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# APPLICATION OF A MONTE CARLO METHOD FOR DIMENSIONAL ANALYSIS IN ADDITIVE MANUFACTURING

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***Abstract.*** *Additive manufacturing is rapidly evolving into a reliable and sustainable manufacturing process, which greatly expands its uses for more than prototyping purposes. However, AM processes lacks the deeper knowledge of traditional manufacturing processes obtained over centuries of experimental and practical use. This makes it necessary to expand the knowledge on such technologies to enable them for industrial scale applications. Dimensional and geometric control methods make processes feasible by increasing standardization while reducing post-production costs. This study proposes a method that relies on Monte Carlo simulations to perform dimensional analysis based on processing windows factors in additive manufacturing. An experimental procedure was carried to analyze the combined effects of two process parameters (layer height and exposure time) in dimensional accuracy of a stereolithography AM process. The experimental data was used to create a statistical model that was able to observe, through randomized sampling, the dimensional behavior of samples within different process windows and thus providing statistical data for dimensional and tolerancing analysis.*

***Keywords:*** *Additive Manufacturing, Stereolithography, Monte Carlo, Dimensional Accuracy, Metrology.*

## 1. INTRODUCTION

Additive manufacturing (AM) has gone through major technological developments over recent years, being increasingly applied for end part production as opposed to rapid prototyping purposes only. Despite this, AM processes in general still lack the extensive knowledge and formal standardization of more traditional manufacturing techniques such as machining (Cooke and Soons, 2010). This by itself constitutes a barrier for a broader adoption of these technologies, making it necessary to develop methodologies to make enable AM processes both technically and commercially. One way of doing that is through tighter quality control, which ensures the functional requirements of the manufactured parts while reducing associated production costs.

Dimensional accuracy control is considered a significant bottleneck to additive manufacturing processes, in part due to the lack of knowledge and the complex physical phenomena associated to these technologies (Huang et al., 2014). In addition, dimensional and geometrical accuracy of AM parts is also known to be influenced by uncontrolled factors due to equipment misfunction and internal process deviations (Grasso and Colosimo, 2017), making the causes for dimensional deviations are often unknown and randomized. These peculiarities of AM process often require extensive and costly experimentation procedures for dimensional analysis.

The need to model stochastic processes arises in many fields. The Monte Carlo simulation method is a simple yet popular technique used to model processes influenced by random variables (Morokoff and Caflisch, 1996). The method uses one or more probability density function as inputs and estimates the outcome behavior of complex systems through random sampling and statistical modeling (Harrison, 2010). For manufacturing systems, the Monte Carlo method is suited for non-linear statistical analysis of tolerances and dimensions, more so in cases where the tolerance behaves differently from a normal statistic distribution (Nigam and Turner, 1995). It simulates a great number of experiments that are carried out repeatedly to randomize the process, recreating the dimensional behavior of manufactured parts without the need for repetitive tests. This work aims to propose a methodology based on the Monte Carlo simulation method for dimensional analysis of an additive manufacturing process. A set of experiments were conducted to evaluate how two controlled variables affect the dimensional accuracy in stereolithography (SLA) and the numerical results provided statistical data required for the Monte Carlo simulations. Ultimately, the effects of the combined processes parameters within different processing windows are analyzed in regards to final dimensional accuracy and tolerancing.

## 2. MATERIALS AND METHODS

### 2.1 Design of Experiments

For the experimental procedure, the process parameters selected were layer height and layer exposure time. Layer height is a process parameter common to all additive manufacturing technologies. It is the physical thickness of each layer and is usually kept constant during the entire build. It is an important parameter as it directly affects the part's final resolution and surface finish, as well as production times. Thinner layers provide the best results in regards to quality but also increase the manufacturing duration linearly. The specific SLA technology used in this study is known as mask projection stereolithography (MPSLA), and specific information as to how it works is found elsewhere (Huang et al, 2020). For such processes, each resin layer is cured uniformly at the same time, as opposed to laser scanning SLA processes in which the layer is traced by a single laser beam. The exposure time determine how long each layer is going to be exposed to the UV light array, thus controlling its solidification. This parameter is also kept constant throughout the process and is vital for the success of the process as unproperly cured layers will cause deformation and ultimately a complete process failure. The layer exposure time also directly influence the total manufacturing time.

