Intelligent Information Management, 2009, 1, 89-97
doi:10.4236/iim.2009.12014 Published Online November 2009 (http://www.scirp.org/journal/iim)

Optimization of Fused Deposition Modelling (FDM) Process Parameters Using Bacterial Foraging Technique

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Abstract: Fused deposition modelling (FDM) is a fast growing rapid prototyping (RP) technology due to its ability to build functional parts having complex geometrical shapes in reasonable build time. The dimensional accuracy, surface roughness, mechanical strength and above all functionality of built parts are dependent on many process variables and their settings. In this study, five important process parameters such as layer thickness, orientation, raster angle, raster width and air gap have been considered to study their effects on three responses viz., tensile, flexural and impact strength of test specimen. Experiments have been conducted using central composite design (CCD) and empirical models relating each response and process parameters have been developed. The models are validated using analysis of variance (ANOVA). Finally, bacterial foraging technique is used to suggest theoretical combination of parameter settings to achieve good strength simultaneously for all responses.

Keywords: fused deposition modelling (FDM), strength, distortion, bacterial foraging, ANOVA, central composite design (CCD)

1. Introduction

Reduction of product development cycle time is a major concern in industries to remain competitive in the marketplace and hence, focus has shifted from traditional product development methodology to rapid fabrication techniques like rapid prototyping (RP) [1–5]. Although RP is an efficient technology, full scale application has not gained much attention because of compatibility of presently available materials with RP technologies [6,7]. To overcome this limitation, one approach may be development of new materials having superior characteristics than conventional materials and its compatibility with technology. Another convenient approach may be suitably adjusting the process parameters during fabrication stage so that properties may improve [8,9]. A critical review of literature suggests that properties of RP parts are function of various process related parameters and can be significantly improved with proper adjustment. Since mechanical properties are important for functional parts, it is absolutely essential to study influence of various process parameters on mechanical properties so that improvement can be made through selection of best settings. The present study focus on assessment of mechanical properties viz. tensile, flexural and impact strength of part fabricated using fused deposition modelling (FDM) technology. Since the relation between a particular mechanical property and process parameters related to it is difficult to establish, attempt has been made to derive the empirical model between the processing parameters and mechanical properties using response surface methodology (RSM). In addition, effect of each process parameter on mechanical property is analysed. Residual analysis has been carried out to establish validity of the model. Development of valid models helps to search the landscape to find out best possible parametric combination resulting in theoretical maximum strength which has not been explored during experimentation. In order to follow search procedure in an efficient manner, latest evolutionary technique such as bacteria foraging has been adopted due to its superior performance over other similar random search techniques [10]. First, bacteria foraging is easier to implement because only few parameters need to be adjusted. Every bacterium remembers its own previous best value as well as the neighbourhood best and hence, it has a more effective memory capability than other techniques. Bacteria foraging is more efficient in maintaining the diversity of the swarm as all the particles use the information related to the most successful particle in order to improve themselves. In contrast, the worse solutions are discarded and only the good ones are saved in genetic algorithm (GA) [11]. Therefore, the population revolves around a subset of the best individuals in GA. Particle swarm optimization (PSO) can be considered as a good option because of its fast convergence but it has the tendency to get trapped at local optimum unless some procedure is adopted to escape [12].

