Improving dimensional accuracy of fused deposition modelling (FDM) parts using response surface methodology

A thesis submitted in partial fulfillment of the requirements for the degree in

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In

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by

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CERTIFICATE

This is to certify that the thesis entitled *"Improving dimensional accuracy of fused deposition modelling (FDM) parts using response surface methodology"* submitted by Mr. Rajan Bansal in partial fulfilment of the requirements for the award of Bachelor of technology Degree in Mechanical Engineering at National Institute of Technology, Rourkela. This is an authentic work carried out by him under my supervision.

To the best of my knowledge the matter embodied in the thesis has not been submitted to any University/Institute for the award of any Degree or Diploma.

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CONTENTS

ABSTRACT

Fused deposition modelling is one of rapid prototyping process that uses plastic materials such as ABS (acrylonitrile-butadiene-styrene) in the semi molten state to produce prototypes. FDM is an additive process and the prototypes are made by layer by layer addition of the semi-molten plastic material onto a platform from bottom to top. Primary process parameters such as layer thickness, raster angle and part orientation in addition to their interactions are studied in the present dissertation that influences the dimensional accuracy of the part produced by the process of Fused Deposition Modelling (FDM). Due to shrinkage of the filaments, the dimensions of the CAD model does not match with the FDM processed part. The shrinkage dominates along length and width of the build part but a positive deviation is observed along thickness direction.

Influence of each parameter on responses such as percentage change in length, width, and thickness of the build part are essentially studied. The effect of process parameters on responses are studied via Response surface methodology (RSM). RSM is used to calculate the regression coefficients and the function is made with the significant factors. Then optimization of process parameters is made by genetic algorithm so as to minimize the percentage change in length, width and thickness.

INTRODUCTION

Chapter1

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. Real practice prototypes can be built by ABS (Acrylonitrile Butadiene Styrene) material using FDM process that is one of RP technology. In general, FDM process includes five basic steps to build a part model automatically: (a) creation of the CAD model of the design. (b) Converting the CAD model to STL (stereolithography) file format. (c) Creation of thin cross sectional layers by slicing STL files. (d) Construction of the model one layer atop another. (e) Cleaning and finishing of the model. Alteration in dimensions of prototype during testing could lead to inaccurate results therefore dimensional accuracy is considered very important. It is important since producing new prototype again, will be expensive, time consuming etc. Hence study of process parameters influencing dimensional accuracy is considered essential.

During manufacturing of the specimen by the FDM machine, presence of shrinkage alters dimensions along length, width and thickness from the exact dimensions framed by the CAD model. Hence it is very essential to study how different process parameters affect the accuracy of the dimensions along length, width and thickness simultaneously. Use of DOE (Design of Experiments) has significantly increased the quality of cost. A rule box is created using Design of Experiments (DOE) to decide about the significant experiment. Response Surface Methodology (RSM) approach is used to calculate regression coefficients from the experimental data and the suitable functions are made using the significant factors affecting dimensional accuracy to the greatest extent. In order to calculate the optimised process parameters various methods such as artificial neural network, Mamdani fuzzy inference system, genetic algorithm etc. are available, but genetic algorithm is preferred to predict the optimised result of all the experiments because of its simplicity and can be easily understood. So it can be made to be used by an unskilled worker. It also considers uncertainty at the shop floor. Hence genetic algorithm is used to predict the optimum parameters which can increase the dimensional accuracy of the FDM processed part

LITERATURE REVIEW

Chapter2

LITERATURE REVIEW

Anitha *et al.* [1]**,** by the use of taguchi method influence of road 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.

Sood *et al*. [2], 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.

Pradhan *et al*. [3], study shows that the quality of product considerably influences the properties of the material. Method of response surface methodology is used to analyse the influence of process parameters on surface roughness. By the use of RSM a correlation between the process variables and response is established. A second order response model of these parameters are developed and found that pulse current, discharge time, and interaction term of pulse current with other parameters significantly affect the surface roughness.

Thrimurthulu *et al*. [4], this paper is an approach 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.

Carley *et al*. [5], various situations are studied in which response surface methodology which mainly consists of experimental strategy can be applied and the desired results can be obtained.

Pandey *et al.* [6], the average part surface roughness and production time is mainly affected by Orientation of the part deposition. In the study, objective functions for build time and average part surface roughness are framed. A set of pareto optimal solutions for part deposition orientation for the two objectives is determined by the use of NSGA-II. From the results it is observed that there are two limiting situations. One is having minimum average part surface roughness but maximum production time, other with minimum production time but maximum average part surface roughness. The system developed also gives intermediate solution sets and depending upon the preference of the user any solution can be used for the two objectives.

Lee *et al*. [7], 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*. [8], 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.

Zhou *et al*. [9],in this study the influence of five control factors like layer thickness, overcure, hatch spacing, blade gap, and part location on build platform and few selected interactions on the accuracy of SLS parts. It is observed that for maximum accuracy the factor settings depend on geometrical features in the part.

EXPERIMENTAL PLAN

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. Three factors viz., layer thickness (A), part build orientation (B), and raster angle (C), each at three levels, as shown in Table1, are considered. They are briefly defined as follows [2].

