# Development of Process Model for Optimal Selection of Process Parameters for Geometric Tolerances and Surface Roughness in Stereolithography

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**Received: 9 May 2016, Revised: 14 June 2016, Accepted: 18 July 2016**

**Abstract:** The accuracy of stereolithography (SL) product is vital for meeting the intended functional applications. The parameters like layer thickness, hatch spacing, hatch overcure contribute significantly to the accuracy of the SL parts. In this paper an attempt has been made to identify the process parameters that influences on the accuracy of the parts made with CIBA TOOL 5530 and optimize the process parameters. A standard test specimen is designed for this study. A process model between the geometric tolerance (parallelism, perpendicularity, angularity, radius fillet), surface roughness and the above mentioned process parameters (layer thickness, hatch spacing, hatch overcure) have been developed. It is found that parallelism, perpendicularity, angularity, radius fillet and surface roughness are influenced significantly by hatch spacing, layer thickness, hatch overcure, hatch spacing and layer thickness respectively. The percentage deviation between the experimental and process model values have also been calculated to validate the developed process model.

**Keywords:** Geometric tolerances, Stereolithography, Surface roughness

**Reference**: Chockalingam, K., Jawahar, N., Chandrasekhar, U., Praveen, J., and Karthic, M., 'Development of Process Model for Optimal Selection of Process Parameters for Geometric Tolerances and Surface Roughness in Stereolithography', Int J of Advanced Design and Manufacturing Technology, Vol. 9/No.3, 2016, pp.103–113.

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## 1 INTRODUCTION

In a customer driven market, every manufacturer wants to produce their products in a very short span of time. This is a prerequisite for survival in the global market. Decrease in product development cycle time and increase in product complexity require new ways to realize innovative ideas. In response to these challenges, a spectrum of new technologies has been evolved to develop new products and to broaden the number of product alternatives. One such technology is Layered Manufacturing, which produces parts by deposition of material, layer by layer. Today the key benefits of Layered Manufacturing are mostly derived from its ability to create physical models directly from Computer Aided Design (CAD) models, regardless of their shapes and complexities.

Geometric tolerance and surface roughness plays a crucial role when it comes to die inserts for injection moulding [1, 10, 12, 14]. These mentioned qualities have to be considered for dimensionally accurate, freely ejectable products without any sorts of premature failure of die inserts. SL process consists of several process parameters with several discrete levels for each one of them. Selection of the most influencing process parameters associated with its optimal level is a challenging task which consumes significant amount of resources like time and money. Due to this nature, the establishment of real mathematical models is hard to derive. The purpose of this paper is to present an efficient method to find the significant process parameters affecting the process performances for SL process and selection of optimal process parameter based on statistical methods. However selection of the process parameters for SL process is difficult and relies heavily on operator's experience. Most of the operators minimize the part built time by compromising the quality of their parts. Part quality can be improved without the necessity of incurring additional expenses. Hence a literature review has been done to find the most influencing process parameters.

Rahmati. S and Ghadami. F [18] proposed a neural network to determine the optimal process parameter setup in SL process to predict the dimensional accuracy of the setting parameters like layer thickness, hatch style, hatch spacing and hatch overcurve. Raju et al. [17] presented an approach for optimizing the SL process for multiple quality characteristics based on taguchi method and grey relational analysis to enhance build part quality. Cho et al. [2] presented an approach to determine the optimal parameter setting based on Genetic Algorithm for minimizing part build error. Chockalingam et al. [22] made an attempt to predict the influence of process parameter on dimension deviation in the part produced by SL process but did not consider the surface roughness. Raju et al. [19] developed a process model for SL process used to determine the strength of the prototype for the given set of parameters like layer thickness, orientation and hatch space. Chockalingam et al. [3] conducted experiments to evaluate the influence of layer thickness on mechanical properties like tensile strength, impact strength and development of residual stress on SL component made out of epoxy resin CIBA tool SL5530.

The literature review reveals that, in all the experiments, contributions of process parameters on dimensional accuracy or surface finish were analyzed separately. Dimensional deviations in various directions were measured independently. In this paper an attempt has been made to identify the process parameters that have an influence on the geometric tolerance and surface finish of the parts made by SL, optimize the parameter levels and evolve process model (empirical / regression equations) for geometric tolerances and surface roughness with their influencing parameters.

This process model can predict the level of performance that the SL process would render for a given set of process parameters, thereby providing the dependency of performance characteristics / response variable on process parameters before actually producing the part and will be useful for both machine designers and the machine users. For this purpose, a standard specimen has been designed which consists of geometric features like parallelism (PL), perpendicularity (PR), angularity (AN) , radius fillet (RA) and surface roughness (SR). A statistical tool Design of Experiments (DOE) is used for the purpose of identification of process parameters, determination of optimal parameter levels and establishment of regression equation. The proposed methodology is verified with the data set of experiments conducted under standard conditions. Table 1, shows the various parameters considered by various researchers for their investigation.

**Table 1** Process parameter considered for parametric optimization of SL parts

| Year | Author | Lt | Hs | Ho | Pc | Or |
|---|---|---|---|---|---|---|
| 1998 | Onuh et al. | ✓ | ✓ | ✓ | X | X |
| 2000 | Cho et al. | ✓ | ✓ | ✓ | X | X |
| 2001 | Lee et al. | ✓ | ✓ | ✓ | X | X |
| 2008 | Chockalingam et al. | ✓ | X | X | ✓ | ✓ |
| 2014 | Raju et.al | ✓ | ✓ | *X* | *X* | ✓ |
| 2014 | Rahmati et.al | ✓ | ✓ | ✓ | X | X |

✓ = considered X = not

The parameters selected for this current work are as follows:

Layer Thickness (Lt): Depth of a layer, the region that is solidified at the same elevation.

Hatch Spacing (Hs): Distance between a couple of adjacent strands, which are the narrow regions solidified by the laser scanning.

Hatch Overcure (Ho): Depth that a strand pierces in to the lower adjacent layer.

Post curing time (Pc): The times taken of cleaned specimens which are exposed to Ultra Violet (UV) light in Post Curing Apparatus (PCA).

Orientation (Or): It refers to the way in which the part is oriented on the build platform with respect to X, Y, Z axes.

Among these process parameters, Layer Thickness (Lt), Hatch Spacing (Hs), Hatch Overcure (Ho) have been considered for this current study.

