint to the entire design space (often based on the result of experimental assessment of only one or two features), or by systematically surveying a huge number of features to produce design rule tables relating two parameters at a time (such as hole diameter and depth). The proposed approach presented here attempts to fit an analytic function to a carefully selected subset of feature types, rather than collect the extensive amount of data other researchers do in their full-factorial experiments ([10], [11]). As a result, the approach presented here represents a middle of the road approach which is more generally applicable (effective across three parameters at once) while requiring an achievable number of features to be manufactured and evaluated.

Since the training data was constructed using a maximum entropy experiment design, the first N points (shapes & orientations) in the experiment can be separately considered as a valid experiment as well. This characteristic is exploited to allow the number of data points considered when selecting the fit to vary from one to the entire MED dataset (55 total). Because 14 of these data points lie on the $\phi = 90°$ face of the parameter space, and because the second support structure added to horizontal features on the test artifacts significantly changes the behavior in the "bar" data (see Section 2.3), the minimum feature size for those 14 DOE points was reevaluated at the same coordinates for r_l and r_w, but with $\phi = 80°$ instead of 90^{o}. This modification to the obtained dataset ensured that the coverage over the entire parameter space was relatively even for the evaluation of the polynomial design rules. Each subset of the data is fit using three polynomial functions (described in the Implementation section as Eqns. (1), (2), and (3), using the modification in Eqn. (4)). The quality of each fit was evaluated by considering the root-mean-square (RMS) error of the predictions compared with the measured values over the separate test dataset. This RMS error is plotted for each fit type in each set of experiments in Fig. 13.

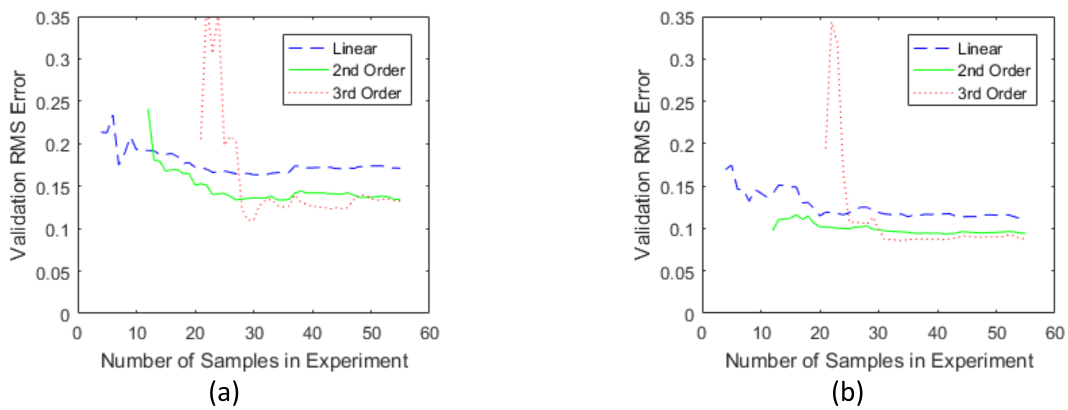


Figure 13: RMS error with respect to the test dataset for fits of different order polynomials considering different amounts of the input data for the material extrusion example process for (a) positive features and (b) negative features.

For positive features from the material extrusion example process, the fits presented show errors on the order of 0.1-0.15 mm, or about 15-25% of the mean minimum feature size of 0.610 mm. Errors computed against the validation (test) dataset and against the entire MED dataset indicate that a 2nd order fit out-performs a first order (linear) one, but while a 3rd order fit with more than 30 samples improves substantially in predicting the MED data itself, it provides little improvement on the validation data. This suggests that the 3rd order polynomial is over-fitting the sampled values and not tracking real trends in the data. For all fits, performance against the validation data improves with increasing number of samples in the experiment, up to around 30. Negative features perform significantly better, with predictive errors on the order of 0.1 mm (15% of the average negative feature diameter of 0.699 mm) and small improvements in fit quality are seen up to around 30 samples. For negative features, the 2nd and 3rd order polynomials achieve very similar error rates using both metrics, suggesting that the higher-order fit does not expose any new dynamics in the data. Note that in each case, the collection of additional data and the use of a higher-order fitting function has a significant effect on the quality of the resulting design rule. The difference between the first linear design rule, using four points in each case, and the best-performing design rule in both validation error metrics above, is almost a 50% reduction (49.4% reduction for negative features and 48.5% reduction for positive).

5. Application Example

Using the proposed approach to characterize an AM system of interest can allow a designer to take more complete advantage of the space of manufacturable features possible. In addition, the design rules are expressed as a function which is differentiable and easy to incorporate into layout, sizing, or topology optimization problems. To demonstrate this capability of the proposed approach, a pre-existing model of the Seattle Space Needle is evaluated to determine the smallest scale at which the model can be manufactured without losing fine detail [32], and Fig. 14 contains several example images of this model. In total, several unique shapes were identified for evaluation as shown in Fig. 14, and for each feature type the design rule function is used to determine the minimum thickness of that feature. The minimum scale at which the model can be manufactured to preserve each feature is defined as the ratio between the minimum manufacturable thickness and the current model thickness.

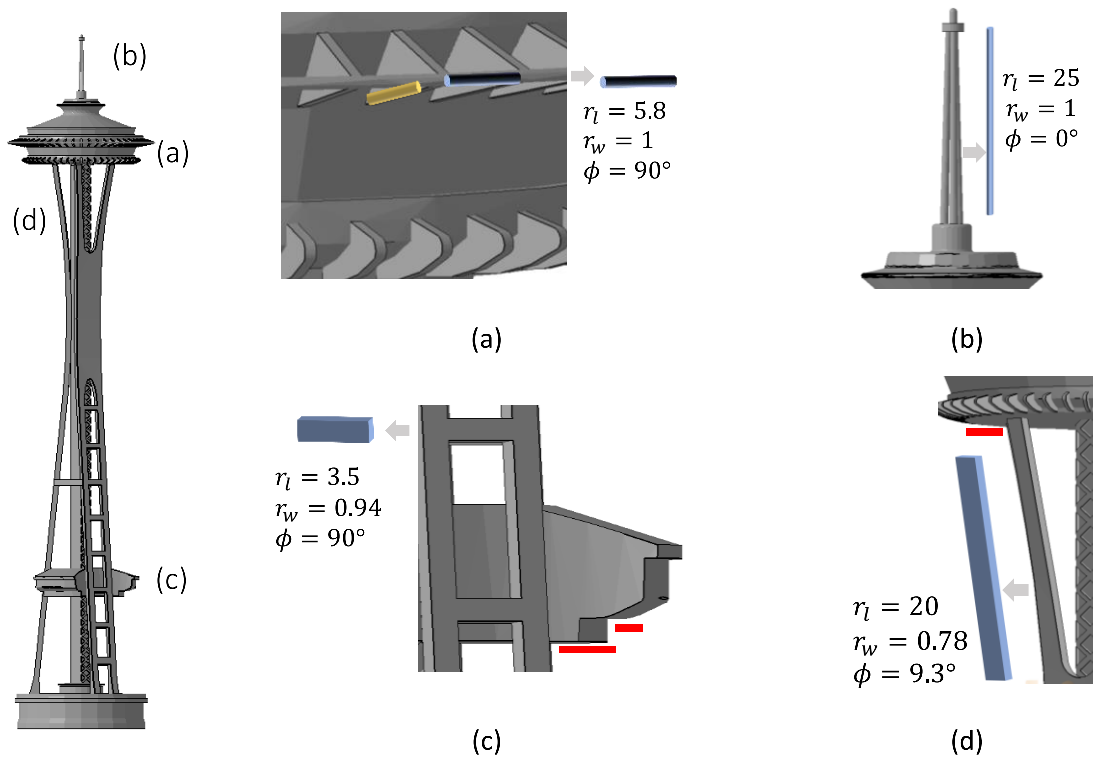
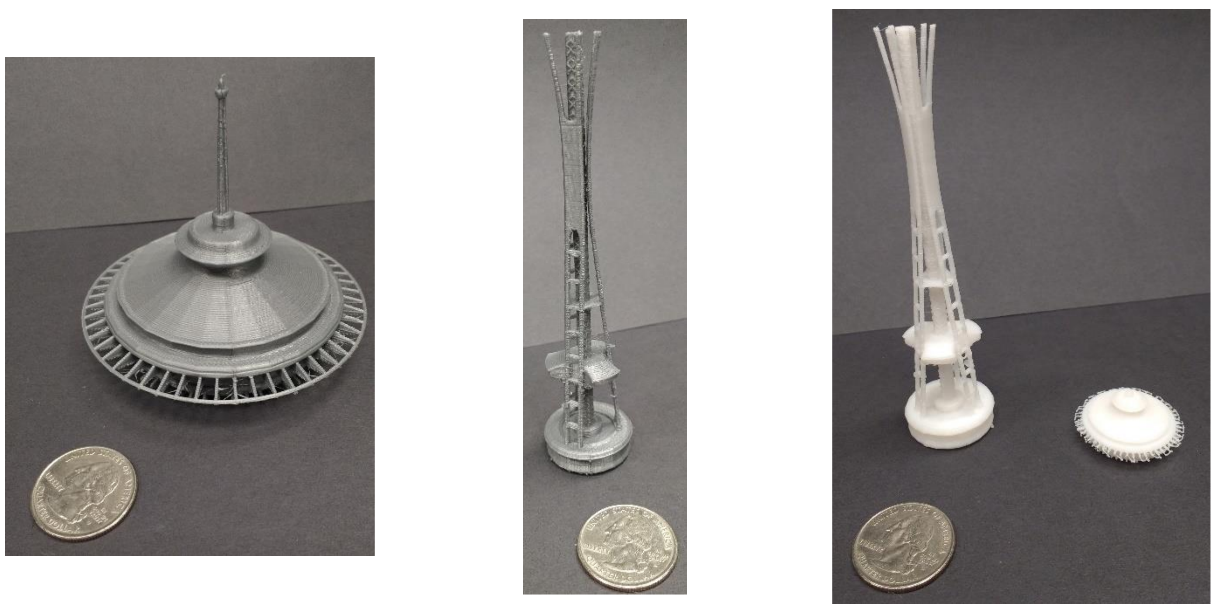


Figure 14: CAD model of an artist's interpretation of the Space Needle, with insets highlighting various features (see text for description). Model courtesy of Thingiverse user Jeepguy42 [32].

