Effects of process parameter variation on the surface roughness of polylactic acid (PLA) materials using design of experiments (DOE)

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Abstract. 3D Printing (3DP) is an additive manufacturing technology used to rapidly build parts that are designed using 3D modeling software. 3DP builds a part by adding one layer of the working material at a time until the process is complete. One main concern with 3D printed samples is the high levels of surface roughness, which can result in the rejection of parts by many precision manufacturing companies. The objective of this research is to use the Design of Experiment (DOE) to analyze which factors influence the surface roughness of the part built from a 3D printer. In this research, a two-level, three-factor, full factorial design of experiment is used to select the best combination of factors that will minimize the surface roughness of parts made from Polylactic Acid (PLA) materials. The selected factors are printing orientation, nozzle diameter, and infill percentage. Based on the preliminary result, it is determined all the factors and their two-factor interactions are shown to significantly affect the surface roughness. However, it is shown that the nozzle diameter has had the most effect on surface roughness. These results will be explained in terms of the optical microscopy of the processed PLA test specimens.

1. Introduction
Fused deposition modeling (FDM) is a process that is used for fabricating solid prototypes from a computer-aided design (CAD) data file [1]. The process fabricates 3-D parts from a build-up of 2-D layers. In this process, Polylactic Acid (PLA) thermoplastic polymer is extruded through a heated nozzle to deposit the layers. In a previous paper, we showed that the orientation of the layers created anisotropic behavior in the tensile strength [2]. Other investigators have also experienced similar results [3].

Previous work has used the design of experiments (DOE) as a method to minimize surface roughness of the FDM-processed specimens of ABS polymers [4–5]. However, many of the factors used for influencing the surface roughness were entirely different in these studies. Also, these statistically designed experiments on FDM processing using PLA materials have not been physically interpreted in terms of the material properties and microstructure.

The purpose of this paper is to use the quality engineering tools to design, analyze and physically interpret our selection of the FDM processing factors and their levels for specifically PLA materials. It is expected that with DOE the best factor combination from the factors such as printing orientation, nozzle diameter, and infill percentage are experimentally determined to achieve the best surface roughness of the prototypes. There will be a total of eight possible growth combinations, in which the
surface roughness produced will be measured. Thereafter, using DOE, a determination can be made of what level each factor should be to consistently get a smoother surface.

2. Material properties
PLA is one of the most common thermoplastic materials used in 3DP because it is environmentally friendly and is a biodegradable polymer created from sugar plants such as tapioca, corn, and sugarcane. It also does not require a heated build plate because PLA melts at a very low temperature. Its melting point is at around 160°C, but bonds better at 180° [6]. PLA is also much more brittle than other thermoplastics. However, some improvements to it are being made in order to increase its flexibility and reduce carbon footprint during the creation process. One of the reasons why it is so popular is because of its ease of creation from whatever natural sugar plants are locally available.

3. Experimental methods
The 12-step Taguchi process was used for our design of experiments (DOE) [7]. First, the problem of concern was the high surface roughness of FDM-processed PLA test specimens. Second, our objective was to minimize surface roughness. Third, the surface roughness was selected as the quality characteristics, i.e., the response. Fourth, the factors were determined by brainstorming and were recorded on a cause and effect diagram [8]. Fifth, three factors and no noise factors were selected. Sixth, a two-level experiment was selected.

Seventh, a $2^3$ orthogonal array was used for the DOE. Eighth, all the selected factors could potentially interact with each other. Ninth, all the interactions were listed. Tenth, the trials were randomized and four specimens per trial were used. Eleventh, the column effects method and plots of the response versus the effects of factors and interactions were used to analyze the data. Twelfth, the 95% statistically significant factors and interactions were identified. Our results were interpreted in terms of surface roughness and microstructure to validate our results.