These parameters were chosen for this study for its high relevancy in projection MPSLA processes (Bonada et al., 2018). Layer height and layer exposure time are also easily controllable in comparison to other environmental factors such as temperature and feedstock material properties. A factorial analysis was performed to access the effects of these two parameters in the final dimensional accuracy. According to Montgomery and Runger (2011), factorial analysis is one of the most efficient experiments for these conditions as each experiment performed evaluates all possible combinations for all chosen levels of each variable. Given the exploratory nature of this study, a reduced number of tests was performed, with a total of nine samples for a $3^2$ factor analysis. The values for the levels were selected according to the manufacturer recommended parameter range and are described in Table 1.

Table 1. Process parameter levels and factorial design ($3^2$).

| Sample | Layer height, mm (LH) | Exposure time, s (ET) |
|---|---|---|
| 1 | 0.02 | 10 |
| 2 | 0.02 | 12 |
| 3 | 0.02 | 14 |
| 4 | 0.03 | 10 |
| 5 | 0.03 | 12 |
| 6 | 0.03 | 14 |
| 7 | 0.04 | 10 |
| 8 | 0.04 | 12 |
| 9 | 0.04 | 14 |

### 2.2 Test Artifact

The test artifact used in the experiments is shown in Figure 1. It is loosely based on the specimen proposed by Moylan *et al.* (2014) from the American National Institute of Standards and Technology (NIST) and simplified by Alves *et al.* (2019) to focus on geometric dimensioning characteristics and tolerances. For this study, only the 4.0 mm corner pins were measured, totalizing four different measurements for each produced sample. The 3D model was created using Creo Parametric and converted to the STL format using Fusion 360 with a triangular mesh of high refinement.

### 2.3 Experimental Procedure

The specimens were manufactured on a Photon S, a desktop MPSLA machine by Anycubic. The UV light array for curing is rated for 405 nm wavelength and the LCD masking screen has resolution of 0.047 mm. All samples were produced using the standard gray photocurable resin for this machine (Shenzhen Anycubic Technology CO, 2019). The STL files were prepared for manufacturing using the Chitubox 3D Slicing software and all process parameters other than the ones observed were kept the constant throughout the experiment (Table 2). The samples were produced with a 25° inclination angle as seen in Figure 2. This was done because parts with relatively large plane layers are prone to contract and deform at the corners if printed parallel to the build platform. By orienting the parts at an angle, the individual layers are reduced in size and therefore avoiding deformations. At this orientation, support structures are required for a proper part adhesion to the build platform as to avoid dislocation or complete detachment during the build process.

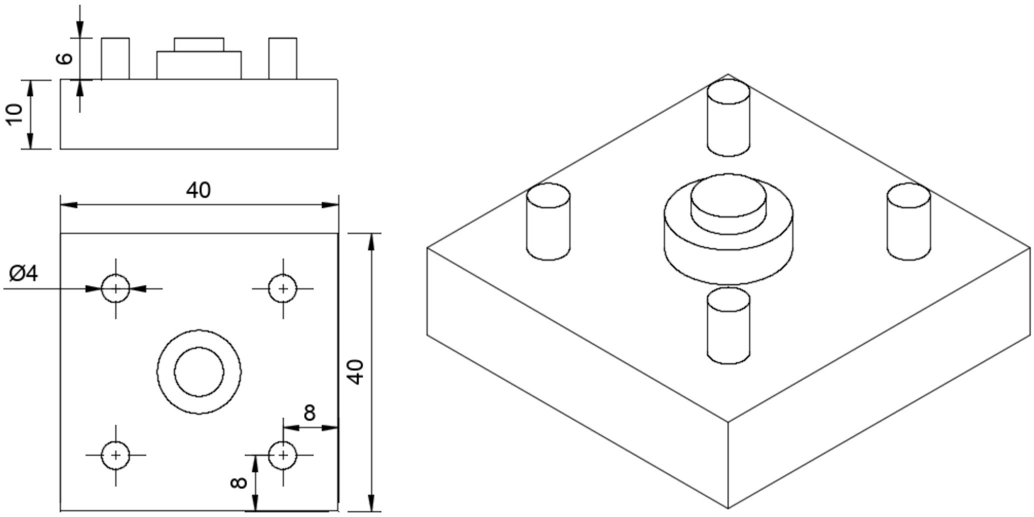


Figure 1. Test artifact used for the experimental phase (dimensions in mm).