In fabricating the Space Needle model using a material extrusion printer, the overhanging features which are not bridging two bodies must be supported. In addition, the equivalent features for the supporting struts for the ring would require the entire model to be much larger than desired, so these struts are supported. In designing the support structures, the design rule function is again used to make sure that the support structures can be manufactured. Finally, because of the very large overhang just below the top of the model, the Space Needle design is cut in two pieces where the top connects to the supporting body, eliminating very long support structures.

As a result of the analysis, the smallest scale the Space Needle model can be manufactured at has a total height of 389 mm (61.4% of the original 634 mm) in this material extrusion process. The scale-limiting feature is the set of three thin antennas on the top of the model, once the overhanging thin fins are supported. The design rule function predicts that the thin ring feature could be manufactured as small as 38% scale, despite appearing to be the most delicate feature in the model. The fabricated top piece is shown Fig. 15.



(a) (b) (c)

Figure 15: Manufactured Space Needle Model (3D model courtesy of Thingiverse user Jeepguy42 [32]). (a) Top part at its minimum predicted scale. (b) Bottom part at its minimum predicted scale. (c) Entire Space Needle manufactured at the bottom part's minimum predicted scale (top of part was NOT predicted to succeed for this case).

The above discussion limits the scale of the entire model. As a further example of the sizing analysis, consider for a moment only the bottom portion of the Space Needle model. The bottom half of the model contains larger features, and applying the same assessment to its features using the appropriate design rules results in a minimum scale of 21.3% (total height of 135 mm). The bottom half was separately manufactured at this scale, and is shown in Fig. 15(b). Of course, if the top half were manufactured at this scale the antenna, ring and support features all fall below the design rule guidelines, and manufacturing fails (see Fig. 15(c)). As a result, for all features in the model to be fully resolved, the larger minimum scale dictated by the top portion of the model should be used.

On the other hand, consider if the design rules derived from the NIST test artifact were used instead (i.e. the smallest manufactured bar was 1.0 mm and smallest manufactured fin was 0.5 mm). In this case, the predicted scale for the top portion of the model would be 100% (634 mm tall), which while manufacturable is significantly larger than necessary. The bottom portion is predicted by the NIST design rule to be manufacturable at 12.7%, significantly less than the scale predicted by the approach presented here (which requires at least 21.3% scale). The part would likely have been manufactured at this smaller scale, only to have it fail and require trial-and-error additional iterations of guessing the scale and manufacturing, wasting time and resources.

6. Conclusions

This paper presented a systematic general approach for exploring the minimum producible size for additively manufactured features of different shapes and orientations, and that approach was applied to a case study experiment focused on an AM machine from the material extrusion process category. The approach presented falls in between two types of feature size assessment approaches seen in the literature: Results are more precise than (1) many studies which include only 2-4 small feature types at 3-6 different scales, yet less thorough than (2) exhaustive studies in which dozens of features of different shapes are manufactured at dozens of scales to produce bitmap-style “pass/fail” design rule tables. Instead of providing design guidelines suitable for use by other researchers, the outcome of this work is a general process by which others can characterize their specific additive manufacturing machines, and thereby develop their own appropriate design rules.

Feature shape and orientation were found to have a strong impact on the minimum feature size for the material extrusion example process, with minimum feature thickness varying by as much as an order of magnitude over the surveyed set of features. In order to capture statistical variation, a single feature shape in a particular orientation must be manufactured many times at various scales before results are reliable. This study, which models the failure of small features using a logistic function, estimates that at least 36 copies of each oriented shape at various scales should be manufactured for the material extrusion example process, 3-8 times the number of samples done in most other studies. By spreading these copies out over several manufacturing runs, an adaptive update scheme is able to adjust the range of feature sizes to maximize useful information gain, which both reduces the total number of copies manufactured and captures run-to-run variability of the process, while also reducing the dependence of the results on the range of features originally selected by the test artifact designer.

The design rules developed are functions of a parameter space of small features and enable more granular predictions of the minimum feature size for specific shapes and orientations of small features. By providing more precise (and therefore less conservative) data-driven estimates of minimum feature size, some features with specific shapes can be manufactured as much as 60 % smaller than design rules derived from the NIST test artifact suggest (some features have design rules as low as 0.180 mm, compared to the NIST minimum manufacturable fin thickness of 0.5 mm). In addition, design for additive manufacturing best practices include an overhang angle constraint to prevent manufacturing difficulties when supports are not used. For cylindrical features, sufficient data was collected to entirely remove the overhang angle constraint, as overhanging features which are more difficult to produce have a correspondingly larger minimum feature size, without penalizing shorter features which can be manufactured at any angle. The presented parametric design rules for minimum feature size and overhang angle can improve design performance and process utilization over existing approaches from the literature, as demonstrated by the provide AM design example.

