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# Experimental Study on Parametric Optimization for Selective Laser Sintering (SLS) Prototype Processing

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## ABSTRACT

*This paper gives an analysis and relevance of a quality prototype in different fields for high integrity components. Since few decades the additive manufacturing (AM) technology developing very fast consisting its ability to fulfill the global market new production requirements. The AM is an umbrella term it has different types of technologies depending on the material type. Selective Laser Sintering (SLS) process is versatile and proven process to build quality prototypes is one of the technologies of AM. In this process parts produced layer by layer and each layer cured instantly by the power of $CO_2$ laser. The development of quality prototype is critical in any additive manufacturing process as it directly relates to its strength and accuracy. This study aims at improving the performance characteristic and process optimization through application of designing an approach of experimentation. The process control parameters are part orientation, part bed temperature and refresh rate. Response parameters viz. Diameter, Thickness, length, and width have been individually assessed. The statistical technique has been used to study the effect of process parameters and its significance. Taguchi method L9 array approach has been used for process design.*

***Keywords:***— *Additive manufacturing (AM), Selective Laser Sintering (SLS, $CO_2$ laser, Prototype*

## I. INTRODUCTION

The current market is characterized by high level of global competition. This competitive and global environment, is a buyer's market, is very beneficial to the consumer. People can buy goods with quality and value. This means that the products must be cheap and of good quality. Creating prototype is a basic job as it works as an idea to produce aquality products. Because prototype features often require high budget and is also time consuming, Therefore it is important to use advanced technologies such as rapid prototypes and indirect prototype tools. The present implementations of digital prototyping and digital manufacturing using the CAD/CAM technologies to prototyping can overcome the conventional manufacturing such as material removal methods. It also produces functional products by additive production methods. Rapid manufacturing technology stands for a class of methods used to produce quickly a replica of an actual part using 3D CAD data. Rapid Prototyping (RP) is a generic word used for a layer over layer additive method, and can be referred in several ways such as reverse engineering, Rapid Manufacturing (RM), Additive Fabrication, Freeform Fabrication (FF), and Direct production, e-Manufacturing, Freeform Manufacturing (FFM), Digital Manufacturing, and Digital Fabrication [1].

## II. Additive Manufacturing

AM is an umbrella term given to all technologies, it processes parts joining material in layers, as opposed to removing material in conventional subtractive processes. The ASTM F42 Technical Committee defines AM as the “method of fuse materials to get articles from 3D model data, such as one sheet upon another sheet, as reversed to the conventional manufacturing processes” [2]. AM technology is the natural extension of RP. RP technologies are used to produce specimen and prototypes leading to the widely accepted term AM, which is used to refer all layer additive fabrication processes. Currently, technology advancement in materials and processes, mean that the parts produced with sufficient material properties to allow end user products and, led to the term RM adopted to differentiate the fully functional nature of the parts manufactured from the previous RP specimen and prototypes.

Now, AM is the general term used, and RP and RM are used to trace out the respective application of AM technologies. There are more technologies which employ this process of manufacturing products, some of them widely used depending on the matter such as solid, liquid, powder and gas based [3][4].

## III. Selective Laser Sintering

Carl Deckard has developed this technology in Texas University while preparing the thesis of his master’s degree, and patented it in the year 1989. This is a three-dimensional printing process in which Parts are built by sintering when a $CO_2$ laser beam hits a thin layer of selectively powdered material. The process begins with a model in CAD software and then translated into an STL file with the pieces cut into slices the information for each layer. The thickness of each layer as well as the replacement there depends on the equipment used. The first completed layer goes below one layer of the object, the roller circulates the next layer of the powder, and this process continued till the product is completed. The powder does not boil during the process or fuse but acts as an inbuilt support structure. Thus the separate support requirements are not required, and when the component is completed the non-fused powder material will completely brush off. Benefits of SLS technology are good part stability and, no need to part supports. Drawbacks are high power consumption, and rough surface finish [5]. The figure 1, shows the schematic diagram of SLS process and figure 2, shows the product modelling process. The SLS allows the production of fully functional prototypes with

- High mechanical and thermal

resistance,

- Strength & rigidity under the extreme conditions of high temperature.

Durable metal parts, mold inserts, direct Low density complex investment casting patterns can be prepared directly from SLS.