The FDM 3D printer used to fabricate the test specimens was the Tevo Tarantula [9]. This is a popular choice of the 3D printer due to its low cost and similarity to other more expensive options such as the Prusa i3. While it lacks the user-friendly features such as automatic bed leveling and filament sensors, the core components are nearly identical to many FDM printers: aluminum frame utilizing 3D printed brackets, belt-driven movement for the bed platform and extruder carriage, threaded rod actuation for the z-axis, use of an Arduino-based motherboard and g-code file format, etc.

The filament material used was a 1.75mm black PLA from Hatchbox [10]. The filament is fed into the heated nozzle, located on the carriage, from a Bowden extruder that is mounted to the frame. This material is melted and extruded out of a brass nozzle to form a molten polymer. The polymer was deposited at locations on the X-Y plane according to the movement dictated by the g-code commands. Then the head is moved vertically in the Z-axis to deposit a new layer on top of the previous one. In this way, the 3-D solid model was built-up by multiple depositions of 2D layers.

Process parameters of interest such as layer thickness and infill density were modified using the 3D printing slicer software Ultimaker CURA 4.1. While changing the diameter of filament extruded can be accomplished solely through the slicer settings, a more extreme difference in filament size can only be accomplished by swapping between two brass nozzles with different internal diameters; in this case, a 0.2 mm nozzle was tested along with a 1.0 mm nozzle. Each layer is formed by first depositing the perimeter (outside contour) around the X-Y plane of the test specimen design and then filling the inside of the perimeter with a raster pattern that had a determined orientation based on the settings used in Cura. The layer is partially bonded to the underlying structure. This process was like the 2D lay-up of 0°/90° and ±45° laminate composites.

The geometry of the test specimens was made using Solidworks 2019 CAD software and consists of a 25.4mm x 76.2mm x 6.35mm rectangular cuboid. This model is then exported as a STL file and loaded into Cura where the g-code that the 3D printer can read is generated based on the selected process parameters. After all the samples were printed, the surface roughness of the 25.4mm x 76.2mm side was measured with the Taylor Hobson Surtronic 25 profile measurement system.
4. Design of Experiments

A cause-effect diagram was used to list the possible causes affecting the surface roughness of the test specimens. Some of the possible causes were the build specifications (road width, layer thickness, raster orientation), machine environment (model temperature), PLA materials (density). Three factors were selected for this experiment: (A) printing orientation, (B) nozzle diameter and (C) infill percentages at two levels, i.e., low (-1) and high (+1), respectively in Table 1. The three factors had a potential effect on the surface roughness of the samples. Infill percentage is the amount of material that is filled in the sample, the sample can be hollow or can be filled with the material up to 100%. The strength of the sample depends on the infill percentage. The second factor is print orientation, the sample can be printed in two orientations, flat or standing. Print orientation decides how it be printed and how much support material would be used. The third factor is nozzle diameter, which affects most in printing the samples. Higher the nozzle diameter, the higher the surface roughness, so the lowest surface roughness can be obtained when the sample is printed with low nozzle diameter.

A \((2^3)\) orthogonal design matrix was utilized as shown in Table 2. Eight experimental trials were conducted which were randomly selected to the run numbers in Table 2. Four replications were conducted for each run.

### Table 1. Factors and levels

| Factors | Parameters          | Low (-1) | High (1) |
|---------|---------------------|----------|----------|
| A       | infill percentage   | 5%       | 100%     |
| B       | orientation         | flat     | standing |
| C       | nozzle diameter     | 0.2 mm   | 1.0 mm   |

### Table 2. Orthogonal experimental design matrix

| Run # | Factors | A | B | C |
|-------|---------|---|---|---|
| 4     |         | -1| -1| -1|
| 5     |         | -1| -1| 1 |
| 3     |         | -1| 1 | -1|
| 8     |         | -1| 1 | 1 |
| 7     |         | 1 | -1| -1|
| 6     |         | 1 | -1| 1 |
| 1     |         | 1 | 1 | -1|
| 2     |         | 1 | 1 | 1 |

The relevant equations used to find the system equation in the DOE analysis are shown below:

\[
\overline{\sigma^2} = \frac{\sum (\sigma_i^2)}{2^k} \tag{1}
\]