2. Literature Review

Fused deposition modelling (FDM) is one of the RP processes that build part of any geometry by sequential deposition of material on a layer by layer basis. The process uses heated thermoplastic filaments which are extruded from the tip of nozzle in a prescribed manner in a semi molten state and solidify at chamber temperature. The properties of built parts depend on settings of various process parameters fixed at the time of fabrication. Recently, research interest has been devoted to study the effect of various process parameters on responses expressed in terms of properties of built parts. Studies have concluded through design of experiment (DOE) approach that process parameters like layer thickness, raster angle and air gap significantly influence the responses of FDM ABS prototype [13,14]. Lee *et al.* [15] performed experiments on cylindrical parts made from three RP processes such as FDM, 3D printer and nano-composite deposition (NCDS) to study the effect of build direction on the compressive strength. Out of three RP technologies, parts built by NCDS are severely affected by the build direction. Wang *et al.* [16] have recommended that material used for part fabrication must have lower glass transition temperature and linear shrinkage rate because the extruded material is cooled from glass transition temperature to chamber temperature resulting in development of inner stresses responsible for appearance of inter- and intra-layer deformation in the form of cracking, de-lamination or even part fabrication failure. Bellehumeur *et al.* [17] have experimentally demonstrated that bond quality between adjacent filaments depends on envelope temperature and variations in the convective conditions within the building part while testing flexural strength specimen. Temperature profiles reveal that temperature at bottom layers rises above the glass transition temperature and rapidly decreases in the direction of movement of extrusion head. Microphotographs indicate that diffusion phenomenon is more prominent for adjacent filaments in bottom layers as compared to upper layers. Simulation of FDM process using finite element analysis (FEA) shows that distortion of parts is mainly caused due to accumulation of residual stresses at the bottom surface of the part during fabrication [18]. The literature reveals that properties are sensitive to the processing parameters because parameters affect meso-structure and fibre-to-fibre bond strength. Also uneven heating and cooling cycles due to inherent nature of FDM build methodology results in stress accumulation in the built part resulting in distortion which is primarily responsible for week bonding and thus affect the strength. It is also noticed that good number of works in FDM strength modelling is devoted to study the effect of processing conditions on the part strength but no significant effort is made to develop the strength model in terms of FDM process parameters for prediction purpose. The present study uses the second order response surface model to derive the required relationship among respective process parameters and tensile, flexural and impact strength. The predictive equations once validated can be used to envisage theoretical possible best parameter settings to attain maximum in response characteristic. Hence, the problem becomes constrained optimization problem. In this study, bacteria foraging approach has been adopted to deal with the optimization problem.

The use of evolutionary algorithms to solve complex optimization problems is very common these days because they provide very competitive results when solving engineering design problems [19,20]. Furthermore, swarm intelligence approaches have been also used to solve this kind of problems [21,22]. However, most of the work is centered on some algorithms such as Particle Swarm Optimization [23], Ant Colony Optimization [24] and Artificial Bee Colony [25]. Recently, another swarm-intelligence-based model known as Bacterial Foraging Optimization Algorithm (BFOA), inspired in the behavior of bacteria E. Coli in its search for food, has been proposed. Three behaviors were modeled by Passino in his original proposal [26]: 1) Chemotaxis, 2) reproduction and 3) elimination-dispersal. BFOA has been successfully applied to solve different type of problems like forecasting [27], transmission loss reduction [28] and identification of nonlinear dynamic systems [29].

3. Experimental Procedure

The tensile test and three-point bending tests were performed using Instron 1195 series IX automated material testing system with crosshead speeds of 1mm/s and 2mm/s respectively in accordance with ISO R527:1966 and ISO R178:1975 respectively. Charpy impact test performed in Instron Wolpert pendulum impact test machine is used to determine the impact strength of specimen in accordance with ISO 179:1982. During impact testing, specimen is subjected to quick and intense blow by hammer pendulum striking the specimen with a speed of 3.8m/s. The impact energy absorbed is measure of the toughness of material and it is calculated by taking the difference in potential energy of initial and final position of hammer. Impact energy is converted into impact strength using the procedure mentioned in the standard.

Three specimens per experimental run are fabricated using FDM Vantage SE machine for respective strength measurement. The 3D models of specimen are modelled in CATIA V5 and exported as STL file. STL file is imported to FDM software (Insight). Here, factors as shown Table 1 are set as per experiment plan (Table 2). All tests are carried out at the temperature 23±2ºC and relative humidity 50±5% as per ISO R291:1977. Mean of each experiment trial is taken as represented value of respective strength and shown in Table 2. The material used for test specimen fabrication is acrylonitrile butadiene styrene (ABS P400).

