Influence of Some Process Parameters on Build Time, Material Consumption, and Surface Roughness of FDM Processed Parts: Inferences Based on the Taguchi Design of Experiments

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Abstract

The rapid prototyping (RP) paradigm has prompted the emergence of rapid manufacturing processes that have gained popularity for the development of parts, tools and dies as well as prototypes. Fused deposition modeling (FDM) is the RP technology that forms 3-D objects from CAD-generated solid or surface models. RP is used to save time and cut costs at every stage of the product development process. A challenging research issue in RP is how to shorten the build time and improve the surface accuracy, especially where numerous interactive process parameters are present.

In this study, a parametric investigation is performed for the evaluation of various process parameters such as slice height, road width, raster angle, number of contours, air gap, STL deviation, and STL angle within a FDM process. The Taguchi design of experiments approach is adopted, and analytic tools such as main effect and the signal to noise (S/N) ratio are implemented for an impact assessment of the process parameters on performance measures that include build time, material consumption and surface roughness. This study is tested and validated with the help of a test model, and the results are provided in the paper. The outcome of this study will help RP users in creating parts with a higher level of accuracy and provides the means for generating smoother surface finishes.

Introduction

In a highly competitive product market, it becomes imperative to capitalize on reduced lead-times and to deliver improved part quality. These requirements can be sought through additive forms of manufacturing. However, when presented with an additive manufacturing system; for example, with FDM, many process parameters are involved when building the part. These process parameters affect the build time, material usage, strength, and surface roughness of the part, which ultimately determines customer satisfaction or dissatisfaction. Furthermore, process parameter selection can result in inverse relationships such as minimal build time coupled with inferior part strength. Therefore, one must weigh tradeoffs when

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selecting these process parameters, and the determination of these tradeoffs is dependent on the end use of the part. This study's overarching aim focuses on identification of the relationship between selected FDM process parameters and performance measures such as build time, material usage, and surface roughness.

Literature Review

FDM is one of the examples of RP commonly used today. In FDM, material is stored as a filament in a spool or cartridge. Rollers then guide the filament to a liquefier where it is heated to a semi-liquid state and extruded through a nozzle [1]. FDM is used for a wide range of materials, making it excellent at producing functional parts and comparable in terms of strength. There are, however, issues present such as accuracy and manufacturing time [1, 2].

A review of research into process parameters that influence the RP process, in particular FDM, was performed. The task of process planning is critical, since various parameters must be adjusted for fabricating high-quality products to meet customer/client needs and, at the same time, be delivered as quickly as possible to maintain a competitive edge on the market. Based on the literature review, the distribution of influential parameters investigated in the fabrication of FDM parts is shown in Figure 1. Some of the more focused parameters are toolpath pattern, model representation, raster width, raster angle, layer thickness, air gap, and part build orientation. Furthermore, knowing the relationship between variations of each parameter or combination of parameters and their associated effect on performance measures such as geometrical accuracy, surface roughness, mechanical properties (tensile strength, impact strength, compressive strength), and build time is essential for optimized process planning. The distribution of performance measures investigated for FDM process can be seen in Figure 2. A brief discussion on some critical issues of the FDM process is presented below.

Sood et al. [3] performed experimental investigations on the influence of FDM process parameters such as layer thickness, part orientation, air gap, raster angle, and raster width on dimensional accuracy of an acrylonitrile-butadine-styrene (ABS) part. Dimensional accuracy was determined by percentage change in width, length and thickness of the part, resulting in three responses or performance measures. Taguchi's parameter design, along with ANOVA, main effect, and S/N ratios, were implemented for proper understanding of the process parameters and their influence on each of these responses. Furthermore, the grey Taguchi method was used to establish the optimal level of process parameters for minimization of all three responses through generation of a single response referred to as grey relational grade. Finally, a back-propagation artificial neural network was proposed to develop a non-linear predictive model.

