Grey Relational Analysis Coupled with Principal Component Analysis for Optimization of Stereolithography Process to Enhance Part Quality

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Abstract: The paper investigates optimization of stereolithography process for SL5530 epoxy resin material to enhance part quality. The major characteristics indexed for performance selected to evaluate the processes are tensile strength, Flexural strength, Impact strength and Density analysis and corresponding process parameters are Layer thickness, Orientation and Hatch spacing. In this study, the process is intrinsically with multiple parameters tuning so that grey relational analysis which uses grey relational grade as performance index is specially adopted to determine the optimal combination of process parameters. Moreover, the principal component analysis is applied to evaluate the weighting values corresponding to various performance characteristics so that their relative importance can be properly and objectively desired. The results of confirmation experiments reveal that grey relational analysis coupled with principal component analysis can effectively acquire the optimal combination of process parameters. Hence, this confirm that the proposed approach in this study can be an useful tool to improve the process parameters in stereolithography process, which is very useful information for machine designers as well as RP machine users.

Keywords: Grey relational analysis, Principal component analysis, Optimization, Stereolithography process

1. INTRODUCTION
The development of technologies for rapid prototyping and rapid manufacturing has been advanced into a stage of considerably in product development. In today’s world, with the increasing number of product variants and a customer driven market, simultaneous engineering
is needed to meet the challenges of a shorter product life cycle. The recent development in RPT technologies accelerate the simultaneous engineering further by providing prototypes and tools with virtually no time penalty and hence implemented in the areas of new product development [1]. Thus followed by this trend, this paper is focused on the optimal process parameters of Stereolithography process for SL5530 epoxy resin. In the present manufacturing sector, quality plays a very important role. The term Quality is the fitness for the use or degree of customer satisfaction as provided by the intended function of the product [2]. Thus, the product quality depends on the desired requirements of the intended functions in the various areas of application [3]. In the field of prototyping, the quality mainly depends upon the built parameters such as layer thickness, Orientation, Post processing time, Hatch Space, Hatch overcure, cure depth, which in turn is influenced by the mechanical and physical quality characteristics of the prototypes [4]-[12]. These mechanical features of the prototypes are directly related to process parameters, i.e., the prototype quality depends on the machine process parameters. Solid freeform fabrication or additive manufacturing is a production process in which physical prototype is created based on the concept of layer manufacturing technology. The invention of the new technology have been fulfilled the engineering applications, especially in case of products which have geometrical complex shape and internal entity. Some of the additive manufacturing techniques which are utilized in industries include fabrication of mold and die [5]-[6], producing of aircraft component prototype for aerodynamic analysis and dynamic testing [7]-[8], and making of full-sized automobile instrument panels [9]. Among the various layered manufacturing processes, Stereolithography (SLA) is being recognized as master of RP process with an innovative technology, which cannot be fully utilized in tooling applications, since it lacks in part quality characteristics. Thus, the main objective is to analyze the strength of the SLA (Epoxy Resin) Component. One of the important applications of SLA process is rapid tooling in dies of Injection molding, pattern of casting [9]-[29]. The Dies made through SLA process are subjected to high tension, compression and impact factor due to high injection pressure. In order to have higher number of injections without premature failure, the die should possess high tensile, flexural and impact strength [10]-[11]. Tensile Strength is more crucial in the case of rapid tooling since the parts have to withstand pressure during the test of fitment and also when used as die for injection moldings. Thus work aims to study the mechanical strength and density of CIBSTOOL SL5530 Resin parts produced by SLA5000 Stereolithography machine and also an efficient method in order to determine the optimal process parameters for multiple quality characteristics, through integrating the grey theory with the principal component analysis.