In Eq. (1), \(\overline{\sigma^2}\) is the pooled variance estimate, \(\sigma_i\) is the individual standard deviation for the factor and \(k\) is the number of factors (3). This equation is used to determine the standard error (se), which is then used to formulate the 95% confidence interval in the DOE plot.

\[
se = \sqrt{\frac{\overline{\sigma^2}}{n \cdot 2^{k-2}}} \tag{2}
\]

In Eq. (2), \(\overline{\sigma^2}\) is the pooled variance estimate, \(N = n \cdot 2^k\) measurements, \(k\) is the number of factors and \(n\) is the number of replications. This equation finds the standard errors. The standard errors are
then used to locate the 95% confidence envelope seen in the DOE plot by taking $\pm 2 \cdot se$. The regression model is given by following equation.

$$Y = \beta_0 + \sum_i \beta_i x_i + \sum_{ij} \beta_{ij} x_i \cdot x_j$$  \hspace{1cm} (3)

In Eq. (3), $\beta_0$ is the grand mean of the regression equation and $\beta_i$ is the coefficients in the regression equation for each of the factors that were found to have a real effect on the system. These coefficients are found by dividing the effect by 2. $x_i$ and $x_j$ are the corresponding high (1) or low (-1) values of the factors with real effects.

This DOE technique has been implemented and proven effective throughout the industry for optimizing processes. It is hypothesized that this DOE technique can be used to effectively reduce the surface roughness of prototypes grown with a Tevo Tarantula 3d printer.

5. Results

The measured surface roughness, in $\mu m$, for each of the 32 samples and the average surface roughness of each run is shown in Table 3.

| Run # | $R_{a1}$ ($\mu m$) | $R_{a2}$ ($\mu m$) | $R_{a3}$ ($\mu m$) | $R_{a4}$ ($\mu m$) | Avg. $R_a$ ($\mu m$) | Variance |
|-------|-------------------|-------------------|-------------------|-------------------|---------------------|----------|
| 4     | 8                 | 9.2               | 14.2              | 10.6              | 12.4                | 7.29     |
| 5     | 26.2              | 33.6              | 40.0              | 28.8              | 34.4                | 37.21    |
| 3     | 14.8              | 15.2              | 16.0              | 15.2              | 15.3                | 0.25     |
| 8     | 44.0              | 44.0              | 45.0              | 43.8              | 44.2                | 0.25     |
| 7     | 16.6              | 12.4              | 12.8              | 14.0              | 14.0                | 3.61     |
| 6     | 28.2              | 24.4              | 24.4              | 23.2              | 25.1                | 4.84     |
| 1     | 14.8              | 15.0              | 14.6              | 20.8              | 16.3                | 9        |
| 2     | 42.2              | 43.2              | 41.8              | 41.0              | 42.1                | 0.81     |

It is clear from Table 3 that the surface roughness varies from a minimum of $12.4 \mu m$ of Run # 4 to a maximum of $44.2 \mu m$ of Run # 8. It represents a decrease in surface roughness by 250%. The response table for computing the effect of each factor and each possible factor interaction is shown in Table 4.

| Run # | $R_{a1}$ ($\mu m$) | $R_{a2}$ ($\mu m$) | $R_{a3}$ ($\mu m$) | $R_{a4}$ ($\mu m$) | Avg. $R_a$ ($\mu m$) | Variance |
|-------|-------------------|-------------------|-------------------|-------------------|---------------------|----------|
| 4     | 8                 | 9.2               | 14.2              | 10.6              | 12.4                | 7.29     |
| 5     | 26.2              | 33.6              | 40.0              | 28.8              | 34.4                | 37.21    |
| 3     | 14.8              | 15.2              | 16.0              | 15.2              | 15.3                | 0.25     |
| 8     | 44.0              | 44.0              | 45.0              | 43.8              | 44.2                | 0.25     |
| 7     | 16.6              | 12.4              | 12.8              | 14.0              | 14.0                | 3.61     |
| 6     | 28.2              | 24.4              | 24.4              | 23.2              | 25.1                | 4.84     |
| 1     | 14.8              | 15.0              | 14.6              | 20.8              | 16.3                | 9        |
| 2     | 42.2              | 43.2              | 41.8              | 41.0              | 42.1                | 0.81     |