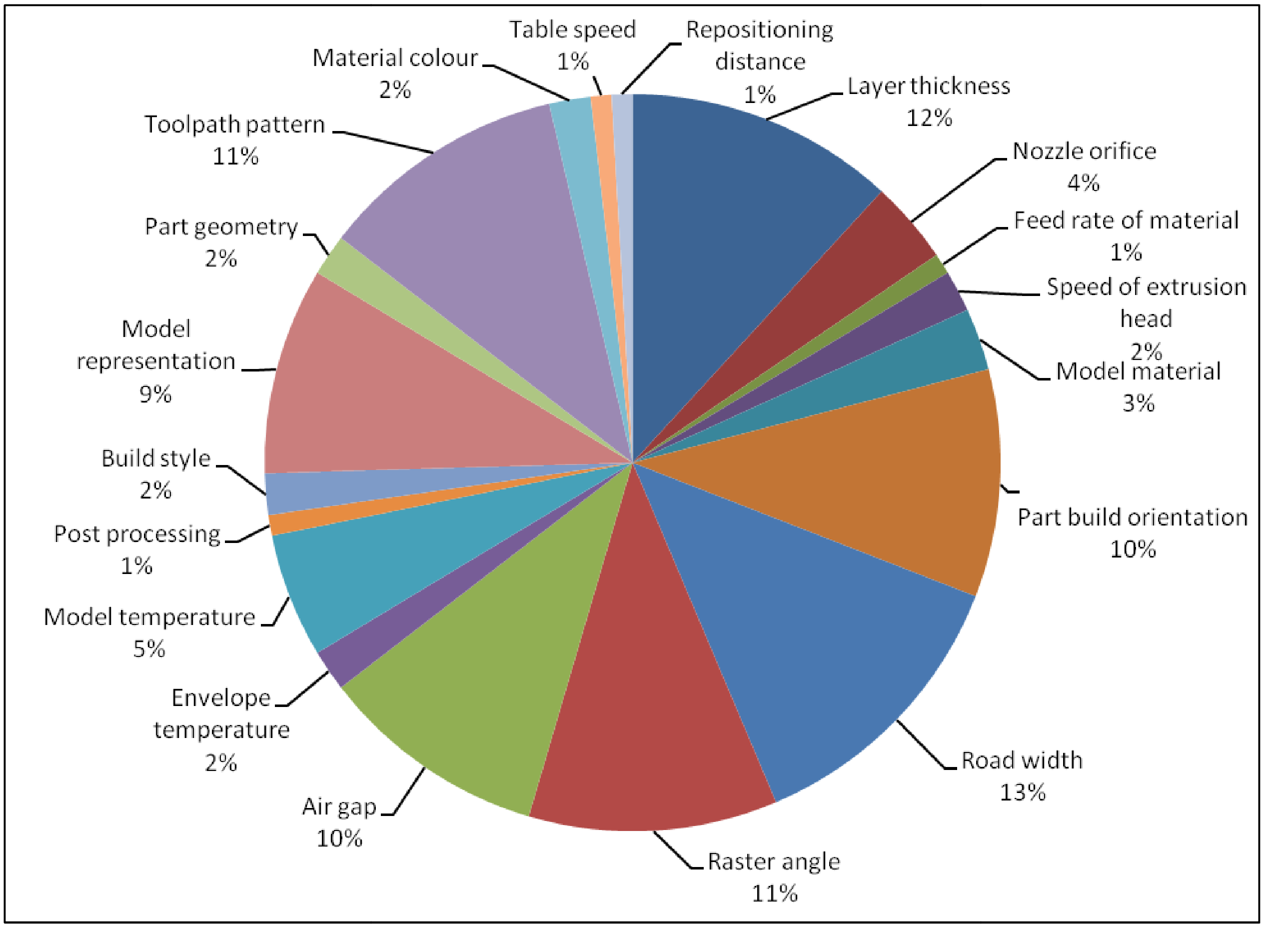

Figure 1. Distribution of influential parameters in the fabrication of FDM parts [3-15]

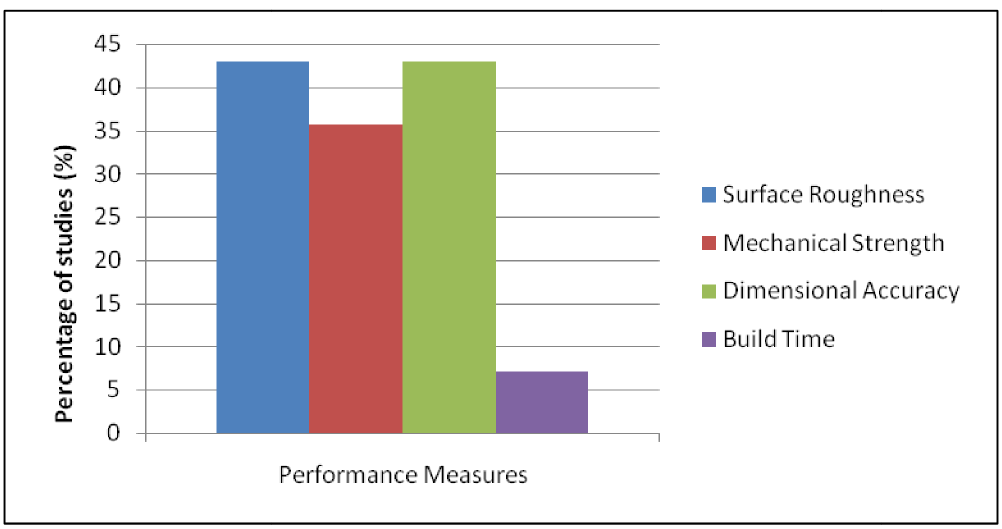

Figure 2. Distribution of critical performance measures for FDM process [3-15]

Sreedhar et al. [15] studied the impact of angular orientation on surface quality of a FDM built part with inclined surfaces ranging from 0-180º. The theoretical surface roughness values were calculated and compared to experimental values obtained with the use of a surface tester. It was observed that surface roughness of the FDM part is excellent when the part is inclined between the angles of 20 to 30º to the build platen. Hence, it was concluded that angular orientation is critical to the surface quality of FDM parts.

Galantucci et al. [8] conducted an experimental study to investigate the influence of chemical treatment (solution of 90% dimethylketone and 10% water) on the tensile strength and flexural strength as well as surface roughness of FDM prototypes made of ABS material. Tensile test results indicate that treated specimens have reduced tensile strength. A general tendency was observed where greater immersion times and lower raster widths resulted in lower tensile strength. However, there is a clear overall increase in flexural strength of untreated and treated specimens. This analysis proved that for the ABS test specimen, treatment improves the flexural strength, reducing its dependency on the raster angle. Furthermore, a general improvement of surface finish was observed for the treated specimens.It was deduced that the chemical bath dissolves the single filaments that subsequently join together, reducing the roughness and increasing the compactness of the structure.