7. Acknowledgments

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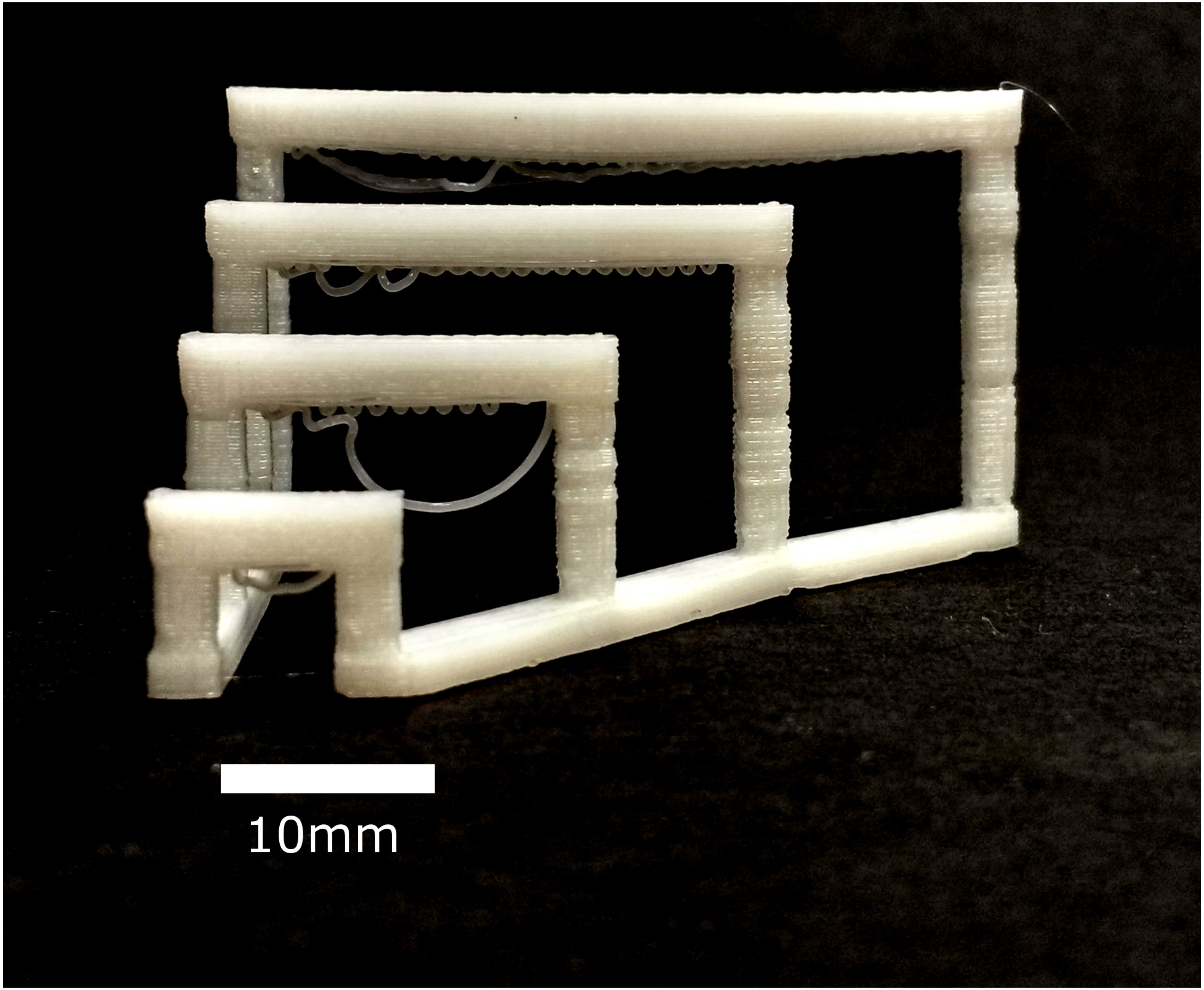
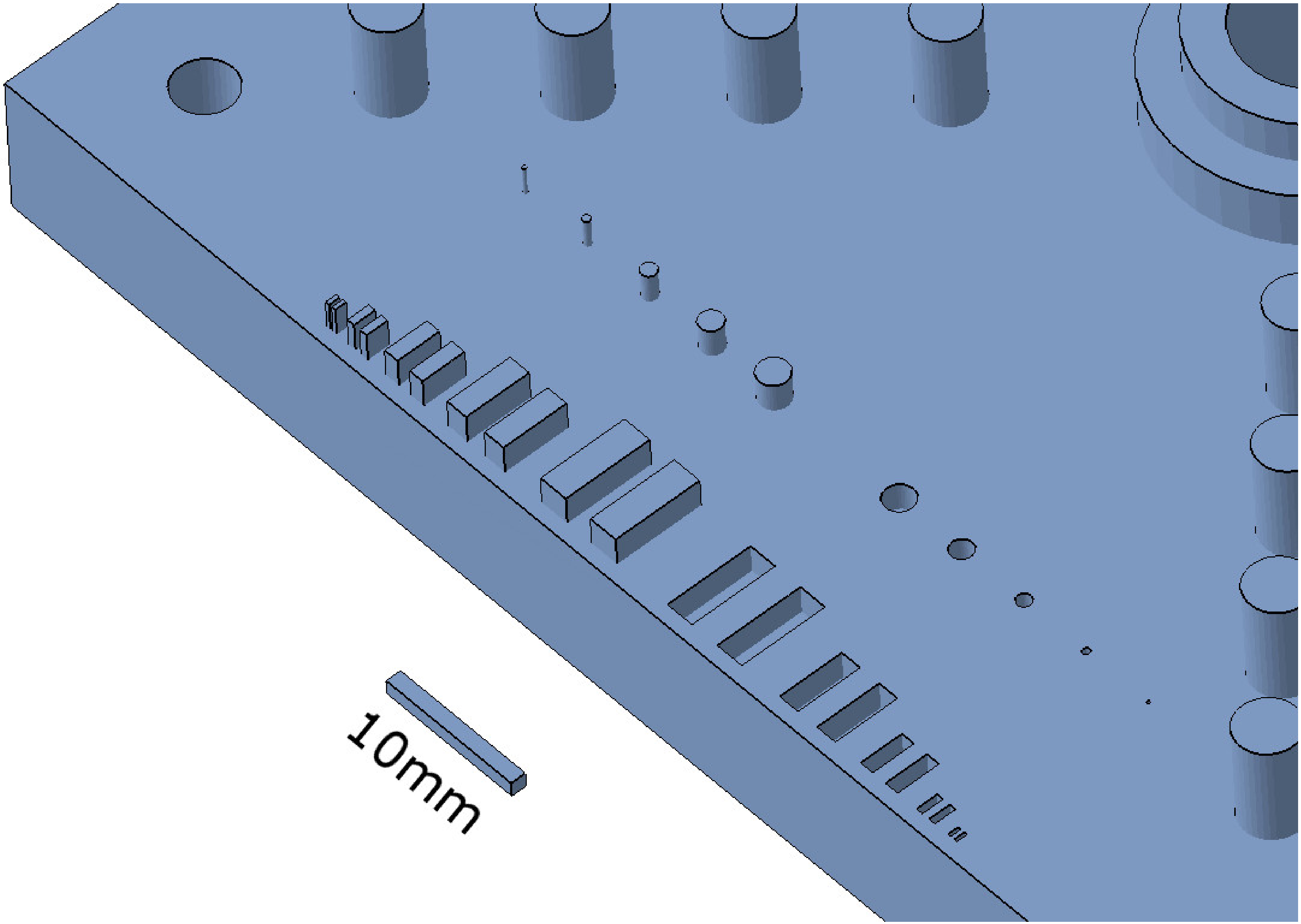
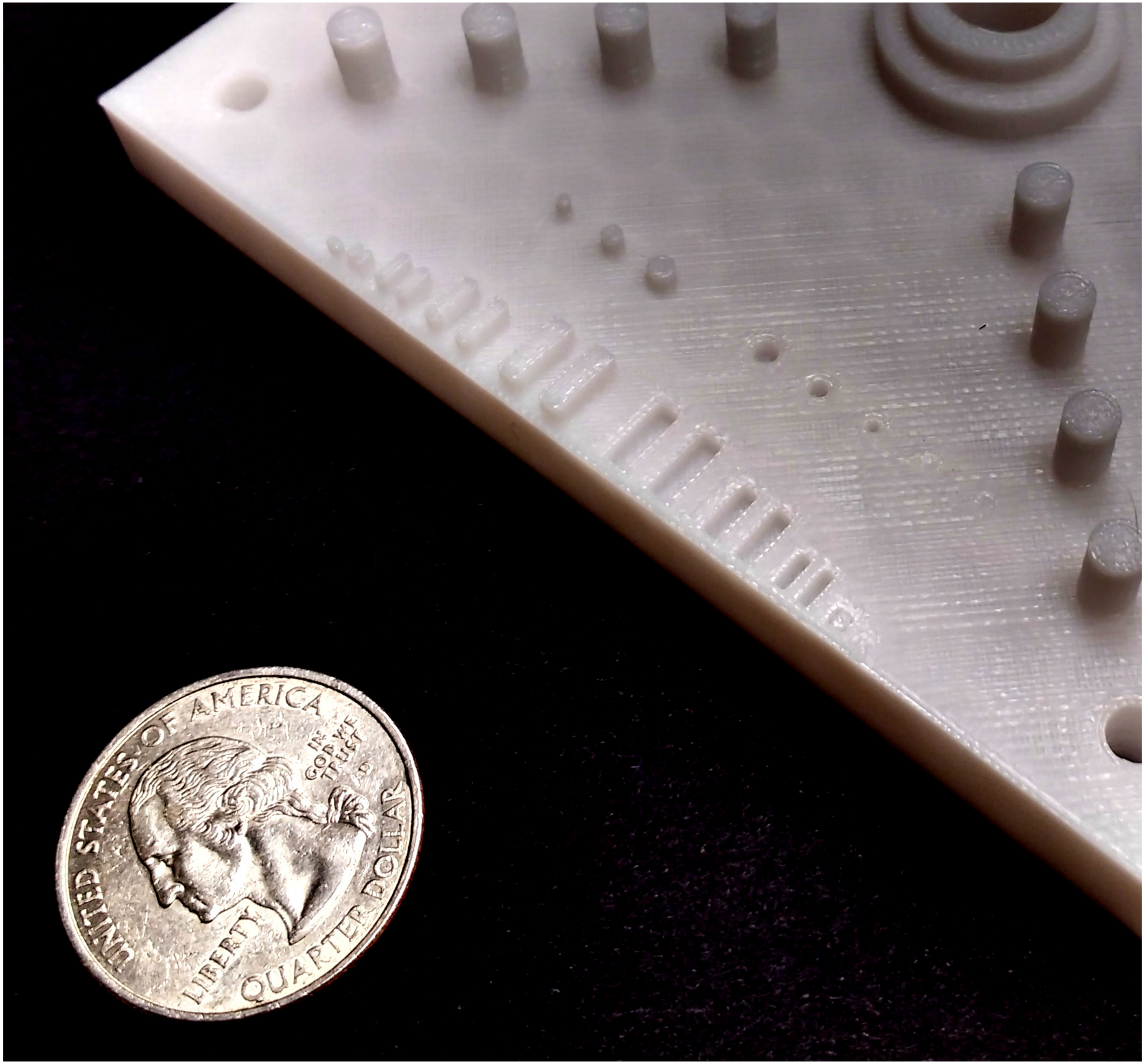