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| Random Order | Std. Order | Response | A | B | C | AB | AC | BC | ABC |
|--------------|------------|----------|---|---|---|----|----|----|-----|
| 4            | 1          | 10.5     | 1.0 | 10.5 | 10.5 | 10.5 | 10.5 | 10.5 | 10.5 |
| 5            | 1          | 32.2     | 32.2 | 32.2 | 32.2 | 32.2 | 32.2 | 32.2 | 32.2 |
| 3            | 3          | 15.3     | 15.3 | 15.3 | 15.3 | 15.3 | 15.3 | 15.3 | 15.3 |
| 8            | 4          | 44.2     | 44.2 | 44.2 | 44.2 | 44.2 | 44.2 | 44.2 | 44.2 |
| 7            | 5          | 14       | 14  | 14  | 14  | 14  | 14  | 14  | 14  |
| 6            | 6          | 25.1     | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 | 25.1 |
| 1            | 7          | 16.3     | 16.3 | 16.3 | 16.3 | 16.3 | 16.3 | 16.3 | 16.3 |
| 2            | 8          | 42.1     | 42.1 | 42.1 | 42.1 | 42.1 | 42.1 | 42.1 | 42.1 |
| Total        |            | 102.2    | 81.8 | 117.9 | 98.1 | 149.8 | 98.6 | 92.1 | 106.7 | 93  | 88.9 | 110.8 | 96.1 | 102.6 |
| # of values  |            | 8        | 4   | 4   | 4   | 4   | 4   | 4   | 4   | 4   | 4   | 4   | 4   | 4   |
| Average      |            | 24.5625  | 23.85 | 25.75 | 20.45 | 29.475 | 38.0 | 24.65 | 23.025 | 26.675 | 25.25 | 22.225 | 27.7 | 24.025 | 26.9 |
| Effects      |            | -1.175   | 9.025 | 21.875 | -1.625 | -3.425 | -5.475 | 1.875 |
The response graph for surface roughness (in micrometer) is shown in Figure 1 with a grand average of 24.965 (μm) by evaluating Table 4. The standard error (se) was computed to be 4.93 (μm). The upper bound is the grand average plus 2se which is 34.8225 (μm) and the lower bound is the grand average minus 2se which is 15.1025 (μm).

![Figure 1. DOE mean plot for average surface roughness data](image1)

The interaction diagram for factor A (infill percentage) and B (orientation) is shown in Figure 2.

![Figure 2. Interaction diagram for factors A and B](image2)

The interaction diagram for factor B (orientation) and C (nozzle diameter) is shown in Figure 3.
The interaction diagram for factor A (infill percentage) and C (nozzle diameter) is shown in Figure 4.

The calculations of variance, standard error, and $Y_{\text{min}}$ is shown below:

\[
\hat{\sigma}^2 = \frac{\sum (\sigma_i^2)}{2^k} = \frac{1555.967}{6} = 194.4458
\]

\[
se = \sqrt{\frac{\hat{\sigma}^2}{n \cdot 2^{k-2}}} = \sqrt{\frac{194.4958}{8}} = 4.93
\]

\[
Y = \beta_0 + \sum \beta_i x_i + \sum \sum \beta_{ij} x_i \cdot x_j = 24.9625 + \left(\frac{21.895}{2}\right)(-1) = 14.025
\]

\[
Y_{\text{min}} = 14.025 \mu m
\]
The $Y_{\text{min}}$ from the system equation validates the minimum surface roughness in Run # 4 in Table 3.