From these studies, it can be seen that improvement of surface quality, mechanical strength, and dimensional accuracy has been achieved by determining ideal process parameter settings. The implementation of systematic methods such as Taguchi design assists with the development of pre-production means for generation of more stable and higher quality products. Hence, the realization of optimal levels of the process parameters through off-line methods will translate into cost savings and reduction in product waste for industry, while achieving products that are robust to withstand changes in operating and environmental conditions [16].

Furthermore, studies [17, 18] have established that in RP systems such as FDM, optimization of process parameters (e.g., build orientation) is influential to part accuracy, reduced production time, and minimal requirement for supports, affecting the cost of building the model, which is crucial to the industrial sector. Górski et al. [19] focused on creating an expert system algorithm to assist in selecting an optimal process and parameters for thin-walled products using rapid manufacturing. This has enabled great time savings that maximize the benefits of RP application. Also, optimization of product properties would satisfy customer needs and help to avoid wasting resources.

Significant cost and time savings can also be achieved by manufacturing multiple parts in a single setup for efficient machine volume utilization. Gogate and Pande [20] developed a comprehensive methodology for optimal layout planning of parts for RP, taking into account various constraints like build time, part quality, and support structures required. Acceptable orientations for all the parts to be produced are initially obtained followed by a rating based on their desirability. Then, optimal placement of parts is attained to realize a reduction in part cost and improved quality using a genetic algorithm-based procedure.

Based on the review of literature, the prominent FDM process parameters were selected for investigation of build time, surface roughness, use of the model, and support material. The selected process parameters for this research include layer thickness or slice height; toolpath factors such as road width, raster angle, number of contours and air gap; as well as various model representation issues such as STL deviation and angle.

Research Methodology

The research methodology followed in this study is shown in Figure 3.

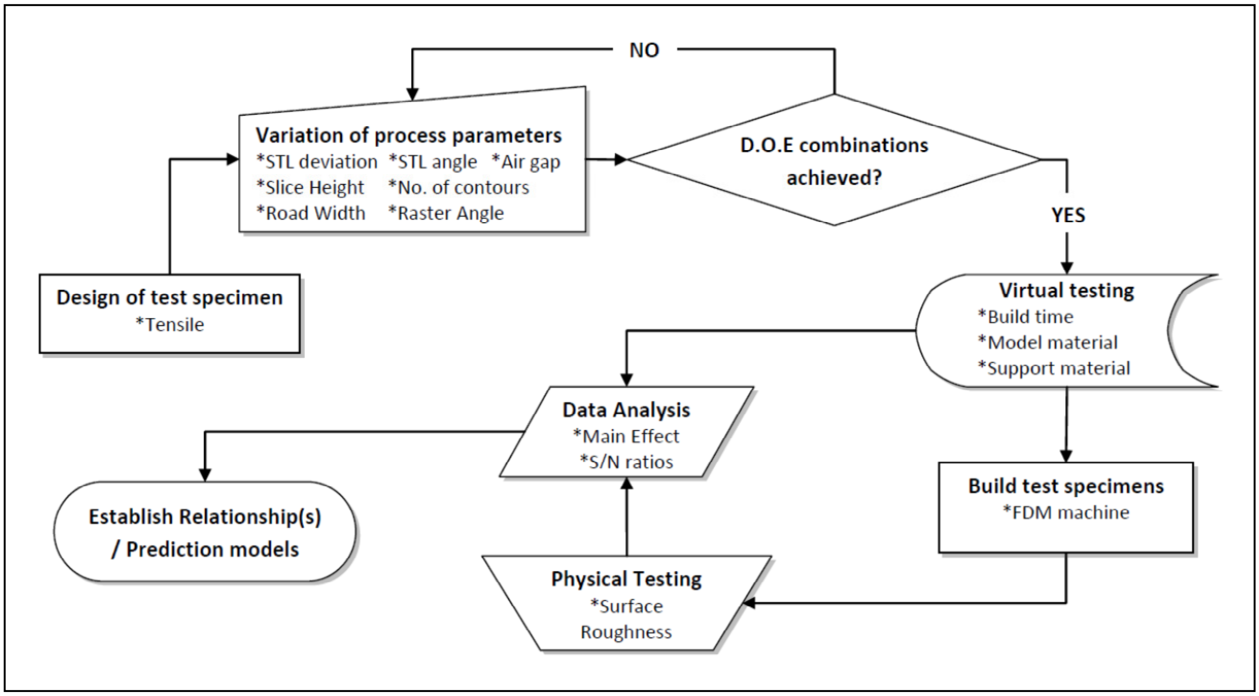

Figure 3. Research methodology

Design of Test Specimen

Firstly, the design of the selected tensile test specimen (Figure 4) was modeled utilizing SolidWorks. This design was based on a functional model implemented by other research studies investigating FDM systems, thus allowing for additional inferences to be drawn through this research [8, 11]. Furthermore, its flat surface characteristics facilitate straightforward surface roughness measurements while its small size is conducive to time and material savings during experimentation.

