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Improving the Dimensional Accuracy And Surface Roughness of Fdm Parts Using Optimization Techniques

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Abstract: *Fused deposition modeling (FDM) is unique of the rapid prototyping methods that use the plastics materials for example ABS (Acrylonitrile – butadiene – styrene) in the semi molten state to harvest the products unswervingly from CAD model. FDM is an additive manufacturing method and the prototypes are made by layer by layer addition of semi-molten plastic material onto the platform from bottom to top. The design inspects the effect of the process parameters layer thickness, raster width, raster angle and air gap that affects the surface roughness of the part produced by the manner of Fused Deposition Modeling. Hence, the Optimization of these process parameters of FDM is able to make the system more specific and repeatable and such progression can guide to use of FDM in rapid manufacturing solicitations rather than only producing prototypes. The novel ABS- M30 biomedical material was used in this research work to build parts. The experimentation has been completed with the help of Taguchi. Taguchi grey relational analysis is used to optimize the process parameters on multiple performance distinctiveness such as length, diameter, width and surface finish. The proposed method enables decision analysts to better recognise the complete evaluation process and provide good surface finish and dimensional accuracy.*

Keywords: *Rapid prototyping, Fused deposition modeling, Grey- Taguchi.*

I. Introduction

Rapid Prototyping (RP) is an additive manufacturing technology that automatically builds functional assemblies using CAD model of the part. In general, RP process includes five basic steps to build a part model automatically: (a) Create a CAD model of the design (b) Convert the CAD model to STL format (c) Slice the STL file into thin cross-sectional layers (d) Construct the model one layer atop another (e) Clean and finish the model. Surface roughness is the key property of RP build parts. Surface finish is considered as a vital feature and parts must be prepared in line with the product finishing specifications

The surface finish of parts obtained through these manufacturing processes is important, especially in cases where the components are in contact with other elements or materials in their service life. For example building moulds to produce components by means of Solid Free Form Manufacturing Processes, or cases of other functional components where their surface characteristics will have a considerable effect on their mechanical properties such as fatigue, wear, and corrosion. Therefore, it is important to have prior knowledge, by means of conceptual models, of the manufacturing process parameters that allow the user to predict the surface finish of manufactured prototypes.

Fused Deposition Modeling (FDM) is a leading RP technology that is used for fabricating solid prototypes in various materials directly from a computer-aided design (CAD) data. The quality and the strength of the FDM build parts are dependent essentially on the process parameters. In order to understand the performance and the behavior of FDM build parts, the influence of the process parameters on outcome quality of the build parts must be studied. Earlier studies (Mahapatra, et al, 2009), (Ahn, et al, 2002) have reported that FDM parameters such as layer thickness, air gap, raster width, and raster orientation were significantly impacting the quality characteristics of build parts. The FDM systems available in the market are different in their build speed, build volume, range of parameter settings and build materials (Masood, et al, 2010). In relevant empirical studies, parametric optimization was used to develop the quality characteristics of FDM parts or the process performance where the number of FDM process parameters were studied and optimized. For instance, (Lee, et al, 2005) and (Laeng, et al, 2006) investigated the elasticity performance of ABS material. Similarly, (Anitha, et al, 2001) optimized the FDM process parameters improving the surface roughness of build parts, while (Gregorian, et al., 2001), (Sood, et al., 2010) have looked into the dimensional accuracy of FDM parts

The material used for the present investigation is ABS M30 plastic

II. Experimental Plan

A trial run was performed in which a series of samples were built on the FDM machine using ABS M30 material. The machine is equipped with Insight software that assists the user to adjust the variable parameters in building part specification. Principally, the FDM variables are considered as four groups of operating parameters, as follows; FDM build specification, FDM environment/machine, and material specification. The full factor experiment was obtained to develop the experimentation plan for five parameters and three levels, considering the highest number of experimentation runs for the specified number of runs and levels in order to optimize the maximum parameters combinations. In this study, Full factor experiment, Box-Behnken design (three levels-five factors) has been selected initially according to the number of FDM variable parameters and number of settings or levels. Four parts per experiment are fabricated by the use of FDM Vantage SE machine. ABS m30 is the material used for fabricating the designed part. The surface roughness is taken to be the representative value respectively. MitutoyoTalysurf is used to measure the surface roughness

Table1: ControlFactors

Control Factors				
Factor	Symbol	Levels		
		1	2	3
Layer Thickness (Mm)	A	0.127	0.178*	0.254
Orientation (°)	B	0	15	30
Raster Angle (°)	C	0	30	60
Raster Width (°)	D	0.4064	0.4564	0.5064
Air Gap (Mm)	E	0	0.004	0.008
*Modified Centre Level Value				