## 2 METHODOLOGY

By means of building standard parts or test specimens, the influencing process parameters are often been found out to achieve the desired quality for specific purposes. As far as experimental design is considered, full factorial method has been used widely. This is favourable only when few factors are to be considered. Full factorial method becomes time consuming and expensive when there is more number of parameters. Taguchi method of design of experiments is used widely when there are large numbers of parameters because of its simple, efficient and systematic approach [21]. Hefin et al. [7] says that Taguchi technique, which is based on statistical DOE, is a proven methodology to establish an optimum process setting or parameters for design of robust process and products. Montgomery [11] pointed out that Taguchi technique is a more refined and advanced version of fractional factorial experiments in DOE. Chockalingam et al. [5] performed optimization of process parameters using Design of Experiments based on Taguchi's Orthogonal Array (OA) for stereolithography process. According to Onuch and Hon [13], Taguchi technique is the most significant problem solving tool which can improve the performance of the product, process design and system with a considerable reduction in experimental time and cost. The importance of Taguchi method has been emphasized by several authors [6, 8, 9, 15, 16]. As far as this paper is concerned, Taguchi method is chosen as the methodology to materialize the objectives. In this paper an attempt has been made to investigate the influence of process parameters on performances like parallelism, perpendicularity, angularity, radius and surface roughness.

The steps of the proposed methodology are explained below:

Step 1: Design of standard part with specified features (parallelism, perpendicularity, angularity, concave radius and surface roughness) for the investigation.

Step 2: Setting of levels and their values for identified parameters to conduct experiments.

Step 3: Selection of Orthogonal Array (OA) to design the experimental runs for experiments.

Step 4: Experimentation for the OA setting to find the values of response variable.

Step 5: Prediction of optimal level for each parameter for the set objective with the response variable data using signal to noise (S/N) ratio.

Step 6: Identification of critical parameter (most influencing) for the response variable with the percentage of contribution of each parameter on the response variable using Analysis of Variance (ANOVA) technique.

Step 7: Establishment of empirical relationship for the response variable in terms of parameters in order to estimate the values of the response under different parameter settings.

### 2.1 Standard part design

Generally SL parts are used as prototypes, concept models, tender models, wind tunnel test models, rapid tool, die inserts and models for stress analysis. In these applications the SL parts have feature for determining geometric tolerances and surface roughness that determine the suitability. In order to properly define various non linear dimensional features and form features, a standard part is to be designed. Among them non linear dimensions (concave radius), parallelism, perpendicularity, angularity and surface roughness of various faces play an important role. Hence these features are taken into considerations while designing the standard part.
The designed part is depicted in Fig. 1, while Fig. 2 shows the part fabricated using SL process, which includes the above mentioned features. It should be noted that vertical (z) direction is the layer build direction. Dimensional features of the standard specimen are mentioned in Table 2.

**Table 2** List of dimensional features of the standard specimen

| Group Name | Symbol | Dimension | Remark |
|---|---|---|---|
| Non linear | R1 | 10mm | Radius |
| Form feature | P1 | $90^o$ | Perpendicular |
| | PR | $0^o$ | Parallelism |
| | θ1 | $45^0$ | Chamfer |
| Surface finish | SSB | | Side surface |

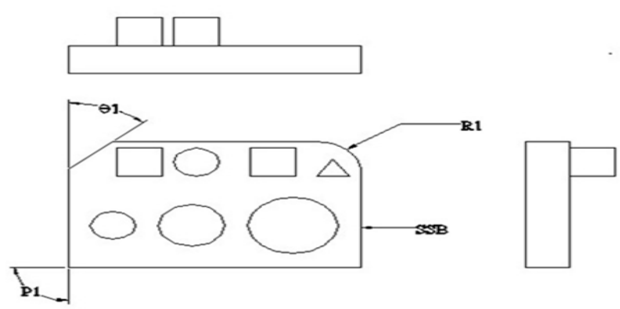


**Fig. 1** Standard Part

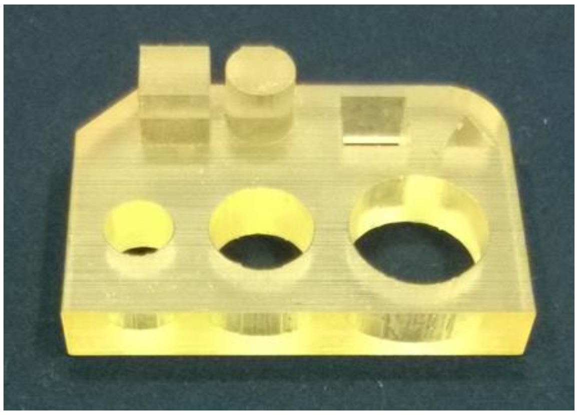

**Fig. 2** SL model

**Table 4** Levels of experimental process parameters

| Experimental run | Parameters | | |
|---|---|---|---|
| | Lt | Hs | Ho |
| 1 | 0.100 | 0.050 | 0.150 |
| 2 | 0.100 | 0.100 | 0.200 |
| 3 | 0.100 | 0.150 | 0.250 |
| 4 | 0.125 | 0.050 | 0.200 |
| 5 | 0.125 | 0.100 | 0.250 |
| 6 | 0.125 | 0.150 | 0.150 |
| 7 | 0.150 | 0.050 | 0.250 |
| 8 | 0.150 | 0.100 | 0.150 |
| 9 | 0.150 | 0.150 | 0.200 |

**Table 5** Values of constant process parameters

| S.No | Setting parameter | value | |
|---|---|---|---|
| 1 | Blade gap | 0.1mm | |
| 2 | Preferred gap | 0.1mm | |
| 3 | X and Y shrink compensation | 0.34% | |
| | PART PARAMETERS | PART | SUPPORT |
| 4 | Hatch type | Box | No Hatch |
| 5 | Stagger weaver | On | NA |
| 6 | Alternate sequencing | On | NA |
| 7 | Refraction start | 0.000 | NA |
| 8 | Refraction end | 0.000 | NA |
| 9 | Fill cure depth | X and Y | No fill |
| 10 | Fill spacing | 0.000 | NA |
| | SLICE OPTIONS | PART | SUPPORT |
| 11 | Beam compensation | On | NA |
| 12 | Beam compensation value | 0.125mm | NA |
| 13 | Auto Z-correction | On | NA |
| 14 | Additional boundary | 0 | NA |
| 15 | Boundary compensation | NA | NA |
| 16 | Minimum width for fill | 0.1mm | NA |
| | RECOAT PARAMETERS | PART | SUPPORT |
| 17 | Z-level wait | 10 s | 10 s |
| 18 | Pre-dip delay | 10 s | 0 s |
| 19 | Z-dip velocity | Normal | Normal |
| 20 | Z-dip distance | 0 mm | 6.25mm |
| 21 | No. of sweep | 1 | 0 |
| 22 | Blade gap % | 300 | NA |

NA- Non applicable

### 2.2 Setting of levels and their values for identified parameters

In Design of Experiments (DOE), the selection of the levels for the chosen factors layer thickness, hatch spacing and hatch overcure is a crucial process. Still from our experience and research it has been realized that these three major control factors dominate the SL process. The interaction among the process parameters is not considered. Since all the factors are multi level variable and their effects are non linear, three levels are desired for each factor. Hence the non-linearity effect is assumed and three levels are set with lower limit, higher limit and the average of these levels as middle limit. Table 3 provides the three levels of process parameter for the main experimentation.

