Improving Dimensional Accuracy and Surface Finish of Parts Produced by FDM using RSM and Genetic Algorithm

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Abstract— Fused Deposition Modeling (FDM) is one of the Rapid prototype (RP) process that produced prototype from plastic material such as ABS(Acrylonitrile-Butadiene-Styrene) by lying track of semi molten plastic filament on to a platform in a layer wise manner from bottom to top. The quality of FDM made parts are highly depends upon various process parameters of FDM process. The process parametersviz., layer thickness, part orientation, raster angle, raster width and air gap. The present paper deals with various part quality measures such as improvement in dimensional accuracy and minimization of surface roughness. Initially the influence of important process parameters along with their interactions has been studied. The part produced from FDM machine does not match with dimension of CAD model due to presence of shrinkage. However, shrinkage is more prominent in length and width direction but a positive deviation is observed in diameter direction. Influence of each parameter on responses such as percentage change in length, width, diameter and surface response of the build part have been studied. The effect of process parameters on responses are studied through Response surface methodology (RSM). Then optimization of process parameters to be done throughgenetic algorithm to minimize the percentage change in length, width, diameter and surface roughness. Hence optimization of FDM process parameters is necessary in order to improve the quality of parts.

Keywords: Fused Deposition Modeling, ABS material, Genetic algorithm, Response surface methodology

I. Introduction

Today there is a great competition in the manufacturing industries for the new products to reach the market as early as competitor.In order to save both cost and time the industries has shifted from traditional product development methodology to rapid prototyping. The Fused deposition modeling is one of the RP technology by which physical objects are created directly from CAD model using layer by layer deposition of extrusion material. But, the quality of FDM produced part is highly depends upon various process parameters used in this process. So, it is necessary to optimize FDM parameters. Optimization of process parameters helps to finding out correct adjustment of parameters which improve the quality of the prototypes. The Taguchi method is most widely used for design of experiments because it can be provide simplification of experimental plans and reduced the number of experimental runs. The most common material used in FDM is ABS polymer, the FDM technology can also be used with polycarbonates,polycaprolactone, polyphenylsulfones and waxes. A "water-soluble" material can be used for making temporary supports while manufacturing is in progress.

FDM machines builds part in an additive manner by building a layer atop another layer. The extrusion of the heated thermoplastic filament (ABS plastic) takes place from the tip of the nozzle. On the FDM machine there are two nozzles, one for the part material deposition and the other to build support structure, both works alternately according to the requirement.The two main qualities in the material selected are rapid solidification upon adhering to the previous layer and the material should melt at a temperature. Five factors viz., layer thickness (A), part build orientation (B), raster angle (C), raster width (D) and air gap (E) each at three level , are considered. They are briefly defined as follows.

1) Orientation: Part builds orientation or orientation referrers to the inclination of part in a build platform with respect to X, Y, Z axis. Where X and Y-axis are considered parallel to build platform and Z-axis is along the direction of part build.
2) Layer thickness: It is a thickness of layer deposited by nozzle and depends upon the type of nozzle used.
3) Contour width: The width of contour deposited by nozzle.
4) Part raster width (raster width): Width of raster pattern used to fill interior regions of part curves.
5) Visible surface: This feature improves the part external appearance.
6) Raster angle: It is a direction of raster relative to the x-axis of build table.
7) Shrinkage factor: Shrinkage factor applied in the x, y and z direction.
8) Raster to raster gap (air gap): It is the gap between two adjacent rasters on same layer.And the other factors are kept fixed.

II. Literature Survey

Zhou et al. (2000), In this study the influence of five control factors like layer thickness, over cure, hatch spacing, blade gap, and part location on build platform and few selected interactions on the accuracy of SLS part s. I t is observed that for maximum accuracy the factor settings depend on geometrical features in the part.

Anitha et al. (2001), by the use of taguchi method influence of raster width, layer thickness and speed of deposition each at three different levels on the surface roughness of the part produced by the process of FDM is determined. From the results, it is indicated that the layer thickness is the most influencing factor greatly affecting surface roughness followed by road width and speed of deposition.

Thrimurthulu et al. (2004), to determine the orientation for optimal part deposition for FDM process. Build time and average part surface roughness are two contradicting objectives, which are minimized by the minimization of their weighted sum. In evaluating the above two objectives the effect of support structure is taken into consideration. Thus, the support structure minimization is also indirectly included in this work In order to determine optimum part deposition orientation the use of adaptive slicing is made simultaneously.