4. Experimental Plan

It is evident from the literature that strength of FDM processed component primarily depend process parameters. Therefore, five important control factors such as layer thickness (A), part build orientation (B), raster angle (C), raster width (D) and raster to raster gap (air gap) (E) are considered in this study. Other factors are kept at their fixed level.

In order to build empirical model for each tensile strength, flexural strength and impact strength, experiments were conducted based on central composite design (CCD) [30]. The CCD is capable of fitting second order polynomial and is preferable if curvature is assumed to be present in the system. To reduce the experiment run, half factorial 2^K design (K factors each at two levels) is considered. Maximum and minimum value of each factor is coded into +1 and -1 respectively using Equation 1 so that all input factors are represented in same range.

$$\xi_{ij} = \left(\frac{x_{ij} - \overline{x_i}}{\Delta x_i}\right) \times 2 \qquad (1)$$

$$\overline{x_i} = \frac{\sum_{j=1}^{2} x_{ij}}{2} \quad \text{and} \quad \Delta x_i = x_{i2} - x_{i1}$$

$$1 \le i \le K \,; \quad 1 \le j \le 2$$

where ξ_{ij} and x_{ij} are coded and actual value of j^{th} level of i^{th} factor respectively.

Apart from high and low levels of each factor, zero level (center point) and ±α level (axial points) of each factor is also included. To reduce the number of levels due to machine constraints, face centred central composite design (FCCCD) in which α=1 is considered. This design locates the axial points on the centres of the faces of cube and requires only three levels for each factor. Moreover, it does not require as many centre points as spherical CCD. In practice, two or three centre points are sufficient. In order to get a reasonable estimate of experimental error, six centre points are chosen in the present work. Table 1 shows the factors and their levels in terms of uncoded units as per FCCCD. For change in layer thickness, change of nozzle is needed. Due to unavailability of nozzle corresponding to layer thickness value at centre point as indicated by Equation 1, modified centre point value for layer thickness is taken. Half factorial 2^5 unblocked design having 16 experimental run, 10 (2K, where K=5) axial run and 6 centre run is shown in Table 2 together with the response value for tensile, flexural and impact strength for each experimental run.

5. Bacteria Foraging Optimization Algorithm (BFOA)

As other swarm intelligence algorithms, BFOA is based on social and cooperative behaviors found in nature. In fact, the way bacteria look for regions of high levels of nutrients can be seen as an optimization process. Each bacterium tries to maximize its obtained energy per each unit of time expended on the foraging process and avoiding noxious substances. Besides, swarm search assumes communication among individuals. The swarm of bacteria, S, behaves as follows:

1) Bacteria are randomly distributed in the map of nutrients.
2) Bacteria move towards high-nutrient regions in the map. Those located in regions with noxious substances or low-nutrient regions will die and disperse, respectively. Bacteria in convenient regions will reproduce (split).

Table 1. Factors and their levels (*modified)

Factor	Symbol	Unit	Low Level (-1)	Centre point (0)	High Level (+1)
Layer thickness	A	mm	0.1270	0.1780*	0.2540
Orientation	B	degree	0.0000	15.000	30.000
Raster angle	C	degree	0.0000	30.000	60.000
Raster width	D	mm	0.4064	0.4564	0.5064
Air gap	E	mm	0.0000	0.0040	0.0080