Table2: Experimental Plan

S.No	A	B	C	D	E	Length	Diameter	Thickness	Roughness
1.	1	1	1	1	1	0.025833	0.9903	4.6667	2.1058
2.	1	1	1	1	2	0.0125	0.9938	2.6667	2.8062
3.	1	1	1	1	3	0.0475	0.9918	3.667	6.9003
4.	1	2	2	2	1	0.071667	0.9899	3.5833	6.372233
5.	1	2	2	2	2	0.06333	0.911	2.5833	2.544867
6.	1	2	2	2	3	0.057	0.9892	2.9167	2.180467
7.	1	3	3	3	1	0.12	0.9899	3.9167	3.611833
8.	1	3	3	3	2	0.106	0.9897	2.5833	3.606433
9.	1	3	3	3	3	0.048	0.9885	2.6667	1.917867
10.	2	1	2	3	1	0.19	0.9914	3.83	3.130267
11.	2	1	2	3	2	0.17	0.9897	2.6667	6.346833
12.	2	1	2	3	3	0.02	0.991	3.1667	4.028567
13.	2	2	3	1	1	0.137	0.9897	4	2.9945
14.	2	2	3	1	2	0.117	0.9894	3.75	2.1671
15.	2	2	3	1	3	0.012	0.9913	2.667	7.254867
16.	2	3	1	2	1	0.0333	0.9925	4.3333	5.599933
17.	2	3	1	2	2	0.07	0.9911	4.5	4.084567
18.	2	3	1	2	3	0.09	0.9922	3.6667	3.707867
19.	3	1	3	2	1	0.14	0.9979	4.833	1.9162
20.	3	1	3	2	2	0.13	0.9929	4.5	2.097433
21.	3	1	3	2	3	0.07	0.9888	3	3.0828
22.	3	2	1	3	1	0.04	0.9968	3.6667	3.638867
23.	3	2	1	3	2	0.06	0.9943	4.5833	3.092767
24.	3	2	1	3	3	0.025	0.9901	2.5883	2.657233
25.	3	3	2	1	1	0.137	0.9936	4	2.646733
26.	3	3	2	1	2	0.117	0.9969	3.75	2.917867
27.	3	3	2	1	3	0.121	0.9889	3.4167	3.0783

III. Grey Relational Analysis

In the grey relation analysis, experiment data, i.e., measured responses are first normalized in the range of 0 to 1. This process is called normalization or grey relation generation. Based on this data, grey relation coefficients are calculated to represent the correlation between the ideal (best) and the actual normalized experimental data. Overall, grey relation grade is then determined by averaging the grey relation coefficient corresponding to selected responses. The overall quality characteristics of the multi-response process depend on the calculated grey relation grade.

A. Normalization

Normalization of the signal to noise ratio is performed to prepare raw data for the analysis where the original sequence is transformed to a comparable sequence. Linear normalization is usually required since the range and unit in one data sequence may differ from the others. There are three different types of data normalization according to the requirement of Lower the Better (LB), Higher the Better (HB), or Nominal the Best (NB) criteria. If the target value of original sequence is infinite, then it has a characteristic of the "higher is better". The original sequence can be normalized as follows:

$$x_i^* = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \qquad (1)$$

When the "Smaller is better" is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x_i^* = \frac{\max x_i^o(k) - x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \qquad (2)$$

However, if there is a definite target value (desired value) to be achieved, the original sequence will be normalized in form:

$$x_i^* = 1 - \frac{|x_i^o(k) - x^o|}{x_i^o(k) - x^o} \qquad (3)$$

Or, the original sequence can be simply normalized by the most basic methodology, i.e. let the values of original sequence be divided by the first value of the sequence:

$$x_i^* = \frac{x_i^o(k)}{x_i^o(1)} \qquad (4)$$

Where i = 1 . . . m; k = 1. . . n. m is the number of experimental data items and n is the number of parameters. $x_i^o(k)$ denotes the original sequence, x_i^* the sequence after the data pre-processing, $\max x_i^o(k)$ the largest value of $x_i^o(k)$, $\min x_i^o(k)$ the smallest value of $x_i^o(k)$ and x^o is the desired value.

B. Determination of deviation sequences 0i(k) :

The deviation sequence, Δ0i(k) is the absolute difference between the reference sequence x0*(k) and the comparability sequence xi*(k) after normalization. It is determined using equation:

$$\Delta 0i(k) = |x_0^*(k) - x_i^*(k)| \qquad (5)$$

C. Calculation of grey relational coefficient (GRC)

GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio. If the two sequences agree at all points, then their grey relational coefficient is 1. The grey relational coefficient ξi(k) for the kth performance characteristics in the ith experiment can be expressed as :

$$\xi_i(k) = \frac{x_i^o(k\Delta\min + \zeta\Delta\max)}{\Delta 0_i(k) + \zeta\Delta\max} \qquad (6)$$

Where ΔOi is the deviation sequence of the reference sequence and $x_0^*(k)$ is the comparability sequence. ζ is distinguishing or identification coefficient: ζ ∈ [0, 1] (the value may be adjusted based on the actual system requirements). A value of ζ is the smaller and the distinguished ability is the larger. ζ = 0.5 is generally used. Grey relational coefficient for 27 comparability sequences.

