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Improving the Surface Roughness of FDM Parts By using Hybrid Methods

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***Abstract*—Fused deposition modeling (FDM) is one of the rapid prototyping process that uses the plastics materials such as ABS (Acrylonitrile – butadiene – styrene) in the semi molten state to produce the products directly from CAD model. FDM is an additive manufacturing process and the prototypes are made by layer by layer addition of semi-molten plastic material onto the platform from bottom to top. . The design investigates the effect of the process parameters layer thickness, raster width, raster angle and air gap that influences the surface roughness of the part produced by the process 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 applications rather than only producing prototypes. The novel ABS- M30 biomedical material was used in this research work to build parts. The effect of process parameters on response is studied via Response surface methodology (RSM). It is used to calculate the regression coefficients and the function is made with the significant factors. Then optimization of process parameters to be done through Genetic algorithm in order to minimize the surface roughness of the part.**

Keywords—Rapid prototyping, fused deposition modelling, Response surface Methodology, Genetic algorithm

I. INTRODUCTION

The competition in the world market is growing tremendously and it is the vital need to make sure that the new products reach the market as soon as possible. Rapid Prototyping (RP) is an additive manufacturing technology that automatically builds functional assemblies using CAD model of the part. These "3D printers" allow designers to quickly create tangible prototypes of their designs, rather than just two-dimensional pictures. 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. However, there are certain materials for which it is difficult to meet the specifications, thus an optimum and achievable choice of material and application conditions is essential. Consequently, the operating conditions that optimally suit a material must be employed and their characteristics have to be taken into account.

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

II. MATERIALS AND METHODS

The material used for the present investigation is ABS M30 plastic. The chemical composition of the material is given in the Table 1.

Table 1: chemical composition of the material

S.No	Properties	Specifications
1.	STRUCTURE	AMORPHOUS
2.	SPECIFIC DENSITY	1.05
3.	WATER ABSORPTION RATE(%)	0.27
4.	ELONGATION (%)	20
5.	TENSILE STRENGTH (MPA)	29.64
6.	COMPRESSION STRENGTH (MPA)	62.05
7.	FLEXURAL STRENGTH (MPA)	63.43
8.	FLEXURAL MODULUS (MPA)	2068.48
9.	IMPACT (JOULES)	8.94
10.	HARDNESS	R110
11.	ULTRASONIC WELDING	EXCELLENT
12.	MACHINING	GOOD
13.	MIN. UTILIZATION TEMP (DEG.C)	-40
14.	MAX. UTILIZATION TEMP (DEG.C)	90
15.	MELTING POINT (DEG.C)	105
16.	COEFFICIENT OF EXPANSION	0.000053
17.	ARC RESISTANCE	80
18.	DIELECTRIC STRENGTH (KV/MM)	16
19.	TRANSPARENCY	TRANSLUCENT
20.	UV RESISTANCE	POOR
21.	CHEMICAL RESISTANCE	GOOD
22.	BONDING	EXCELLENT

A. *Response Surface Methodology*

RSM is a combination of experimental designs and statistical techniques for empirical model building and optimization. RSM was originally developed for the model-fitting of physical experiments by Box and Draper and later extended to other fields. RSM is very useful for modeling and analysis where a response of interest is influenced by several variables and the objective is to optimize this response. By conducting experiments and the posterior application of regression analysis a model of the response variable of interest is obtained. The real relationship between the response and the independent variables is unknown. For that reason, the first step in RSM is to find an approximation of the true functional relationship between the response and the independent variables.