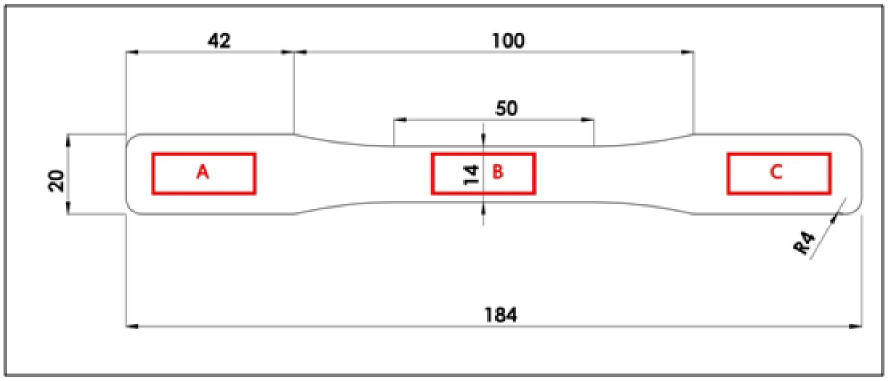

Figure 4. Selected tensile test specimen with dimensions (in mm) and measurement zones for surface roughness

Variation of Process Parameters

A design of experiments (DOE) framework was developed based on the number of selected process parameters and their levels. When possible, three levels were used for each process parameter to generate more realistic responses and provide more meaningful and accurate estimations (Table 1).

Table 1. Selected process parameters and level settings

Process Parameters Varied	**Levels**		
	1	**2**	**3**
Slice Height (mm)	0.1778	0.2540	——
Road Width (mm)	0.4064	0.5334	0.6604
Raster Angle (^{o})	30	60	90
Number of Contours	1	3	5
Air Gap	Negative	None	Positive
STL Deviation (mm)	0.2204	0.1148	0.0092
STL Angle (^{o})	0.5	15.25	30

Due to the availability of printing tips, only two levels were considered for slice height. However, having several other process parameters at three levels would require an extensive number of experiments using the traditional full-factorial method. Therefore, the Taguchi method was adopted to obtain statistically valid results from fewer experiments. In Taguchi design, a special set of arrays called orthogonal arrays, is available for designating experimental conditions. Based on the total degree of freedom, the appropriate orthogonal array is selected. In this case, L18 orthogonal array (Table 2) was chosen for both virtual and

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physical testing to accommodate mixed levels of parameters. This array determines process parameters settings for each trial or experiment required. For instance, the first row of Table 2 specifies that experiment 1 was conducted with all of the process parameters at the associated level 1 setting as shown in Table 1. STL deviation and STL angle were varied while generating the STL model from the tensile specimen CAD model. All generated STL models were then imported into the FDM system, where the remaining process parameters were varied.

Table 2. L18 Taguchi orthogonal array

Expt. No.	Slice Height	Road Width	Raster Angle	No. of Contours	Air Gap	STL Deviation	STL Angle
1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2
3	1	1	3	3	3	3	3
4	1	2	1	1	2	2	3
5	1	2	2	2	3	3	1
6	1	2	3	3	1	1	2
7	1	3	1	2	1	3	2
8	1	3	2	3	2	1	3
9	1	3	3	1	3	2	1
10	2	1	1	3	3	2	2
11	2	1	2	1	1	3	3
12	2	1	3	2	2	1	1
13	2	2	1	2	3	1	3
14	2	2	2	3	1	2	1
15	2	2	3	1	2	3	2
16	2	3	1	3	2	3	1
17	2	3	2	1	3	1	2
18	2	3	3	2	1	2	3

Testing

After variation of all process parameters, STL models were sliced and toolpaths generated within the FDM system. Subsequently, through virtual testing, estimates of the volumes of model and support material used for fabrication, as well as the build time for each STL model, were calculated. All STL models were then built using the Stratasys FDM 400mc machine with poly-carbonate material, followed by physical testing. This involved measurements for surface roughness, obtained by using Mitutoyo SJ-400 surface roughness tester. Measurements were taken at three zones, A, B, and C, for the top surface as shown in Figure 4. Average roughness (R_a) values were taken, based on their wide use in research and hence determined to be a standard measurement accepted [4, 8, 21]

Data Analysis

To determine which process parameters gave rise to a specific response, whether higher or lower, main effect plot of factor means was used. For a process parameter, the mean ($\overline{y}$) of the responses were found and plotted against each level. This was repeated for each of the selected process parameters.

The mean is found by the equation, $\overline{y} = \frac{\sum_{i=1}^{n}(y_i)}{n}$ (1)

where:
y - the response
n - the number of observations.

Furthermore, as part of designing robust builds, S/N ratios were used. This yielded a combination of process parameters that led to responses with minimum variation from the intended target. It would also expose those process parameters which, when changed, created large amounts of variation. Since the smaller is better and larger is better responses were more sensitive to shifts in the mean value, the nominal is best response was chosen, and the S/N ratios were plotted as per the process parameters that are under consideration [22]:

$$S/N_{NB} = -10\log_{10}[S^2] \tag{2}$$

where:
y_i - response
n - number of observations
S^2 - sample variance; given by the equation:
$$S^2 = \frac{\sum_{i=1}^{n}(y_i - \overline{y})^2}{n-1}$$

Prediction Model

A multiple regression approach, which is a combination of linear regressions in an enhanced mathematical format, was used, to develop an equation that best fits the results of the experiment. Using this equation, it is possible to predict the value of the response, given a certain combination of process parameters. The general form is

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k \tag{3}$$

where
x - process parameter
y - response
b - coefficient of the process parameter
k - number of process parameters considered

Discussion

Utilizing the main effect plot of factor means, the effect of varying process parameters on build time, volume of support, and model material used during fabrication as well as surface roughness of top surface was analyzed in the following sections.