Lee et al. (2007), in the study for improving the flexibility of the FDM part significant parameters and their levels were identified. From the results, layer thickness, raster angle and air gap are found to be significant and they are affecting the elastic performance of the compliant FDM ABS prototype.

Chattoraj et al. (2007), in this study the method of Genetic Algorithm is used for the optimization of magnetized FMSA. A code of genetic Algorithm for magnetized ferrite micro strip antenna is developed using C++ language and fitness function is obtained. The comparison of the optimized results with the results obtained using GA optimizer of MATLAB is done.

Sood et al. (2009), the effect of orientation, layer thickness, raster angle, raster width, and raster to raster gap is studied with the help of taguchi method on dimensional accuracy. Significant factors and their interaction are found out using taguchi method. The optimum settings of the parameters are found out so that all the three dimensions show minimum deviation from actual value simultaneously and the common factor settings need to be explored.

III. EXPERIMENTAL DETAILS

A detailed survey has been carried out to find out how the machining parameters affect surface roughness, dimensional accuracy onFDM machine. Based on this, the five machining parameters are layer thickness, part build orientation, raster angle, raster width and air gap were selected) each at three level. Taguchi's L46 (5ˋ3) orthogonal array in the design of experiments (DOE) technique has been implemented to conduct the experiments. The selected parameters with three levels each and then 3x3x3x3x3=243 runs were required in the experiments for five independent variables. But using Taguchi's orthogonal array, the number of experiments reduced to 46 experiments from 243 experiments. All the experiments were conducted on FDM. The specifications of the machine are: Power required - 230V, AC Motor - 50/60 Hz, 3ΦMax. Room temperature - 29.3^{o}C and Size of the system - 1277mm wide * 874 mm deep * 1950 mm height. The machining parameters used and their levels chosen are presented in Table 1.

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

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 1: Levels of process parameters

With the help of CATIA V5 software 3D solid model of prototype is modelled and the file converted into STL file. STL file is imported to FDM software (Insight). Now, control factors listed in Table1 are set as per shown experiment plan (Table 4). Four parts per experiment are fabricated by the use of FDM Vantage SE machine. ABS P400 is the material used for fabricating the designed part. The mean of the three readings each of length, width and diameter is taken to be the representative value respectively. Mitutoyo vernier caliper having least count of 0.01mm is used to measure the dimensions. Measurement of the dimensions shows that there is shrinkage in dimensions a long length (L), width (W), and diameter (D).Equation is used to analyze percentage change in dimensions of the build part. Reference taken from [4]

$$\text{section.percenage change in dimensions} = \frac{(X-XCAD)}{XCAD} * 100 \quad (1)$$

Sl.NO	A	B	C	D	E
1	-1	0	0	0	1
2	0	0	1	0	-1
3	-1	-1	0	0	0
4	1	0	1	0	0
5	-1	0	0	0	-1
6	0	0	1	-1	0
7	1	0	0	-1	0
8	0	-1	0	0	-1
9	-1	0	-1	0	0
10	0	0	0	-1	-1
11	1	-1	0	0	0
12	0	0	-1	-1	0
13	0	0	0	0	0
14	-1	1	0	0	0
15	1	0	-1	0	0
16	0	-1	0	1	0
17	1	0	0	0	1
18	-1	0	1	0	0
19	0	1	-1	0	0
20	0	0	0	1	1
21	0	0	1	1	0
22	0	0	0	0	0
23	0	-1	0	0	1
24	0	1	0	0	-1
25	0	1	0	1	0
26	0	0	-1	0	1

27	0	0	0	0	0
28	1	0	0	0	-1
29	0	-1	1	0	0
30	0	0	-1	1	0
31	-1	0	0	1	0
32	0	-1	0	-1	0
33	0	-1	-1	0	0
34	0	0	0	0	0
35	1	0	0	1	0
36	0	0	1	0	1
37	0	0	0	-1	1
38	0	1	0	-1	0
39	-1	0	0	-1	0
40	0	0	0	0	0
41	0	1	0	0	1
42	1	1	0	0	0
43	0	1	1	0	0
44	0	0	-1	0	-1
45	0	0	0	1	-1
46	0	0	0	0	0