A. Layer thickness: It denotes the thickness of the layer being deposited by the nozzle and is dependent on the type of nozzle.
B. Part build orientation: It is the inclination of the part in a build platform with respect to X, Y, Z axis in which Z-axis is along the direction of the build part and, X and Y axis are considered parallel to the build platform.
C. Raster angle: it is the direction of the raster with respect to X-axis of the build table.

And the other factors are kept fixed.

With the help of CATIA V5 software 3D solid model of prototype is modelled and are the converted to STL file. STL file is imported to FDM software (Insight). Now, control factors listed in Table1 are set as per shown experiment plan (Table2). Three parts per experiment are fabricated by the use of FDM Vantage SE machine. ABSP400 is the material used for fabricating the designed part. The mean of the three readings each of length, width and thickness is taken to be the representative value respectively. Mitutoyo vernier calliper having least count of 0.01mm is used to measure the dimensions. Measurement of the dimensions shows that there is shrinkage in dimensions along length (L), width (W), but thickness (T) is more than the exact value depicted in the CAD model.
Equation (1) is used to analyse percentage change in dimensions of the build part.
Reference taken from [2] section.

$$\%\boldsymbol{change\ in\ dimensions} = ((\boldsymbol{X} - \boldsymbol{X_{CAD}})/\boldsymbol{X_{CAD}}) * \mathbf{100}\ldots \qquad (1)$$

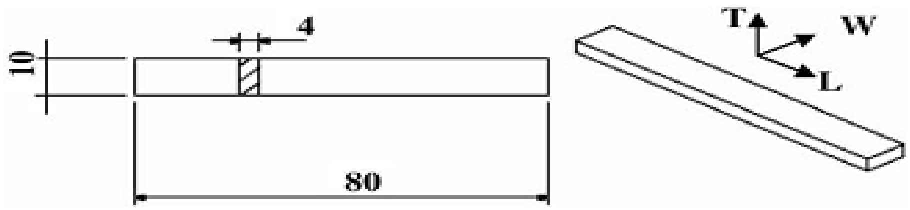

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FIGURE1: showing the Dimensions of test specimen in mm

EXPERIMENTAL DATA:

Table1: Levels of process parameters [2]

Factors	Symbol	Levels			
		-1	0	1	
Layer thickness	A	.127	.178	.254	mm
Orientation	B	0	15	30	degree
Raster Angle	C	0	30	60	degree

Here -1, 0, and 1 represent three different levels in coded form.

Table2: Experimental plan based on RSM [2]

Expt. No.	A	B	C	% change in length	% change in width	% change in thickness
1	1	-1	0	0.041666	0.18	8.6666
2	-1	1	0	0.17666	0.43333	2.666
3	0	0	0	0.140833	0.433333	4.833333
4	1	0	-1	0.063333	0.42	9.58329
5	-1	0	1	0.1375	0.666666	4
6	0	1	1	0.0475	0.36666	3.66666
7	0	1	-1	0.070072	0.49999	4.50002
8	0	0	0	0.139999	0.463226	4.26666
9	1	0	1	0.060833	0.4	8.5833
10	-1	-1	0	0.069321	0.56932	2.66667
11	0	-1	-1	0.01249	0.2	2.666
12	0	0	0	0.149012	0.493212	4.29999
13	0	-1	1	0.075833	0.36666	2.9999
14	1	1	0	0.096532	0.568123	6.41667
15	-1	0	-1	0.119999	0.433333	3.91665

The experiments are planned with A, B, and C taken in coded form.

Chapter4

METHODOLOGY

METHODOLOGY:

4.1 RESPONSE SURFACE METHODOLOGY:

One of the useful modern techniques used for predicting and optimising the machining performance is response surface methodology (RSM). In the present study, dimensional accuracy of the part processed by the FDM machine is predicted and also the machining parameters are optimized. Response surface methodology (RSM) is an assembly of statistical and mathematical functions that are used for improvement and optimization of the process. The quality characteristic that is influenced by the input parameters is called response. Response surface methodology includes planning of experimental strategy for development of an approximate relationship between the process parameters and the response [5].

The relationship between process variables $\xi_1, \xi_2, \dots \dots \dots \dots \xi_k$ and the response Y is,

$$Y = f(\xi_1, \xi_2, \dots \dots \dots \dots \dots \dots \xi_k) + \varepsilon \quad \dots\dots(4.1)$$

Where ε includes factors such error in the measurement of the response, the effect of other variables, background noise, and so ε is considered as a statistical error and often assumed having a normal distribution with variance σ^2 and mean zero.

$$\text{So,} E(y) = \eta = E[f(\xi_1, \xi_2, \dots \dots \dots \xi_k)] + E(\varepsilon) = f(\xi_1, \xi_2, \dots \dots . \dots \xi_k) \quad \dots\dots(4.2)$$

The variables $\xi_1, \xi_2, \dots \dots \dots \dots \dots \dots \xi_k$ in equation (4.2) are expressed in natural units of measurements, such as degrees Celsius, pounds per square inch, etc. and are known as natural variables. The natural variables are suitably transferred to coded variables $(x_1, x_2, \dots . , x_k)$ using RSM and are defined to be dimensionless having zero as mean and the standard deviation remains the same. The response function equation in terms of the coded variables is given as

$$\eta = f(x_1, x_2, \dots . , x_k) \quad \dots\dots(4.3)$$

For developing a suitable approximation, generally a low order polynomial (first order or second order polynomial) is used over a small region of independent variable space. If the experimenter is interested in the approximation of the true response over a little expanse of the independent variable space in the location where response function has little curvature, than first order model is mostly used. The first-order model in terms of the coded variables for the case having two independent variables, is shown below,