10mm


10mm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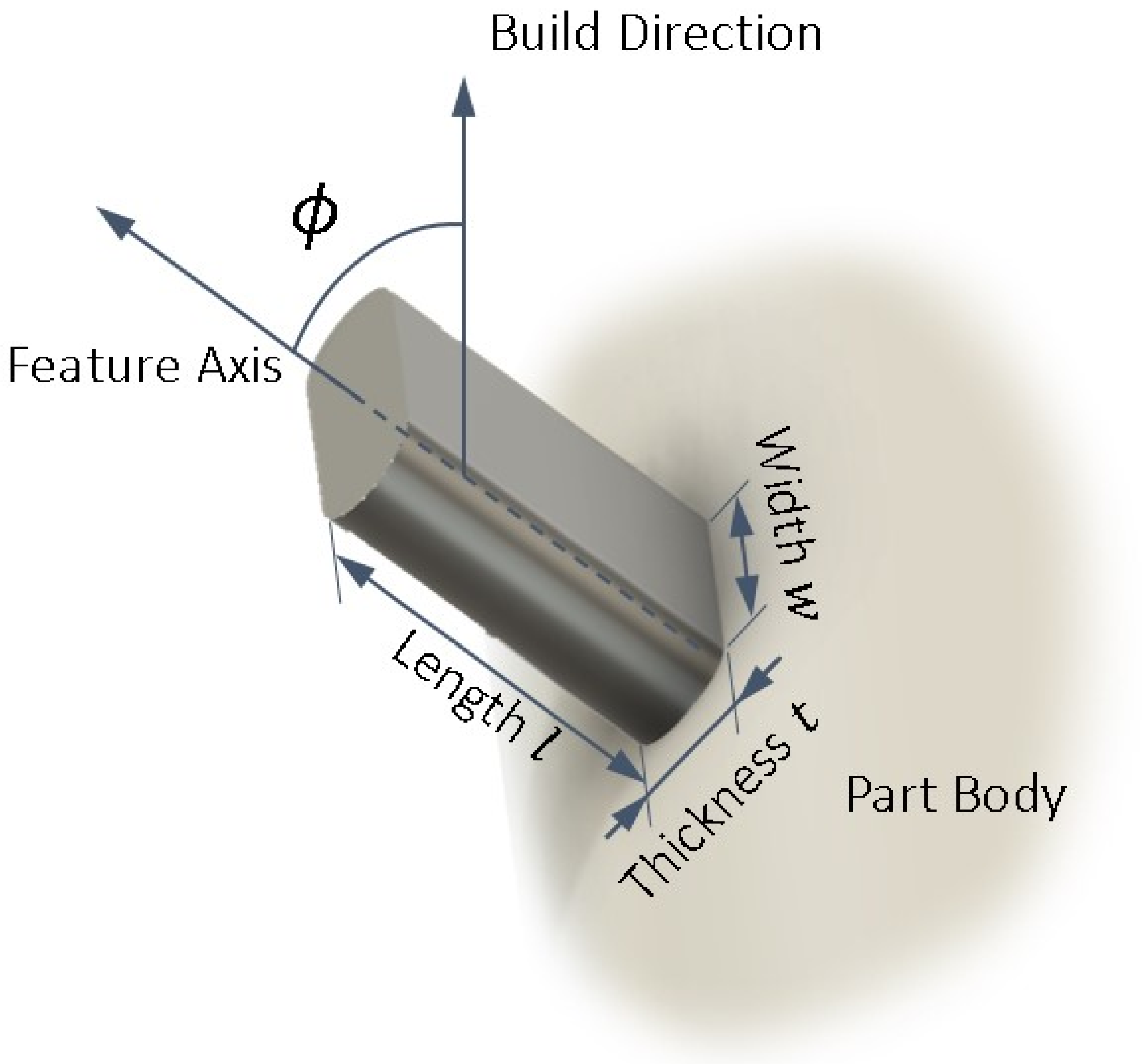
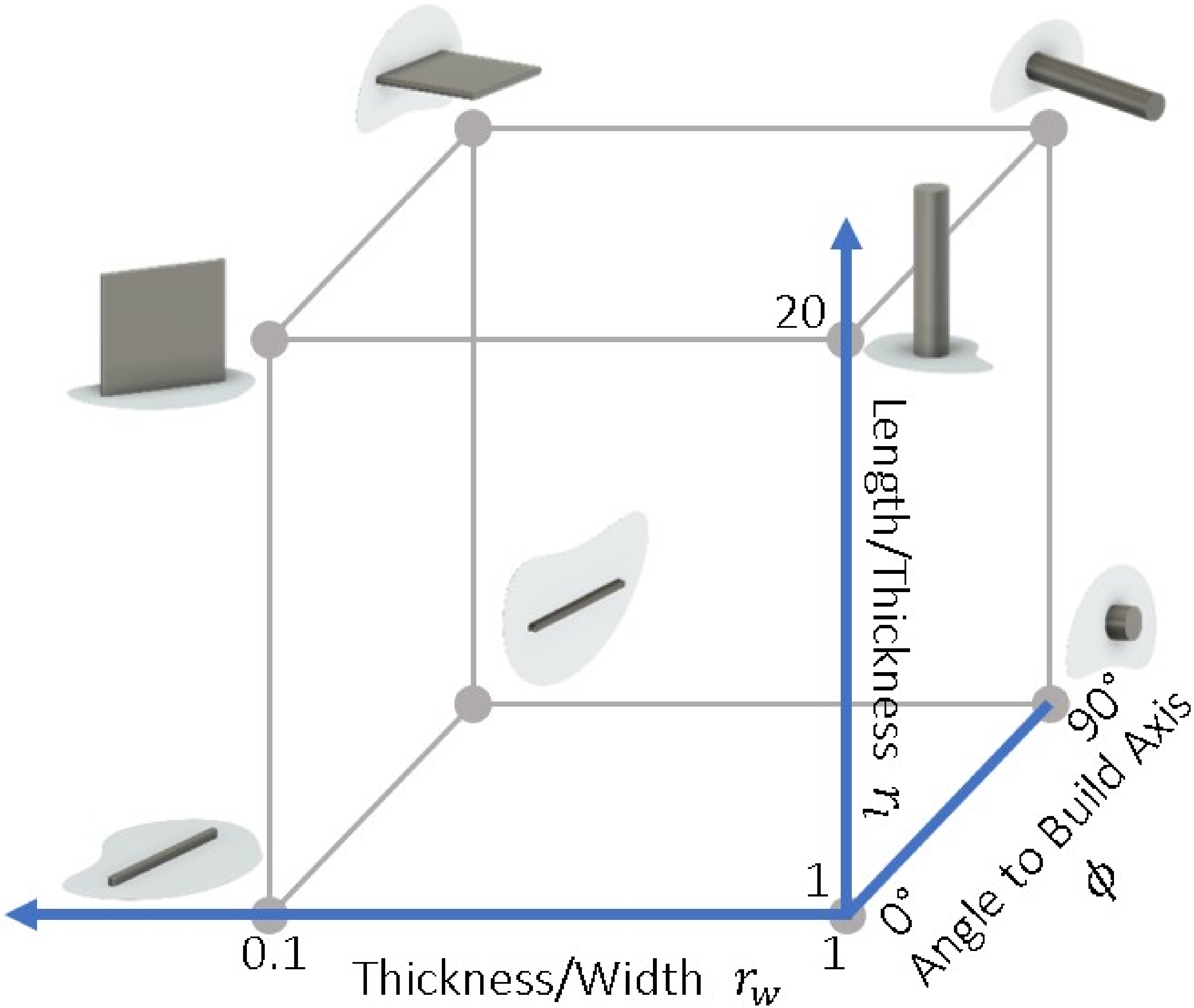
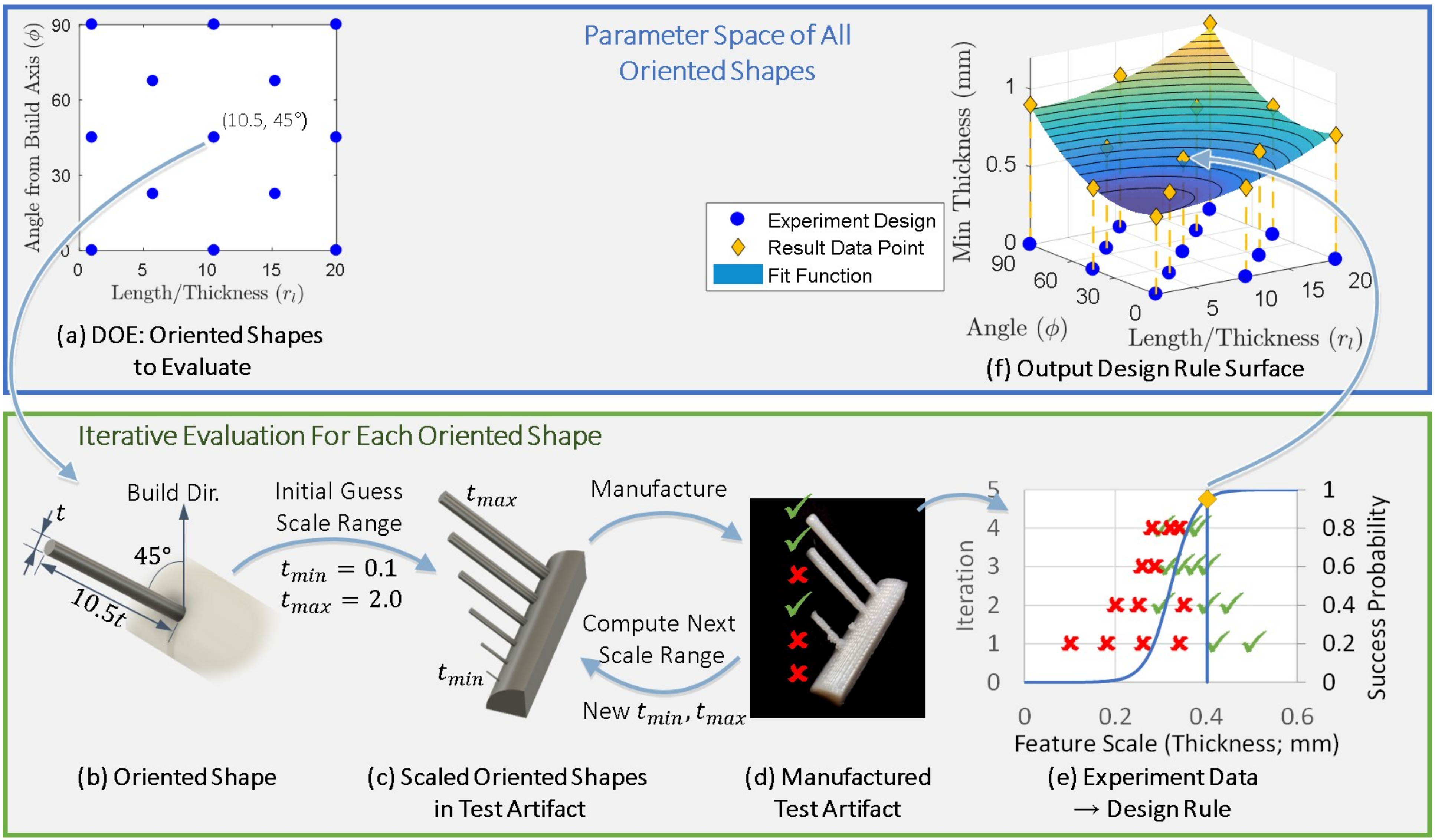
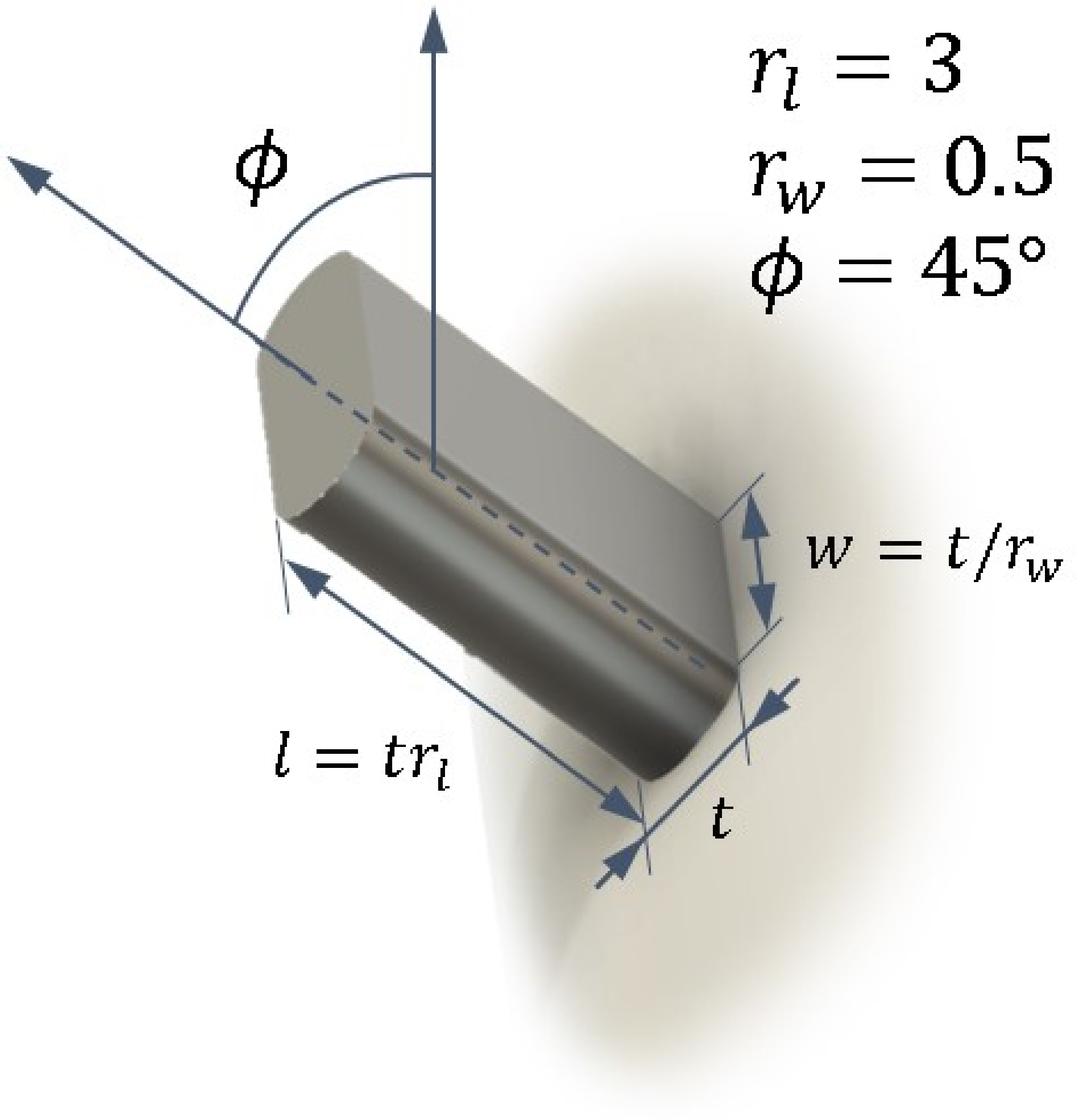