Table 2. Experimental data obtained from the FCCCD runs

RunOrder	Factor (Coded units)					Tensile Strength (MPa)	Flexural Strength (MPa)	Impact Strength (MJ/m^2)
	A	B	C	D	E			
1	-1	-1	-1	-1	+1	15.6659	34.2989	0.367013
2	+1	-1	-1	-1	-1	16.1392	35.3593	0.429862
3	-1	+1	-1	-1	-1	9.1229	18.8296	0.363542
4	+1	+1	-1	-1	+1	13.2081	24.5193	0.426042
5	-1	-1	+1	-1	-1	16.7010	36.5796	0.375695
6	+1	-1	+1	-1	+1	17.9122	38.0993	0.462153
7	-1	+1	+1	-1	+1	18.0913	39.2423	0.395833
8	+1	+1	+1	-1	-1	14.0295	22.2167	0.466667
9	-1	-1	-1	+1	-1	14.4981	27.6040	0.342708
10	+1	-1	-1	+1	+1	14.8892	34.5569	0.429167
11	-1	+1	-1	+1	+1	11.0262	20.0259	0.379167
12	+1	+1	-1	+1	-1	14.7661	25.2563	0.450001
13	-1	-1	+1	+1	+1	15.4510	36.2904	0.375000
14	+1	-1	+1	+1	-1	15.9244	37.3507	0.437785
15	-1	+1	+1	+1	-1	11.8476	22.9759	0.419792
16	+1	+1	+1	+1	+1	15.9328	28.8362	0.482292
17	-1	0	0	0	0	13.4096	27.7241	0.397222
18	+1	0	0	0	0	15.8933	33.0710	0.44757
19	0	-1	0	0	0	14.4153	34.7748	0.402082
20	0	+1	0	0	0	9.9505	25.2774	0.388539
21	0	0	-1	0	0	13.7283	27.5715	0.382986
22	0	0	+1	0	0	14.7224	30.0818	0.401388
23	0	0	0	-1	0	13.5607	28.9856	0.401041
24	0	0	0	+1	0	13.8388	28.8622	0.395833
25	0	0	0	0	-1	13.6996	28.8063	0.405555
26	0	0	0	0	+1	13.8807	29.0359	0.409028
27	0	0	0	0	0	14.4088	29.7678	0.407292
28	0	0	0	0	0	13.0630	31.6717	0.396373
29	0	0	0	0	0	13.8460	30.1584	0.406558
30	0	0	0	0	0	13.8727	31.0388	0.397712
31	0	0	0	0	0	13.5914	29.1475	0.401156
32	0	0	0	0	0	13.2189	31.9426	0.410686

3) Bacteria are located in promising regions of the map of nutrients as they try to attract other bacteria by generating chemical attractants.

4) Bacteria are now located in the highest-nutrient region.

5) Bacteria now disperse as to look for new nutrient regions in the map.

Three main steps comprise bacterial foraging behavior: 1) Chemotaxis (tumble and swimming), 2) reproduction and 3) elimination-dispersal. Based on these steps, Passino proposed the Bacterial Foraging Optimization Algorithm which is summarized in pseudo-code as follows:

Pseudo-Code for BFOA

Begin

Initialize input parameters: number of bacteria (S_b), chemotactic loop limit (N_c), swim loop limit (N_s), reproduction loop limit (N_{re}), number of bacteria for reproduction (S_r), elimination-dispersal loop limit (N_{ed}), step sizes (C_i) depending on dimensionality of the problem and probability of elimination dispersal (P_{ed}).

Create a random initial swarm of bacteria $\theta^i(j, k, l)\ \forall_i$, $i = 1, \ldots, S_b$

Evaluate $f(\theta^i(j, k, l))\ \forall_i$, $i = 1, \ldots, S_b$

For l=1 to N_{ed} Do

For k=1 to N_{re} Do

For j=1 to N_c Do

For i=1 to S_b Do

Perform the chemotaxis step (tumble-swim or tumble-tumble) for bacteria θi(j, k, l)

End For

End For

Perform the reproduction step by eliminating the S_r (half) worst bacteria and duplicating the other half

End For

Perform the elimination-dispersal step for all bacteria $\theta^i(j, k, l)\ \forall_i$, $i = 1, \ldots, N_b$ with probability $0 \le P_{ed} \le 1$

