SAND20XX-XXXXR

LDRD PROJECT NUMBER: 184022

LDRD PROJECT TITLE: Solving the Big Data (BD) Problem in Advanced Manufacturing (Subcategory for work done at Georgia Tech: Study Process and Design Factors for Additive Manufacturing Improvement)

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ABSTRACT

3D printing originally known as additive manufacturing is a process of making 3 dimensional solid objects from a CAD file. This ground breaking technology is widely used for industrial and biomedical purposes such as building objects, tools, body parts and cosmetics. An important benefit of 3D printing is the cost reduction and manufacturing flexibility; complex parts are built at the fraction of the price. However, layer by layer printing of complex shapes adds error due to the surface roughness. Any such error results in poor quality products with inaccurate dimensions. The main purpose of this research is to measure the amount of printing errors for parts with different geometric shapes and to analyze them for finding optimal printing settings to minimize the error. We use a Design of Experiments framework, and focus on studying parts with cone and ellipsoid shapes. We found that the orientation and the shape of geometric shapes have significant effect on the printing error. From our analysis, we also determined the optimal orientation that gives the least printing error.

INTRODUCTION

3D printing is a type of Rapid Prototyping (RP), developed during the last couple of decades and used extensively in industries. 3D printing is a process of building prototypes in slices using a layered approach, hence, also known as additive manufacturing. A 3D printer uses a three dimensional object design, like CAD, for printing. 3D printing enables prototyping structures with complex and intricate details. It significantly reduces the time taken for prototyping and, in turn, testing, when compared to earlier methods, like, machining, casting, clay making, etc. Moreover, it also reduces manufacturing costs by eliminating the need of specialized tooling or dies to manufacture prototype parts. Thus, the time and cost benefits of 3D printing has made it popular among industries for prototyping. It is also drawing attention for mass scale production in recent years.

Due to its benefits, 3D printing has found wide application in several areas. For example, in medicine, additive manufacturing can be used for biomaterials tests for regenerative medicine, building replacement organ with patient's own cell. There is also several other ongoing research on producing drugs with this technology. Other important application areas include manufacturing, structural analysis in industrial projects, and also sculptures building.

In conjunction to it benefits, 3D printing has a critical existing problem of printing error due to surface roughness caused by the layer-by-layer printing approach. As we can see in Figure 1, the cross-section of a printed object has inherent roughness. Such roughness may have severe effects in sophisticated applications, like human body part printing for surgical replacement. Thus, even minor printing error may have catastrophic consequences. Due to the nascent stage of this technology, not many studies have been done on error analysis of 3D printing. In this research, we perform experiments and study the errors in a 3D printing process.

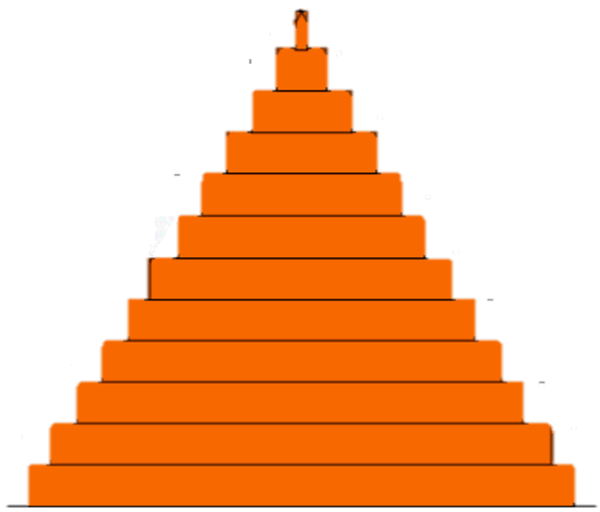


Figure 1 Surface roughness (error) due to layer by layer printing

A 3D printing process involves design and process parameters. Process parameters refer to control factors, for example printing orientation, layer width, supports, washing material, etc. Orientation is the direction with respect to the part in which the printing layers are built in the machine. Layer width is the width of each printed layer, which can be fixed or adaptive in advanced machines. A support material is also created if the object cannot stay in rest, either due to its shape or the printing orientation. Washing material is used post printing to remove remnants of foreign matter, like support material, on the printed part. Each of these parameters can have certain impact on the resulting error in the printed part. In this research, we focus on studying the effect of shape and orientation.

A typical process of any 3D printer is to create a stereolithography (STL) file from the CAD (Computer Aided Design) model of a part of the complete prototype and feed it into the machine's computer. The orientation for printing is either fixed manually or automatically by the machine. Finally a layer thickness is fixed, following which, the part is printed layer by layer in the desired orientation. Post printing, the part is washed and cured. Printing error can be computed as the average of absolute deviations of the surface from the CAD model found from a 3D laser scanner.