The grey system theory proposed by Deng in 1982 has been proven to be useful for dealing with the problems with poor, insufficient and uncertain information. The Grey relational analysis based on this theory can further be effectively adopted for solving the complicated interrelationship among the designated performance characteristics [13]. Principal component analysis (PCA) was proposed by pearson in 1901, and evolved as statistical tool n 1993. The main advantage is significantly alleviating loading and complexion of information by simplifying several correlated variables into fewer uncorrelated and independent principal components and preserving as original information as possible using linear combination. Presently the PCA has gradually become an analytical tool for the optimization of a system with multiple performance characteristics [14]. The context is organized in the following manner; the analysis method and the experimental design are described first. Then, the optimization of the Stereolithography process based on the Grey relational analysis coupled with principal
component analysis is presented in detail. Finally the paper is concluded with summary of thesis study.

2. Analysis Method

2.1 Signal-to-noise ratio

An experimental design which is standardized to use the full factorial method but which is time consuming and expensive, hence the Taguchi methods of experimental design provide a simple, efficient and systematic approach known as fractional factorial method for minimizing the total number of experimental runs [15,16]. Taguchi technique is the most efficient problem solving tool which can improve the performance of the product, process, design and system with a significant slash in experimental time and cost. Taguchi technique increases the power of analysis of experimental data by complex analysis of variance and an efficient way to determine the optimum factor level [17-18]. Thus, the benefits of the S/N Ratio include increasing the factor weighting effect, decreasing mutual action, simultaneously processing the average and variation, and improving engineering quality. Depending upon the required objective quality characteristics, different computations can be applied as follows:

- When the required quality objective value is less, the smaller-the-Better (SB) method applies; such as in surface roughness and dimension accuracy error.

\[ \eta = -10 \log \left( \frac{1}{n} \sum_{k=1}^{n} y_k^2 \right) \]  

- When the required quality objective value is high, the larger-the-better (LB) method applies, such as in material removal rate and mechanical properties such as tensile, impact and flexural strength.

\[ \eta = -10 \log \left( \frac{1}{n} \sum_{k=1}^{n} y_k^2 \right) \]  

- When the required quality objective value is particular (preferable), the nominal-the-better (NB) method applies, such as in coating depth and others.

\[ \eta = -10 \log \left( \frac{1}{n-1} \sum_{k=1}^{n} \left( y_k - \mu \right)^2 \right) \mu = \frac{1}{n} \sum_{k=1}^{n} y_k \]

2.2. Grey relational analysis

2.2.1 Grey relation Generation

The grey theory investigates a system model with uncertainty and insufficient information [19]-[21]. The grey relational analysis among sequence group requires that all sequences satisfy comparability conditions, for instance, non-dimension, scaling and polarization attributes. If comparability does not exist within sequence, the grey relationship generating approach can be adopted to transform the original sequence factor space into measurable space, generating a comparable sequence with three different comparability types as follows,
• The larger-the better (LB): the larger objective value is better and the property can be represented by the following equation,

\[ x_i^* = \frac{x_i^{(0)}(k) - \min x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \]  

• The smaller-the-better (SB): the smaller objective value is better.

\[ x_i^*(k) = \frac{\max x_i^{(0)}(k) - x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \]  

• The nominal-the-better (NB): the value closer to the objective value OB is better,

\[ x_i^{(0)}(k) = 1 - \frac{\left[x_i^{(0)}(k) - OB\right]}{\max\left[\max x_i^{(0)}(k) - OB : OB - \min x_i^{(0)}(k)\right]} \]  

Where \( x_i^*(k) \) is the value after Grey relation generating process and \( \min x_i^{(0)}(k) \), \( \max x_i^{(0)}(k) \) denotes the minimum and maximum of \( x_i^{(0)}(k) \) respectively. The grey relational grade in the grey relational analysis is defined as the relative degree between two sequences. Only one sequence \( x_0(k) \) selected as the reference sequence is called the localized grey relational grade, i.e., one sequence exists in the grey relational space \( \{P(X); \tau\} \) [20].