Table 2. Fixed process parameters used for sample production.

| Parameter | Value |
|---|---|
| Bottom layer count | 8 |
| Bottom exposure time, s | 10 |
| Light-off delay, s | 3 |
| Bottom light-off delay, s | 3 |

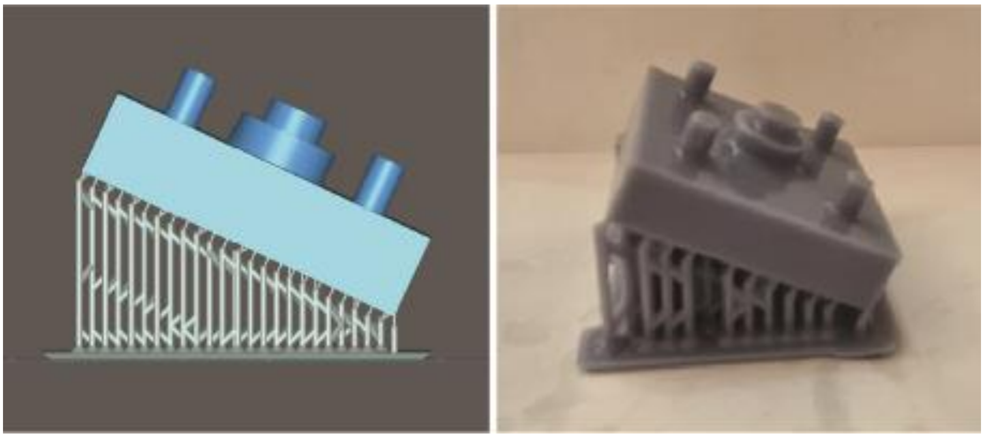

Figure 2. (a) CAD model and (b) produced sample in an inclined orientation to avoid process issues.

All samples were produced in separate batches at a dark environment to avoid unwanted resin curing. Once manufactured, all support structures were removed from the specimens prior to a two-step wash in isopropyl alcohol to remove leftover liquid resin. The samples were left to dry and finally post-cured in a 36 W UV light cabin for 5 minutes on each side (top and lower). Each pin was measured 4 times consecutively by a digital caliper with a resolution of 0.01 mm, in a total of 16 measurements for specimen.

## 3. RESULTS AND DISCUSSION

### 3.1 Experimental Results

The results for each pin average diameter (mm) of all samples are displayed in Table 3. The influence of layer height (LH) and exposure time (ET) in pin diameter were plotted separately for a preliminary analysis and is seen on Figure 3.

Table 3. Average pin diameter (mm) and standard deviation for all specimens produced.

| Sample | Pin 1 (mm) | Pin 2 (mm) | Pin 3 (mm) | Pin 4 (mm) | Mean (mm) | σ |
|---|---|---|---|---|---|---|
| 1 | 4.14 | 4.15 | 4.15 | 4.16 | 4.15 | 0.01 |
| 2 | 4.19 | 4.21 | 4.25 | 4.19 | 4.21 | 0.03 |
| 3 | 4.27 | 4.33 | 4.39 | 4.36 | 4.34 | 0.05 |
| 4 | 4.10 | 4.13 | 4.15 | 4.15 | 4.13 | 0.02 |
| 5 | 4.18 | 4.16 | 4.20 | 4.19 | 4.18 | 0.02 |
| 6 | 4.28 | 4.27 | 4.24 | 4.27 | 4.26 | 0.02 |
| 7 | 4.09 | 4.11 | 4.14 | 4.10 | 4.11 | 0.02 |
| 8 | 4.19 | 4.20 | 4.16 | 4.15 | 4.17 | 0.02 |
| 9 | 4.24 | 4.25 | 4.21 | 4.21 | 4.23 | 0.02 |