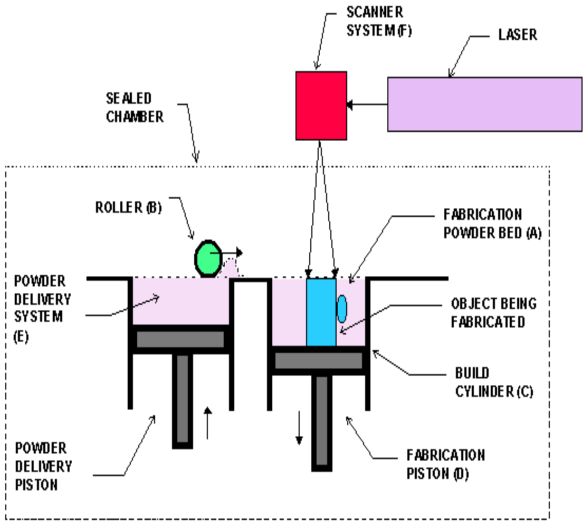


*Figure 1: Selective Laser Sintering*

The basic methodology for SLS rapid prototyping technique can be summarized as follows:

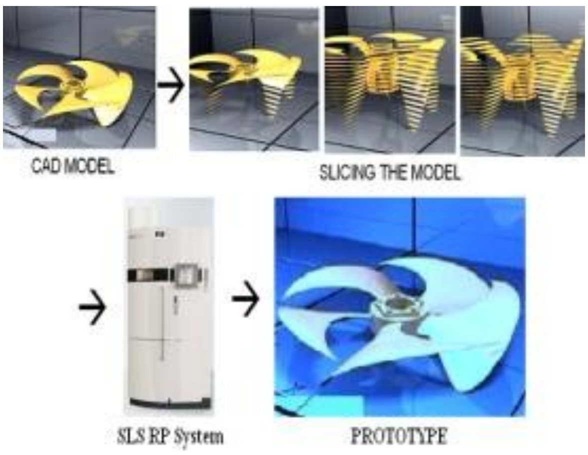


*Figure 2: Selective Laser Sintering Modelling Process*

## IV. Test Strategies

Engineers and scientists are most often faced with two process development positions. One process situation is to find a parameter that will improve performance characteristics to an acceptable or optimum value. Second situation is to find a less expensive, alternative design, material or method which will provide equivalent performance. Depending on which situation the experimenter is facing, different strategies may be used. Dr. Genichi Taguchi has developed a family of fractional factorial experiments (FFE) matrices which can be utilized in various situations. Taguchi Orthogonal Array (OA) design is a type of general fractional factorial design [6]. It is a highly fractional orthogonal design that it allows you to consider a selected subset of combinations of multiple factors at multiple levels. Taguchi Orthogonal arrays are balanced to ensure that all levels of all factors are considered equally. For this reason, the factors can be evaluated independently of each other despite the fractional of the design. The Taguchi method involves reducing the variation in a process through robust design of experiments. The overall objective of the method is to produce high quality product at low cost to the manufacturer. Therefore, poor quality in a process affects not only the manufacturer but also society. This is a method for designing experiments to investigate how different parameters affect the mean and variance of a process performance characteristic that defines how well the process is functioning [7]. The table1 gives the three levels of the control parameters for the experimentation given below. The Taguchi design L9 orthogonal array is used in the present research experiment for three levels, three factor settings as shown in table 2.

**Table 1: Illustration of Experimental Control Parameters**

| Symbol | Parameters | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| A | Orientation | $0_o$ | $45_o$ | $90_o$ |
| B | Temperature | 173 $c_o$ | 170 $c_o$ | 167 $c_o$ |
| C | Refresh rate | 0 % | 30 % | 60 % |

**Table 2: L9 Orthogonal Array**

| Expt runs (j) | Levels | | |
|---|---|---|---|
| | A | B | C |
| 1 | 1 | 1 | 1 |
| 2 | 1 | 2 | 2 |
| 3 | 1 | 3 | 3 |
| 4 | 2 | 1 | 2 |
| 5 | 2 | 2 | 3 |
| 6 | 2 | 3 | 1 |
| 7 | 3 | 1 | 3 |
| 8 | 3 | 2 | 1 |
| 9 | 3 | 3 | 2 |