End For

End

The chemotactic step was modeled by Passino with the generation of a random direction search (Equation 2)

$$\varphi(i) = \frac{\Delta(i)}{\sqrt{\Delta(i)^T \Delta(i)}} \quad (2)$$

where $\Delta\ (i)^n$ is a randomly generated vector with elements within the interval [−1, 1]. After that, each bacteria $\theta^i(j, k, l)$ modifies its positions as indicated in Equation 3.

$$\theta^i(j+1,\ k,\ l) = \theta^i(j,\ k,\ l) + C(i)\,\Phi\ (i) \quad (3)$$

Equation 2 represents a tumble (search direction) and Equation 3 represents a swim. The swim will be repeated N_s times if the new position is better than the previous one: $f(\theta^i(j + 1, k, l)) < f(\theta^i(j, k, l))$. The reproduction step consists on sorting bacteria in the population $\theta^i(j, k, l)\ \forall_i$, $i = 1, \ldots, N_b$ based on their objective function value $f(\theta^i(j, k, l))$ and to eliminate half of them with the worst value. The remaining half will be duplicated as to maintain a fixed population size. The elimination-dispersal step consists on eliminate each bacteria $\theta^i(j, k, l)\ \forall_i$, $i = 1, \ldots, N_b$ with a probability $0 \le P_{ed} \le 1$. It should be noted that BFOA requires 7 parameters and the n step sizes depending of the number of variables of the problem to be fine-tuned by the user.

5. Results and Discussions

Analysis of the experimental data obtained from FCCCD design runs is carried out using MINITAB R 14 software for full quadratic response surface model as given by Equation 4.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i x_i + \sum_{i<j} \sum \beta_{ij} x_i x_j \quad (4)$$

where y is the response, x_i is i^{th} factor

For significance check, F value given in ANOVA table is used. Probability of F value greater than calculated F value due to noise is indicated by p value. If p value is less than 0.05, significance of corresponding term is established. For lack of fit, p value must be greater the 0.05. An insignificant lack of fit is desirable because it indicates any term left out of model is not significant and developed model fits well. Based on analysis of variance (ANOVA), full quadratic model is found to be suitable for tensile strength, flexural strength and impact strength (Table 3) with regression p-value less than 0.05 and lack of fit more then 0.05. For tensile strength, all the terms are significant where as square terms are insignificant for

Table 3. Analysis of variance (ANOVA) table

Source	DOF	Tensile strength				Flexural strength				Impact strength			
		SS	MS	F	p	SS	MS	F	p	SS	MS	F	p
Regression	20	112.482	5.6241	11.65	0.000	799.058	39.953	14.96	0.000	0.0293	0.00146	16.72	0.000
Linear	5	64.373	12.8750	26.66	0.000	611.818	122.36	45.81	0.000	0.0258	0.00515	58.88	0.000
Square	5	14.966	2.9932	6.20	0.006	4.470	0.894	0.330	0.882	0.0019	0.00038	4.30	0.021
Interaction	10	33.143	3.3143	6.86	0.002	182.771	18.277	6.840	0.002	0.0016	0.00016	1.85	0.164
Residual	11	5.312	0.4829			29.383	2.671			0.0010	8.8E-05		
Lack of fit	6	4.116	0.6861	2.870	0.134	23.245	3.874	3.160	0.114	0.0008	0.00013	4.03	0.074
Pure error	5	1.196	0.2392			6.138	1.228			0.0002	3.3E-05		
Total	31	117.794				828.442				0.0302			