In this research, we develop experiment design using Design of Experiments (DOE) concepts for studying the effect of shape and orientation parameters on the induced error. For the shape parameter, we use*cone*

and *ellipsoid* with different dimensions, printed at different *angles* as the orientation parameter. We also aim to recommend the angle and orientation minimizing the errors. This research can help improve the quality of additively manufactured parts, which in turn will facilitate the scale-up of the additive manufacturing. Moreover, reducing the error of 3D Printing machines will reduce cost by eliminating wastes and rework caused by poor printing.

In the following section, we explain the experimentation in detail. Thereafter, we show our results, and discuss it. Finally, we recommend optimal parameters for minimal errors, and conclude in the last section.

DETAILED DESCRIPTION OF EXPERIMENT/METHOD

In this research, we use full factorial design for the experimentation. A factorial design is a common experimentation method in which effect of two or more factors on a desired response is analyzed. Each factor takes different discrete possible values or "levels". A full factorial design tests all combinations of the different levels of each factor. For example, an experiment with two factors, each having three levels, will have 3×3 combinations to be tested. A full factorial design allows us to study the main effect of each factor and the interaction effects between them.

As explained in previous section, we analyze printing error in *cones* and *ellipsoids*. We study them separately in two different experimentations. For both experiments, we set four levels of the *orientation* parameter at 0°, 30°, 60° and 90°. Within each experiment, different shape parameters levels were set, viz. cones *angle* at three levels (30°, 60° and 90°) and ellipsoid axes were (2,2), (1,3) and (3,1), denoted as *perimeter* in rest of the report. The different parameter levels are shown pictorially in Figure2-5.