**Table 3** Levels of the process parameters set for the experiment

| Process parameters | Levels | | | Units |
|---|---|---|---|---|
| | 1 | 2 | 3 | |
| Layer thickness (Lt) | .100 | .050 | .150 | mm |
| Hatch spacing (Hs) | .125 | .100 | .150 | mm |
| Hatch overcurve (Ho) | .150 | .200 | .250 | mm |

### 2.3 Selection of Orthogonal Array (OA)

To optimize the process, based on the experimental data, the traditional statistical regression requires a large amount of data. This causes difficulty in treating the typical normal distribution of the data, reducing experimental run. As the SL machine is heavily used for various production and research purpose, the availability of the machine and resin material are very limited. Hence Taguchi method is chosen to tackle this situation. For ‘m’ factors and ‘n’ number of levels, the total number of experiments to be conducted is $n^m$. OA forms the basis for conducting fractional factorial experiments [11, 20]. Table 4 shows the L9 Orthogonal array (OA) selected to carry out the experimentation. It is selected based on number of factors, number of levels of each factors and interaction between them.

### 2.4 Model construction process

A standard part which comprises of linear dimensions (in X, Y, Z direction), non-linear dimensions (concave radius), form features (parallelism, perpendicularity) and different surfaces to measure surface roughness were constructed using the high temperature resistant Stereolithography material CIBA tool ® SL 5530. The process is as follows: Models were created using Pro/engineer CAD package and converted in to (Standard Tessellation Language) STL format. This format was imported to the Light year software where a series of operations were conducted namely verification for correcting the errors formed during the conversion of software and creating supports. A fine point type support was used to construct as they would provide good surface finish. The constant process parameters for building the standard part are listed in Table 5. The desired valves of layer thickness, hatch spacing and hatch over cure of the models were exported to 3D build software for building the models in 3 D System's SLA 5000 machine. X-facto knife was used to separate the fabricated specimens from the platform and then they were cleaned with Trichloro ethane. The cleaned specimens are then post cured by exposing them to Ultra Violet (UV) light in Post Curing Apparatus (PCA). In order to get meaningful measurement results, 3 identical parts were built for each case, which resulted in a total of 27 parts.

### 2.5 Measurement Technique

The following responses are measured using appropriate measurement techniques.

1. Dimensional deviations in concave radius in mm.
2. Perpendicularity between two perpendicular surfaces measured over the length in mm.
3. Parallelism between two parallel surfaces measured over the length in mm.
4. Bottom slope angle of the chamfer in mm.
5. Surface roughness at Side Surface Base (SSB) in micron.

In order to assure the resolution of the measurement, Den ford Coordinate Measuring Machine (CMM) was used. The Co-ordinate Measuring Machine is a reliable and high performance inspection station with high-speed direct computer control capabilities. The controller servo board is capable of 1 micron accuracy. In order to assure the integrity of each part measurement procedure, a fixture was fabricated and used for each part therefore errors in placing the part on the Coordinate Measuring Machine were eliminated. The surface roughness of the component was measured with Mitutoyo Surface III of accuracy 1 micron, which has moving magnet system (speed transducer) to access the Ra (Centre line average) of the roughness available on the surface of the SL standard part at three different faces. Among them SSB is considered for this current study. Experimentally measured deviations of the various responses are tabulated in the Table 6.

**Table 6** Measurement of deviation from the actual value

| Expt. No | Deviation from the actual values | | | | |
|---|---|---|---|---|---|
| | PL | PR | AN | RA | SR |
| 1 | 0.680 | 0.580 | 0.086 | 0.606 | 1.167 |
| 2 | 0.368 | 0.464 | 0.070 | 0.43 | 1.000 |
| 3 | 0.511 | 0.662 | 0.259 | 0.478 | 1.167 |
| 4 | 0.641 | 0.652 | 0.025 | 0.512 | 1.500 |
| 5 | 0.458 | 0.641 | 0.255 | 0.488 | 1.333 |
| 6 | 0.720 | 0.589 | 0.041 | 0.518 | 2.000 |
| 7 | 0.510 | 0.603 | 0.045 | 0.608 | 1.333 |
| 8 | 0.562 | 0.663 | 0.177 | 0.422 | 2.000 |
| 9 | 0.691 | 0.623 | 0.066 | 0.34 | 2.000 |

### 2.6 Statistical Analysis

#### 2.6.1 Signal-to-Noise ratio

Taguchi has created a transformation of the repetition data to another value, which is a measure of the variation present. The transformation is called as signal-to-noise (S/N) ratio. The S/N ratio consolidates several repetitions (at least two data points are required) into one value that reflects the amount of variation present. There are several S/N ratios available depending on the type of characteristics among which lower is better (LB) is used for this problem. The formula for calculating S/N ratios for LB characteristic is given by Eq. (1), lower is better.

$$S/N_{LB}\ \eta = -10 \log \{1/n \sum_{i=1}^{i=n} y_i^2 \} \quad (1)$$

The average S/N ratio '$\eta_{avg}$' for each process parameter at each level is the average of $\eta_{ij}$ at their respective levels. Table 7, gives the S/N ratio calculated for each response with respect to the experiment run. The average S/N ratio '$\eta_{avg}$' for each process parameter at their respective levels are tabulated in the Table 8.