Build Direction
ϕ
Feature Axis
Width w
Length l
Thickness t
Part Body

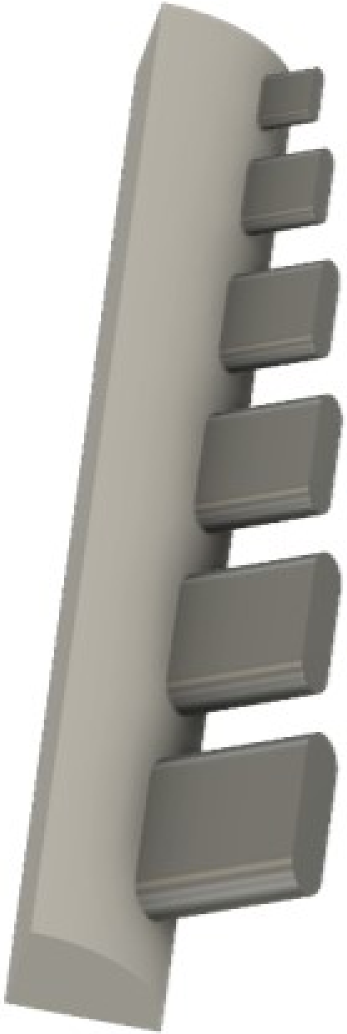

20
Length/Thickness r_l
1
90°
0°
Angle to Build Axis ϕ
0.1
1
Thickness/Width r_w



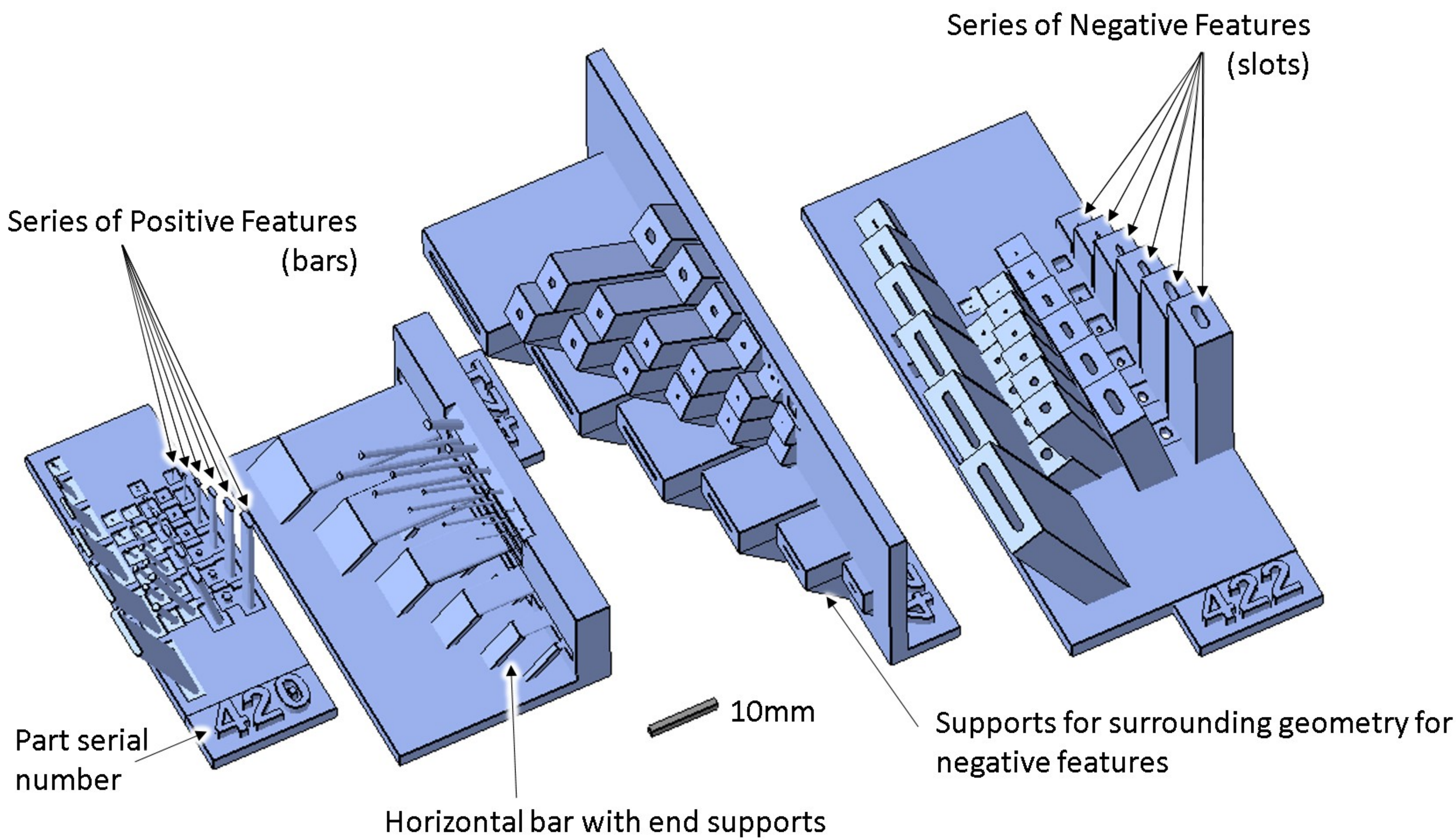
Parameter Space of All Oriented Shapes
Angle from Build Axis (ϕ)
Length/Thickness (r_l)
(10.5, 45°)
(a) DOE: Oriented Shapes to Evaluate
Experiment Design
Result Data Point
Fit Function
Min Thickness (mm)
Angle (ϕ)
(f) Output Design Rule Surface
Iterative Evaluation For Each Oriented Shape
Build Dir.
45°
t
$10.5t$
Initial Guess Scale Range
$t_{min} = 0.1$
$t_{max} = 2.0$
t_{max}
t_{min}
Manufacture
Compute Next Scale Range
New t_{min}, t_{max}
Iteration
Success Probability
Feature Scale (Thickness; mm)
(b) Oriented Shape
(c) Scaled Oriented Shapes in Test Artifact
(d) Manufactured Test Artifact
(e) Experiment Data → Design Rule