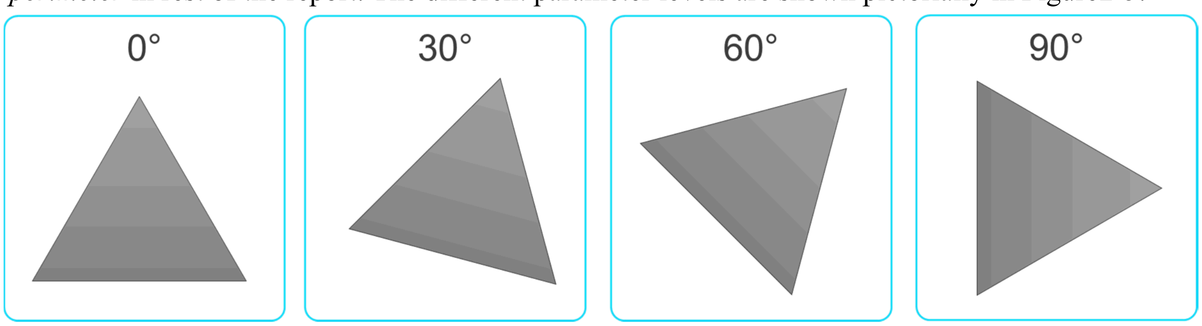


Figure 2 Orientations levels for cone

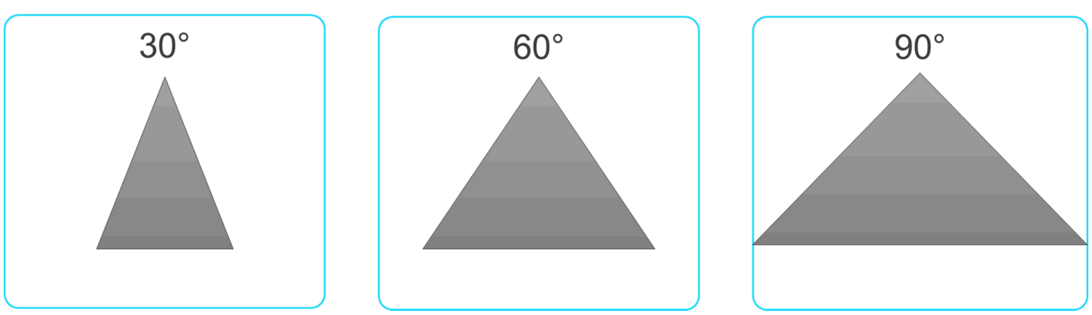


Figure 3 Angle levels for cone

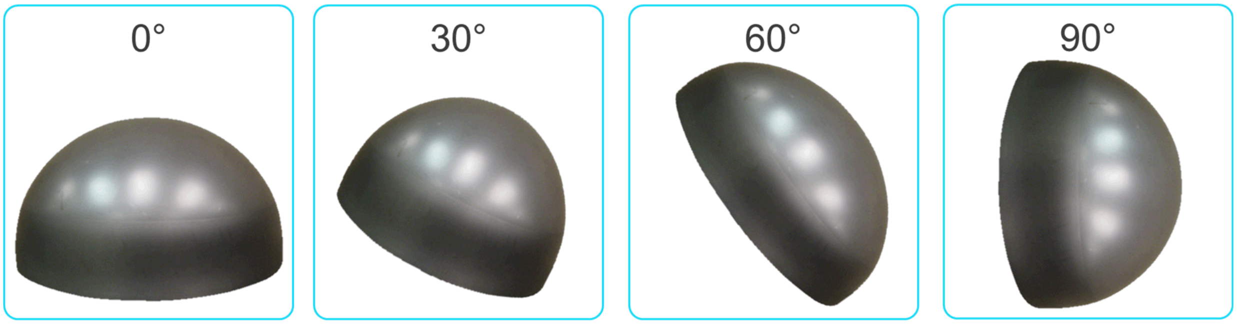


Figure 4 Orientation levels for ellipsoid

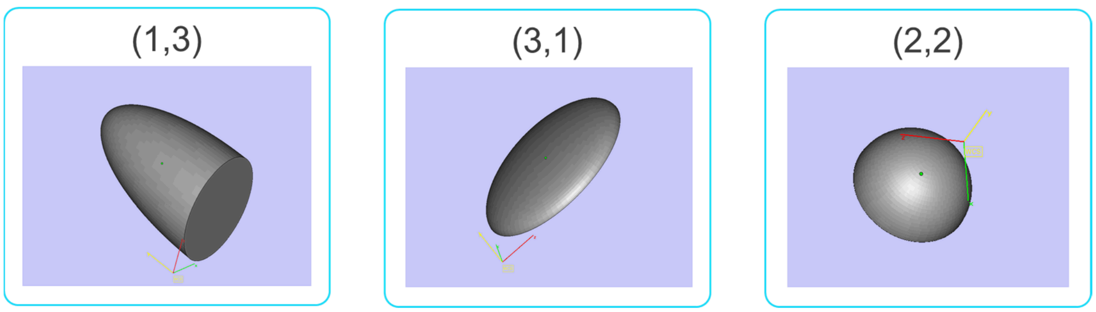


Figure 5 Perimeter (axes) levels for ellipsoid

Since there are three and four levels for the each parameter, we get 12 combinations for the full factorial experiment design. The experiment is replicated twice, resulting into 24 experimentation for each part type, *cones* and *ellipsoids*. The replication is termed as block to verify any blocking effect of time of experimentation. Figure 6 shows the full factorial experiment design for cones. The factorial design for ellipsoids can be derived similarly by replacing the *angle* column with *perimeter*.

	Blocks	Angle	Orientation
1	1	30	0
2	1	30	30
3	1	30	60
4	1	30	90
5	1	60	0
6	1	60	30
7	1	60	60
8	1	60	90
9	1	90	0
10	1	90	30
11	1	90	60
12	1	90	90
13	2	30	0
14	2	30	30
15	2	30	60
16	2	30	90
17	2	60	0
18	2	60	30
19	2	60	60
20	2	60	90
21	2	90	0
22	2	90	30
23	2	90	60
24	2	90	90

Figure 6: Different combinations with the factors and levels for cones

Following the setup of experiment design, parts are printed for each experiment scenario. As explained in the previous section, CAD model is developed for each setup and fed in the machine. The printing orientation is set as per the experiment. Post printing, the part is taken out and washed using water jet to remove any support material. To minimize the effect of noise factors, the order of printing is randomized. However, in batch processing, it was found that the addictive manufacturing machine does its own order which facilitated our work.

After the part is printed, we use Coordinate Measurement Machine (CMM) to measure the error between the original design's CAD and the printed parts. The CMM machine scans and aligns the printed part with CAD using Polyworks software. Examples of deviation maps from Polyworks are shown in Figures 7 and 8. The average mean of absolute deviations is used as a measure of net error for each part. Following the above procedure, we find printing error for the experiment setups for cones and ellipsoids. In next section, we will show the results derived from our observations.