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \qquad \text{…………………….. ……………………….(4.4)}$$

If the interaction between the variables is considered then the first order model is easily expressed as,

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 \qquad \text{……………… ………………………...(4.5)}$$

Curvature is induced with the addition of the interaction between the variables. Due to curvature, a second-order model is used because first order model is inadequate to approximate the curvature of the true response surface which is generally strong. The second-order model for the case of two variables is given by:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} * (x_1\text{^}2) + \beta_{22} * (x_2\text{^}2) + \beta_{12} x_1 x_2 \qquad \text{………(4.6)}$$

This model would likely be useful as an approximation to the true response surface in a relatively small region. The parameters can be easily estimated in the second order model by using the method of least square.

In general, first order model can be written as

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots\dots.. + \beta_k x_k \qquad \text{……………………………………(4.7)}$$

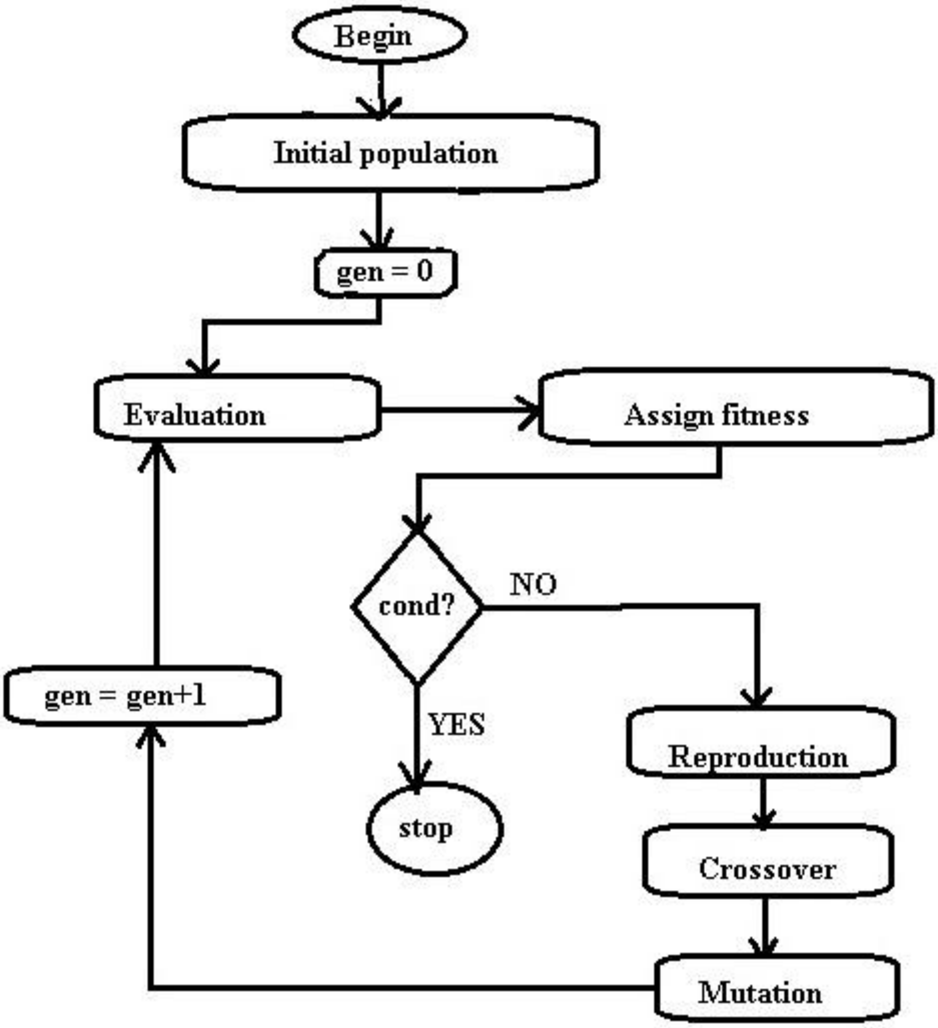
And the second order model can be given by,

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} {x_j}^2 + \Sigma_{i<} \sum_{j=2}^{k} \beta_{ij} x_i x_j \qquad \text{......................................(4.8)}$$

Whereβ's are unknown parameters and for the estimation of the values of these parameters experimental data is needed.

4.2 GENETIC ALGORITHM:

Genetic algorithm uses iterative optimization procedure and it works with number of solutions in every iteration rather than one solution. The solutions are known as ‘population’. The basic working principle is shown with the help of a flowchart below,



Each string created in the genetic algorithm is either a population and is assigned a fitness value. The fitness value for minimisation problems is given by the formula,

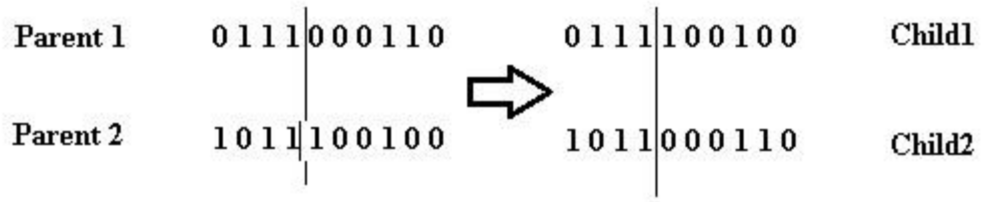
$$\text{Fitness} = \frac{1}{1+f(x_1, x_2, \ldots\ldots x_N)}$$

The string is in the form of binary digits like a four bit string ‘1001’.The three basic operators used in genetic algorithm are reproduction, crossover and mutation [8].