## V. EXPERIMENTAL PROCEDURE

The proposed design is similar to that of the standard design specifications is shown in figure which is designed as a single component which rapid prototyping can only fabricate. The prototype specimens are prepared using solid works 2018 software to design CAD model, which is converted into STL format and then uploaded into the machine FORMIG P 100 through the Magics software. The cad drawings can be seen in the figures. The CAD modeling is done with the aid of Solid works[8]. The part designed must first be aligned and positioned in an RP software package, e.g. Magics RP. There are some special aspects that must be taken into account for the laser sintering process. In the initial stage of the data preparation process the component that is to be prototyped is imported into the Magics RP software which is then suitable for converting into STL format with suitable modifications on it, [9]. Figure 3 shows the Test sample drawing for dimensional Analysis component imported and converted into STL. Figure 4 shows the test sample in the STL format, the part data is transformed into layer data using the EOS RP- Tools. The part produced from FORMIG P 100 SLS system, with the material PA2200 shown in figure 5.

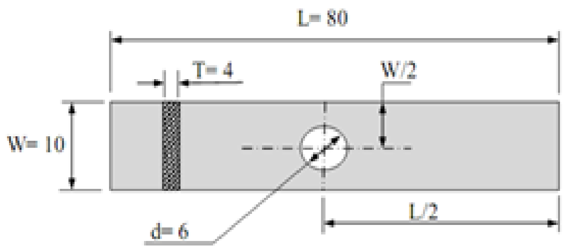


*Figure 3: Test sample drawing for dimensional Analysis (all dimensions are in mm)*

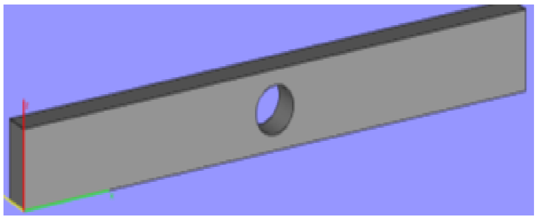

*Figure 4: The test sample in the STL format*

*Figure 5: The test sample prepared from FORMIGA P 100 SLS RP system*

## VI. ANALYSIS OF DIMENSIONS

This study carried out for the dimensions of the specimens of poly amide PA2200 were produced for L9 Orthogonal array settings, triplicate each using 3D system SLS FORMIGA P100 EOS machine and the prototypes shown in fig 4. The dimensions of prototypes diameter (D), thickness (T), length (L), and width (W) are measured using Mitutoyo digital Vernier Caliper. The percentage change in dimensions is calculated using equation (6.1).

$\Delta X \% = [(X - XCAD) / (XCAD)] \times 100$........................................... (6.1)

Where X represents measured value of dimensions, $X_{CAD}$ represents measured value of respective CAD model;

ΔX% represents relative percentage change in X. The experimental results of ΔD%, ΔL%, ΔT% and Δw% are shown in table 3.The respective response tables and figures for Signal to Noise Ratio of ΔD%, ΔL%, ΔT% and Δw% are given. The analysis of S/N Ratio gives the way to select the optimum factor level based on the minimum variation around the target and also on the average value nearest to the target [10]. The main aim of the experimental plan is to reduce the relative change in diameter (ΔD), length (ΔL), thickness (ΔT) and width (Δ w) as small as possible. So here the "the smaller the better" quality feature is used. For "smaller the better" quality feature, the S/N ratio (Y) is express by the equation (6.2)

$Y = 10 \log_{10} (MSD)$ …………………(6.2)

$MSD = \alpha_2 + (m_{avg} - m_o)$ ……………..(6.3)

Where $\alpha_2$ is called variance, $m_{avg}$ is the average of the data, and $m_o$ is the target value in this case it is zero. Experiment analysis carried out using Minitab-R18 software. The main effect plot SN ratio is used to determine optimum factor level. Respective influence of each factor is estimated by ANOVA[11]. Calculations necessary for ANOVA are given in equation 6.3.

$$Ts = \sum_{k=1}^{N} (Y_k - \overline{Y})^2 \qquad (6.4)$$

Where $T_s$ is the total sum of squares, N is number of observations and $Y$ is the overall mean of SN Ratio.

$$TTj = \sum_{k=i}^{j} (Y_{ji} - \overline{Y})^2 \qquad (6.5)$$

Where TTj is sum of square deviation of jth factor, i is level of $j^{th}$ factor.

$$Uj = \frac{TTj}{Fj} \qquad (6.6)$$

Where Uj, and Fj, are variance and degrees of freedom respectively of $j^{th}$ parameter.