DOF= degree of freedom; SS= sum of square; MS= mean sum of square

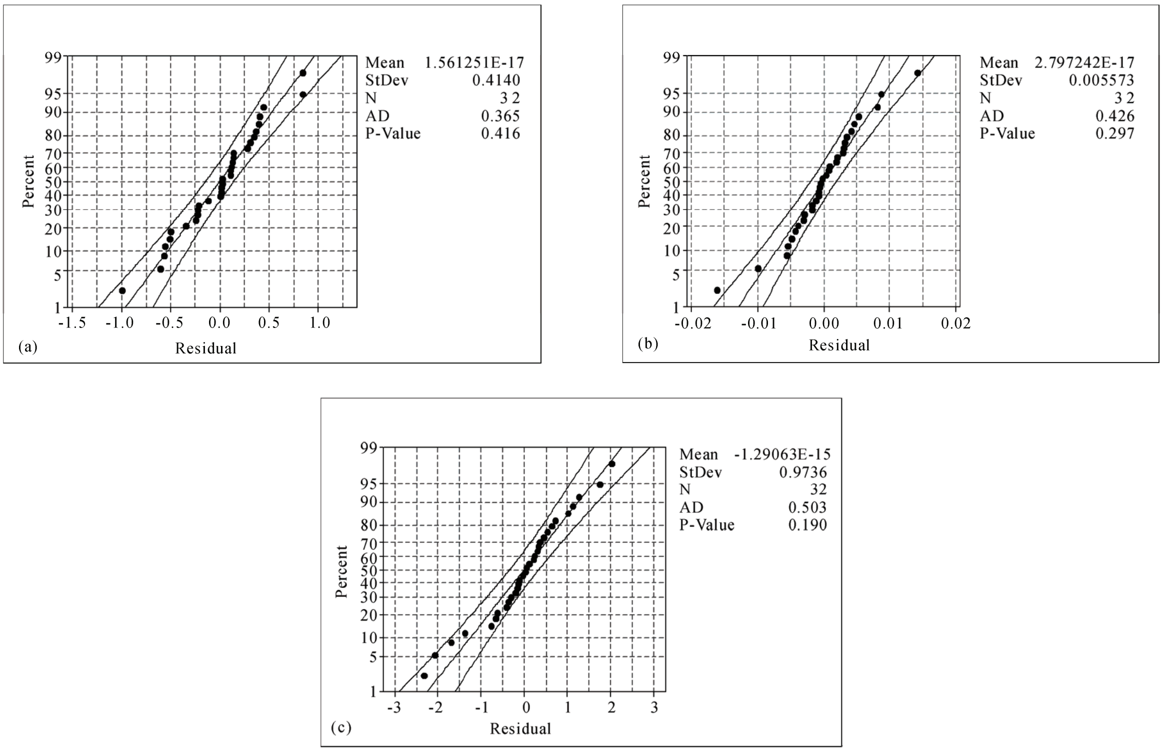

Figure 1. Normal probability plot of residual at 95% of confidence interval (a) Tensile strength (b) Impact strength (c) Flexural strength

flexural strength and interaction terms do not impart significant effect on impact strength.

The t-test was performed to determine the individual significant term at 95% of confidence level and final response surface equations in uncoded form for tensile strength (T_S), flexural strength (F_S) and impact strength (I_S) are given from Equation 5 to Equation 7 respectively in terms of coded units. The coefficient of determination (R^2) which indicates the percentage of total variation in the response explained by the terms in the model is 95.5%, 96.5% and 96.8% for tensile, flexural and impact strength respectively.

$$\begin{aligned} T_S = {} & 13.5625 + 0.7156\,A - 1.3123\,B + 0.9760\,C \\ & + 0.5183\,E + 1.1671\,A^2 - 1.3014\,B^2 - 0.4363\,(A\times C) \\ & + 0.4364\,(A\times D) - 0.4364\,(A\times E) + 0.4364\,(B\times C) \\ & + 0.4898\,(B\times E) - 0.5389(C\times D) + 0.5389\,(C\times E) \\ & - 0.5389\,(D\times E) \end{aligned} \tag{5}$$

$$\begin{aligned} F_S = {} & 29.9178 + 0.8719\,A - 4.8741\,B + 2.4251\,C \\ & - 0.9096\,D + 1.6626\,E - 1.7199\,(A\times C) \\ & + 1.7412\,(A\times D) - 1.1275\,(A\times E) + 1.0621\,(B\times E) \\ & + 1.0621\,(C\times E) + 1.0408\,(D\times E) \end{aligned} \tag{6}$$

$$\begin{aligned} I_S = {} & 0.401992 + 0.034198\,A + 0.008356\,B + 0.013673\,C \\ & + 0.021383\,A^2 + 0.008077\,(B\times D) \end{aligned} \tag{7}$$