(A). **Reproduction** Reproduction selects good strings or ’parents’ from the initial population with the best fitness value to reproduce offspring with best fitness. The parents are selected by means of selection procedures where they go for reproduction [8]. There are various methods available for selection of the parents such as proportionate selection operator in which the string is selected having probability proportional to their corresponding fitness, ranking selection scheme in which the strings are placed according to the ascending order of their fitness value and the strings with the best fitness are selected, tournament selection procedure in which two random strings are chosen from the population and the one with the better fitness survives, etc.

The selected strings are placed in a mating pool from where reproduction phase starts making the use of crossover operator.

(B) **Crossover** Crossover operator works by selecting random points [8]. The crossover operation is as shown by the diagram,



In the crossover operator two strings at random are picked from the mating pool and both the selected strings are made to cut at an arbitrary place and the portion on the right side of the strings are exchanged between the strings to create two new strings known as child. The crossover operator is stopped until the new gen is completely comes to existence.
Although new generation that come into existence with the help of reproduction and crossover, is a combination of extant characteristics of the parents. Sometimes occasional random alteration in the string position value is done hoping to make a better offspring, the process is known as mutation [8].

(C) **Mutation** In mutation one bit is chosen at random and is flipped from '1' to '0' or vice versa. Mutation is shown below as,

In order to maintain the diversity in the population mutation is done.

As soon as the mutation is over, the fitness is evaluated. The members in the new generation with better fitness replace the old members with less fitness. The replacement of the old generation by the new generation might happen partially or fully that depends upon the fitness value. The process is repeated again and again unless fitness of the members become same expect for those that are mutated [8]. When this point is reached genetic algorithm is stopped.

CHAPTER 5

RESULTS AND DISCUSSIONS

RESULTS AND DISCUSSONS:

Analysis of the experimental data obtained from box-behnken design runs is done on minitab 15 software by the use of full quadratic response surface model which is given by,

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

Where x_i is i^{th} factor and $\boldsymbol{Y}$ 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.

5.1 Response Surface Regression: % change in Length versus A, B, C

The analysis was done using coded units

Table 3: Estimated Regression Coefficients for % change in Length

Term	Coef	SE Coef	T	P
Constant	0.143281	0.012712	11.271	0.000
A	-0.030139	0.007784	-3.872	0.012
B	0.023932	0.007784	3.074	0.028
C	0.006971	0.007784	0.896	0.412
A*A	-0.001647	0.011458	-0.144	0.891
B*B	-0.045590	0.011458	-3.979	0.011
C*C	-0.046218	0.011458	-4.034	0.010
A*B	-0.013118	0.011009	-1.192	0.287
A*C	-0.005000	0.011009	-0.454	0.669
B*C	-0.021479	0.011009	-1.951	0.109

S=0.0220177 PRESS=0.038100

R-Sq = 92.39% R-Sq (pred.) = 0.00% R-Sq (adj) = 78.68%

In the analysis, the factors A and B, and interaction B*B, C*C 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 = 92.39%, which indicate the high significance of the model.

F(% change in Length) = 0.143281 - 0.030139*A + 0.023932*B – 0.045590*(B*B) – 0.0462181*(C*C)

Table4: Analysis of Variance for % change in Length:

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.029411	0.029411	0.003268	6.74	0.025
Linear	3	0.012238	0.012238	0.004079	8.41	0.021
Square	3	0.014540	0.014540	0.004847	10.00	0.015
Interaction	3	0.002634	0.002634	0.000878	1.81	0.262
Residual Error	5	0.002424	0.002424	0.000485		
Lack-of-Fit	3	0.002374	0.002374	0.000791	31.91	0.031
Pure Error	2	0.000050	0.000050	0.000025		
Total	14	0.031835				

Surface Plots of % change in Length:

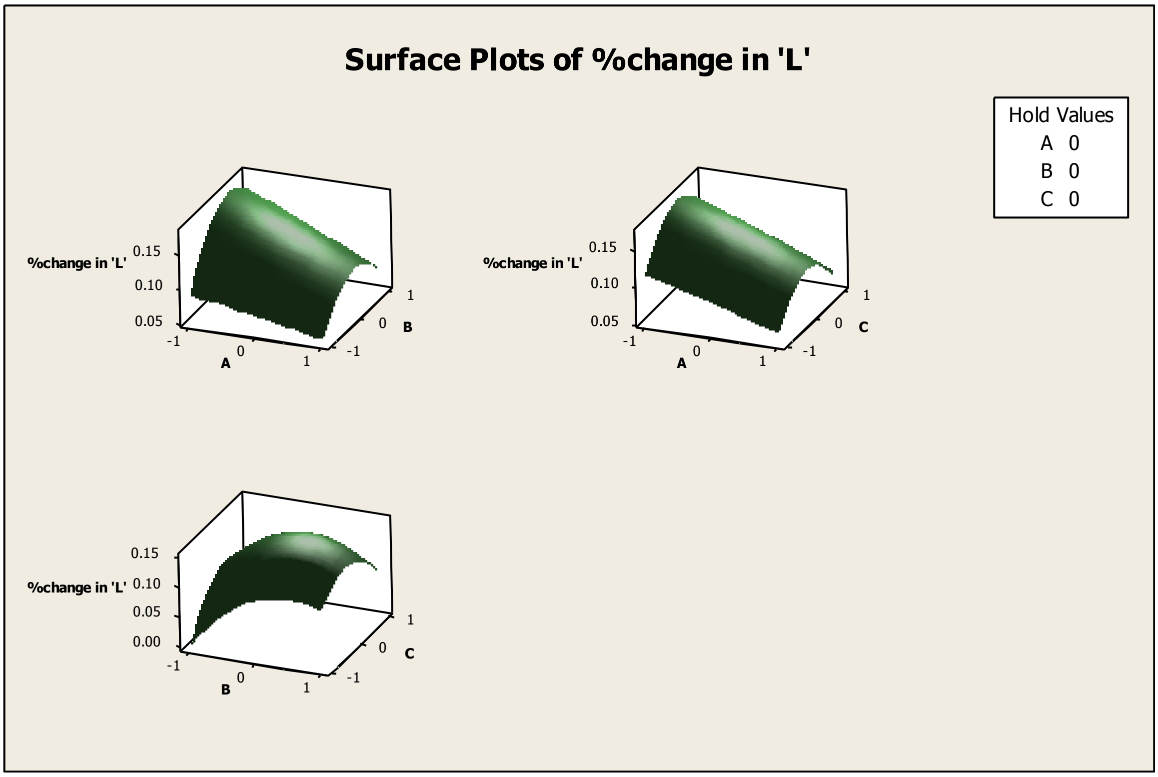


FIGURE2: Surface Plots of % change in Length w.r.t all pair of factors

5.2 Response Surface Regression: % change in Width versus A, B, C

The analysis was done using coded units.

Table5: Estimated Regression Coefficients for % change in Width

Term	Coef	SE Coef	T	P
Constant	0.46326	0.02035	22.767	0.000
A	-0.06682	0.01246	-5.362	0.003
B	0.06902	0.01246	5.539	0.003
C	0.03083	0.01246	2.475	0.056
A*A	0.04805	0.01834	2.620	0.047
B*B	-0.07362	0.01834	-4.014	0.010
C*C	-0.03131	0.01834	-1.707	0.148
A*B	0.13103	0.01762	7.436	0.001
A*C	-0.06333	0.01762	-3.594	0.016
B*C	-0.07500	0.01762	-4.256	0.008

S = 0.0352428 PRESS = 0.0747141

R-Sq = 97.29% R-Sq(pred) = 67.35% R-Sq(adj) = 92.40%

In the analysis, all the factors, and interaction A*A, B*B, A*B, A*C, B*C 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 = 97.29%, which indicate the high significance of the model.

F(% change in width) = 0.463257 - 0.0668157*A + 0.0690154*B + 0.0308329*C – 0.0480543*(A*A) – 0.0736180*(B*B) + 0.131028*(A*B) – 0.0633332*(A*C) – 0.0749975*(B*C)

Table 6: Analysis of Variance for % change in Width

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.222616	0.222616	0.024735	19.91	0.002
Linear	3	0.081425	0.081425	0.027142	21.85	0.003
Square	3	0.033974	0.033974	0.011325	9.12	0.018
Interaction	3	0.107217	0.107217	0.035739	28.77	0.001
Residual Error	5	0.006210	0.006210	0.001242		
Lack-of-Fit	3	0.004418	0.004418	0.001473	1.64	0.400
Pure Error	2	0.001793	0.001793	0.000896		
Total	14	0.228826				

Surface Plots of %change in Width:

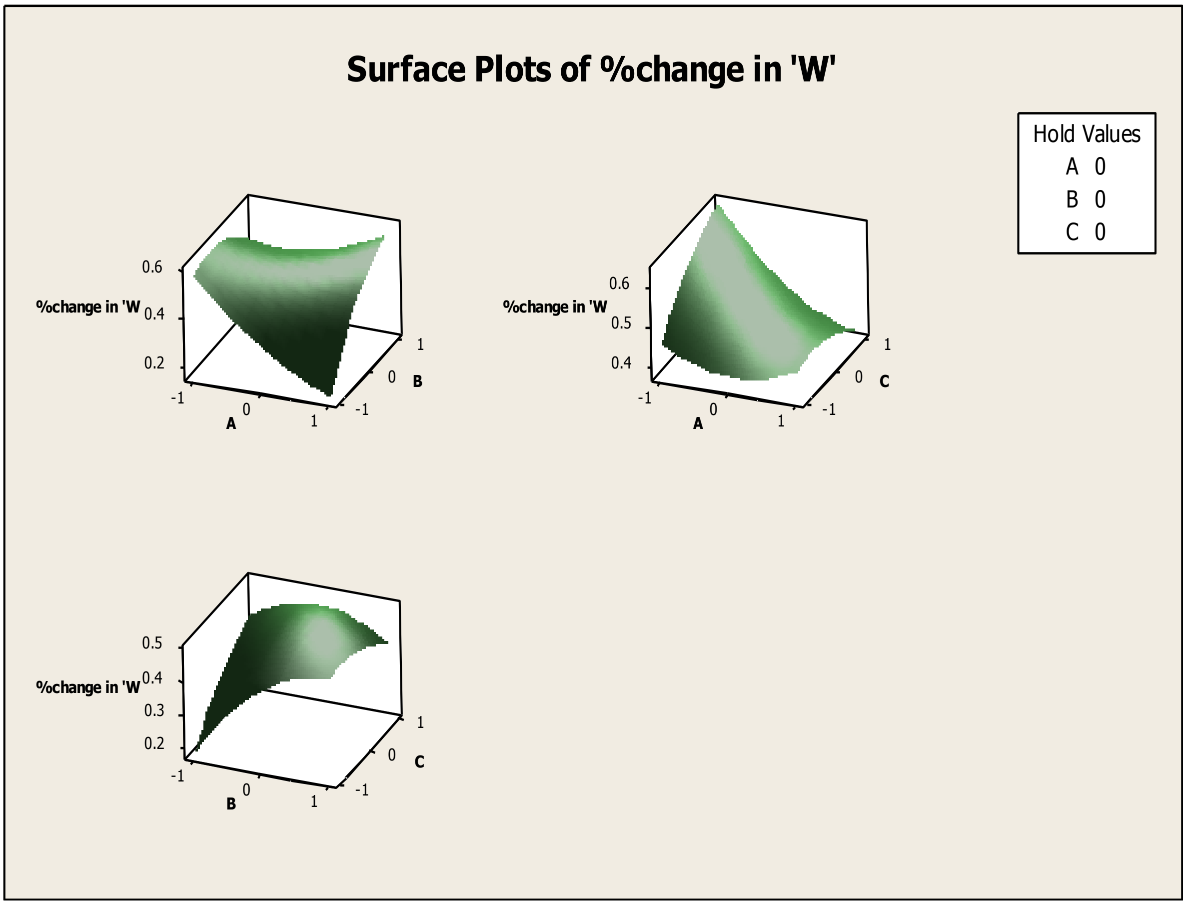


FIGURE3: Surface Plots of % change in Width w.r.t all pair of factors

5.3 Response Surface Regression: %change in Thickness versus A, B, C

Table7: Estimated Regression Coefficients %change inT

Term	Coef	SE Coef	T	P
Constant	4.46666	0.4529	9.862	0.000
A	2.50007	0.2774	9.014	0.000
B	0.03127	0.2774	0.113	0.915
C	-0.17701	0.2774	-0.638	0.551
A*A	1.84999	0.4083	4.531	0.006
B*B	-1.21267	0.4083	-2.970	0.031
C*C	0.20415	0.4083	0.500	0.638
A*B	-0.56231	0.3922	-1.434	0.211
A*C	-0.27083	0.3922	-0.690	0.521
B*C	-0.29182	0.3922	-0.744	0.490

S = 0.784487 PRESS = 46.4530

R-Sq = 95.89% R-Sq(pred) = 37.89% R-Sq(adj) = 88.48%

In the analysis, the factor A, and interaction A*A, B*B 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 = 95.89%, which indicate the high significance of the model.

F(% change in Thickness) = 4.46666 + 2.50007*A + 1.84999*(A*A) – 1.21267*(B*B)

Table8: Analysis of Variance for % change in Thickness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	71.7101	71.7101	7.9678	12.95	0.006
Linear	3	50.2612	50.2612	16.7537	27.22	0.002
Square	3	19.5501	19.5501	6.5167	10.59	0.013
Interaction	3	1.8988	1.8988	0.6329	1.03	0.455
Residual Error	5	3.0771	3.0771	0.6154		
Lack-of-Fit	3	2.8749	2.8749	0.9583	9.48	0.097
Pure Error	2	0.2022	0.2022	0.1011		
Total	14	74.7872				

Surface Plots of % change in Thickness:

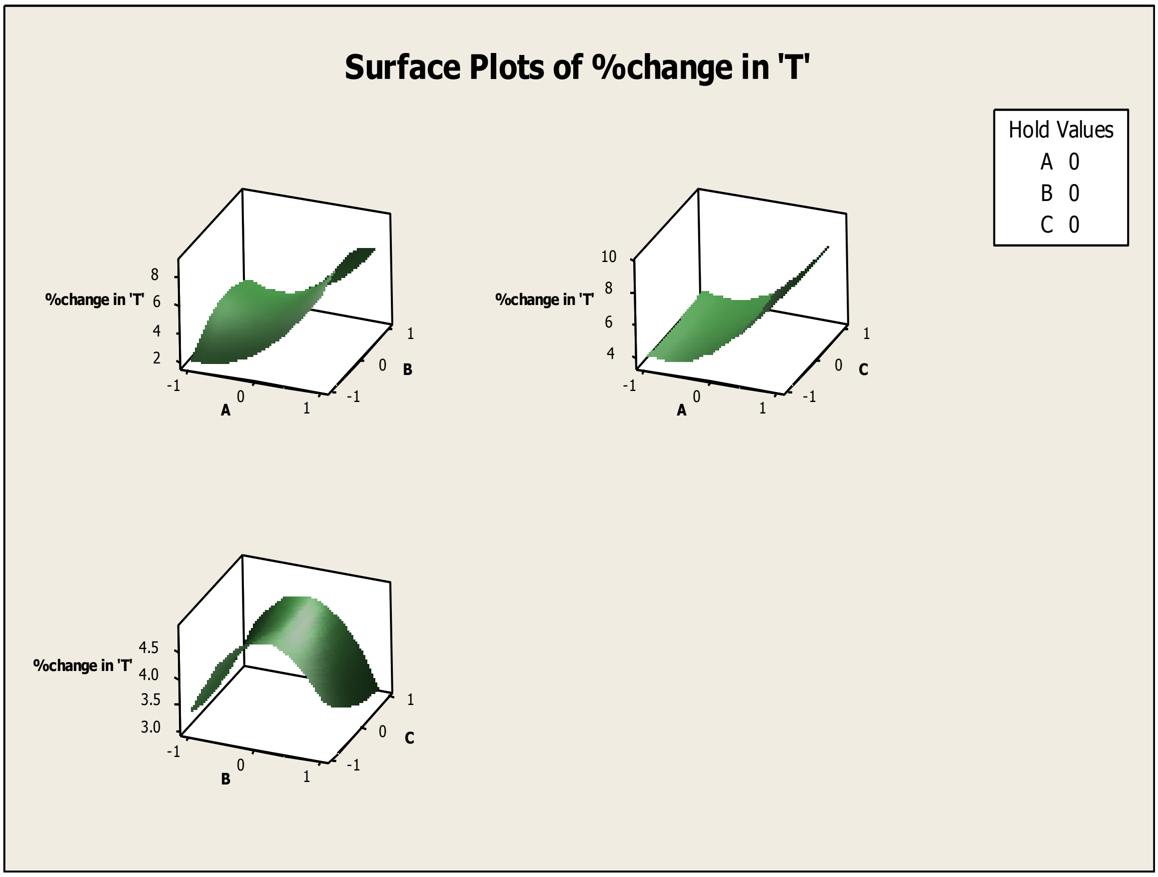


FIGURE4: Surface Plots of % change in Thickness w.r.t all pair of factors

OPTIMIZTION OF PARAMETERS USING GENETIC ALGORITHM:

Fitness function is given by,

$$F(\%\ \text{change in dimensions}) = F(\%\ \text{change in Length}) + F(\%\ \text{change in Width}) + F(\%\ \text{change in Thickness}) = 5.073198 + 2.4031148*A + 0.0929472*B - 0.0308329*C + 1.8980443*A^2 - 1.3318775*B^2 - 0.0462181*C^2 + 0.131028*A*B - 0.0633332*A*C - 0.0749975*B*C$$

GENETIC ALGORITHM TOOL IN MATLAB 2010 is used to optimise 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'