**Table 3: Experimental Results of Change of Dimensions and Their Respective S/N Ratios**

| Expt No | Factors | | | Change in Dimensions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | ΔD% | S/N Ratio | ΔL%, | S/N Ratio | ΔT% | S/N Ratio | Δ w% | S/N Ratio |
| 1 | 1 | 1 | 1 | -4.778 | -13.585 | 0.400 | 7.9588 | 0.667 | 3.518 | 2.033 | -6.1642 |
| 2 | 1 | 2 | 2 | -2.889 | -9.215 | 0.237 | 12.505 | 2.417 | -7.666 | 0.333 | 9.5424 |
| 3 | 1 | 3 | 3 | -1.056 | -0.470 | 0.042 | 27.535 | 3.000 | -9.542 | -0.367 | 8.7146 |
| 4 | 2 | 1 | 2 | -7.833 | -17.879 | 0.033 | 29.6297 | 2.250 | -7.044 | 3.333 | -10.4576 |
| 5 | 2 | 2 | 3 | -5.278 | -14.449 | 0.021 | 33.5556 | 1.000 | 0.000 | 2.233 | -6.9791 |
| 6 | 2 | 3 | 1 | -6.111 | -15.722 | 0.271 | 11.3406 | 3.192 | -10.081 | 1.333 | -2.4988 |
| 7 | 3 | 1 | 3 | -5.056 | -14.075 | 0.213 | 13.4324 | 6.833 | -16.692 | 2.167 | -6.7158 |
| 8 | 3 | 2 | 1 | -5.222 | -14.357 | 0.246 | 12.1813 | 7.000 | -16.902 | 1.667 | -4.4370 |
| 9 | 3 | 3 | 2 | -3.833 | -11.672 | 0.171 | 15.3401 | 5.333 | -14.539 | 1.667 | -4.4370 |

**Table 4: Analysis of Variance of response ΔD%**

| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| A-Orientation | 2 | 18.38 | 61.56% | 18.379 | 9.190 | 2061.32* | 0 |
| B-Temperature | 2 | 7.606 | 25.48% | 7.606 | 3.803 | 853.01* | 0.001 |
| C-Refresh Rate | 2 | 3.861 | 12.93% | 3.861 | 1.930 | 433 | 0.002 |
| Error | 2 | 0.009 | 0.03% | 0.009 | 0.004 | | |
| Total | 8 | 29.85 | 100.00% | | | | |

* Significance at 95 % Confidence Level

Fj is F statistics of j$^{th}$ factor and Ue is variance of error If error degree of freedom becomes zero, then it is not possible to calculate F-value and analysis variance ANOVA. In such cases it can predict and verify improvements in observed values through the use of factor level combination

As given in equation (6.7)

$$Fj = \frac{Uj}{Ue} \qquad (6.7)$$

$$Y_{pred} = \bar{Y} + (\bar{A}i - \bar{Y}) + (\bar{B}j - \bar{Y}) + (\bar{C}_k - \bar{Y}) \qquad (6.8)$$

Where $Y_{pred}$ is predicted S/N ratio of response, $Y$ is sum of experimental average, $(\bar{A}i)$, $(Bj)$, and $(C_k)$ are average response for factors of A, B, and C, at respective levels i, j, and k ( i, j, k = 1,2,3).

**Table 5: Response Table for S/N Ratio of ΔD%**

| Level | A- orientation | B- Temperature | C-Refresh Rate |
|---|---|---|---|
| 1 | -7.756 | -15.180 | -14.555 |
| 2 | -16.017 | -12.674 | -12.922 |
| 3 | -13.368 | -9.288 | -9.665 |
| Delta | 8.261 | 5.892 | 4.890 |
| Rank | 1 | 2 | 3 |

From Table 4: Analysis of Variance of response ΔD% and the Response Table5 for S/N Ratio of ΔD% and figure 6, the S/N Ratio for graph for % change in diameter observed as a miner decrease in diameter. From the main effect plot it shows that the significant factor determined at 95% confidence level, F statics value, which factors have more contribution.