**Table 7** S/N ratio values of each responses

| Expt No | S/N ratio (db) of responses | | | | |
|---|---|---|---|---|---|
| | PL | PR | AN | RA | SR |
| 1 | 3.349 | 4.731 | 21.31 | -1.341 | 4.350 |
| 2 | 8.683 | 6.669 | 23.09 | 0.000 | 7.330 |
| 3 | 5.831 | 3.582 | 11.73 | -1.341 | 6.411 |
| 4 | 3.862 | 3.715 | 32.04 | -3.521 | 5.814 |
| 5 | 6.782 | 3.862 | 11.86 | -2.496 | 6.231 |
| 6 | 2.853 | 4.597 | 27.74 | -6.020 | 5.713 |
| 7 | 5.848 | 4.393 | 26.93 | -2.496 | 4.321 |
| 8 | 5.005 | 3.569 | 15.04 | -6.020 | 7.493 |
| 9 | 3.210 | 4.110 | 23.60 | -6.020 | 9.370 |

The variation of average S/N ratio with respect to their levels for all process parameters is shown in Fig 3-7.The objective is to minimize the deviation in the parts fabricated using SL process. To achieve this, the S/N ratio should be as small as possible. Thus the level with lower S/N ratio is selected as the optimum level as the contributing factor for lower deviation in parallelism of the SL parts. Hence, the optimum levels contributing to lower deviation in responses are mentioned in Table 8.

**Table 8 Average** S/N (db) ratio values of all the responses

| Parameters | Level | PL | PR | AN | RA | SR |
|---|---|---|---|---|---|---|
| Lt | 1 | 5.99 | 4.99 | 18.71* | 6.03 | -0.89* |
| | 2 | 4.50* | 4.06 | 23.88 | 5.92* | -4.01 |
| | 3 | 4.68 | 4.02* | 21.86 | 7.06 | -4.85 |
| Hs | 1 | 4.35 | 4.28 | 26.76 | 4.83* | -2.45* |
| | 2 | 6.82 | 4.70 | 16.67 | 7.02 | -2.84 |
| | 3 | 2.86* | 4.10* | 10.09* | 7.17 | -4.46 |
| Ho | 1 | 3.74* | 4.30 | 21.36 | 5.91 | -4.46 |
| | 2 | 5.25 | 4.83* | 26.25 | 7.52 | -3.18 |
| | 3 | 6.15 | 3.95 | 16.85* | 5.62* | -2.11* |