In general, the relationship between the response y and independent variables $\xi 1, \xi 2 \ldots \xi k$ is

$$Y = f(\xi 1, \xi 2 \ldots\ldots\ldots\ldots\ldots\ldots \xi k) + \varepsilon \qquad (1)$$

Where ε includes effects such as measurement error on the response, background noise, the effect of other variables, and so on. Usually ε is treated as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ2. Then,

$$E(y) = \eta = E\,[f(\xi 1, \xi 2 \ldots\ldots \xi k)] + E(\varepsilon) = f(\xi 1, \xi 2 \ldots\ldots \xi k) \; (2)$$

The variables ξ1, ξ1…., ξk in equation (2) are usually called the natural variables, because they are expressed in the natural units of measurement, such as degrees Celsius, pounds per square inch, etc. in much RSM work it is convenient to transform the natural variables to coded variables x1, x2, …, xn, which are usually defined to be dimensionless with mean zero and the same standard deviation. In terms of the coded variables the response function will be written as f (x1, x2… xn); is called response surface. In most of the RSM problems the form of relationship between the response and the independent variable is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between Y and set of independent variables employed. Usually a second order model is utilized in RSM.

$$\eta = \beta 0 + \sum kj{=}1\ \beta j Xj + \sum kj{=}1\ \beta jj Xj2 + \sum kj{=}2\ \beta ij Xi Xj \qquad (3)$$

The β coefficients, used in the above model can be calculated by means of using least squares technique. The second order model is normally used when the response function is not known or nonlinear.

B. *Optimization by Genetic Algorithm*

Genetic algorithms are search procedures that emulate the process of evolution in nature, as Darwin's theory explains. They were proposed by Holland in the early 70's, and developed later on by Goldberg Based on survival of the fittest and reproduction, they search for new solutions in each stage or generation. A solution is coded in a chromosome. The most frequently used way of encoding is binary codification, although other systems like real value numbers have been used. The solution of the optimization problem with GA begins with a set of potential solutions or chromosomes that are randomly generated and selected the entire set of chromosomes comprises a population. The chromosomes evolve during several iterations or generations. New generations are generated using a crossover and mutation technique. Crossover involves splitting two chromosomes and then combining one half of each chromosome with other pair. Mutation involves flipping a single bit of a chromosome. The chromosomes are then evaluated using a certain fitness criteria and the best ones are kept while the others are discarded. This process is repeated until one chromosome has the best fitness and thus is taken as the best solution to the problem.

III. 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. The dimensions of the samples were selected according to specimen as shown in figure 1.

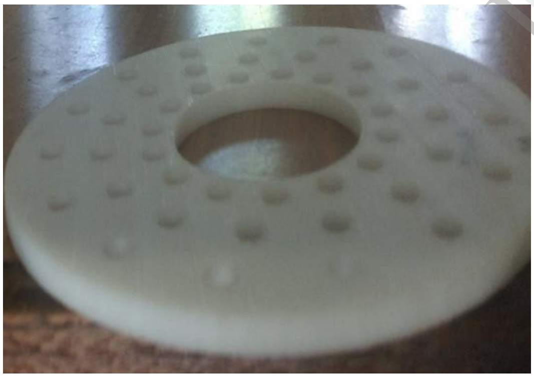

Figure 1: specimen

Figure 2: measuring of surface roughness by using talysuf

With the help of CATIA V5 software 3D solid model of prototype is modeled and are the converted to STL file. STL file is imported to FDM software (Insight). Now, control factors listed in Table3 are set as per shown experiment plan (Table 2). 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. Mitutoyo Talysurf is used to measure the surface roughness

Table 2: Fixed factors for FDM machine

FIXED FACTORS	
Factor	Value
Part fill style	Perimeter Raster
Counter width (mm)	0.464
Part interior style	Solid Normal
Visible surface	Normal raster
XY&Z shrink factor	1.0038
Perimeter to raster air gap (mm)	0

Table 3: Control factors for FDM machine

CONTROL FACTORS				
Factor	Symbol	Levels		
		-1	0	1
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				