Table 2: Experimental plan

IV. METHODOLOGY

A. *Response Surface Model Formulation:*

The response surface methodology is a widely adopted tool for the quality engineering field. The Response surface methodology (Montgomery, 1984) is a collection of mathematical and statistical techniques that are useful for modeling, analysis and optimizing the process in which response of interest is influenced by several variables and the objective is to optimize this response. Response Surface Methodology uses quantitative data from appropriate experiments to determine and simultaneously solve multi-variable equation. The response surface methodology comprises regression surface fitting to obtain approximate responses, design of experiments to obtain minimum variances of the responses and optimizations using the approximated responses.In statistical modeling to develop an appropriate approximating model between the response 'Y' and independent variables {x1x_1, $x_2 \ldots x_n$} in general, the relationship is written in the form of

$$Y = f(x_1, x_2, \ldots, x_n) + \varepsilon \text{ ; -------------------- (2)}$$

Where the form of the true response function Y is unknown and perhaps very complicated, and ε is a term that represents other sources of variability not accomplished for in Y. usually ε includes effects such as measurement error on response, back ground noise, the effect of the other variables and so on. Usually ε is treated as statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2.

$$E(y) = \widehat{Y} = E\,[f\,(x_1, x_2, \ldots, x_n)] + E\,(\varepsilon) = f\,(x_1, x_2, \ldots, x_n)\text{;----- - (3)}$$

The variables $x_1, x_2, \ldots, x_n$ Eq.(2) are usually called the natural variables, because they are expressed in the natural units of measurements such as degrees, Celsius, pounds/square inch etc. in much RSM work it is convenient to transform the natural variables to coded variables $x_1, x_2, \ldots, x_n$, 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 $(x_1, x_2, \ldots, x_n)$;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 variablesemployed. Usually a second order model is utilized in RSM.

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \sum_{j=1}^{k} \beta_{jj} X^2{}_j + \sum_{i<} \sum_{j=2}^{k} \beta_{ij} X_i X_j \text{ (4)}$$

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 (GA) are computerized search and optimization algorithms based on the mechanics of natural selection and natural genetics (Goldberg, 1989; Deb Kalyanmony, 1991) GA simulates the biological evolutionary process: Darwin's theory of survival of the fittest. The solution of the optimization problem with GA begins with a set of potential solutions or a chromosome that is randomly generated and selected the entire set of chromosomes comprises a population. The chromosomes evolve duringseveral 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.

V. RESULTS AND DISCUSSION

The L46 orthogonal array was adopted for the present investigation. So 46 experiments were conducted and the average change on length of all these components was measured and was used to build mathematical model using RSM. The second order response surface representing the surface roughness can be expressed as function of process parameters such as, layer thickness, part build orientation, raster angle, raster width and air gap.

The relationship between the change in length and machining parameters has been expressed as follows. From the observed data for change in length, the estimated regression coefficients for average change in lengthin un-coded units have been determined using least square technique. The multiple regression coefficient of the second order model was found to be 0.9239. This shows that second order model can explain the variation of the extent of 92.39%. The adjusted R2 is 78.68%. The estimated regression coefficients are presented in Table 3.

F (% change in Length) = 0.098288 - 0.048334*A + 0.024167*B + 0.0051843*C - 0.07*(B*D) + 0.033335*(B*E).

Results of ANOVA for the response function change in lengthare presented in the Table 4. This analysis is carried out for a level of significance of 5% i.e., for a level of confidence

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

Table.3. Estimated regression coefficients for length

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	20	0.026614	0.026624	0.0029572.83		0.132
Linear	5	0.016153	0.016253	0.005384	5.16	0.055
Square	5	0.004685	0.004675	0.001562	1.50	0.323
Interaction	10	0.005776	0.005766	0.001925	1.84	0.257
Residual Error	25	0.005222	0.005232	0.001044		
Lack-of-Fit	20	0.002278	0.002288	0.000759	0.52	0.712
Pure Error	5	0.002944	0.002954	0.001472		
Total	45	0.031836				

Table 4: Analysis of Variance for % change in Length

The relationship between the change in width and machining parameters has been expressed as follows.From the observed data for change in width, the estimated regression coefficients for average change in widthin un-coded units have been determined using least square technique. The multiple regression coefficient of the second order model was found to be 0.9752. This shows that second order model can explain the variation of the extent of 97.52%. The adjusted R2 is 93.47%. The estimated regression coefficients are presented in Table 5.

F(% change in width) = 0.424424 + 0.048334*A + 0.044167*B + 0.003335*(A*B) + 0.003335*(B*E).