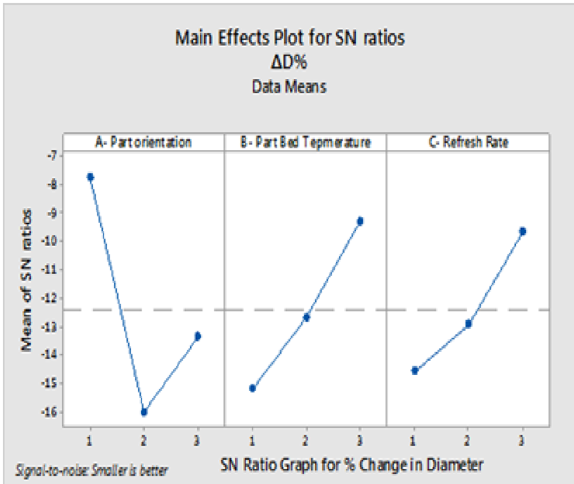


*Figure 6: S/N Ratio for graph for % change in diameter*

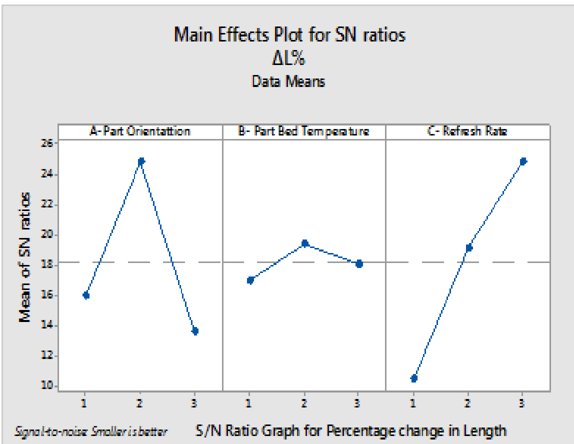

**Table 6: Analysis of Variance for Response ΔL%**

| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| A-Orientation | 2 | 2.7694 | 29.63% | 2.769 | 1.384 | 1.208* | 0.455 |
| B- Temperature | 2 | 0.1157 | 1.24% | 0.115 | 0.057 | 0.05 | 0.952 |
| C- Refresh Rate | 2 | 4.1516 | 44.42% | 4.15 | 2.075 | 1.80* | 0.357 |
| Error | 2 | 2.3087 | 24.70% | 2.308 | 1.154 | | |
| Total | 8 | 9.3454 | 100.00% | | | | |

* Significance at 95 % Confidence Level

*Figure 7: S/N Ratio for graph for % change in length*

**Table 7: Response Table for S/N Ratios of ΔL%**

| Level | A-Orientation | B-Temperature | C-RefreshRate |
|---|---|---|---|
| 1 | 16.00 | 17.01 | 10.49 |
| 2 | 24.84 | 19.41 | 19.16 |
| 3 | 13.65 | 18.07 | 24.84 |
| Delta | 11.19 | 2.41 | 14.35 |
| Rank | 2 | 3 | 1 |

From Table 6: Analysis of Variance of response ΔL% and the Response Table7 for S/N Ratio of ΔL% and figure 6, the S/N Ratio for graph for % change in length observed as a miner increase in length. From the main effect plot it shows that the significant factor determined at 95% confidence level, F statics value, which factors have more contribution.

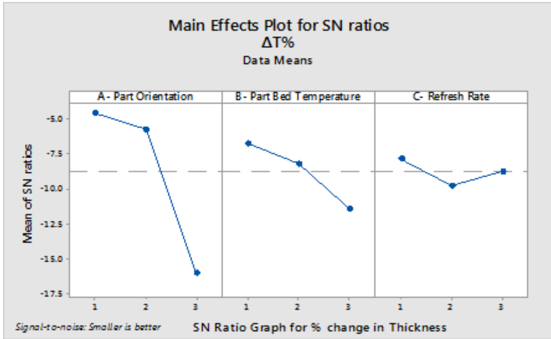


*Figure 8: S/N Ratio for graph for % change in Thickness*

**Table 9: Response Table for S/N Ratios of ΔT%**

| Level | A-Orientation | B-Temperature | C-RefreshRate |
|---|---|---|---|
| 1 | -4.563 | -6.739 | -7.822 |
| 2 | -5.708 | -8.189 | -9.750 |
| 3 | -16.045 | -11.388 | 8.745 |
| Delta | 11.481 | 4.648 | 1.928 |
| Rank | 1 | 2 | 3 |