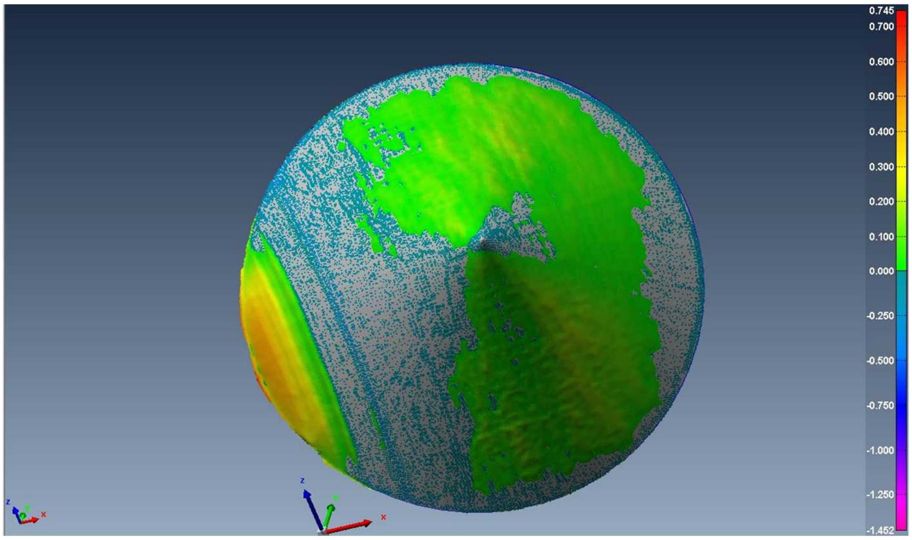


Figure 7: Deviation error map for cone

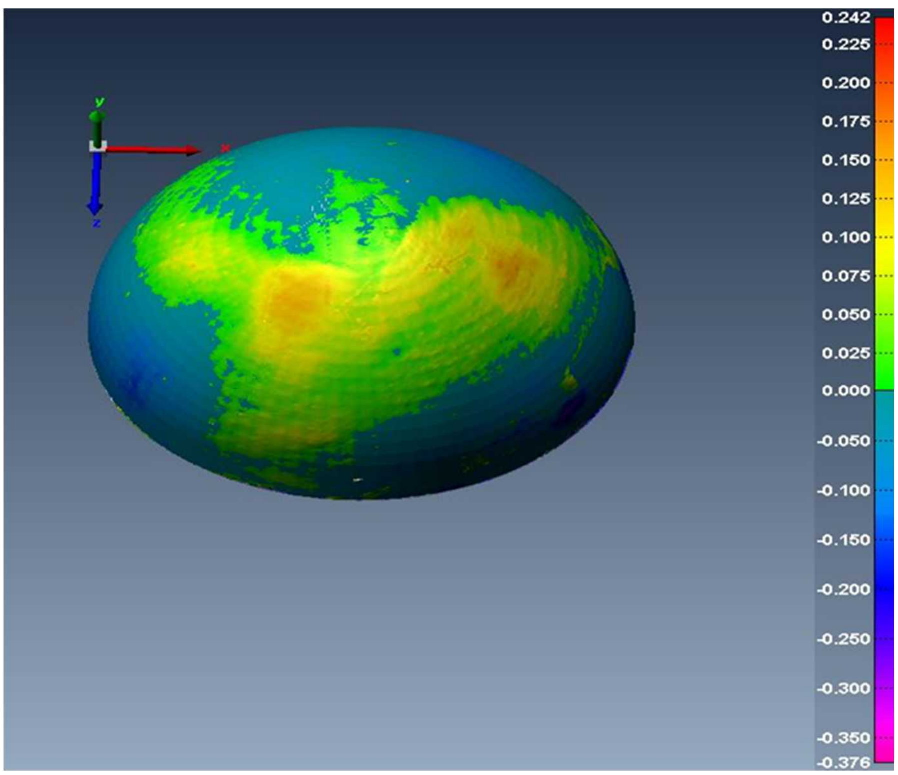


Figure 8: Deviation error map for ellipsoid

RESULTS and DISCUSSION

In this section, we show the results from our study on effect of parameters on printing error. For the analysis we established the hypothesis as following:

H0: The effects of parameters are statistically not significant

H1: The effects are statistically significant

- *Confidence Interval of 95%*
- *α= 0.05*

The results of our experimentation on *cones* and *ellipsoids* are given below.