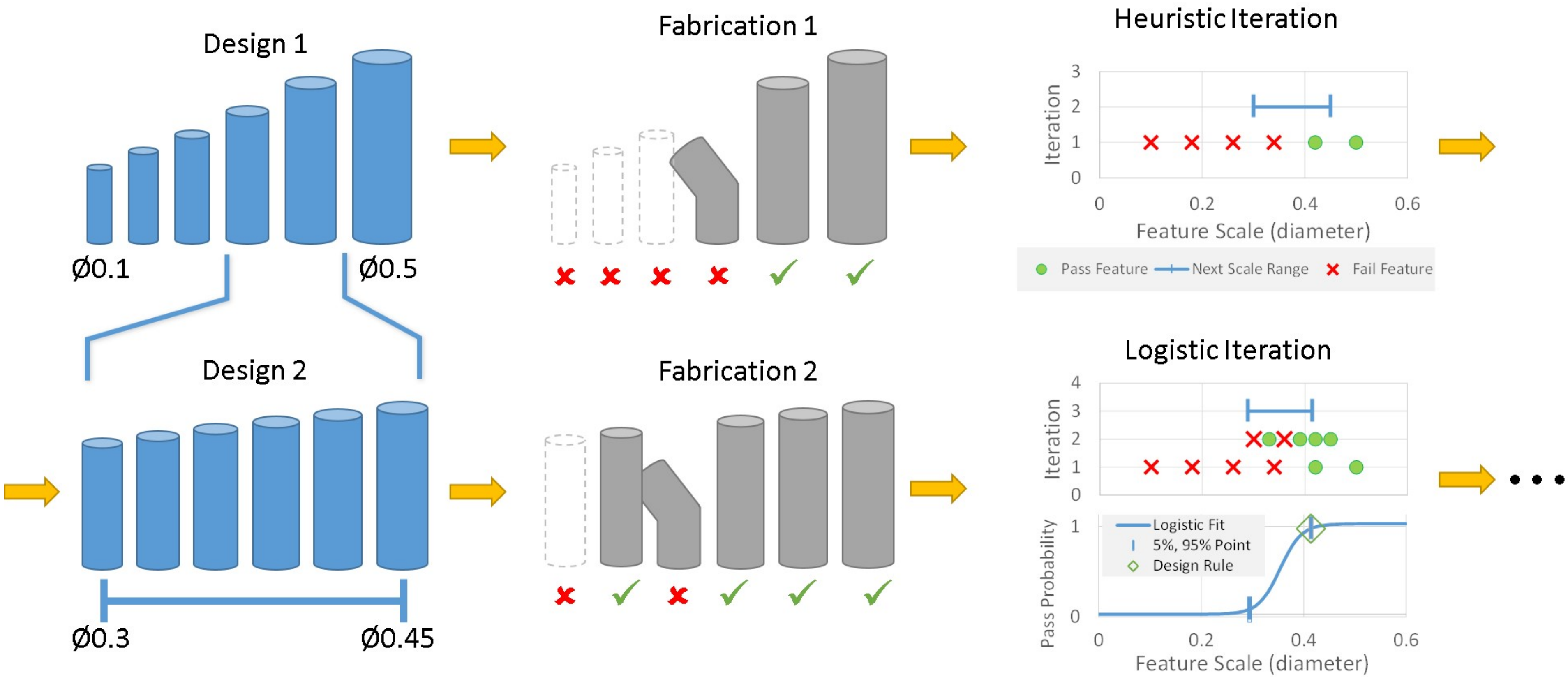


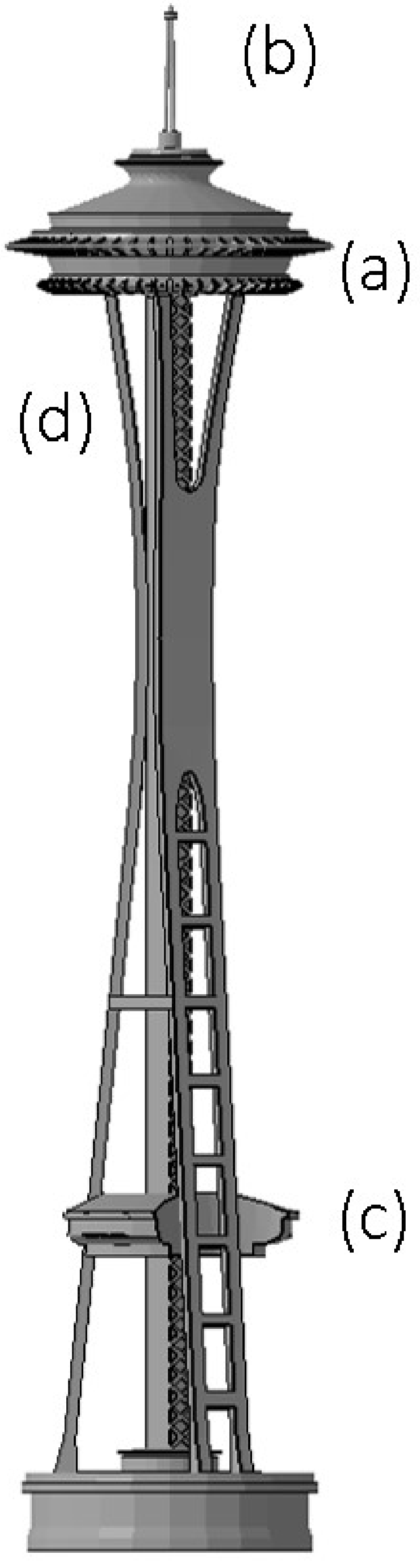
$r_l = 3$
$r_w = 0.5$
$\phi = 45°$
ϕ
$w = t/r_w$
$l = tr_l$
t