Build Time

On analysis of the main effect plot for build time (refer to Figure 5), variation of slice height, road width, and air gap were identified as the process parameters that had significant impact. These are discussed below.

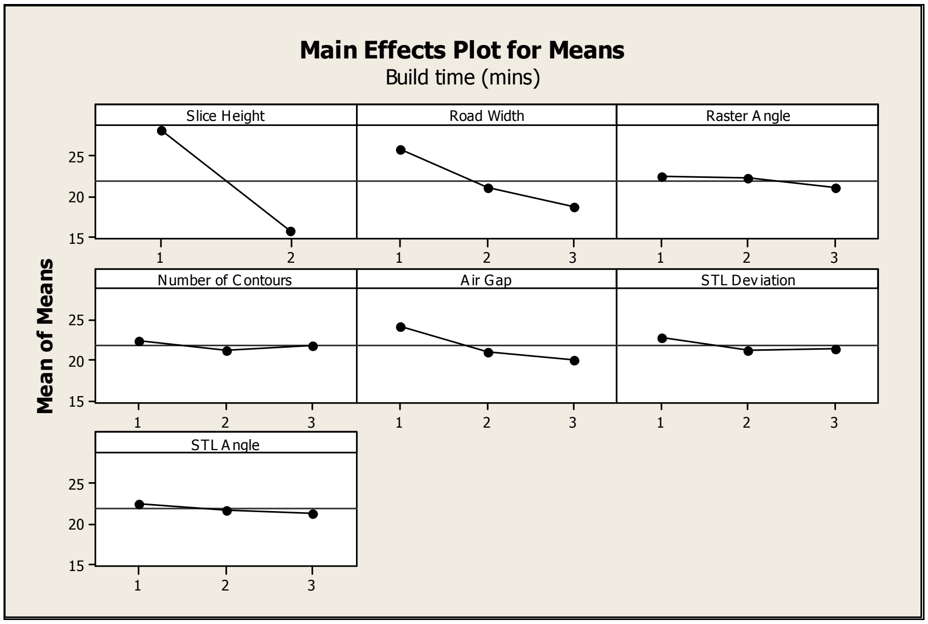

Figure 5. Main effect plot for build time

Effect of Slice Height. For the smaller slice height, 0.178 mm, time increases by approximately 12 minutes when compared to the larger slice height of 0.254 mm. This is because with a smaller slice height, more slices are generated to fulfill the aggregate model thickness. Having extra slices means that the extrusion head has to make additional passes to complete the part. Furthermore, after completing a slice during fabrication, the extrusion nozzle would pause to allow for cleaning, which takes, on average, 30 to 60 seconds. These factors account for the significant increase in time for a smaller slice height.

Effect of Road Width. A smaller road width increased the build time in a non-linear manner. This response may be due to automatic changes of determining factors such as extrusion height, travel speed, and extrusion flow rate to accommodate variations in road width. Furthermore, a small road width requires the nozzle to travel a finer path to fill each slice, as shown in Figure 6 below. This would involve more passes to be made by the nozzle, resulting in increased build time.

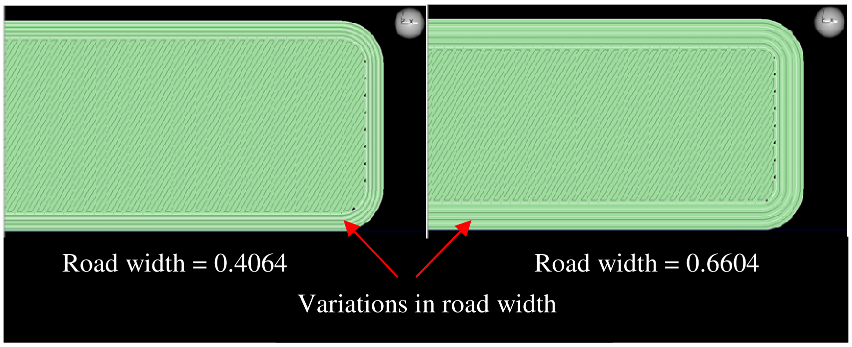

Figure 6. Road width variation

Effect of Air Gap. A negative air gap (level 1) increased the build time when compared to no air gap and a positive air gap. This is because toolpaths are closer together and require extra time for the nozzle to complete a slice, as shown in Figure 7 below. With a positive air gap (level 3), the spacing between toolpaths increases, effectively replacing some of the material-filled areas with air. Hence there is less distance for the extrusion head to cover before finishing each individual slice.