- ***Printed Cones***

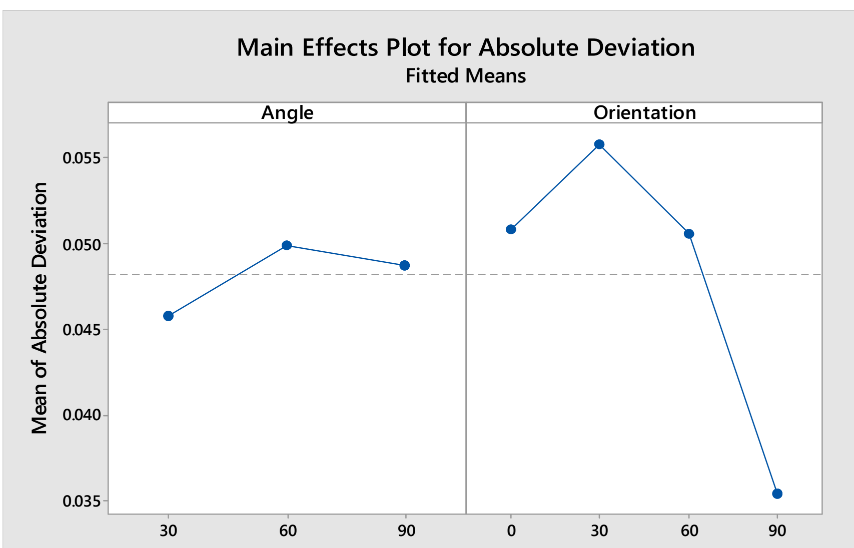
Table 1, given below, shows the ANOVA of the parameter effects on the mean absolute error (MAE). The blocking effect is not significant. This is an important result, indicating that the time of printing has no effect on the error. Therefore, we can infer that there is no systemic error in the printing machine.

We also see no significant effect of angle of cone. Graph 1, showing the fixed effects, also indicates small effect of angle on MAE. However, we should note significant effect of interaction between the angle and orientation (see Graph 2 for visual interpretation). This implies that the error effected by different combinations of angle and orientation. For example, MAE decrease and then increase for increasing cone angle when orientation is 60 degree, while it is the vice-versa for orientation of 30 degrees, hence indicating a significant interaction.

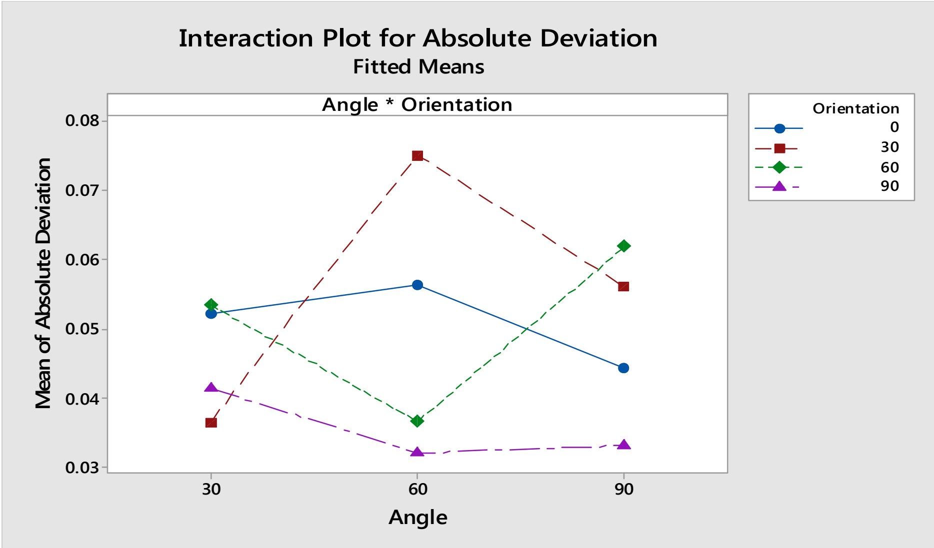
The parameter orientation has a significant main effect on MAE. Also indicated from Graph 1, there is a significant decreasing effect of orientation on MAE. Thus, we have significant effect of orientation and the interaction between the orientation and angle on cones' MAE.

Factor	P-Value	Conclusion
Batch (Blocks)	0.949	Not Significant
Angle	0.683	Not Significant
Orientation	0.019	Significant
Angle*Orientation	0.019	Significant

Table 1: Result from Analysis 1



Graph 1: Main Effects Plot for Absolute Deviation with 2 factors



Graph 2: Interaction Plot for Absolute Deviation with 2 factors

Moreover, we use the interaction plot (Graph 2) to find the robust setting for minimal MAE. From the plot we can observe that orientation of 90° is the most robust solution, i.e., the MAE is least for all levels of angle at this orientation. This result is important because, in practice, we are given with a design parameter (angle) which cannot be changed, however, we can set the process parameter (orientation) to get minimal error.

In addition to the above analysis, we used the same data to add another parameter – cone height – for error analysis. As shown in Figure 9, we divide a cone into three with equidistant parallel planes. In the previous analysis the cone height was 2 cm, which is, this, divided into three virtual cones of height ¼ cm, 1 cm and 2 cm.