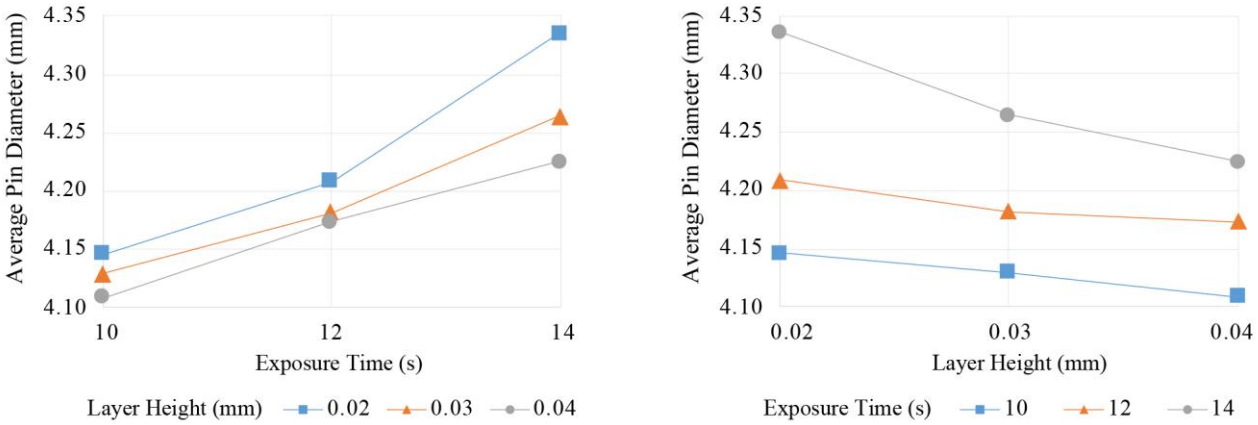


Figure 3. Average pin diameter (mm) in relation to layer height (mm) and exposure time (s).

### 3.2 Statistical Analysis

To confirm the relevance of the chosen factors and their interactions within the experiment, a two-way analysis of variance (ANOVA) was performed on the measured data. The values for the F-test and P-value are displayed in Table 4 and they show the statistical relevance of both factors as well as their interaction and the null hypothesis rejection. For the Monte Carlo simulations, the interactions between layer height and exposure time towards dimensional accuracy were then fitted into two separate linear regression models. The results for the linear regression and the coefficients are shown in Table 5 and 6, respectively. The values for the Multiple R in Table 5 show a strong positive correlation while the R-squared values show that 88% of this model variation can be explained by the correlation coefficients. Finally, Figure 4 shows linear regression graphical results including each of the regression residuals.

Table 4. Results for the two-way analysis of variance (ANOVA).

| Factor | F | P-value |
|---|---|---|
| Layer height (LH) | 17.15257 | 1.56E-05 |
| Exposure time (ET) | 98.46297 | 3.95E-13 |
| Interaction LH x ET | 2.98371 | 3.67E-03 |

Table 5. Linear regression results.

| Regression Statistic | Value |
|---|---|
| Multiple R | 0.94 |
| R-square | 0.88 |
| Adjusted R-square | 0.86 |
| Standard error | 0.03 |
| Observations | 36 |

Table 6. Coefficients for the linear regression.

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | -0.483 | 0.124 | -3.889 | 4.79E0-04 | -0.736 | -0.230 |
| Layer height (LH) | 8.021 | 3.993 | 2.009 | 4.90E-02 | -0.113 | 16.155 |
| Exposure Time (ET) | 0.064 | 0.010 | 6.269 | 4.99E-07 | 0.043 | 0.085 |
| LH x ET | -0.922 | 0.330 | -2.796 | 8.68E-03 | -1.594 | -0.250 |