Table 4: Experimental plan based on RSM

S.NO	**A**	**B**	**C**	**D**	**E**	**Surface roughness**
1	-1	0	0	0	1	4.86
2	0	0	1	0	-1	4.417
3	-1	-1	0	0	0	9.178
4	1	0	1	0	0	9.883
5	-1	0	0	0	-1	4.9418
6	0	0	1	-1	0	4.9932
7	1	0	0	-1	0	4.2356
8	0	-1	0	0	-1	4.8067
9	-1	0	-1	0	0	4.1415
10	0	0	0	-1	-1	4.9056
11	1	-1	0	0	0	8.8538
12	0	0	-1	-1	0	4.6988
13	0	0	0	0	0	5.005
14	-1	1	0	0	0	4.1372
15	1	0	-1	0	0	9.419
16	0	-1	0	1	0	6.8732
17	1	0	0	0	1	5.5376
18	-1	0	1	0	0	4.0672
19	0	1	-1	0	0	4.4592
20	0	0	0	1	1	4.076
21	0	0	1	1	0	5.5603

22	0	0	0	0	0	5.0454
23	0	-1	0	0	1	5.0544
24	0	1	0	0	-1	340648
25	0	1	0	1	0	4.173
26	0	0	-1	0	1	4.5032
27	0	0	0	0	0	4.2956
28	1	0	0	0	-1	5.1026
29	0	-1	1	0	0	4.68
30	0	0	-1	1	0	4.8993
31	-1	0	0	1	0	4.4412
32	0	-1	0	-1	0	5.331
33	0	-1	-1	0	0	4.554
34	0	0	0	0	0	5.1948
35	1	0	0	1	0	11.046
36	0	0	1	0	1	8.728
37	0	0	0	-1	1	6.217
38	0	1	0	-1	0	5.6863
39	-1	0	0	-1	0	5.7563
40	0	0	0	0	0	5.1333
41	0	1	0	0	1	4.195
42	1	1	0	0	0	4.5153
43	0	1	1	0	0	9.7465
44	0	0	-1	0	-1	6.4857
45	0	0	0	1	-1	5.4303
46	0	0	0	0	0	6.5212

IV. RESULTS AND DISCUSSIONS

Analysis of the experimental data obtained from Box-Behnken design runs is done on minitab16 software by the use of full quadratic response surface model which is given by

$$Y = \beta 0 + \sum_{n=i}^{k} \beta_{ii} x_i x_i + \sum i < j \sum \beta_{ij} x_i x_j$$

$$Y = \beta 0 + \sum_{n=i}^{k} \beta_{ii} x_i x_i + \sum i < j \sum \beta_{ij} x_i x_j$$

Where xi is ith factor and Y is the response.

In the ANOVA table the value of F is checked. Probability of F value is greater than calculated F value due to noise is indicated by P value. The significance of corresponding term is established, if P value is less than 0.05. The value of P must be greater the 0.05 for the lack of fit. An insignificant lack of fit is desired because it is the indication that anything left out of the model is not important and the developed model fits.

Based on analysis of variance (ANOVA) test full quadratic model was found to be suitable for surface roughness with regression p-value less than 0.05 and lack of fit more than 0.05.

Response Surface Regression: Surface Roughness Vs A, B, C, D, E. The analysis was done using coded units

Table-5.estimated regression coefficients for % change in surface roughness

Term	Coef	SE Coef	T	P
Constant	0.098288	0.01866	15.268	0.000
A	-0.048334	0.00497	-4.075	0.043
B	0.024167	0.004497	3.982	0.035
C	0.0051843	0.00497	0.486	0.031
D	-0.055528	0.00497	-1.457	0.157
E	0.013461	0.00497	0.299	0.767
A*A	-0.002969	0.01608	-0.049	0.961
B*B	-0.037414	0.01608	-3.614	0.544
C*C	-0.069676	0.01608	-4.144	0.263
D*D	-0.044359	0.01608	0.729	0.473
E*E	-0.037692	0.01608	-0.619	0.541
A*B	-0.023335	0.01809	-1.037	0.441
A*C	-0.004164	0.01809	-0.463	0.647
A*D	-0.066667	0.01809	-1.741	0.465
A*E	-0.031666	0.01809	-0.352	0.728
B*C	-0.0233333	0.01809	-1.483	0.151
B*D	-0.070000	0.01809	-0.778	0.044
B*E	0.033335	0.01809	0.371	0.014
C*D	-0.058530	0.01809	-0.651	0.521
C*E	0.193016	0.01809	2.146	0.052
D*E	0.102698	0.01809	1.142	0.264

In the analysis, the factor A, B,C and interaction B*E, B*D are important because their P value is less than 0.05. The coefficient of determination (R-Sq) which indicates the goodness of fit for the model so the value of R-Sq = 85.32%, which indicate the high significance of the model.