2.2.2 Entropy weighting

Entropy weighting employs the entropy concept to determine the relative weighting factor for each attribute. Computing entropy value through the selected case effect for each attribute determines the uncertain deliverable degree of information for the entire decision making process. The entropy value for each attribute is determined by comparing which determines the relative importance among all the available attributes, or the relative weighting factor. The relative weighting factors obtained by entropy weighting apply evaluated attribute information among all selected cases, not including the artificial subjective factor of decision maker; hence, entropy weighting belongs to the objective-weighting factor. Entropy weighting is determined as shown below in the following steps (22, 23):

i) Compute each attributes summation value for all sequences, \( D_k \)

\[ D_k = \sum_{i=1}^{m} x_i(k) \]  

ii) Compute the normalization coefficient \( K \)

\[ K = \frac{1}{\sqrt{06487n}} \]  

iii) Find the entropy for the specific attribute, \( e_k \)

\[ e_k = K \sum_{i=1}^{m} w_e(Z_i) \]  

\[ w_e(Z_i) = Z_i e^{(1-Z_i)} + (1 - z_i) e^{z_i} - 1 \]  

\[ Z_i = \frac{x_i(k)}{D_k} \]

iv) Compute the total entropy value, \( E \):
\[ E = \sum_{k=1}^{n} e_k \]  

v) Determine the relative weighting factor, \( \lambda_k \).  
\[ \lambda_k = \frac{1}{n - E} \left[ 1 - e_k \right] \]  

vi) Using the normalization method, each attribute weight or quality characteristic, can be calculated as  
\[ \omega_j = \frac{\lambda_k}{\sum_{k=1}^{n} \lambda_i} \]  

2.2.3 Grey relation Grade  

The major computations for the grey relational grade is as follows [19-21]:  
i) Endowing the weighting factor: According to the grey relational generating data, the weighting factors of each attribute are known.  
ii) After selecting the weighting factor, the following equation is used to determine the difference between the ideal sequence and specific relative sequence.  
\[ \Delta_\text{ref}(k) = |x_0(k) - x_i(k)| \]  
Where \( i = 1, 2, \ldots, m \), \( k = 1, 2, \ldots, n \) \( j \in i \).  
\( x_0 \) represents the weighting factor for each attribute; hence, \( x_0(k) \) and \( x_i(k) \) are the reference (ideal) sequence and the specific relative sequence respectively.  
iii) Calculate the grey relational Grade \( \Gamma_j \) through the following equation [24,25]  
\[ \Gamma_j = \frac{\Delta_\text{min} + \Delta_\text{max}}{\Delta_j + \Delta_\text{max}} \]  
where \( \Delta_j = \frac{1}{\sigma_{ij}} \sum_{k=1}^{n} \Delta_j(k) \) and \( \Delta_\text{min} \) , \( \Delta_\text{max} \) are constants as  
\[ \Delta_\text{min} = \forall j \in i \forall k \min |x_0(k) - x_j(k)| \]  
\[ \Delta_\text{max} = \forall j \in i \forall k \max |x_0(k) - x_j(k)| \]  

2.3 Principal component analysis  

Pearson and Hotelling developed PCA to explain the structure of variance-covariance by way of linear combinations of each quality characteristics. The procedure is described as follows [14]:  

1. The original multiple quality characteristic array  
\[ x_{ij} \], \( i = 1, 2, 3, \ldots, m \); \( j = 1, 2, 3, \ldots, n \)  
Where \( m \) is the number of experiment and \( n \) is the number of quality characteristics. In this paper, \( x \) is the grey relational coefficient of each quality characteristics, \( m = 9 \), \( n = 4 \).  