6. Physical Interpretation

The selected process factors must physically alter the surface structure of the 3D printed samples to vary the measured surface roughness values between the eight specimens. Any variation in surface roughness is the result of the different factors used, and these changing factors are also visible in the optical microscopy of the specimens. Per the results obtained, build orientation (flat or standing) and extruder nozzle diameter (0.2 or 1.0 mm) had the largest impact on surface roughness and the most obvious impact on the physical appearance of the samples. While the amount of infill used can impact the surface quality of some 3D printed models [1], for the combination of process parameters used in this study, there was no statistically significant impact on surface roughness due to infill percentage. However, it is hypothesized that lowering the number of layers above the infill (this setting is called “Top Layers” in Cura) would result in infill percentage having more of an effect on surface roughness as there would be fewer layers bridging the gap between infill lines and smoothing out the surface.

![Figure 5. Physical interpretation](image)

When looking for the physical interpretation of these results through digital microscopy, the differences in surface roughness values become evident. Figure 5 shows the pictures obtained by digital microscopy of four specimen surfaces where the only difference between the sets is to build orientation and extruder nozzle diameter. Pictures (A) and (B) show the samples that were printed using a 0.2mm nozzle where pictures (C) and (D) are from samples printed with a 1.0mm nozzle. Similarly, (A) and (C) are from the samples printed flat on the build plate and (B) and (D) are from samples printed standing vertically on the build plate.

To show the physical effects of build orientation on surface roughness, Figure 5 (A) and (C) picture the horizontal surface of a single layer where the nozzle both deposits the material and critically irons out any bumpy sections, creating a smoother, more uniform plane. Pictures (B) and (D) on the other hand show the layer lines as the model is built vertically. Due to the way that FDM printers must not only deposit material but also ensure that the deposited plastic fuses with the layer below it, the layers must be squeezed together with the force which causes the edges of the layers to bulge outwards as the molten material is compressed by the nozzle into the solid layer beneath. This manifests in Figure 5 as
dark shadows in the pictures as the bulging layer lines block light from entering the valleys between the layers. Now looking into the physical impact of the two nozzle sizes, the extruded lines of plastic in (A) and (B) are quite small, around 0.2mm wide in both cases and exhibit mild waviness throughout the model. It can be seen in these photos that the defects of a single line are contained within a small area and thus provide a small amount of surface roughness. Essentially the printer is extruding these smaller lines closer together which gives it less room for error. Conversely, in pictures (C) and (D), the gaps between solid layers and lines are larger and show more extreme bumps in the form of large dark shadows. Here the larger nozzle exacerbates the natural defects inherent in all FDM 3D printing by extruding a larger layer or line of plastic. One of these defects present here includes hair-like strings of plastic caused by the larger nozzle knocking into the neighboring lines and pulling the plastic into strings. This is evident in Figure 5 and confirmed by the results obtained for surface roughness for each of the samples.

7. Discussion
Since all factors in the response graph except C (nozzle diameter) (Figure 1) are within ±2se from the grand average we can conclude that nozzle diameter has a significant effect on surface roughness of 3DP samples. Since nozzle diameter showed a significant effect on the surface roughness, further a regression equation is useful to predict surface roughness. It is seen in the response graph (Figure 1) above that factor C, nozzle diameter, has the largest range.

Since there is no intersection seen in the interaction diagrams (Figures 2 – 4) it is concluded that there were no real effects to surface roughness due to the interaction of the chosen three factors.

8. Conclusion
After completing this experimental study, the following conclusions can be made:

- The hypothesis that the DOE technique can effectively be used to minimize the surface roughness of RP prototypes is accepted.
- The lowest surface roughness of 12.4 μm is achieved in Run # 4, which uses low (5%) infill percentage, flat orientation and nozzle diameter (0.2 mm).
- Using statistical analysis including interaction diagrams and a response graph, it is shown that from infill percentage, print orientation, and nozzle diameter, nozzle diameter has the most impact on the surface roughness.
- The interaction graphs show that all factors are independent of each other.
- The experiment can be repeated with different factors and different levels by replicating more samples per run.

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