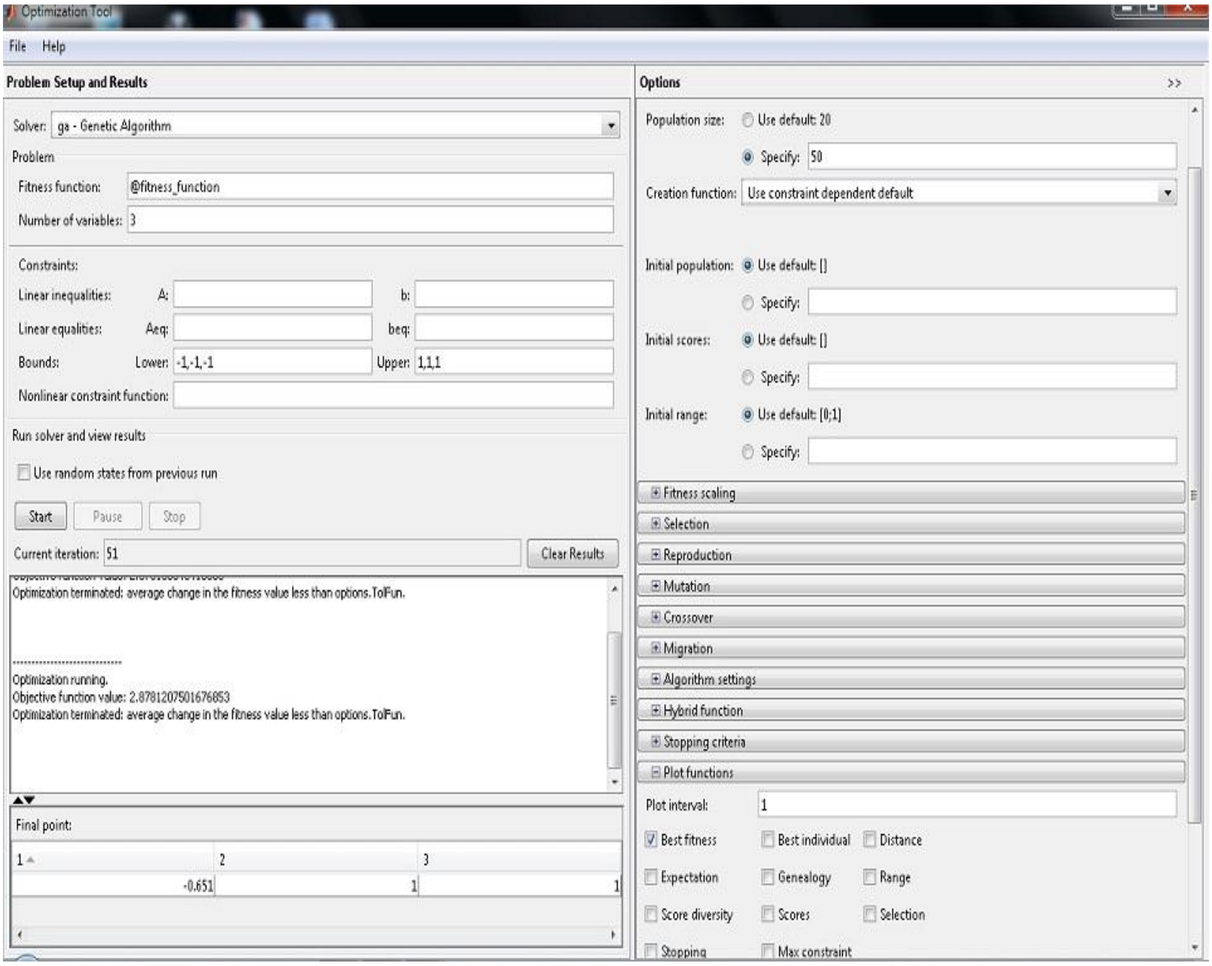


FIGURE 5: Optimization of parameters by Genetic Algorithm in Matlab

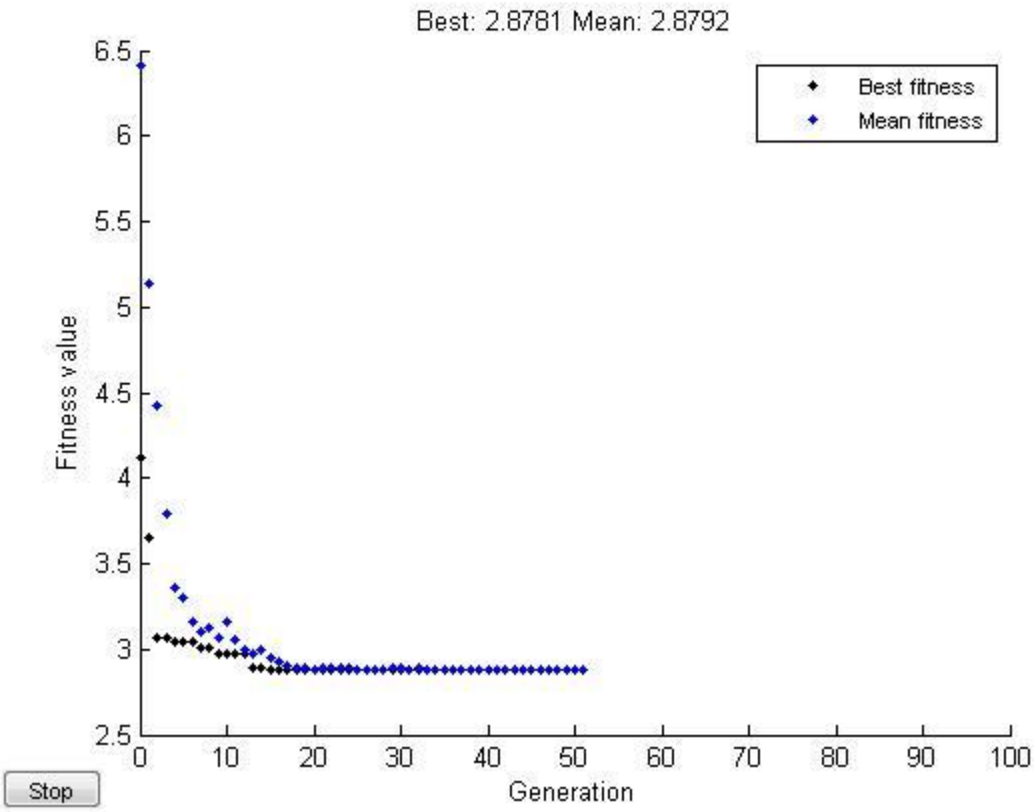


FIGURE6: PLOT OF FITNESS VALUE vs GENERATION'

The optimised results obtained in coded form are:

A= -0.651, B = 1, C = 1

The optimized values of the process parameters in uncoded form are:

A= 1.44mm, B = 30°, and C = 60°

CONCLUSION:

In the present study, influence of three process parameters namely, layer thickness, part build orientation, and raster angle each taken at three different levels are studied for the accuracy of the dimensions of the FDM processed part. Response surface methodology's design of experiment is 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 thickness is always more than the desired value. With the help of RSM significant factors and their interaction are identified. In order to improve dimensional accuracy 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 is increased. Genetic algorithm shows that layer thickness of $1.44mm$, part build orientation of $30°$ and the raster angle of $60°$ will fabricate the part with overall improvement in accuracy of dimensions. Percentage deviation of 2.8781% is observed in dimensional accuracy with the optimum values. Small percentage error establishes the fitness of the present model.

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