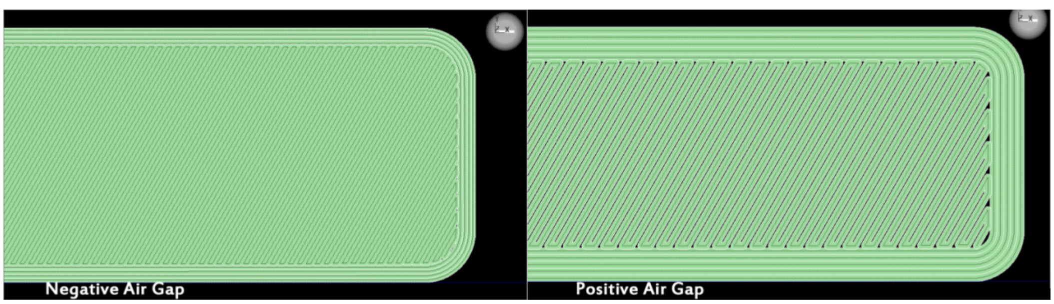

Figure 7. Air gap variation

Prediction Model. The multiple regression approach was adopted to predict the various performance measures based on the seven process parameters selected. The calculations were performed using Minitab, and the coefficients, along with the regression p-values, yielded for build time are shown in Table 3.

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Table 3. Build time regression values

Process Parameter	Co-efficient	p-value
Constant	56.56	-
Slice height	-12.44	0.000
Road width	-3.58	0.000
Raster angle	-0.75	0.219
Number of contours	-0.33	0.573
Air gap	-2.08	0.005
STL deviation	-0.67	0.271
STL angle	-0.58	0.332

Process parameters with p-values greater than 0.05 were considered insignificant and therefore not included in the prediction model. The multiple regression equation for build time is build time (mins) = 56.56 – 12.44 slice height – 3.58 road width – 2.08 air gap.

This regression equation further validates that the critical process parameters for build time are slice height, road width, and air gap.

Support Material

Analyzing the main effect plot for volume of support material consumed (Figure 8) indicates that variation of slice height was the only process parameter that had a significant impact on slice height. This is further discussed below.

Effect of Slice Height. A smaller slice height required less support material. This occurs since the models built with different slice heights; all required a consistent five slices of support material to be generated. Hence the total volume of support material used is proportional to the aggregate height of these five slices given that the area of the part is constant. The total height of support material with 0.1778 mm slice thickness is 0.8890 mm; and total height of support material with 0.2540 mm slice thickness is 1.2700 mm.

Prediction Model. Following the same procedure adopted for build time, the multiple regression equation developed for the support material consumed is represented as support material (cm^3) = 0.499 + 0.241 slice height.

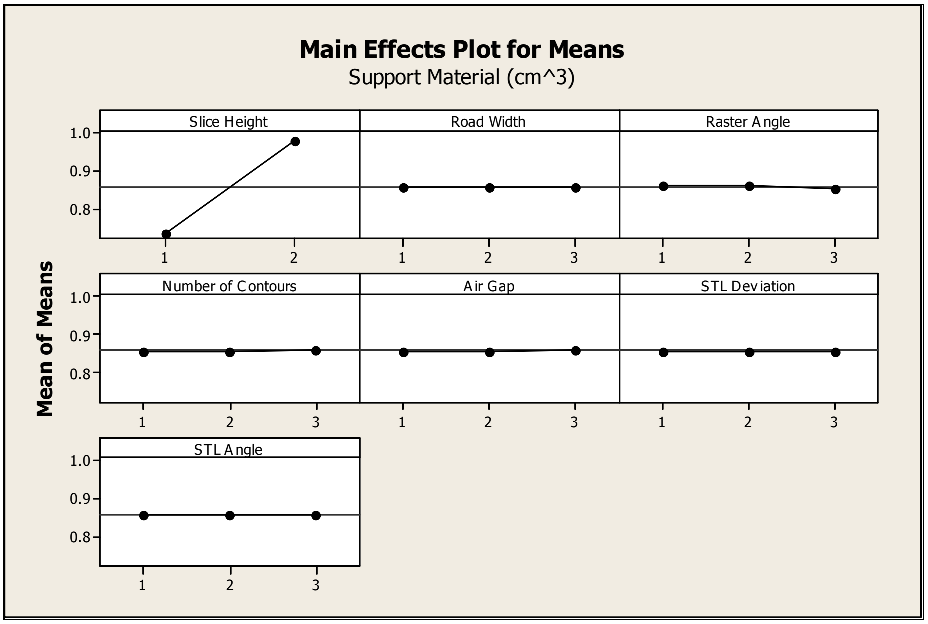

Figure 8. Main effect plot for support material

Model Material

On analysis of the main effect plot for volume of model material consumed (Figure 9); variation of slice height and air gap had a significant impact.