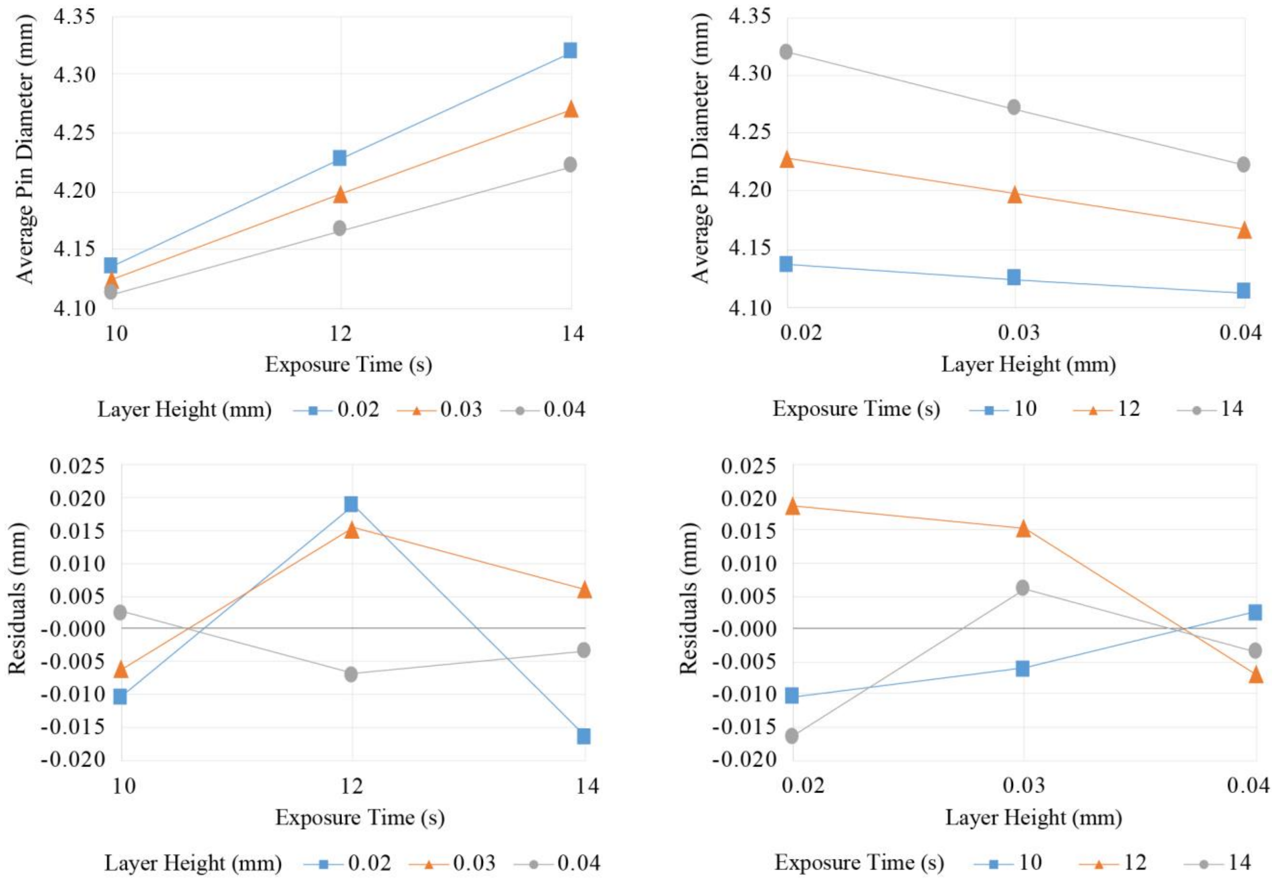


Figure 4. Linear regression graphical results.

With the correlation models validated, a series of Monte Carlo simulations were carried out randomly varying the chosen factors within range of the samples of the experiment: from 0.02 mm to 0.04 mm in layer height and from 10 to 14 seconds in exposure time. A total of 10,000 experiments were simulated to guarantee the accuracy of the results (Harrison, 2010). This relative high sampling may look excessive and could potentially lead to computational issues, but for simple models such as the one from this study the risk is minimal. The simulations resulted in a log-normal curve with an average of 0.19 mm of error for the diameter of the pin, a kurtosis of 2.24, and an asymmetry of 0.30 (Table 7). The graphical representation of the results is displayed in Figure 5 as a histogram in regards to the dimensional deviation in pin diameter (mm).