* denotes significant values

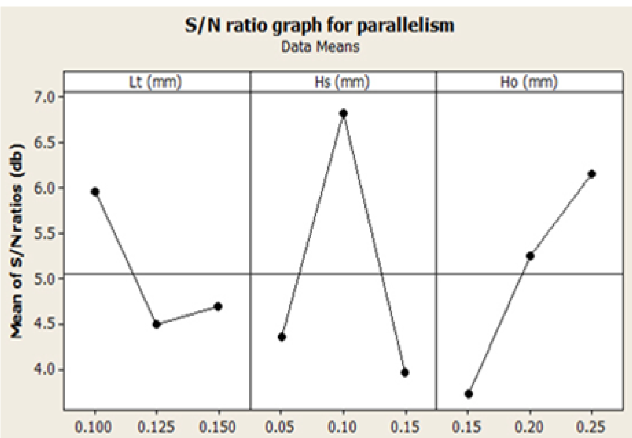


**Fig. 3** S/N ratio graph for parallelism

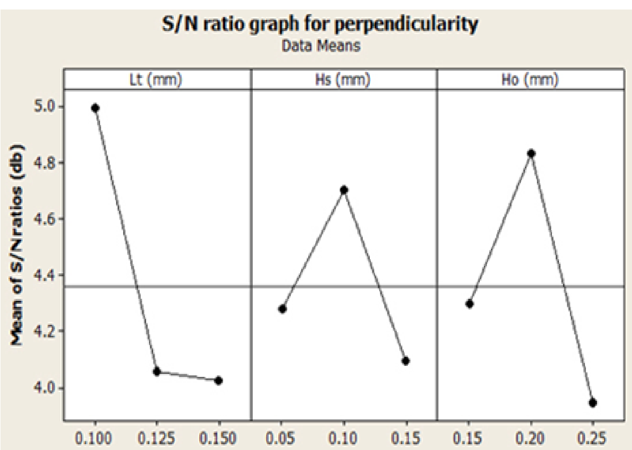


**Fig. 4** S/N ratio graph for perpendicularity

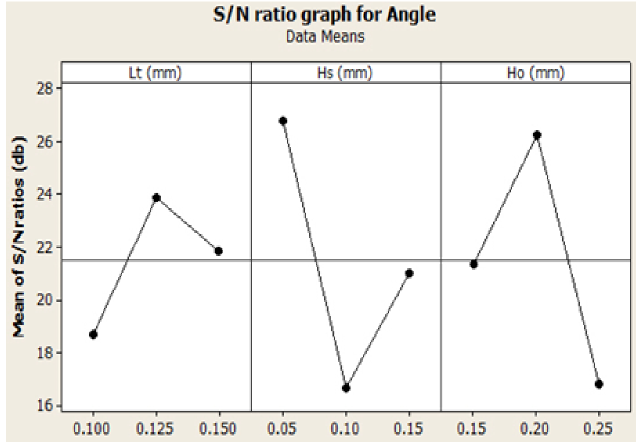


**Fig. 5** S/N ratio graph for angle

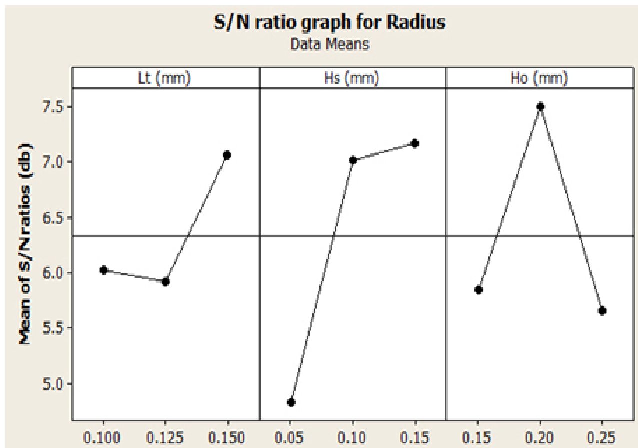


**Fig. 6** S/N ratio graph for radius

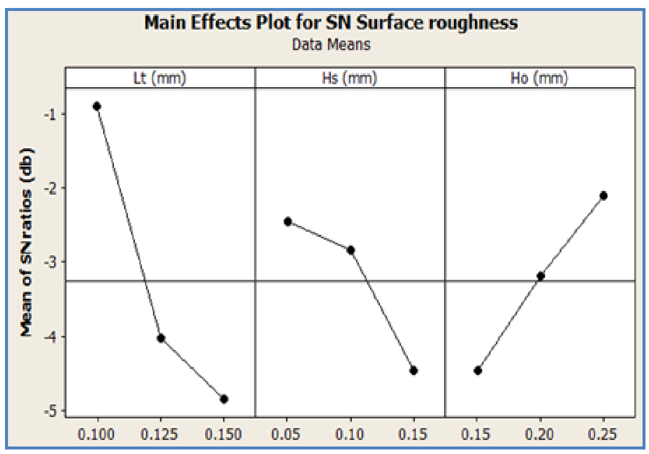


**Fig. 7** S/N ratio graph for surface roughness

### 2.6.2 Analysis of variance

The purpose of Analysis of Variance (ANOVA) is to investigate which SL process parameters significantly affect the performance characteristics/ Response variable. The percentage of contribution by each process parameters can be used to evaluate the importance of process parameters change on the performance characteristics. In this analysis decisions are taken by considering the variation in the performances taken into account. Table 9, shows the ANOVA for the response parallelism. From Table 9, Hatch Spacing is found to be the most influencing process parameter and Hatch overcure forms the second most influencing process parameter. From Table 10 & 13, Layer thickness is found to be the most influencing process parameter as far as perpendicularity and surface roughness is concerned.

**Table 9** ANOVA analysis for parallelism

| Parameter | Sum of square | DOF | Mean SOM | Fs | % of contribution |
|---|---|---|---|---|---|
| Lt (%) | 0.012 | 2 | 0.0062 | 1.40 | 10.88 |
| Hs (%) | 0.054 | 2 | 0.0272 | 6.12 | 47.41 |
| Ho (%) | 0.038 | 2 | 0.0194 | 4.38 | 33.96 |
| Error | 0.008 | 2 | 0.0044 | | 7.74 |
| Total | 0.114 | 8 | | | |

**Table 10 ANOVA** analysis for perpendicularity

| Parameter | Sum of square | DOF | Mean SOM | Fs | % of contribution |
|---|---|---|---|---|---|
| Lt (%) | 0.007 | 2 | 0.0071 | 0.0035 | 23.05 |
| Hs (%) | 0.002 | 2 | 0.0019 | 0.0010 | 6.16 |
| Ho (%) | 0.005 | 2 | 0.0047 | 0.0023 | 15.01 |
| Error | 0.017 | 2 | 0.0173 | | 55.77 |
| Total | 0.031 | 8 | | | |

**Table 11 ANOVA** analysis for angle

| Parameter | Sum of square | DOF | Mean SOM | Fs | % of contribution |
|---|---|---|---|---|---|
| Lt (%) | 0.003 | 2 | 0.0029 | 0.0014 | 4.26 |
| Hs (%) | 0.020 | 2 | 0.0203 | 0.0101 | 29.83 |
| Ho (%) | 0.027 | 2 | 0.0271 | 0.0135 | 39.90 |
| Error | 0.018 | 2 | 0.0177 | | 26.01 |
| Total | 0.039 | 8 | | | |

**Table 12 ANOVA** analysis for radius

| Parameter | Sum of square | DOF | Mean SOM | Fs | % of contribution |
|---|---|---|---|---|---|
| Lt (%) | 0.004 | 2 | 0.0018 | 1.05 | 6.17 |
| Hs (%) | 0.032 | 2 | 0.0159 | 9.47 | 55.69 |
| Ho (%) | 0.018 | 2 | 0.0092 | 5.48 | 32.25 |
| Error | 0.003 | 2 | 0.0017 | | 5.88 |
| Total | 0.057 | 8 | | | |

From Table 11, Hatch over curve is found to be the most influencing process parameter for the response of angularity. From Table 12, Hatch spacing is found to be the most influencing process parameter for the response concave radius.

**Table 13 ANOVA** analysis for surface roughness

| Parameter | Sum of square | DOF | Mean SOM | Fs | % of contribution |
|---|---|---|---|---|---|
| Lt (%) | 0.721 | 2 | 0.3607 | 38.80 | 56.47 |
| Hs (%) | 0.240 | 2 | 0.1205 | 12.96 | 18.86 |
| Ho (%) | 0.296 | 2 | 0.1483 | 15.95 | 23.22 |
| Error | 0.018 | 2 | 0.0093 | | 1.46 |
| Total | 1.277 | 8 | | | |

### 2.6.3. Establishment of empirical relationship / process model

From the Analysis of Variance (ANOVA), it is evident that the process parameters layer thickness, hatch spacing and hatch overcure contribute significantly towards geometric tolerances and surface roughness. Establishment of process model for the geometric tolerances and surface roughness in terms of the process parameters layer thickness, hatch spacing and hatch overcure would be helpful to predict how much tolerance and surface roughness can be achieved for a given set of process parameters. Thus the prior knowledge of the tolerances and surface roughness of the parts can be predicted before actually making SL parts. This regression equation gives an idea about the dependency of surface roughness and geometric tolerances with respect to the process parameters for RP machine users and rapid tool designers. Montgomery [12] suggests that orthogonal polynomial is a useful method for developing process model (regression equation) with orthogonal array data. A quadratic polynomial model Eq. (2) is proposed to establish a process model between response variable and process parameters:

$$RV = \beta_0 + \sum_{i=1}^{g}[\beta_{i1} P_1(i) + \beta_{2i} P_2(i)] + \epsilon \quad (2)$$

Where, RV: response variable(parallelism, perpendicularity, angularity, radius and surface roughness); i: process parameter identifier; $\beta_0$: constant coefficient $= \sum_{i=1}^{N} y_i / (nN)$; $\beta_{i1}$: linear coefficient for $i^{th}$ parameter $= \sum_{i=1}^{N}(\beta_1^j)_i / \sum_{i=1}^{N}(c_{ij}^1)^2$ ; $\beta_{i2}$: non linear coefficient for $i^{th}$ parameter $= \sum_{i=1}^{N}(\beta_2^j)_i / \sum_{i=1}^{N}(c_{ii}^2)^2$ ; $C_{ii}^1$: orthogonal contrast coefficient of linear term for $i^{th}$ parameter in $j^{th}$ experiment; $C_{ii}^2$: orthogonal contrast coefficient of non linear term for $i^{th}$ parameter in $j^{th}$ experiment; $\in$: error component; $P_1(i)$: $1^{st}$ order orthogonal polynomials of parameter i = $\lambda_1$[ (i $-\bar{m}_i$)/$d_i$ ]; $P_2(i)$: $2^{nd}$ order orthogonal polynomials of parameter i = $\lambda_2$[[ (i $-\bar{m}_i)^2/d_i$ ] – [ $(L_i^2 - 1)/12$]];$\lambda_1$: constant polynomial for $1^{st}$ order orthogonal polynomial for parameter 1; ($\lambda_1$ = 1 when number of parameters are three); $\lambda_2$: constant polynomial for