Anderson-Darling (AD) normality test results are shown in Figure 1 for respective strength residue. P-value of the normality plot is more than 0.05 and signifies that residue follows the normal distribution.

Once the empirical models are validated for tensile, flexural, and impact strength of FDM built parts, next step is to search the optimization region for finding out suitable parameter settings that maximize responses beyond the experimental domain. Here, the objective function to be maximized is given as:

$$\text{Maximize} \quad (T_S \text{ or } F_S \text{ or } I_S). \tag{8}$$

Subjected to constraints:

$$A_{min} \le A \le A_{max} \tag{9}$$

$$B_{min} \le B \le B_{max} \tag{10}$$

$$C_{min} \le C \le C_{max} \tag{11}$$

$$D_{min} \le D \le D_{max} \tag{12}$$

$$E_{min} \le E \le E_{max} \tag{13}$$

The min and max in constraints 9-13 show the lowest and highest control factors settings (control factors) used in this study (Table 1). The constraints to be selected must be relevant to the response as shown in Equations 5-7. In order to apply BFOA, initial parameters of the are set as: number of bacteria, S_b=50, chemotactic loop limit, N_c=30, swim loop limit, N_s=100, reproduction loop limit, N_{re}=20, number of bacteria for reproduction, S_r=50%, elimination-dispersal loop limit, N_{ed}=50, step sizes, C_i

=1% of the difference of the maximum and minimum value of the variable, and probability of elimination dispersal, P_{ed}=0.05. The algorithm is coded in MATLAB and run on IBM Pentium IV desktop computer. The convergence curve for different responses is shown in Figure 2. The response values and optimal parameter settings are shown in Table 4. It can be observed from it that the response values significantly (in the tune of three to four times of experimental values) improve only setting the parameters within available range. Layer thickness (A) should be maintained at lower limit for improving tensile and flexural strength whereas it is to be set at higher range for the improvement of impact strength. Same trend of setting has also been observed for part orientation (B). Raster angle (C) and raster width (D) must be set at higher ranges for improving all responses. However, air gap (E) should be set at higher and medium range for improvement of tensile and flexural strength respectively whereas it does not play significant role for improvement of impact strength Lower layer thickness and air gap helps to occur diffusion in an effective manner causing better bonding among layers and better heat dissipation.

6. Conclusions

In this work, functional relationship between process parameters and strength (tensile, flexural and impact) forFDM process has been developed using response surface methodology for prediction purpose. The process pa rameters considered are layer thickness, orientation, raster angle, raster width and air gap. The empirical models