Results of ANOVA for the response function change in widthare presented in the Table 6. This analysis is carried out for a level of significance of 5% i.e., for a level of confidence of 95%.

Term	Coef	SE Coef	T	P
Constant	0.424424	0.07343	5.780	0.000
A	0.048334	0.04497	1.075	0.043
B	0.044167	0.04497	0.982	0.035
C	0.021843	0.04497	0.486	0.631
D	-0.065528	0.04497	-1.457	0.157
E	0.013461	0.04497	0.299	0.767
A*A	0.002969	0.06089	0.049	0.961
B*B	0.037414	0.06089	0.614	0.544
C*C	0.069676	0.06089	1.144	0.263
D*D	0.044359	0.06089	0.729	0.473
E*E	-0.037692	0.06089	-0.619	0.541
A*B	0.003335	0.08993	0.037	0.041
A*C	-0.041664	0.08993	-0.463	0.647
A*D	-0.066667	0.08993	-0.741	0.465
A*E	-0.031666	0.08993	-0.352	0.728
B*C	-0.133333	0.08993	-1.483	0.151
B*D	-0.070000	0.08993	-0.778	0.444
B*E	0.033335	0.08993	0.371	0.014
C*D	-0.058530	0.08993	-0.651	0.521
C*E	0.193016	0.08993	2.146	0.052
D*E	0.102698	0.08993	1.142	0.264

Table 5: Estimated regression coefficients for width

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	20	0.57117	0.571166	0.028558	0.88	0.608
Linear	5	0.14783	0.147826	0.029565	0.91	0.488
Square	5	0.09450	0.094496	0.018899	0.58	0.712
Interaction	10	0.32884	0.328844	0.032884	1.02	0.458
Residual Error	25	0.80881	0.808807	0.032352		
Lack-of-Fit	20	0.65196	0.651965	0.032598	1.04	0.536
Pure Error	5	0.15684	0.156842	0.031368		
Total	45	1.37997				

Table 6: Analysis of Variance for % change in Width

The relationship between the change in diameter and machining parameters has been expressed as follows.From the observed data for change indiameter, the estimated regression coefficients for average change in diameterin un-coded units have been determined using least square technique. The multiple regression coefficient of the second order model was found to be 0.8532. This shows that second order model can explain the variation of the extent of 85.32%. The adjusted R2 is 88.57%. The estimated regression coefficients are presented in Table 7.

F (% change in diameter) = 5.00833 – 0.80204*A + 0.80729*B + 0.27085 *(A*B) + 0.20833*(B*C) + 1.95833*(B*D)

Results of ANOVA for the response function change in diameterare presented in the Table 8. This analysis is carried out for a level of significance of 5% i.e., for a level of confidence of 95%.

Term	Coef	SE Coef	T	P
Constant	5.00833	0.8463	5.918	0.000
A	-0.80204	0.5182	-1.548	0.034
B	0.80729	0.5182	1.558	0.042
C	0.08480	0.5182	0.164	0.871
D	0.75175	0.5182	1.451	0.159
E	-0.79663	0.5182	-1.537	0.137
A*A	-0.22319	0.7017	-0.318	0.753
B*B	0.03379	0.7017	0.048	0.962
C*C	-1.19073	0.7017	-1.697	0.102
D*D	-0.26714	0.7017	-0.381	0.707
E*E	0.53336	0.7017	0.760	0.454
A*B	0.27085	1.0365	0.261	0.046
A*C	-0.52100	1.0365	-0.503	0.620
A*D	-0.22915	1.0365	-0.221	0.827
A*E	1.47917	1.0365	1.427	0.166
B*C	0.20833	1.0365	0.201	0.042
B*D	1.95833	1.0365	1.889	0.032
B*E	0.04165	1.0365	0.040	0.968
C*D	-0.12083	1.0365	-0.117	0.908
C*E	-0.61403	1.0365	-0.592	0.559
D*E	0.63502	1.0365	0.613	0.546

Table 7: Estimated regression coefficients

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	20	89.026	89.026	4.4513	1.04	0.461
Linear	5	40.031	40.031	8.0062	1.86	0.137
Square	5	19.954	19.954	3.9907	0.93	0.479
Interaction	10	29.041	29.041	2.9041	0.68	0.736
Residual Error	25	107.427	107.427	4.2971		
Lack-of-Fit	20	83.973	83.973	4.1986	0.90	0.617
Pure Error	5	23.454	23.454	4.6909		
Total	45	196.453				

Table 8: Analysis of Variance for % change in diameter

The relationship between the surface roughness and machining parameters has been expressed as follows.From the observed data for surface roughness, the estimated regression coefficients for average change in diameterin un-coded units have been determined using least square technique. The multiple regression coefficient of the second order model was found to be 0.9239. This shows that second order model can explain the variation of the extent of 92.39%. The adjusted R2 is78.68%. The estimated regression coefficients are presented in Table 9.