2. Correlation coefficient array  
The correlation coefficient array is evaluated as follows;  
\[ \frac{\text{cov}(x_i', x_i')}{\sigma_i^2} \]
where $(x^1, x^2)$: The covariance of sequences,

the standard deviation of sequence $x^1$
\[ \sigma_x(I) : \text{standard deviation of sequence } x^1 \]

3. Determining the Eigen values and Eigen vectors: The Eigen values and Eigen vector are determined from the correlation coefficient array

$$( R - \lambda_k I ) v_k = 0 \quad \text{....................(17)}$$

4. Principal components

The uncorrected principal component is formulated as

$$n \chi_m (i) v_k \quad \text{..........................18}$$

The principal components are aligned in descending order with respect to variance and therefore first principal component $Y_{m1}$ accounts for the most variance in the data.

3. Experimental Design And Results

The controlled parameters and their corresponding design levels are shown in Table 1 and the orthogonal array adopted in the experimental work is $L_9$ as shown in Table 2 with larger the better for the mechanical part quality characteristics and smaller the better for the physical part quality characteristics.

| Table 1 Parameter Levels for main experiment |
|---------------------------------------------|
| Symbol | Response Parameter / Variable | LEVEL 1 | LEVEL 2 | LEVEL 3 |
|--------|--------------------------------|---------|---------|---------|
| A      | Layer Thickness - $L_t$       | 0.075   | 0.10    | 0.125   |
| B      | Orientation - $O$             | 0       | 45      | 90      |
| C      | Hatch Space - $H_s$           | 0.01    | 0.015   | 0.02    |

| Table 2 Design of $L_9$ ($3^3$) orthogonal array with experimental results and S/N ratio |
|------------------------------------------------------------------------------------------|
| Experimental Run | Control parameters | Experimental Value |
|------------------|---------------------|---------------------|
|                  | $L_t$ | $O$ | $H_s$ | Tensile Strength (N/mm$^2$) | S/N Ratio | Flexural Strength (N/mm$^2$) | S/N ratio | Impact Strength (J/m) | S/N ratio | Density analysis (Kg/m$^3$) | S/N ratio |
| 1                | 1     | 1   | 1     | 55.46 | 34.89 | 116.67 | 41.34 | 20.8 | 26.36 | 1.2345 | -1.83 |
| 2                | 1     | 2   | 2     | 54.57 | 34.74 | 113.92 | 41.13 | 22   | 26.85 | 1.3855 | -2.83 |
| 3                | 1     | 3   | 3     | 55.07 | 34.82 | 114.08 | 41.14 | 21.1 | 26.48 | 1.3235 | -2.44 |
| 4                | 2     | 1   | 2     | 58.46 | 35.34 | 115.7  | 41.26 | 20.3 | 26.15 | 1.2405 | -1.87 |
| 5                | 2     | 2   | 3     | 54.51 | 34.73 | 110.0  | 40.82 | 17.9 | 25.05 | 1.2395 | -1.86 |
| 6                | 2     | 3   | 1     | 58.59 | 35.36 | 115.6  | 41.26 | 21.3 | 26.57 | 1.2255 | -1.76 |
| 7                | 3     | 1   | 3     | 58.62 | 35.36 | 115.8  | 41.27 | 21.4 | 26.61 | 1.4055 | -2.96 |
| 8                | 3     | 2   | 1     | 55.34 | 34.86 | 114.8  | 41.99 | 19.9 | 25.98 | 1.3450 | -2.57 |
| 9                | 3     | 3   | 2     | 61.73 | 35.81 | 118.7  | 41.49 | 23.6 | 27.46 | 1.3568 | -2.65 |
The Table 3 shows the grey relational grade for each experiment using $L_9$ orthogonal array. The higher grey relational grade represents that the corresponding experimental result is closer to the ideally normalized value. These data were used to evaluate the correlation coefficient matrix and to determine the corresponding Eigen values as and the Eigen vector corresponding to each Eigen values and the contribution of each individual quality characteristics for the first principal component is listed in Table 4. Experiment no 9 has the best multiple performance characteristics among nine experiments, because which has the highest grey relational grade. In other words, Optimization of the complicated multiple performance characteristics can be converted into optimization of a single grey relational grade. Since the experimental design is orthogonal, it is possible to separate out the effect of each built parameters on the grey relational grade at different levels. The grey relational grade mean for each level of the parameter is summarized and as shown in the Table 5. The total mean of the grey relational grade for the nine experiments is computed and listed in Table 5. Figure 1 shows the grey relational grade graph for the levels of the parameters. Basically, the larger the grey relational grade, the better is the multiple performance characteristics.