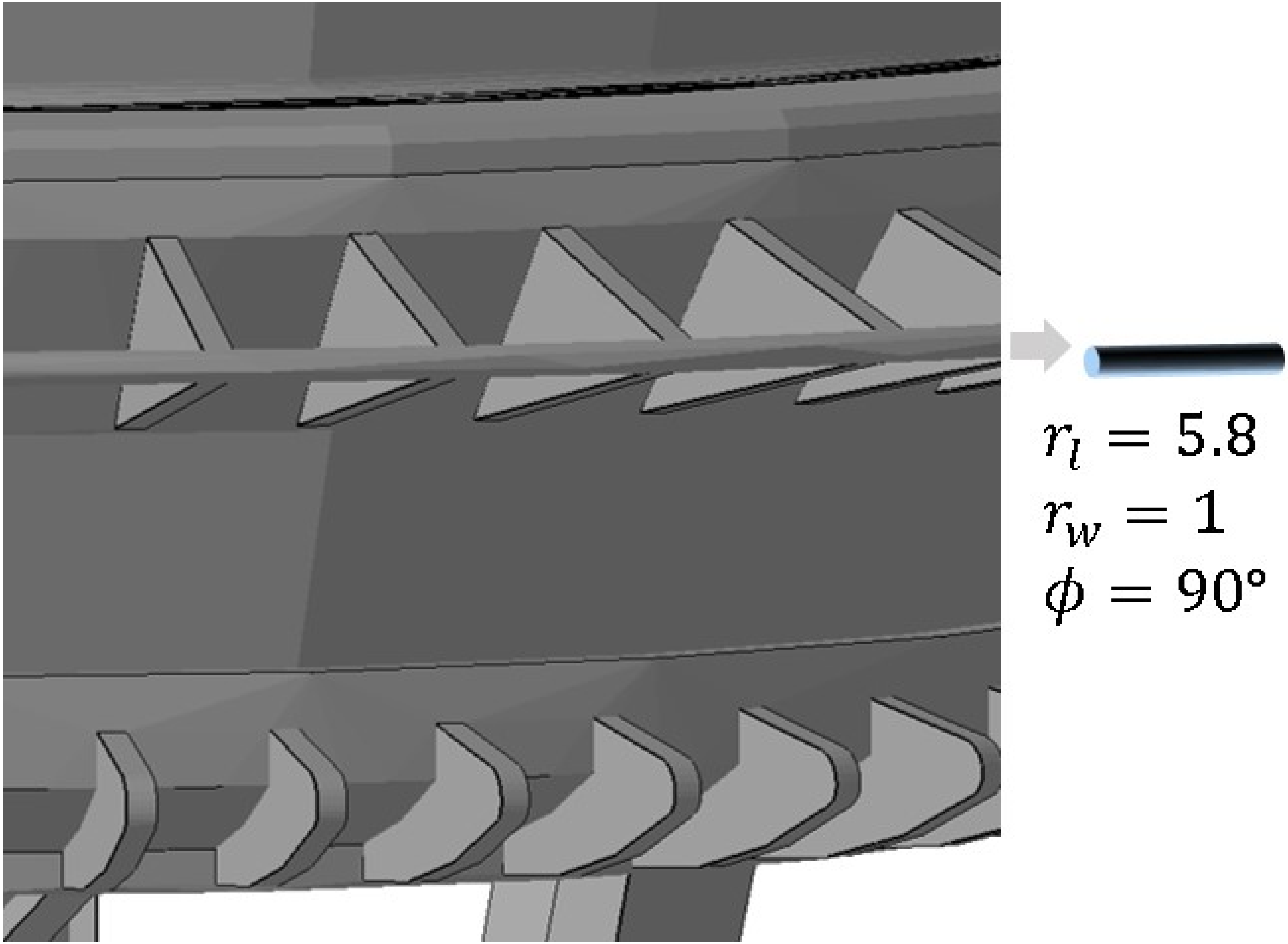


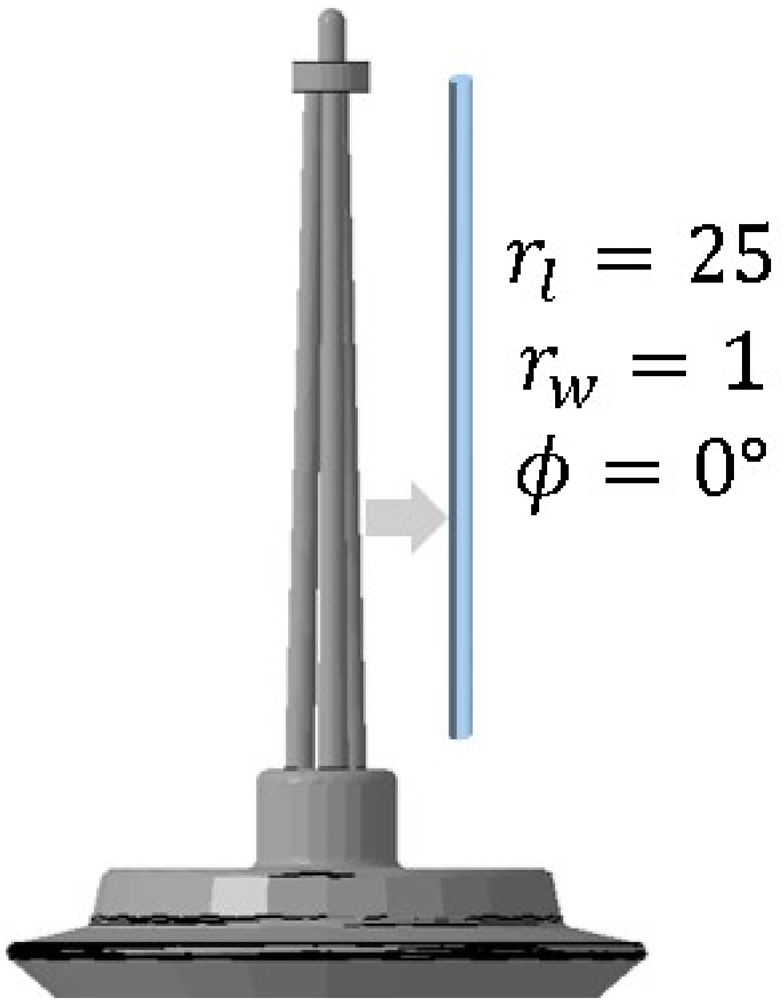
t (mm)	w (mm)	l (mm)
1	2	3
1.4	2.8	4.2
1.8	3.6	5.4
2.2	4.4	6.6
2.6	5.2	7.8
3	6	9


Series of Negative Features
(slots)
Series of Positive Features
(bars)
420
422
Part serial
number
10mm
Supports for surrounding geometry for
negative features
Horizontal bar with end supports

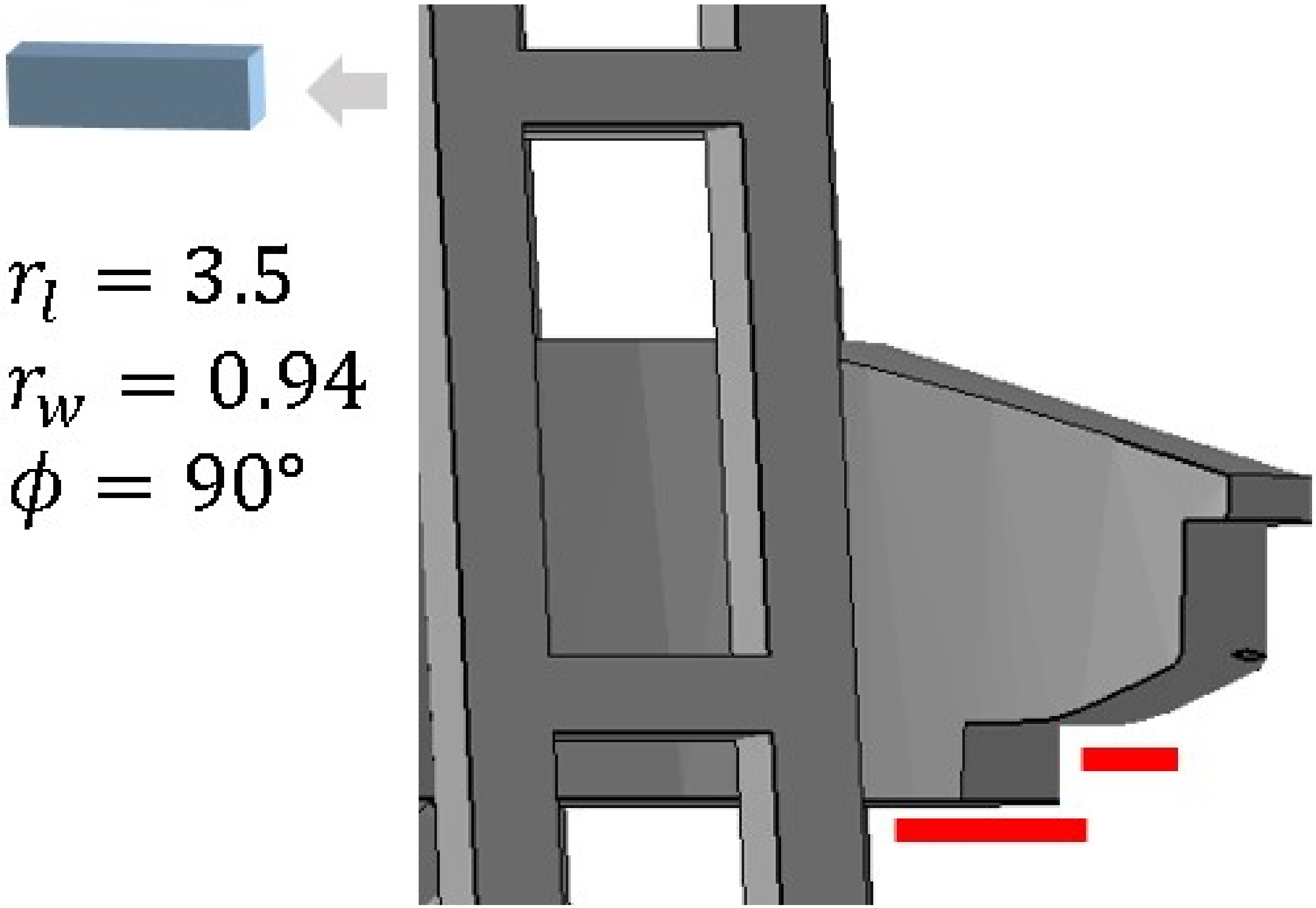

Design 1
Ø0.1
Ø0.5
Fabrication 1
Heuristic Iteration
Iteration
Feature Scale (diameter)
Pass Feature
Next Scale Range
Fail Feature
Design 2
Ø0.3
Ø0.45
Fabrication 2
Logistic Iteration
Pass Probability
Logistic Fit
5%, 95% Point
Design Rule