According to the model, if 10,000 parts were produced randomly varying both the layer height and exposure time within the process window selected, the dimensional deviation distribution of all sampled parts would be as shown in Figure 5. This analysis shows all the possible outcomes in relation to dimensional accuracy for a given process window. Bigger processing windows better accommodate parameter variation, and even that is even more relevant for factors that have directly influence over production times as layer height and exposure time.

This process could be improved in terms of dimensional accuracy by narrowing the process window regarding better accuracy. This can be achieved by reducing the range of input values from the linear regression model towards the values that showed better results. In this sense, a second Monte Carlo simulation was performed, but this time for layer heights ranging from 0.03 mm to 0.04 mm and exposure time of 10 to 12 seconds. Once again, a number of 10,000 experiments was simulated and the results for the second iteration is found in both Table 8 and Figure 6. The dimensional accuracy was in fact enhanced, with an average diameter deviation reduced from 0.197 mm to 0.150 mm, as well as the standard deviation from 5% to 2%.

Table 7. Numerical results from the first Monte Carlo simulation.

| **Parameter** | **Value** |
|---|---|
| Mean, mm | 0.197 |
| Number of trials | 10,000 |
| Standard error | 0.05% |
| Minimum, mm | 0.11 |
| Maximum, mm | 0.32 |
| Median, mm | 0.19 |
| Range, mm | 0.21 |
| Standard deviation | 0.046 |
| Variance | 0.002 |
| Skewness | 0.30 |
| Kurtosis | 2.24 |

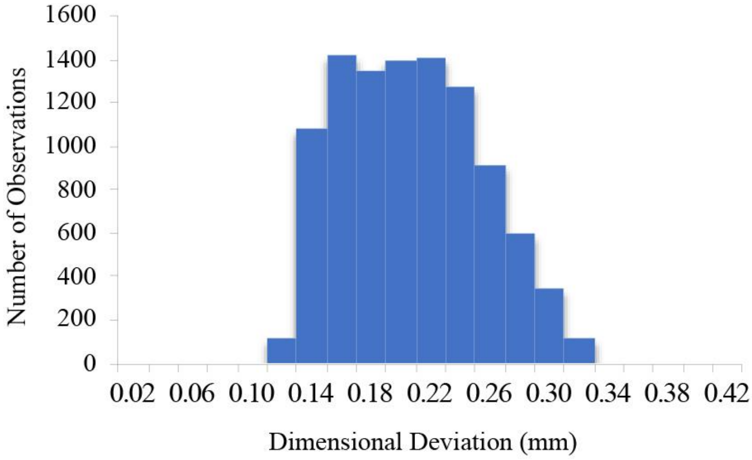


Figure 5. Graphical results (histogram) from the first Monte Carlo simulation.

A third simulation was also performed, this time for the range of 0.030 mm to 0.035 mm of layer height and exposure time of 10 to 11 seconds, with the results also shown in Table 8 and Figure 7. The average diameter error in mm was further reduced to 0,138 mm and the standard deviation to 1%, a considerable difference when compared to the first simulation. The second and third Monte Carlo analysis fundamentally show how the dimensional accuracy is affected by a narrowing down the processing window. This analysis can be helpful for both process planning and dimensional tolerancing tasks. It can also be beneficial to production systems where process parameters are not fixed and dependent of exterior factors such as total manufacturing time and energy consumption.

Table 8. Results from the second and third Monte Carlo simulation.

| **Second Simulation** | | **Third Simulation** | |
|---|---|---|---|
| Layer height range, mm | 0.03 – 0.04 | Layer Height range, mm | 0.030 – 0.035 |
| Exposure time range, s | 10 – 12 | Exposure time range, s | 10 – 11 |
| Mean, mm | 0.150 | Mean, mm | 0.138 |
| Number of trials | 10,000 | Number of trials | 10,000 |
| Standard error | 0,02% | Standard error | 0.01% |
| Minimum, mm | 0.11 | Minimum, mm | 0.12 |
| Maximum, mm | 0.20 | Maximum, mm | 0.16 |
| Median, mm | 0.15 | Median, mm | 0.14 |
| Range, mm | 0.08 | Range | 0.04 |
| Standard deviation | 0.020 | Standard deviation | 0.01 |
| Variance | 0 | Variance | 0 |
| Skewness | 0.13 | Skewness | 0.05 |
| Kurtosis | 2.03 | Kurtosis | 1.94 |