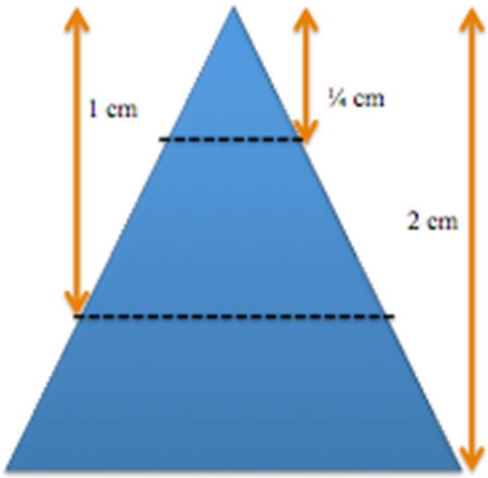


Figure 9: New Factor the Height

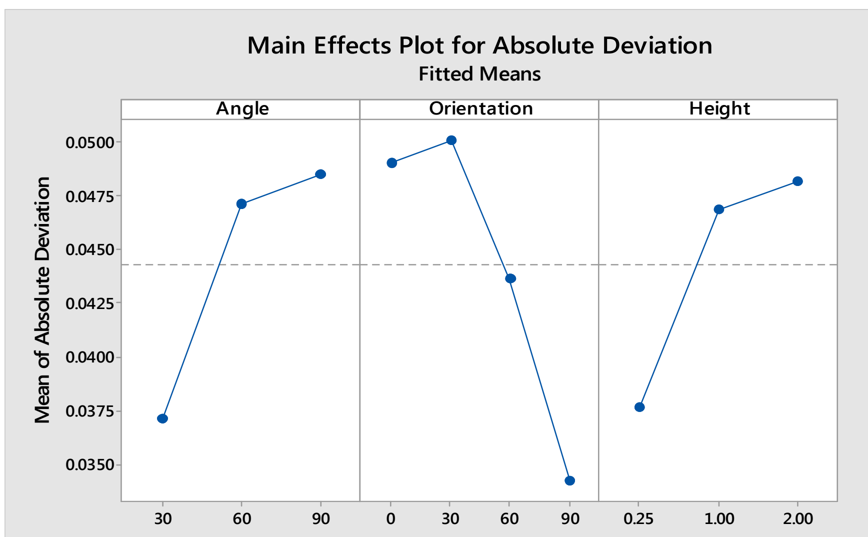
Table 2 shows the ANOVA on the augmented parameter data.

Factor	P-Value	Conclusion
Batch (Blocks)	0.482	Not Significant
Angle*Height	0.327	Not Significant
Orientation*Height	0.749	Not Significant
Angle*Orientation*Height	0.959	Not Significant
Angle	0.003	Significant
Orientation	0.001	Significant
Height	0.006	Significant
Angle*Orientation	0.002	Significant

Table 2: Results from Analysis on augmented data

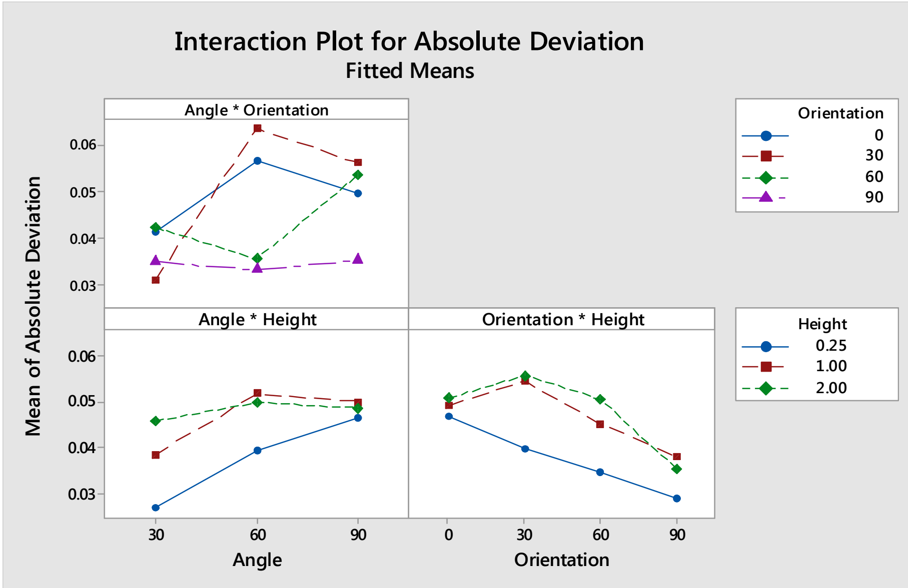
We observe that, after adding the *height* parameter, the effect of *angle* becomes statistically significant. *Height* has a significant main effect on MAE, and similar to previous observation, *orientation* main effect and its interaction with *angle* is significant. Graph 3 shows the MAE increases with increasing *angle* and height. An interesting outcome of this analysis is the accentuating the significant effect of *angle*, which was subdued by noise, otherwise.