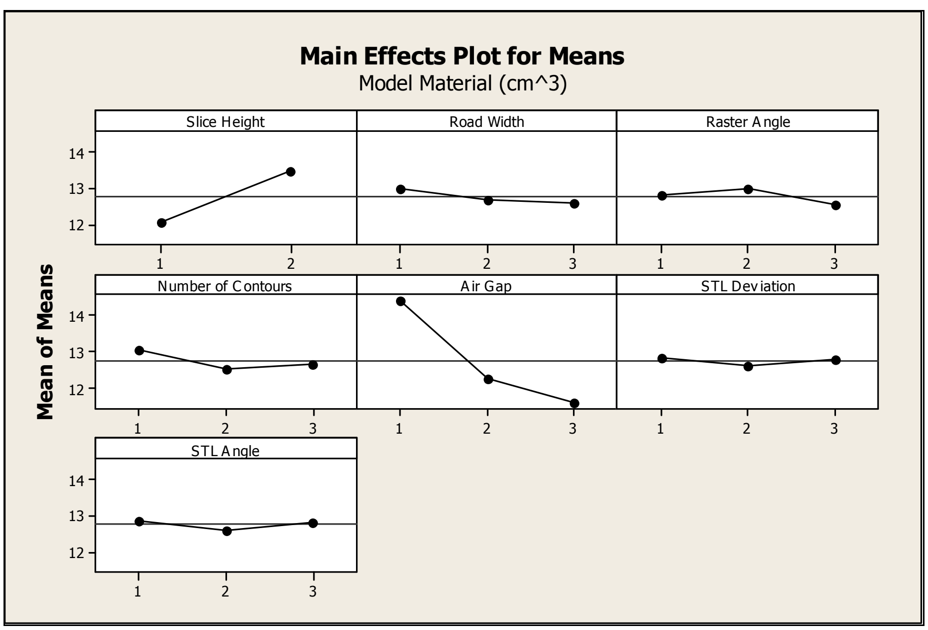

Figure 9. Main effect plot for model material

Effect of Air Gap. By adjusting the air gap from negative to positive, the volume of model material consumed decreases considerably. This can be explained by the resultant increase in spacing between road widths thus requiring less deposited material per slice.

Effect of Slice Height. The number of slices generated for both slice heights can be seen in Table 4. Also, the resulting part thickness is downsized when the slice height selected is not a multiple of the original part thickness. In addition, this reduction is greater with a smaller slice height, thereby resulting in less volume of model material to be used. Furthermore, filling a slice according to a raster pattern often results in the creation of voids near its boundaries. Thus, using a smaller slice height increases the number of slices to define the part thickness and results in a greater number of voids with a reduction in the required volume of model material.

Table 4. Comparison in number of slices

Slice Height(mm)	0.178	0.254
Number of Slices	18	13
Estimated Height(mm)	3.204	3.302
Actual Height(mm)	3.33	3.33

Prediction Model. The multiple regression equation for assessment of the model material consumption was developed and is represented as model material (cm^3) = 14.58 + 1.4 slice height – 1.4 air gap

Surface Roughness

On analysis of the main effect plot for the surface roughness (refer to Figure 10), variation of air gap, raster angle, and road width were the process parameters that had significant impact.

Effect of Air Gap. Models built with a negative air gap had a flawed surface finish and in order to protect the surface roughness tester stylus, no measurements were taken. However, with a positive air gap, the surface roughness is greater than with no air gap. The rougher surface for a positive air gap is caused by the creation of spaces in-between adjacent road widths. This space creates a depression that allows the tester stylus to travel beneath the mean line for a longer period of time. Since the average surface roughness is given as the sum of the difference from the mean line, these depressions increase the roughness of the surface.

Effect of Raster Angle. As the raster angle approaches 90°, surface roughness decreases. A possible explanation is that for the other raster angles, synchronization of both X and Y axis servo motors is required for deposition of the roads. Due to the servo motors' slack timing belts, fluctuations in the straightness of the deposited roads develop. These fluctuations cause voids, which increase the surface roughness (Figure 11).

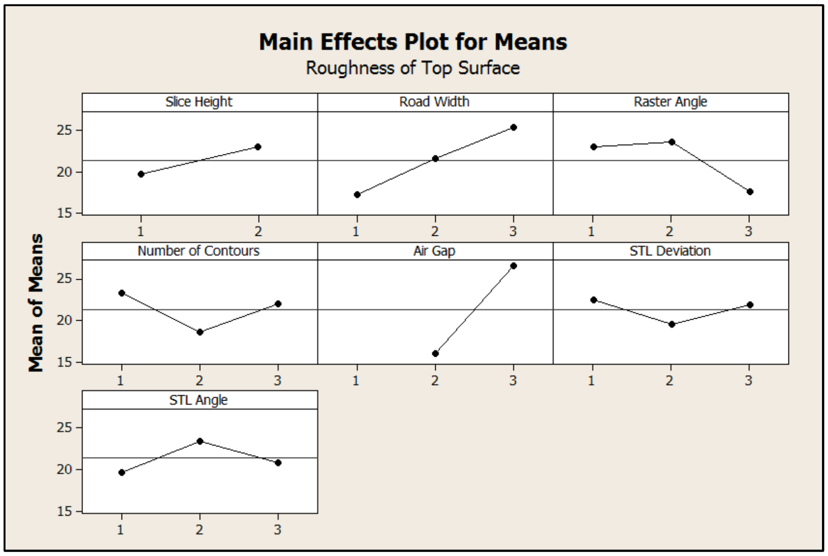

Figure 10. Main effect plot for surface roughness

Effect of Road Width. The road width governs the horizontal length of the deposited bead from the extrusion head. Having a larger road width would result in an increase of the perimeter of the deposited bead. This therefore, increases the distance the stylus travels beneath the mean line, leading to a larger surface roughness.