2nd order orthogonal polynomial for parameter 1; ($\lambda_2$ = 3 when number of parameters are three); $\bar{m}_i$: mean value of the levels of parameter i; $d_i$: spacing between the values of levels of parameter i; $L_i$: total number of levels for parameter i.

$$RV = \beta_{2Lt} \times \lambda_2 \left[\left[\frac{Lt-\bar{m}_{Lt}}{d_{Lt}^2}\right] - \left[\frac{L_{Lt}^2-1}{12}\right]\right] + \beta_{1Lt} \times \lambda_1 \left[\frac{Lt-\bar{m}_{Lt}}{d_{Lt}}\right] +$$

$$\beta_{2Hs} \times \lambda_2 \left[\left[\frac{Hs-\bar{m}_{Hs}}{d_{Hs}^2}\right] - \left[\frac{L_{Hs}^2-1}{12}\right]\right] +$$

$$\beta_{1Hs} \times \lambda_1 \left[\frac{Hs-\bar{m}_{Hs}}{d_{Hs}}\right] +$$

$$\beta_{2Ho} \times \lambda_2 \left[\left[\frac{Ho-\bar{m}_{Ho}}{d_{Ho}^2}\right] - \left[\frac{L_{Ho}^2-1}{12}\right]\right] +$$

$$\beta_{1Ho} \times \lambda_1 \left[\frac{Ho-\bar{m}_{Ho}}{d_{Ho}}\right] + \beta_o \qquad (3)$$

#### 2.6.4. Empirical relation for parallelism:

The empirical equation for Response Variable (RV) in terms of the process parameters Layer thickness, hatch space and Hatch overcure is given by Eq. (3). Coded value of Orthogonal Array is used in this paper. The lower, middle and higher value of the process parameters are coded as -1, 0 and 1 respectively. Thus, the mean value of the levels of process parameter ($\bar{m}_i$) becomes zero and the spacing between the levels of the process parameters ($d_i$) becomes one. For three parameters study, $\lambda_1$ equals to 1 and $\lambda_2$ equals to 3. Thus the equation (3) becomes:

$$RV = \beta_{2Lt} \times 3 \times \left[[Lt^2] - \left[\frac{L_{Lt}^2-1}{12}\right]\right] + \beta_{1Lt} \times 1 \times [Lt] +$$

$$\beta_{2Hs} \times 3 \times \left[[Hs^2] - \left[\frac{L_{Hs}^2-1}{12}\right]\right] +$$

$$\beta_{1Hs} \times 1 \times [Hs] +$$

$$\beta_{2Ho} \times 3 \times \left[[Ho^2] - \left[\frac{L_{Ho}^2-1}{12}\right]\right] +$$

$$\beta_{1Ho} \times 1 \times [Ho] + \beta_o \qquad (4)$$

**Table 14** Orthogonal contrast coefficients ( linear and non linear for different levels)

| S.No | Levels | $C_{ij}^1$ | $C_{ij}^2$ |
|---|---|---|---|
| 1 | Lower | -1 | 1 |
| 2 | Medium | 0 | -2 |
| 3 | Higher | 1 | 1 |

Table 14 provides the values of the orthogonal contrast coefficients for linear $C_{ij}^2$ terms. Similarly, Table 15 provides the calculation details for obtaining the constant, linear and non linear coefficients for all three parameters with respect to parallelism. The values are $\beta_{1Lt}$ = 0.034; $\beta_{1Hs}$ =0.01516; $\beta_{1Ho}$ =-0.0805; $\beta_{2Lt}$ = -0.01755; ;$\beta_{2Hs}$ = 0.05427; $\beta_{2Ho}$ = 0.00227 ; $\beta_o$ = 0.5712.Substituting the above values in the equation (4), the regression equation/process model for parallelism (PR) is derived and given in the equation (5). The equations (6), (7), (8) & (9) give the regression equation/process model for perpendicularity (PR), angularity (AN), concave radius (RA) and surface roughness (SR).

$$PL = -0.05265\ Lt^2 + 0.034Lt + 0.16281\ Hs^2 + 0.01516\ Hs + 0.00681\ Ho^2 - 0.0805\ Ho + 0.4957 \qquad (5)$$

$$PR = -0.02814\ Lt^2 + 0.0305\ Lt + 0.02883\ Hs^2 + 0.0065\ Hs + 0.0432\ Ho^2 - 0.0123\ Ho + 0.579 \qquad (6)$$

$$AN = 0.01014\ Lt^2 - 0.02166\ Lt + 0.0801\ Hs^2 + 0.035\ Hs + 0.09015\ Ho^2 + 0.0425\ Ho + 0.1002 \qquad (7)$$

$$RA = -0.021\ Lt^2 - 0.020\ Lt + 0.063\ Hs^2 + 0.066\ Hs + 0.096\ Ho^2 - 0.001\ Ho + 0.39 \qquad (8)$$

$$SR = -0.165\ Lt^2 + 0.333\ Lt + 0.081\ Hs^2 + 0.194\ Hs + 0.00\ Ho^2 - 0.222\ Ho + 1.556 \qquad (9)$$