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

Results of ANOVA for the response function change in diameter are presented in the Table 10. This analysis is carried out for a level of significance of 5% i.e., for a level of confidence of 95%.

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

Table 9 : Estimated regression coefficients

Source	DF	Seq SS	AdjSS	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				

Table 10: Analysis of Variance for surface roughness

Fitness function is given by,

F (% change in performance) = F(% change in Length) + F(% change in Width) + F (% change in diameter)+ F(surface roughness)

F(% change in performance) =5.531042 - 0.80204*A + 0.875624*B + 0.0051843*C + 0.274185*(A*B) + 0.20833*(B*C) + 1.8883*(B*D) + 0.03667*(B*E).

Sl.NO	**% change in length**	**% change in width**	**% change in diameter**	**Surface roughness**
1	0.041666	0.18	0.99037	2.86
2	0.17666	0.43333	0.993889	1.417
3	0.140833	0.433333	0.991852	9.178
4	0.063333	0.42	0.989907	9.883
5	0.1375	0.666666	0.991111	4.9418
6	0.0475	0.36666	0.989259	1.9932
7	0.070072	0.49999	0.989907	4.2356
8	0.139999	0.463226	0.989722	4.8067
9	0.060833	0.4	0.988519	1.1415
10	0.069321	0.56932	0.991481	3.9056
11	0.01249	0.2	0.989722	8.8538
12	0.149012	0.493212	0.988519	4.6988
13	0.075833	0.36666	0.991481	5.005
14	0.096532	0.568123	0.989722	2.1372
15	0.119999	0.433333	0.989444	9.419
16	0.0575	0.6	0.991296	6.8732
17	0.12	0.433333	0.992593	5.5376
18	0.106667	0.833333	0.991111	4.0672
19	0.048333	0.733333	0.992222	2.4592
20	0.190833	0.5	0.997963	3.076
21	0.060833	0.3	0.992963	5.5603
22	0.05666	0.5	0.988889	5.0454
23	0.14	0.456	0.996852	5.0544
24	0.012	0.18567	0.994352	3.0648
25	0.02576	0.1756	0.994352	4.173
26	0.0575	0.6	0.990185	4.5032
27	0.12	0.433333	0.993611	4.2956
28	0.106667	0.833333	0.996944	5.1026
29	0.048333	0.733333	0.988981	4.68
30	0.190833	0.5	0.989907	3.8993
31	0.176667	0.433333	0.989722	3.4412
32	0.028333	0.533333	0.988519	5.331
33	0.1375	0.666667	0.991481	2.554
34	0.1175	0.633333	0.989722	5.1948
35	0.0125	0.2	0.988519	11.046
36	0.033333	0.766667	0.991481	8.728
37	0.07	0.5	0.989722	2.217
38	0.096667	0.366667	0.989444	3.6863
39	0.140833	0.433333	0.991296	5.7563
40	0.1325	0.366667	0.992593	5.1333
41	0.075833	0.366667	0.991111	4.195
42	0.091667	0.666667	0.992222	4.5153
43	0.0475	0.366667	0.989722	9.7465
44	0.071667	0.12	0.988519	6.4857
45	0.063333	0.42	0.991481	3.4303
46	0.149167	0.24	0.989722	3.5212

Table 11: Experimental Results.

VI. GENETIC ALGORITHM

The maximizing the dimensional accuracyand minimizing surface roughness within the ranges of process parameters to be determined using a global optimization method: genetic algorithm (GA). The dimensional accuracyand surface roughness optimization problem for the FDM can be defined in the standard mathematical format as below

- Find: Dimensional accuracy, Surface roughness
- To maximize: dimensional accuracy
- Minimize: surface roughness.