**Table 3** Priority list of weighted grey relationship for multiple building quality characteristics

| No | Grey relationship generating | Grey relational analysis | Grey relational grade |
|----|-----------------------------|--------------------------|-----------------------|
|    | TS  | FS  | IS  | DA  | Weighting via entropy method | $\Gamma_j$ | Rank |
|    |     |     |     |     | 0.3538 | 0.1934 | 0.2016 | 0.2512 |     |
| 1  | 0.1454  | 0.7667  | 0.5087  | 0.95  | 0.0514  | 0.1483  | 0.1026  | 0.2386  | 0.7550  | 4  |
| 2  | 0.0083  | 0.4506  | 0.7193  | 0.1111 | 0.0029  | 0.0871  | 0.0908  | 0.0279  | 0.6414  | 9  |
| 3  | 0.0776  | 0.4689  | 0.5614  | 0.4556 | 0.0275  | 0.0907  | 0.0945  | 0.1145  | 0.6777  | 7  |
| 4  | 0.5471  | 0.6552  | 0.4211  | 0.9167 | 0.1936  | 0.1267  | 0.0849  | 0.2303  | 0.7948  | 2  |
| 5  | 0    | 0    | 0    | 0.9222 | 0    | 0    | 0    | 0.2316  | 0.6481  | 8  |
| 6  | 0.5651  | 0.6437  | 0.5965  | 1    | 0.1999  | 0.1245  | 0.1202  | 0.2512  | 0.7772  | 3  |
| 7  | 0.5693  | 0.6667  | 0.6141  | 0    | 0.2014  | 0.1289  | 0.1238  | 0    | 0.7216  | 5  |
| 8  | 0.1150  | 0.5517  | 0.3508  | 0.3361 | 0.0406  | 0.1067  | 0.0707  | 0.0844  | 0.6698  | 6  |
| 9  | 1    | 1    | 1    | 0.2706 | 0.3538  | 0.1934  | 0.2016  | 0.0679  | 0.8853  | 1  |
Table 4: The contribution of each individual quality characteristics for the first principal component

| Quality Characteristics | Contribution |
|-------------------------|--------------|
| Tensile strength        | 0.3538       |
| Flexural Strength       | 0.1934       |
| Impact strength         | 0.2016       |
| Density                 | 0.2512       |

Table 5: Response table for the grey relational grade

| Symbol | Parameter     | Level 1 | Level 2 | Level 3 | Max-Min |
|--------|---------------|---------|---------|---------|---------|
| A      | Layer Thickness| 0.6914  | 0.7400  | 0.7589  | 0.0675  |
| B      | Orientation   | 0.7571  | 0.6531  | 0.7800  | 0.1269  |
| C      | Hatch spacing | 0.734   | 0.7738  | 0.5791  | 0.1947  |

Total mean grey relational grade = 0.7186

Fig 1: Grey relational grade graph

4. ANALYSIS OF VARIANCE

Analysis of Variance (ANOVA) is a method of determining the variation of an output to the various inputs [26]. The main purpose of the ANOVA is to identify the influential built parameters, which significantly affect the quality performance characteristics [27, 28], which is accomplished by separating the total variability of the grey relational grades, which is measured by the sum of the squared deviations from the total mean of the grey relational grade, into the contributions by each parameter and the error. First, the total sum of the squared deviations $SS_T$ from the total mean of the grey relational grade $\gamma_m$ can be calculated as