(b)
(a)
(d)
(c)

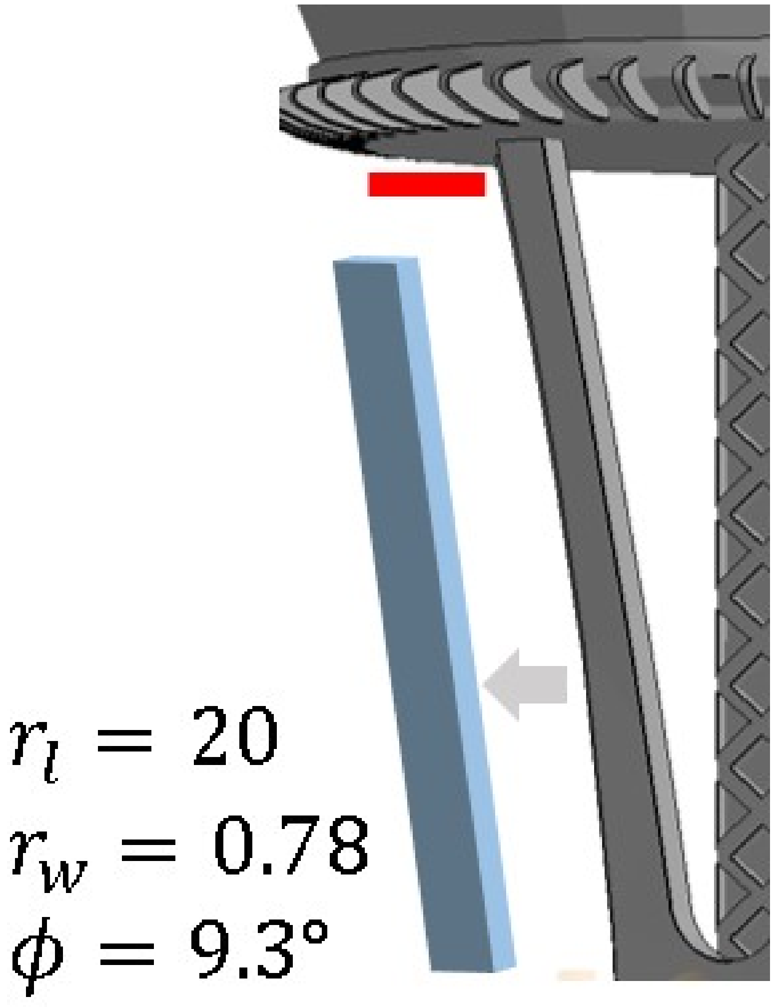

$r_l = 5.8$
$r_w = 1$
$\phi = 90°$

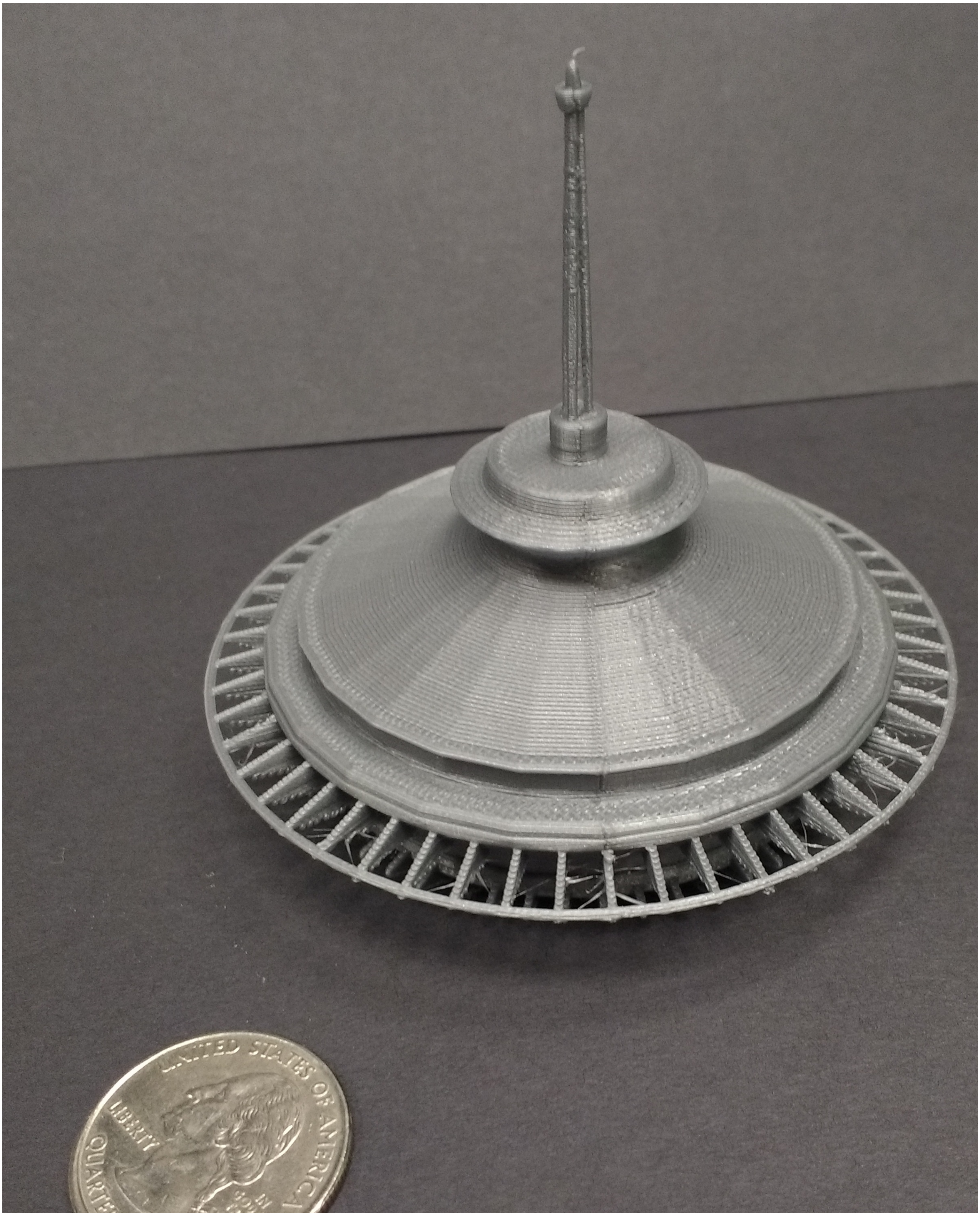


$r_l = 25$
$r_w = 1$
$\phi = 0°$



$r_l = 3.5$
$r_w = 0.94$
$\phi = 90°$


$r_l = 20$
$r_w = 0.78$
$\phi = 9.3°$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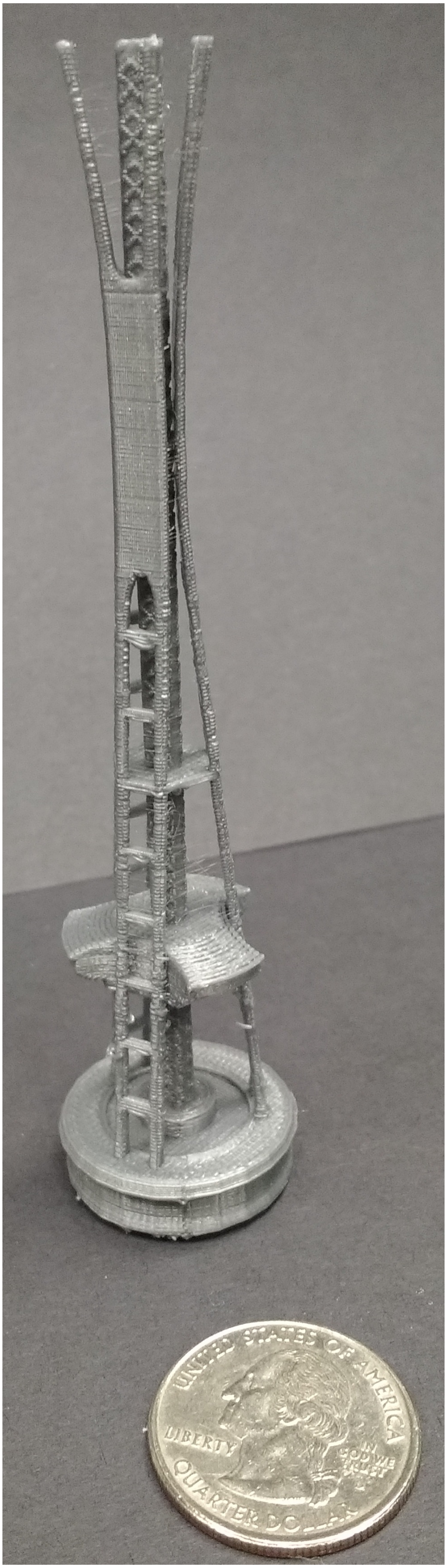
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