**Table 15** Calculation of constants and coefficients for parallelism

| Expt.No | $PL_j$ | Coded value of the levels | | | Orthogonal contrast for linear term $C^1_{ij}$ | | | Orthogonal contrast for non linear term $C^2_{ij}$ | | | $(\beta_1^j)_{Lt}$ | $(\beta_2^j)_{Lt}$ | $(\beta_1^j)_{Hs}$ | $(\beta_2^j)_{Hs}$ | $(\beta_1^j)_{Ho}$ | $(\beta_2^j)_{Ho}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Lt | Hs | Ho | Lt | Hs | Ho | Lt | Hs | Ho | | | | | | |
| 1 | 0.680 | -1 | -1 | -1 | -1 | -1 | -1 | 1 | 1 | 1 | -0.680 | 0.680 | -0.680 | 0.680 | -0.680 | 0.680 |
| 2 | 0.368 | -1 | 0 | 0 | -1 | 0 | 0 | 1 | -2 | -2 | -0.368 | 0.368 | 0.000 | -0.736 | 0.000 | -0.736 |
| 3 | 0.511 | -1 | 1 | 1 | -1 | 1 | 1 | 1 | 1 | 1 | -0.511 | 0.511 | 0.511 | 0.511 | 0.511 | 0.511 |
| 4 | 0.641 | 0 | -1 | 0 | 0 | -1 | 0 | -2 | 1 | -2 | 0.000 | -1.282 | -0.641 | 0.641 | 0.000 | -1.282 |
| 5 | 0.458 | 0 | 0 | 1 | 0 | 0 | 1 | -2 | -2 | 1 | 0.000 | -0.916 | 0.000 | -0.916 | 0.458 | 0.458 |
| 6 | 0.720 | 0 | 1 | -1 | 0 | 1 | -1 | -2 | 1 | 1 | 0.000 | -1.440 | 0.720 | 0.720 | -0.720 | 0.720 |
| 7 | 0.510 | 1 | -1 | 1 | 1 | -1 | 1 | 1 | 1 | 1 | 0.510 | 0.510 | -0.510 | 0.510 | 0.510 | 0.510 |
| 8 | 0.562 | 1 | 0 | -1 | 1 | 0 | -1 | 1 | -2 | 1 | 0.562 | 0.562 | 0.000 | -1.124 | -0.562 | 0.562 |
| 9 | 0.691 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | -2 | 0.691 | 0.691 | 0.691 | 0.691 | 0.000 | -1.382 |

**Table 16** Comparison between experimental and regression value for parallelism

| Settings | Lt (mm) | Hs (mm) | Ho (mm) | Experiment Value (EV) | Process Model Value (PMV) | Percentage of Deviation \|{(EV – PMV) / EV } X 100\| |
|---|---|---|---|---|---|---|
| OA Settings | 0.100 | 0.050 | 0.150 | 0.680 | 0.644 | 5.29 |
| | 0.100 | 0.100 | 0.200 | 0.368 | 0.409 | 11.14 |
| | 0.100 | 0.150 | 0.250 | 0.511 | 0.513 | 0.3 |
| | 0.125 | 0.050 | 0.200 | 0.641 | 0.643 | 0.3 |
| | 0.125 | 0.100 | 0.250 | 0.458 | 0.422 | 7.8 |
| | 0.125 | 0.150 | 0.150 | 0.720 | 0.760 | 5.55 |
| | 0.150 | 0.050 | 0.250 | 0.510 | 0.551 | 8.0 |
| | 0.150 | 0.100 | 0.150 | 0.562 | 0.564 | 0.3 |
| | 0.150 | 0.150 | 0.200 | 0.691 | 0.655 | 5.20 |
| | | | | Average percentage of deviation | | **4.87** |
| Non OA Settings | 0.100 | 0.100 | 0.250 | 26 | 25.34 | 2.56 |
| | 0.125 | 0.100 | 0.200 | 37 | 37.67 | 7.63 |
| | 0150 | 0.150 | 0.250 | 43 | 44.33 | 3.10 |
| | | | | Average percentage of deviation | | **2.24** |

## 3 PERFORMANCE EVALUATION

The validation of the regression equation is the final step in the process parameter design. Table 16b shows the comparison between the experiment value and regression value of the response Parallelism (PL) at various levels of process parameters (nine OA settings and three non OA settings). The average percentage of deviation between regression equation and experimental value is 4.87%. Similarly, the average percentage deviation for the responses perpendicularity (PR), Concave Radius (RA), Angularity (AN) and Surface roughness (SR) are tabulated in the Table 17 for both OA and Non OA settings.

**Table 17** Comparison between experimental and regression value

| | PL | PR | AN | RA | SR |
|---|---|---|---|---|---|
| Average % deviation OA | 4.87 | 6.33 | 42.42 | 19.77 | 2.67 |
| Average % deviation Non OA | 2.24 | 5.41 | 53.37 | 15.01 | 4.25 |

## 4 CONCLUSION AND FUTURE SCOPE

In this paper, an attempt has been made to analyse the process parameters and its influence on performance characteristics / Response Variable like parallelism, perpendicularity, concave radius, angularity and surface roughness of the SL parts for the sake of rapid tooling applications. The most influencing process parameter for PL, PR, AN, RA and SR are indicated in Table 18. The optimal values of the analysis are tabulated in the Table 19.

**Table 18** Most influencing process parameter for all responses

| | PL | PR | AN | RA | SR |
|---|---|---|---|---|---|
| Most influencing parameter | Hs | Lt | Ho | Hs | Lt |

**Table 19** Optimal levels of process parameters for the responses

| Response | Optimal Levels | | | Units |
|---|---|---|---|---|
| | Lt | Hs | Ho | |
| Parallelism | 0.100 | 0.100 | 0.250 | mm |
| Perpendicularity | 0.100 | 0.100 | 0.200 | mm |
| Angularity | 0.100 | 0.050 | 0.250 | mm |
| Concave radius | 0.150 | 0.050 | 0.200 | mm |
| Surface roughness | 0.125 | 0.050 | 0.250 | mm |

Besides, the regression equation / process model has been developed for the SL process with respect to performance characteristics/Response Variable (parallelism, perpendicularity, surface roughness, concave radius, angularity) and process parameters (Layer thickness, hatch space and hatch overcure). Prior knowledge of the mentioned responses can be obtained using the developed regression equation with respect to the set of process parameters. This process model will be useful for both machine designers and the machine users. The average percentage deviation between experimental value and regression value of the responses for parallelism, perpendicularity, angularity, concave radius and surface roughness are 4.87%, 6.33%, 42.42%, 19.77% and 2.67% in OA settings and 2.24%, 5.41%, 53.37%, 15.01% and 4.25% in NON OA settings. Uncertainties in measurements have to be considered to guarantee precision in any results. The regression equation can be further refined using non-classical optimization approaches such as genetic algorithm, particle swarm optimization and neural network to reduce the average percentage of deviation between experimental value and regression value.