$$SS_T = \sum_j\left(\gamma_j - \gamma_m \right)^2$$

where $p$ is the number of experiments in the orthogonal array and $\gamma_j$ is the mean grey relational grade for the $j^{th}$ experiment. The total sum of the squared deviations $SS_T$ which consists of the sum of the squared deviation ($SS_d$) due to each built parameter and the sum of the squared error ($SS_e$). The percentage contribution by each of the built parameters in the total sum of the
squared deviations which can be used to evaluate the importance of the built parameter change on the performance characteristics. In addition, the Fisher's F-test can be used to determine which machining parameters have a significant effect on the performance characteristics [26]. The results of ANOVA for overall grey relational grade is shown in Table 6, which indicates that the orientation is the most significant built parameter which affects the multiple performance characteristics. Thus, the optimal built parameters are Layer thickness at level 3, orientation at level 3 and Hatch space at level 2.

Table 6 Parameter variance and contribution analysis for multiple quality characteristics based

| Parameter | Sum of Squares | Degree of Freedom | Mean sum of squares | F Statistics | F tabulated | % of contribution | Significant |
|-----------|----------------|------------------|--------------------|--------------|-------------|------------------|-------------|
| L_1       | 0.0072         | 2                | 0.0036             | 1.4694       | 13.79       | No               |
| O         | 0.0274         | 2                | 0.0137             | 5.5918*      | 3           | 52.49            | Yes         |
| H_s       | 0.0127         | 2                | 0.00635            | 2.5918       | 24.33       | No               |
| Error     | 0.0049         | 2                | 0.00245            |              |             |                  |
| Total     | 0.0522         | 8                | 0.0261             |              |             |                  |

*Significance at 75% confidence Level ( F Statistics > F Tabulated)

4.1 CONFIRMATION EXPERIMENT

Once obtaining the optimal parameter settings, the final stage is to predict and verify the enhancement of the quality characteristics using the optimal parametric combination [16-18]. The estimated Grey relational grade $\gamma$ predicted using the optimal level of the design parameters can be calculated as:

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{q} \left( \gamma_i - \gamma_m \right)$$

Where $\gamma_m$ is the total mean Grey relational Grade, $\gamma_i$ is the mean Grey relational grade at the optimal level and $q$ is the number of the main design parameters that affect the quality characteristics [2]. Based on the equation 20 the estimated grey relational grade using the optimal built parameters can be obtained. The Table 7 indicates the confirmation experiment using the optimal parameter settings.

Table 7 Results of confirmation test

| Parameters            | Initial process parameters | Optimal machining parameters |
|-----------------------|---------------------------|------------------------------|
| A1/B1/C1              | A3/B3/C2                  | A3/B3/C2                     |
| Tensile Strength      | 55.46                     | 61.73                        |
| Flexural Strength     | 116.67                    | 118.7                        |
| Impact strength       | 20.8                      | 23.6                         |
| Density analysis      | 1.2345                    | 1.3568                       |
| Overall Grey relational grade | 0.7550                  | 0.8755                       |
| Improvement in Grey relational grade | 0.1303 |

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The Tensile strength is improved from 55.46 to 61.73 N/mm$^2$, the flexural strength from 116.67 to 118.7 N/mm$^2$ and the impact strength from 20.8 to 23.6 J/m. It is clearly shown that multiple performance characteristics in the built process are greatly improved through this study.

5 Conclusion

The use of an orthogonal array with grey relational analysis to optimize the built parameters with multiple performance characteristics has been reported in the paper. The grey relational analysis of the experiment results of tensile, flexural and impact strength can convert optimization of the multiple performance characteristics into the optimization of the single performance characteristics called the grey relational grade. The study has concentrated on the application of Taguchi method coupled with Grey relation analysis for solving multi criteria optimization problem in the field of rapid prototyping process. Experimental results have shown that the mechanical strength of the Stereolithography parts are enhanced by using Grey based Taguchi method. The optimal combination of process parameters based on multiple quality characteristics are A3/B3/C2 i.e., 0.125 Layer thickness, 90$^\circ$ Orientation and 0.015 hatch spacing.

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