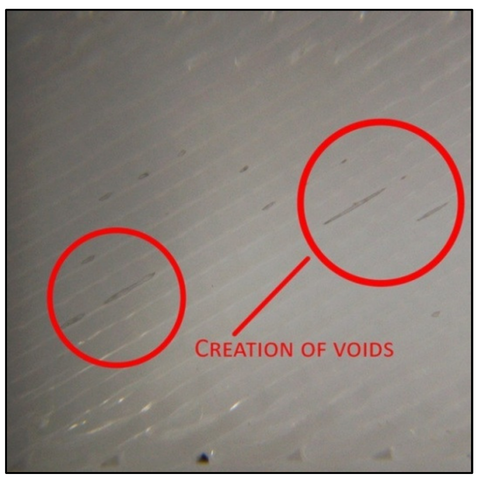

Figure 11. Voids present in test specimen 16 with a raster angle of 60°

Signal to Noise Ratios

For each zone (A, B, C) shown in Figure 4, three surface roughness measurements were taken for a total of nine measurements for each prototype. To assess the extent to which each process parameter affected the variability of surface roughness, S/N ratios were used. The nominal is the best scenario implemented, and the higher value of the S/N ratio reflects the process parameters, reducing surface roughness variability. Main effect plot for S/N ratios is shown in Figure 12.

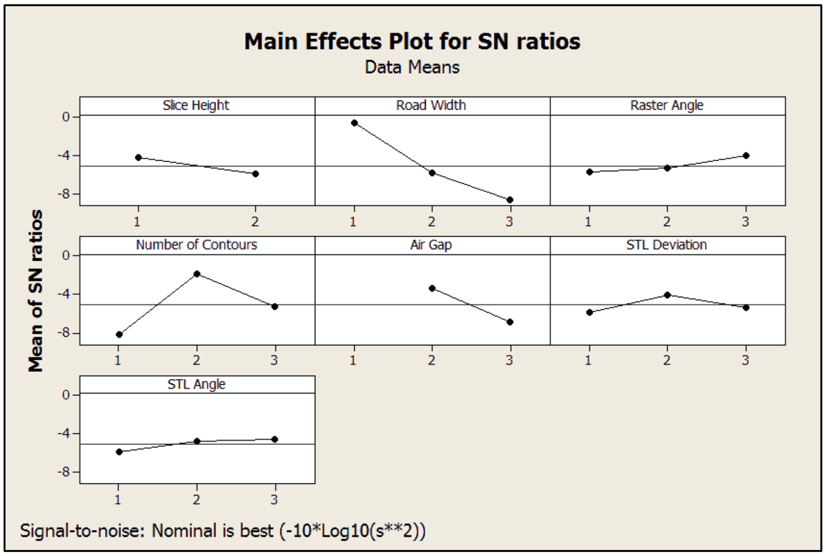

Figure 12. Surface roughness main effect plot for S/N ratios

Effect of Road Width. The value of road width thickness is controlled by the machine, using a combination of either extrusion height, extrusion nozzle speed of travel, or extrusion rate of the material. A smaller road width, in this case, reduces the variability of roughness on the surface. This can be due to some combination of the three factors above that result in straighter road widths to be extruded. The opposite could be said for a larger road width and its effect of raising the variability in the process. An alternative reason could be that since the road widths are smaller, any variation in their linearity is far less pronounced as compared to a larger road width.

***Effect of Air Gap*.** For a positive air gap, there are spaces on the sides of each laid road width. When the material is initially extruded, it exists in a semi-liquid state and can flow into these spaces in an unpredictable manner. This is what could have led to the higher amount of variation. With no air gap, road widths are laid adjacent to each other impeding flow. Instead, fusion takes place along these lines in a more expected manner.

Conclusion

The present work has made an attempt to study the effect of seven process parameters—slice height, road width, raster angle, number of contours, air gap, STL deviation and angle—on the build time, material usage, and surface roughness of an FDM-built part. For minimizing build time, a larger slice height (0.2540 mm), larger road width (0.6604 mm), and positive air gap was more effective. For minimizing support material consumption, a smaller slice height (0.1778 mm) is recommended, and for minimizing model material consumption, smaller slice heights (0.1778 mm) and positive air gaps are preferred. Additionally, the optimal values for build time, support and model material consumption are 13 minutes, 0.737 cm^3 and 10.799 cm^3, respectively. Moreover, the optimal values derived from the predictive regression models are build time of 14.7 minutes, support material consumption of 0.740 cm^3, and model material consumption of 11.780 cm^3. By comparing these values, it can be seen that reasonable parameter estimation was achieved.

Furthermore, the optimal top surface roughness value of 7.434 μm was obtained due to some influential process parameters, such as road width of 0.4064 mm, raster angle of 90°, and no air gap. Also, the STL deviation and STL angle process parameters had minimal effect on all performance measures. In addition, each performance measure has its unique optimal parameter level settings and combinations. As such, it is required to make trade-offs either to save on time/ material or to produce a smooth/ rough surface.

Also, maximum build time, support, model material consumption, and surface roughness values from the experimental runs are 39 minutes, 0.983 cm^3, 16.092 cm^3, and 36.72 μm, respectively. When considering optimal experimental values, there are savings of 67% for build time, 25% for support material, 33% for model material, and 80% improvement of surface quality. Total material savings can further translate into $5 per part. With these guidelines, RP users can benefit by saving cost and time when determining the optimal process parameter settings suited for their needs.

Future Research

The future aim of this work is to investigate additional process parameters, such as build orientation and shrinkage factor, to study holistically the relationship and interactions of all critical FDM process parameters as well as on various performance measures. Furthermore, this would lead to the development of non-linear predictive models and, thus, a multi-objective optimization algorithm.

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