F (surface roughness) = 0.098288 - 0.048334*A + 0.024167*B + 0.0051843*C -0.07*(B*D) + 0.033335*(B*E)

Table-6.Analysis of variance for % change in surface roughness

Source	DF	Seq SS	ADj SS	ADjMS	F	P
A	1	249.7	249.7	249.7	2.88	0.109
B	1	427.7	427.7	427.7	4.93	0.041
C	1	1096	1096	1096	12.6	0.003
D	1	3.35	3.35	3.35	0.04	0.847
E	1	39.6	39.6	39.6	0.46	0.508
A*B	1	17.49	17.49	17.49	0.2	0.659
A*C	1	0.37	0.37	0.37	0	0.949
A*D	1	60.78	60.78	60.78	0.7	0.415
A*E	1	90.12	90.12	90.12	1.04	0.323
B*C	1	221.6	221.6	221.6	2.55	0.13
B*D	1	0.88	0.88	0.88	0.01	0.921
B*E	1	5.04	5.04	5.04	0.06	0.813
C*D	1	49.15	49.15	49.15	0.57	0.463
C*E	1	1.61	1.61	1.61	0.02	0.893
D*E	1	11.21	11.21	11.21	0.13	0.724
Error	16	1388.2	1388.2	86.77		
Total	31	3663.2				

Optimization of Parameters using Genetic Algorithm

Fitness function is given by,

F (surface roughness) = 0.098288 - 0.048334*A + 0.024167*B + 0.0051843*C -0.07*(B*D) + 0.033335*(B*E)

Genetic algorithm tool in MATLAB 2010 is used to optimize the process parameters in coded form.The fitness function is saves in Matlab and is called in the column named fitness function by „@fitness_function"

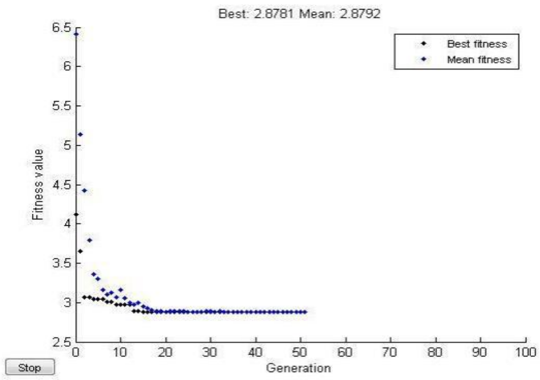

FIGURE 2 : FITNESS GRAPH

The optimized results obtained in coded form are:

A= 0.967, B = 0.935, C = 0.309, D = 0.976, E = -0.067

The optimized values of the process parameters in un-coded form are:

A= 0.25, B = 290, C = 380, D = 0.5063, E = 0.004

V. CONCLUSION

In the present work, influence of five process parameters namely, layer thickness, part build orientation, raster angle, raster width and air gap each taken at three different levels are studied for the surface finish of the FDM processed part. The surface roughness value at initial stage is 9.12 microns. The effect of process parameters on response is studied via Response surface methodology (RSM). With the help of RSM significant factors and their interaction are identified. In order to improve surface roughness of the build part it is required that the parts are manufactured with optimum process variables through a structured method. The method of genetic algorithm is used to get the optimum process parameters so that surface roughness is increased. Genetic algorithm shows that layer thickness, part build orientation, raster angle of will fabricate the part with overall improvement in accuracy of dimensions. Percentage deviation is observed in surface roughness with the optimum values. Small percentage error establishes the fitness of the present model. The obtained optimum values are surface roughness is 3.046 microns.

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