D. Calculation of grey relational grade (GRG)

After the grey relational coefficient is derived, it is usual to take the average value of the grey relational coefficients as the grey relational grade. The grey relational grade is defined as follows:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi i(k) \qquad (7)$$

However, in a real engineering system, the importance of various factors varies. In the real condition of unequal weight being carried by the various factors, the grey relational grade was extended and defined as above. The grey relational grade γi represents the level of correlation between the reference sequence and the comparability sequence. If the two sequences are identical, then the value of grey relational grade is equal to 1. The grey relational grade also indicates the degree of influence that the comparability sequence could exert over

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the reference sequence. Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference sequence, then the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades.

IV. Analysis And Discussion Of Experimental Results

The grey relational grade $\gamma_i$represents the level of correlation between the reference sequence and the comparability sequence.

Table-3: Weighted grey relational grade

Experiment number	Weighted grey relational grade
1.	0.510162
2.	0.407108
3.	0.599026
4.	0.576186
5.	0.421949
6.	0.406057
7.	0.551818
8.	0.472138
9.	0.378184
10.	0.608945
11.	0.616917
12.	0.435521
13.	0.556437
14.	0.500997
15.	0.523656
16.	0.592386
17.	0.58513
18.	0.532652
19.	0.788065
20.	0.608259
21.	0.438725
22.	0.575819
23.	0.601407
24.	0.378296
25.	0.588118
26.	0.635007
27.	0.502116

The weighted grey relational grade calculated for each sequence is taken as a response for the further analysis. The larger-the-better quality characteristic was used for analyzing the GRG, since a larger value indicates the better performance of the process. The number of repeated test is one, since only one relational grade was acquired in each group for this particular calculation of S/N. The grey relation grades are now analyzed with Taguchi in Minitab17 software. This result shows that the best processing condition is the (A3, B1, C1, D2, and E1).

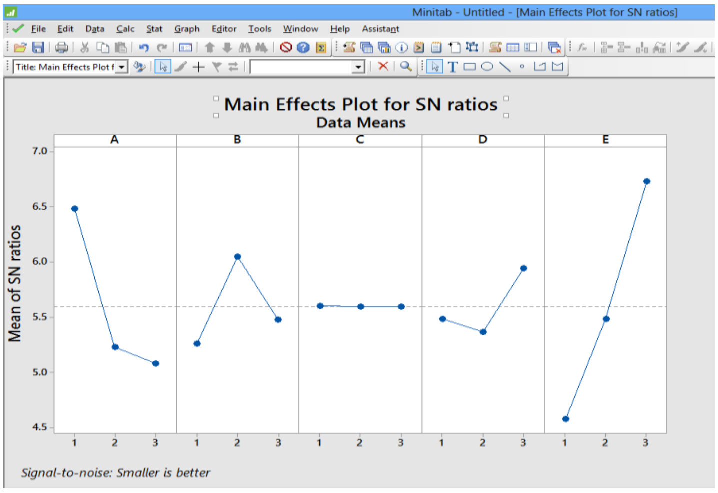

Fig: 1 Optimum results in Minitab

Table4: Optimum conditions

	Layer thickness	Part orientation	Raster angle	Raster width	Air gap
Level	A3	B1	C1	D2	E1
Values	0.254	0	0	0.4564	0.000

After determining the optimum conditions, confirmation test is to be done to check the responses obtained from the optimum conditions. The obtained optimum values are

- ✓ Length - 139.76 mm,
- ✓ Thickness - 3.43 mm,
- ✓ Diameter - 49.5mm and
- ✓ Surface roughness -4.059 microns.
- ✓

V. Conclusion

The selection of right combination of input parameters in FDM is difficult as the process involves a large number of control variables. The effects of input layer thickness, raster width, raster angle and air gap on surface roughness, length, diameter, while machining the ABS M30 material were analyzed with the experimental data obtained after conducting the experiments as per the Design of Experiments.

Grey Relational Analysis (GRA), for finding the optimal parameters affecting Surface Roughness4.059 microns are found atA3,B1,C1,D2andE1. Further study Artificial intelligent system such as the fuzzy logic system, simulated annealing, genetic algorithms might be used to enhance the ability of the prediction system.

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