## 5 NOMENCLATURE

| | |
|---|---|
| CF | Correction Factor |
| DOF | Degree of freedom |
| $DOF_E$ | Degrees of freedom of errors |
| $DOF_i$ | Degrees of freedom of $i^{th}$ parameter (i is Lt/Hs/Ho) $j^{th}$ experiment |
| Or | Orientation |
| i | Parameter identifier |
| j | Identifier for experimental run (j varies from 1 to N) |
| MSE | Mean Square Error of the response variable |
| $MSS_i$ | Mean Sum of Square for $i^{th}$ parameter (i may be Lt/Hs/Ho) |
| $MSS_T$ | Total Mean Sum of Square |
| n | Number of repetitions of the experiment |
| N | Total number of experiments |
| Pc | Post curing time |
| PMV | Process model value |
| $(P_{AN})_i$ | Percentage of contribution of $i^{th}$ parameter on angularity |
| $(P_{PL})_i$ | Percentage of contribution of $i^{th}$ parameter on parallelism |
| $(P_{PR})_i$ | Percentage of contribution of $i^{th}$ parameter on perpendicularity |
| $(P_{RA})_i$ | Percentage of contribution of $i^{th}$ parameter on radius |
| $(P_{SR})_i$ | Percentage of contribution of $i^{th}$ parameter on surface roughness |
| $SS_E$ | Sum of squares of errors |
| $SS_i$ | Sum of squares of parameter i |
| $SS_{RV}$ | Sum of squares of response variable |
| SST | Total sum of squares |
| v1 | Degrees of freedom for parameter |
| v2 | Degrees of freedom for error |
| $y_j$ | Measured value of the response variable RV in $j^{th}$ experimental run. |

## ACKNOWLEDGMENTS

The authors thank the management of Thiagarajar College of Engineering, Madurai and the Director, Gas Turbine Research Establishment (GTRE), Bangalore for providing the necessary facilities to carry out this work.

## REFERENCES

[1] Charity Lynn-Charney, David W. Rosen, "Usage of accuracy models in stereolithography process planning", Rapid Prototyping Journal, Vol. 6, 2000, pp.77 – 87.

[2] Cho, H. S., Park, W. S., Cho, B. W., and Leu, M. C., "Determining Optimal Parameters for Stereolithography Processes via Genetic Algorithm", Journal of Manufacturing Systems, Vol. 1, 2000, pp.18 – 27.

[3] Chockalingam, K., Jawahar, N., Chandrasekhar, U., "Influence of layer thickness on mechanical properties in stereolithography", Rapid Prototyping Journal, Vol. 2, 2006, pp. 106-113.

[4] Chockalingam, K., Jawahar, N., Chandrasekhar, U., Ramanathan, K. N., "Establishment of process model for part strength in sterelithography", Journal of Material Processing Technology, Vol. 208, 2008, pp. 348-365.

[5] Chockalingam, K., Jawahar, N., Ramanathan, K. N., Banerjee, P. S., "Optimization of stereolithography process parameters for part strength using design of experiments", International Journal of Advanced Manufacturing Technology, Vol. 29, 2006, pp.79-88.

[6] Ghani. J. A., Choudhury. I.A., Hassan. H.H., "Application of Taguchi method in the optimization of end milling parameters", Journal of Materials Processing Technology, Vol. 145, 2004 pp. 84–92.

[7] Hefin. R., Fiju. A., Graeme. K,, "An application of experimental design for process optimization", Rapid Prototyping Journal, Vol. 2, 2000, pp.78-83.

[8] Kang. J., Had Field. M., "Parameter Optimization by Taguchi Methods for Finishing Advanced Ceramics Balls Using a Novel Eccentric Lapping Machine", Proceedings of institute of mechanical engineers, Vol. 215B, 2001, pp. 69-78.

[9] Koman Durai, R., Jiang, M., "Application of Taguchi Method for Optimization of Finishing Conditions in Magnetic Float Polishing", Wear, Vol. 213, 1997, pp. 59-71.

[10] Vaezi, M., Safaeian, D., Chua, C. K., "Gas turbine blade manufacturing by use of epoxy resin tooling and silicone rubber molding techniques", Rapid Prototyping Technology, Vol. 2, 2011, pp.107-115.

[11] Montgomery, D. C., "Design and analysis of experiments", Third edition, John Wiley & sons Inc, New York, 2001.

[12] Naga Hanumaiah, B. Ravi, "Rapid tooling form accuracy estimation using region elimination adaptive search based sampling technique", Rapid Prototyping Journal, Vol.13, 2007 pp.182 – 190.

[13] Onuch. S. O., Hon. K. K., "Application of Taguchi method and new style for quality improvement on Stereolithography", Proceedings of institute of mechanical engineers, Vol. 212(B), 1998, pp. 461-472.

[14] Ratnadeep Paul, Sam Anand, "Optimal part orientation in Rapid Manufacturing process for achieving geometric tolerances", Journal of Manufacturing Systems, Vol. 30, 2011, pp. 214– 222.

[15] Syrcos, G. P., "Die casting process optimization using Taguchi methods", Journal of Materials Processing Technology, Vol. 135, 2003, pp. 68–74.

[16] Tosun, N., Cogun, C., Gul. T., "A study on kerf and material removal rate in wire electrical discharge machining based on

Taguchi method", Journal of Materials Processing Technology, Vol. 152(3), 2004, pp. 316-322.

[17] Raju, B.S., Chandra Sekhar, U., Drakshayani, D. N., "Optimizing multiple quality characteristics of Stereolithography process via taguchi method-based grey analysis for SL530 epoxy resin material to enhance of part quality", Procedia materials science Vol.5, 2014, 2532- 2541.

[18] Rahmati, S., and Ghadami, F., "Process Parameters optimization to improve dimensional accuracy of stereolithography parts", International journal of Advanced design and maufacturing technology, Vol. 7, 2014, pp. 59-65.

[19] Raju, B. S., Chandra Sekhar, U., Venkateswarlu, K., Drakashayani, D. N., "Extablishment of process model for rapid prototyping technique (stereolithography) to enhance the part quality by taguchi mehod", Procedia technolgy Vol.14, 2014, 380- 389.

[20] Ross, P., Taguchi Techniques for Quality engineering Second edition, McGraw Hill, 1996.

[21] Taguchi. G., Introduction to Quality Engineering, Asian productivity organization, Tokyo, 1990.

[22] Chockalingam. K., Jawahar. N., Pakeermohideen. P., Prashad. P., "Evolution of coefficient of stereolithography process – Error relationship", Proceedings of National conference 21st AIMTDR, Vellore Institute of Technology, Vellore, India. pp: in CD, 2004.

[23] Lee. S. H., Park. W. S., Cho. H. S., Zhang. W., Leu, M. C., "A neural network approach to the Modeling and Analysis of Stereolithography Process", Proceedings of institute of mechanical engineers, Vol. 215(B): 2001, pp.18 – 27.