As it can be seen in the Graph 3 there is variability in the factors angle, orientation and height, which means they are affecting the output of the 3D Printing machine supporting the results from Table 3.



Graph 3: Main Effects Plot for Absolute Deviation with 3 factors

Similar to our previous observation for robust setting, orientation of 90° is still the best for minimal error (see Graph 4).



Graph 4: Interaction Plot for Absolute Deviation with 3 factors

- ***Printed Ellipsoid***

For printing ellipsoids, glossy material was used. Due to production issue, the observation for 90 degree orientation was different from other orientations, in terms of the washing process. Hence, we used this occurrence to test the effect of washing process first.

Table 3, below shows the ANOVA, where we can see there is significant effect of the washing process.

Analysis of Variance

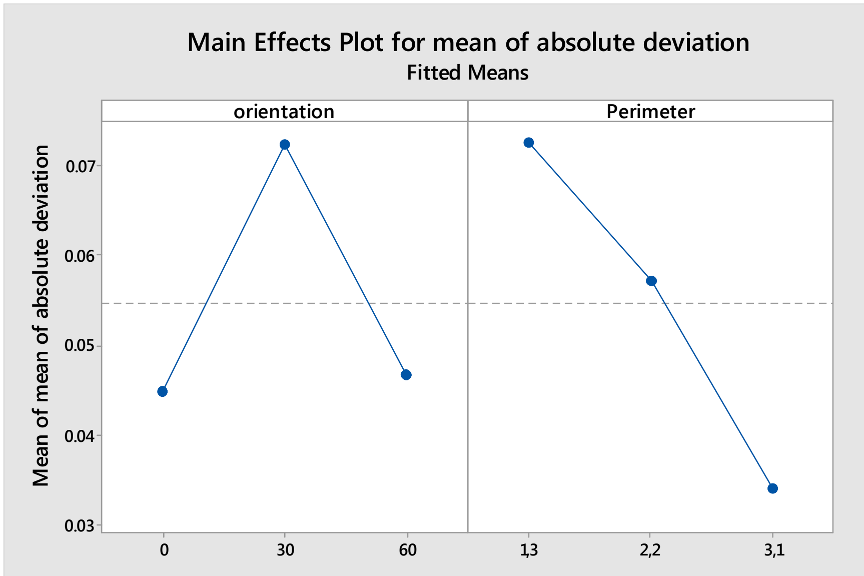
Source	DF	Adj SS	Adj MS	F-Value	P-Value
washed out parts	**1**	**0.038042**	**0.038042**	**5.33**	**0.032**
Perimeter	2	0.001973	0.000986	0.14	0.872
Error	20	0.142616	0.007131		
Lack-of-Fit	8	0.043259	0.005407	0.65	0.722
Pure Error	12	0.099357	0.008280		
Total	23	0.182631			

Washed out parts have a p-value ≤ 0.05 has a significant effect.

Table 3: Results from Analysis on washing process on ellipsoids

The 90 degrees orientation setup, thus, became an outlier to the remaining data. Therefore, we remove the observations from this setup in further analysis.

We plot the main effects of parameters in Graph 5. We can observe that *orientation* seems to have a quadratic effect on MAE. Thus we fit a quadratic model in ANOVA. Table 4, shown below, gives the ANOVA for linear and quadratic effects of parameters.