Within parameter ranges:

0.127mm ≤ Layer thickness ≤ 0.254mm

0° ≤ Orientation≤ 30°

0° ≤ Raster angle ≤ 60°

0.4064 mm≤ Raster width ≤ 0.5064 mm

0 mm ≤Air gap ≤ 0.008mm

To solve the above optimization problem efficiently, an effective GA has been written in MATLAB programming language. The developed GA is coupled with the RS model forthe dimensional accuracy and the surface roughnessto yield a global optimum. The critical parameters in GAs are the size of population, cross over probability, mutation rate, number of generations (i.e., iterations), etc. In this study population size of 50, crossover rate of 0.9, mutation rate is of constraint dependent and the number of generations of 50 and constrained solver FMINCON as hybrid function are employed. The developed GA in this study, stochastic uniform selection has been used to select the chromosomes. Fitness values of the chromosomes are biased towards the minimize objective value and the least infeasible sets in crossover phase. GA is the surface roughnessof the FDM Machine from 9.12µ to 4.059µ by about 44.5% after optimization. The Dimensional accuracy and Surface roughness, corresponding optimum process parameters and initial process parameters are compared in Table.

	Before optimization	**After optimization**
Layer thickness mm	0.25	0.25
Orientation	15^0	29^0
Raster angle	34^0	38^0
Raster widthmm	0.4054	0.5063
Air gap mm	0.004	0.004
% change in length	0.025	0.0017
% change in width	0.069	0.02
% change in diameter	0.03	0.01

Surface roughness	9.12	4.059

Table 12: Comparison Results

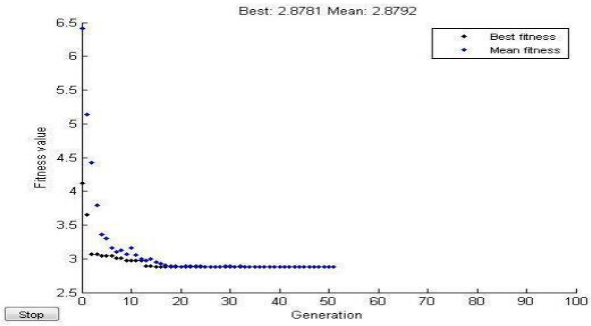

Fig. 1 : Fitness graph

VII. CONCLUSIONS

In this study, an efficient optimization methodology using RSM and GA is introduced in minimizing the surface roughness and maximizing the dimensional accuracy of FDM. To achieve the minimum surface roughness, the appropriate process parameters such as Layer thickness, part orientation, raster angle, raster width and air gap.Response surface methodology & design of experiment are used to make the experimental plan. It is observed that the reduction dominates in length and width of the specimen, but the value of the diameter is always less than the desired value. With the help of RSM significant factors and their interaction are identified. In order to improve dimensional accuracy and surface roughness of the build part it is required that the parts are manufactured in such a way that the minimum deviation of all the dimensions from the actual value is obtained. Therefore optimum process variables should be obtained through a structured method. The method of genetic algorithm is used to get the optimum value of the process parameters so that dimensional accuracy and surface roughness are 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 dimensional accuracy and surface roughness with the optimum values. Small percentage error establishes the fitness of the present model.Surface roughness is improved by about 44.5%.

REFERENCES

[1] Zhou Jack G, Daniel H, Chen Calvin C. “Parametric process optimization to improve the accuracy of rapid prototyped stereo lithography parts”, International Journal of Machine Tools and Manufacture, Vol.40, 2000, pp.363–379.

[2] Anitha R, Arunachalam S, Radhakrishnan P, “Critical parameters influencing the quality of prototypes in fused deposition modelling”, Journal of Material Process Technologies, Vol. 118, 2001, pp.(385-388).

[3] Thrimurthulu k, Pandey P.M. and Reddy N.V., “Optimum part deposition orientation in fused deposition modelling”, International Journal of Machine Tools & Manufacture 44 2004, pp.585–594.

[4] LeeB.H., Abdullah J and KhanZ.A “Optimization of rapid prototyping parameters for production of flexible ABS object, Journal of materials processing technology, vol.169, 2005, pp.54–61

[5] Chattoraj N and Roy J.S., “Application of Genetic Algorithm to the Optimization of Gain of Magnetized Ferrite Micro strip Antenna”, Engineering Letters, 14:2, EL_14_2_15 (Advance online publication: 16 May 2007).

[6] SoodA.K., OhdarR.K. and MahapatraS.S., “Improving dimensional accuracy of Fused Deposition Modelling processed part using grey Taguchi method”, Journal of materials and design, Vol.30(9),2009, pp. (4243-4252)