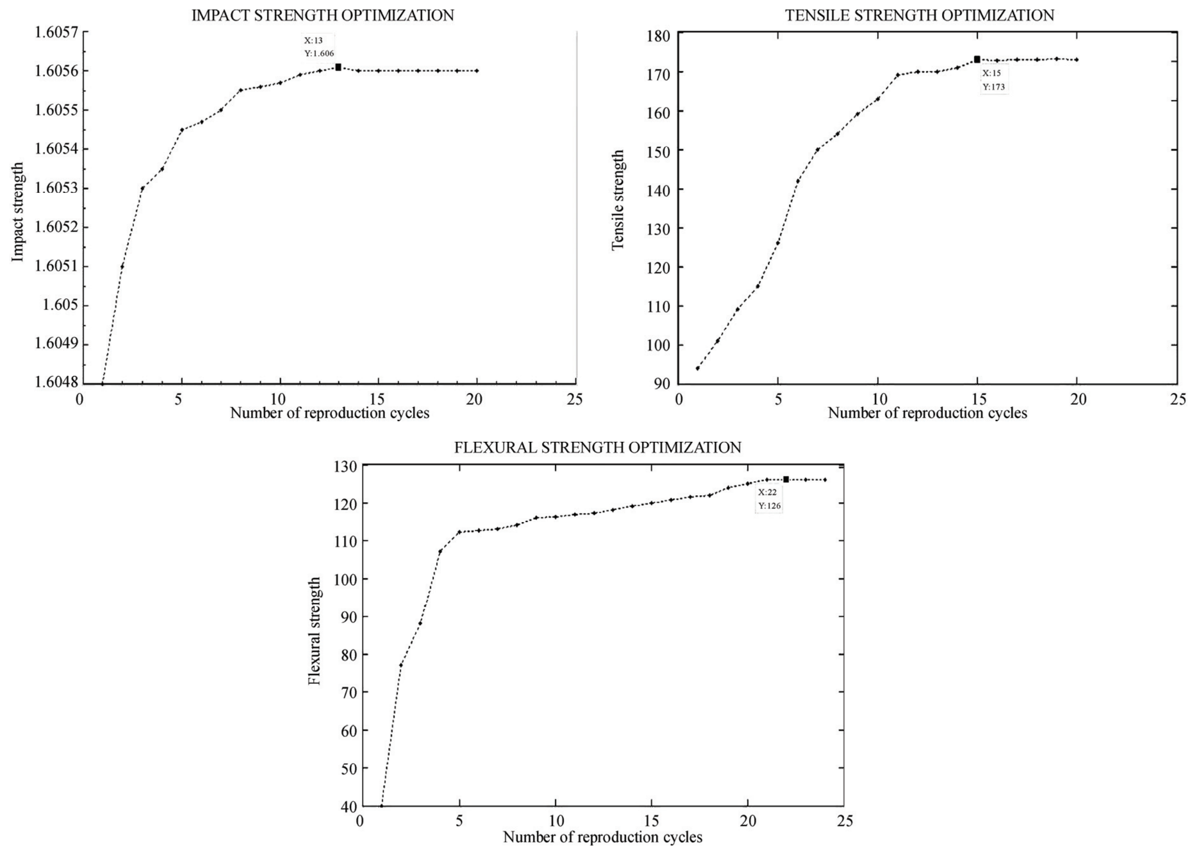

Figure 2. Convergence curves

Table 4. Optimal parameter settings with response values

Responses	Value	Layer thickness (A)	Orientation (B)	Raster angle (C)	Raster width (D)	Air gap (E)
Tensile strength	174.3177	0.1318	9.6100	59.9937	0.4196	0.0074
Flexural strength	126.4818	0.1278	4.9504	54.7311	0.4960	0.0034
Impact strength	1.6056	0.2531	29.9963	59.9951	0.5063	Not applicable

developed here have passed all the known statistical tests and can be used in practice. Since FDM process is a complex one, it is really difficult to obtain good functional relationship between responses and process parameters. A latest evolutionary approach such as bacterial foraging has been used to predict optimal parameter settings. It predicts parameters in universal range of values that may not exist in the experimental system set up. Therefore, this technique suggests alternative system settings so as to produce optimum results in the process. The parameter settings seem to be logical from the practical point of view. Number of layers in a part depends upon the layer thickness and part orientation. If number of layers is more, it will result in high temperature gradient towards the bottom of part. This will increase diffusion between adjacent rasters and strength will improve. Small raster angles are not preferable as they will results in long rasters which will increase the stress accumulation along the direction of deposition resulting in more distortion and hence weak bonding. Thick rasters results in high temperature near the boding surfaces which may improve the diffusion and may result in strong bond formation. The study can also extended in the direction of studying compressive strength, fatigue strength and vibration analysis.

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