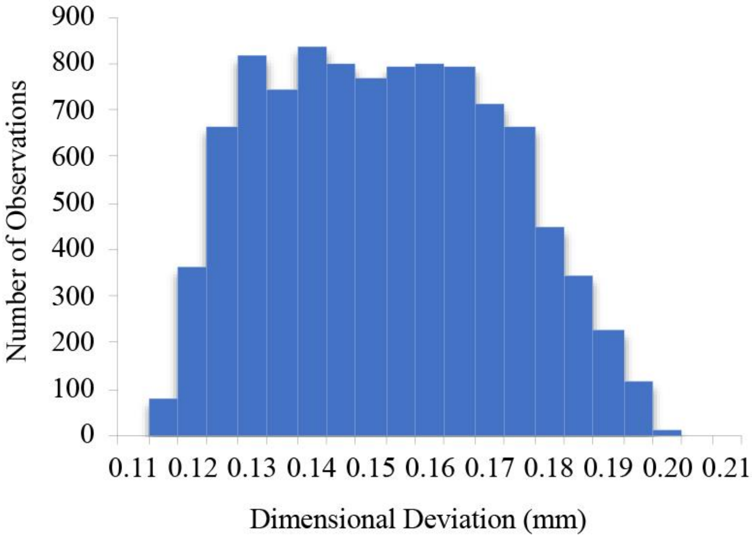


Figure 6. Graphical results (histogram) from the second Monte Carlo simulation.

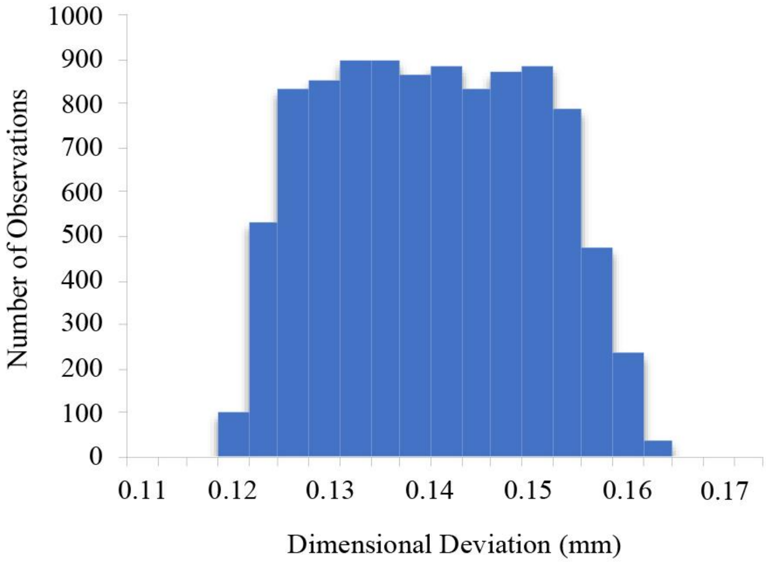


Figure 7. Graphical results (histogram) from the third Monte Carlo simulation.

## 4. CONCLUSION

Additive manufacturing technologies are becoming mature enough for end part manufacturing in industrial scale production. However, the inherent complexity of these processes allied with the lack of deep knowledge and formal standardization still prevent the technology to be more rapidly expanded. In terms of quality control, AM still poses challenges and often requires extensive experimental studies that are both costly and time-consuming.

In this study, a methodology based on Monte Carlo simulations was developed to analyze how process parameters affect the dimensional accuracy in an additive manufacturing process within selected process windows. An experimental procedure was conducted in a stereolithography MPSLA machine for accessing the simultaneous effects of two process parameters (layer height and exposure time) and the correspondent probabilistic curves for these factors were then used as input for the Monte Carlo simulations.

The proposed methodology simulates the dimensional outcome of thousands of parts as if produced by the parameters within the different process windows. This technique shows great potential for dimensional, tolerance and statistical analysis of complex and expensive manufacturing processes. Future works include expanding the amount of process parameters studied within the stereolithography process, as well as applying this methodology to other additive manufacturing processes.

## 5. ACKNOWLEDGEMENTS

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