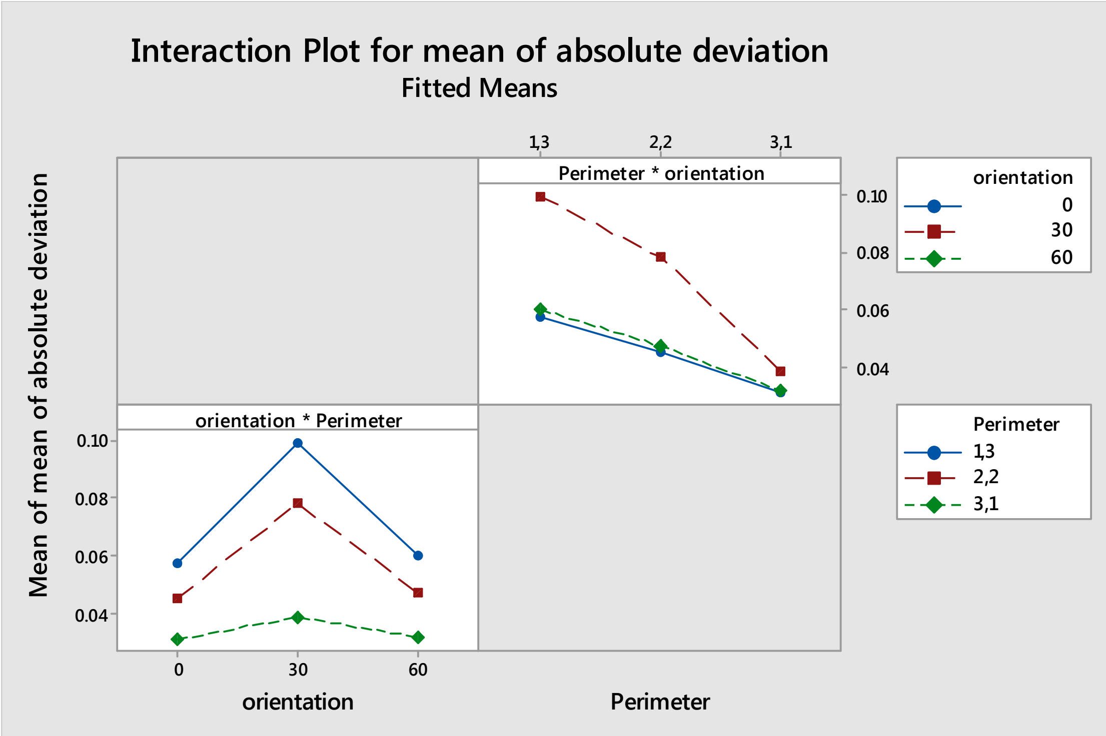
Graph 5: Main effects of parameters on error in ellipsoids

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	0.007335	0.001467	2.68	0.075
Linear	2	0.004190	0.002095	3.83	0.052
orientation	1	0.000013	0.000013	0.02	0.878
Perimeter	**1**	**0.004183**	**0.004183**	**7.65**	**0.017**
Square	2	0.002929	0.001465	2.68	0.109
orientation*orientation	**1**	**0.002853**	**0.002853**	**5.22**	**0.041**
Perimeter*Perimeter	1	0.000060	0.000060	0.11	0.747
2-Way Interaction	1	0.000003	0.000003	0.01	0.940
orientation*Perimeter	1	0.000003	0.000003	0.01	0.940
Error	12	0.006563	0.000547		
Lack-of-Fit	4	0.000983	0.000246	0.35	0.836
Pure Error	8	0.005580	0.000698		
Total	17	0.013898			

Table 4: Results from Analysis on ellipsoids

As we can see in the table above, linear effect of perimeter (ellipsoid axes) is significant, and also the quadratic effect of orientation is significant. This supports our visual interpretations from Graph 5. We notice that there are no significant interaction effects in ellipsoids. We can also see it in Graph 6, where we observe almost parallel interaction lines. This is a useful outcome, indicating that the process parameter (orientation) can be set independent of the design parameter (ellipsoid axes). Thus, we can also propose that an orientation of 0 or 60 degrees would give minimal error, irrespective of the ellipsoid axes level.



Graph 6: Interaction effects of parameters on error in ellipsoids

ANTICIPATED IMPACT

This study helped identify and characterize sources of error related to build orientation and part geometry when using layer-by-layer additive manufacturing processes. As additive manufacturing continues to enter mainstream production these types of studies will be crucial for understanding the sources of error and improving the processes. Characterizing error related to orientation and design geometry will also influence the development of design systems that will be used for designing parts for additive manufacturing (topology optimization as an example). This study characterized some basic sources of error on simple primitive shapes. Follow-on work would need to continue to gather data on more complex geometries to further characterize the error and then develop guidelines or best practices that will mitigate the error. A better understanding of these errors will also be a catalyst for improving the additive manufacturing machines themselves to eliminate these sources of error.

CONCLUSION

3D printing has emerged as a revolutionary new approach for rapid and cost effective prototyping and found applications in wide areas including manufacturing, medicine, art, etc. In this research, we showed a critical deficiency of 3D printers in terms of surface roughness (or error), and explained its adverse effects. We designed an experiment to analyze the effects of design and process parameters on the printing error. We performed the experiment on *cones* and *ellipsoids*, and tested their shape (design) and orientation (process) parameters. We discussed the significant effects and recommended optimal printing settings for minimal error.