**Table 8: Analysis of Variance for Response ΔT%**

| Parameters | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| A- Orientation | 2 | 37.0186 | 84.00% | 37.0186 | 18.5093 | 5.82* | 0.147 |
| B- Temperature | 2 | 0.5359 | 1.22% | 0.5359 | 0.2680 | 0.08 | 0.922 |
| C- Refresh Rate | 2 | 0.1592 | 0.36% | 0.1592 | 0.0796 | 0.03 | 0.976 |
| Error | 2 | 6.3572 | 14.42% | 6.3572 | 3.1786 | | |
| Total | 8 | 44.0708 | 100.00% | | | | |

*Significance at 95% Confidence Level

From Table 8 Analysis of Variance of response ΔT% and the Response Table 9 for S/N Ratio of ΔL% and figure 8, the S/N Ratio for graph for % change in Thickness observed as a miner increase in Thickness. From the main effect plot it shows that the significant factor determined at 95% confidence level, F statics value, which factors have more contribution

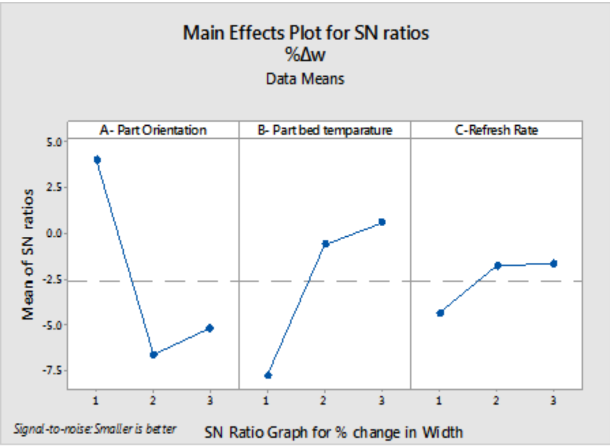


*Figure 9: S/N Ratio for graph for % change in width*

**Table 10: Response Table for S/N Ratios of ΔW%**

| Level | A-Orientation | B-Temperature | C-Refresh Rate |
|---|---|---|---|
| 1 | 4.0309 | -7.7792 | -4.3666 |
| 2 | -6.6451 | -0.6245 | -1.7840 |
| 3 | -5.1966 | 0.5929 | -1.6601 |
| Delta | 10.6761 | 8.3721 | 2.7065 |
| Rank | 1 | 2 | 3 |

From Table 11 Analysis of Variance of response ΔW% and the Response Table 10 for S/N Ratio of ΔW% and figure 9, the S/N Ratio for graph for % change in Width observed as a miner increase in Width. From the main effect plot it shows that the significant factor determined at 95% confidence level, F statics value, which factors have more contribution.

## VII. Significant Parameters Recognition

The process parameter (Orientation, Temperature & Refresh rate) which influences much on response variable is identified through the percentage of contribution of each parameter. A parameter with a more percentage of contribution is an important parameter for the response of a variable. ANOVA is widely used to determine the importance of independent variables in influencing dependent variables and determining the percentage of contributions of these dependent variables to response variable[12]. Tables of Analysis of variance for corresponding response variables are shows the percentage of contribution of the parameters. Hence, from the ANOVA table the significance of each parameter is identified

## VIII. Conclusions

The experimental Analysis carried out using Taguchi method L9 orthogonal array settings. The optimization of parameters for

**Table 11: Analysis of Variance for Response ΔW%**

| Parameters | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| A- Orientation | 2 | 2.6672 | 51.23% | 2.6672 | 1.333 | 3.67* | 0.214 |
| B- Temperature | 2 | 1.6272 | 31.26% | 1.6272 | 0.813 | 2.24* | 0.309 |
| C-Refresh Rate | 2 | 0.1857 | 3.57% | 0.1857 | 0.092 | 0.26 | 0.796 |
| Error | 2 | 0.7261 | 13.95% | 0.7261 | 0.363 | | |
| Total | 8 | 5.2062 | 100.00% | | | | |

*significance at 95% confidence level

Tensile Strength and relative change in dimensions, diameter (ΔD), Thickness (ΔT), Width (ΔW), and length (ΔL) are discussed. Building of a quality prototype by SLS process for various part orientations, part bed temperature, and refresh rate is analysed. The parameters identified for significance at 95% confidence level using ANOVA. The study of Signal to Noise Ratio for dimensional analysis "smaller the better" is used. It is evident that from this analysis the significant parameters play a vital role in building quality prototype.

This method is applied for other rapid prototyping processes to optimize parameters with different materials. This process model may be further refined by using non- conventional optimization techniques such as neural networks and genetic algorithm.

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