International Journal of Applied Engineering Research ISSN 0973-4562 Volume 14, Number 13, 2019 (Special Issue)

Parametric Optimization of FDM Processed Part for Improving Surface Finish Using MOORA Technique and Desirability Function Analysis

Abhishek Barua*, Siddharth Jeet, Hemanta Cherkia
Department of Mechanical Engineering,
Centre for Advanced Post Graduate Studies, BPUT, Rourkela, Odisha, India.

Dilip Kumar Bagal
Department of Mechanical Engineering,
Government College of Engineering, Kalahandi, Bhawanipatna, Odisha, India.

Bibhuti Bhusan Sahoo
Department of Mechanical Engineering,
Indira Gandhi Institute of Technology, Sarang, Dhenkanal, Odisha, India.

Abstract

Fused deposition modelling (FDM) is a fast budding rapid prototyping (RP) technology due to its ability to manufacture functional parts with complex geometrical shapes in reasonable build time without any tooling requirement and human interface. It has a complex part building contrivance making it challenging to obtain reasonably noble functional relationship among responses and process parameters. The properties of FDM built parts i.e. dimensional accuracy, surface roughness, mechanical strength etc. and above all functionality of built parts exhibit high dependence on many process variables and their settings. Present study determines the relationship between 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., surface roughness of the top, bottom, and side face of the built part. Twenty-seven experiments have been conducted using Taguchi's design and two different optimizations has been used i.e. Desirability Function analysis and MOORA technique. Finally, the confirmation test was carried out to validate the obtained results and the models are validated using analysis of variance (ANOVA).

Keywords: Rapid Prototyping, Fused Deposition Modelling, ABS M30, Desirability Function Analysis, MOORA.

Introduction

Decline of product improvement cycle time is a chief 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). Fused deposition modeling (FDM) is a rapid prototyping (RP) technology that fabricates parts by piling and bonding layers in one direction. This method uses heated thermoplastic filaments which are extruded from the tip of nozzle in a prearranged manner on before deposited layer to build the parts layer by layer [1-4].

For wide-ranging manufacturing applications, the FDM processed parts sometimes become unsuitable because surface finish is unsurprisingly extremely rough, especially on the inclined surfaces of the parts. As a result, considerable efforts have been dedicated by numerous researchers to improve the surface finish of the parts. In broad continuum of RP, investigators have proposed many experimental models through experimental data analysis. A critical analysis of literature reveals that most of the surface roughness models consider layer thickness and build orientation neglecting many other parameters involved during actual part building stage [1-7].

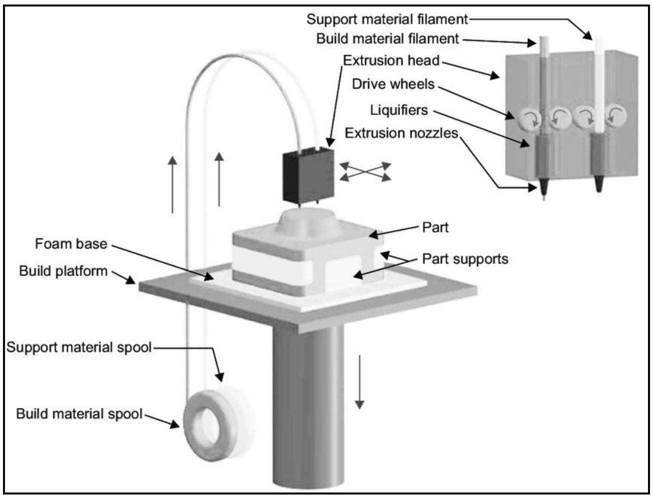

Figure 1: FDM process

The present study focus on assessment of surface roughness of the top, bottom, and side face of part fabricated using fused deposition modelling (FDM) technology. The whole experimentations are planned in Taguchi method using L27 Orthogonal array. From the experimental data, the process parameters such as layer thickness, part build orientation, raster angle, raster width, and air gap which significantly influence the dimensional accuracy and mechanical strength of processed part are to be optimized. Therefore, the present study considers the same process parameters as above to study their effect on surface roughness and subsequent optimization of process parameters to minimize roughness using Taguchi based Desirability function analysis and MOORA technique for multi-objective optimization of part build characteristics.

Experimental Analysis and Methodology

Material Used for Fabrication

The material used for test specimen fabrication is acrylonitrile butadiene styrene (ABS M30). It contains 90-100% acrylonitrile/butadiene/styrene resin and may also contain mineral oil (0-2%), tallow (0-2%) and wax (0-2%). Acrylonitrile is a synthetic monomer produced from propylene and ammonia; butadiene is a petroleum hydrocarbon obtained from the C_4 fraction of steam cracking; styrene monomer is made by dehydrogenation of ethyl benzene - a hydrocarbon obtained in the reaction of ethylene and benzene. ABS is made by polymerizing styrene and acrylonitrile in the presence of poly-butadiene. The result is a long chain of poly-butadiene criss-crossed with shorter chains of poly (styrene-co-acrylonitrile). ABS-M30 is 25-70% stronger, has greater tensile, impact and flexural strength than standard ABS. Layer bonding is significantly stronger than that of standard ABS M30, an ideal material for conceptual modeling, functional prototyping, manufacturing tools and production parts.

Table 1: Properties of commercially available ABS M30

Parameter	Value
Density	1040 kg/m^3
Hardness Rockwell	109.5 HRC
Tensile Strength, Ultimate	36 MPa
Tensile Strength, Yield	32 MPa
Modulus of elasticity	2.413 GPa
Elongation at Break	7 %
Layer thickness	0.18 - 0.25 mm

Specimen Fabrication

The 3D models of specimens are generated using CATIA V5 R21 solid modelling software and exported as STL file to FDM software (Insight). Here, factors are set as per experiment plan. Software breaks the STL model into individual slices and generate tool path. After this, data is sent to the FDM hardware for modelling. The article forming material (ABS M30), in the form of a flexible strand of solid material is supplied from a supply source spool to the head of the machine. Specimens are fabricated using FORTUS 400mc machine for respective characteristic measurement.

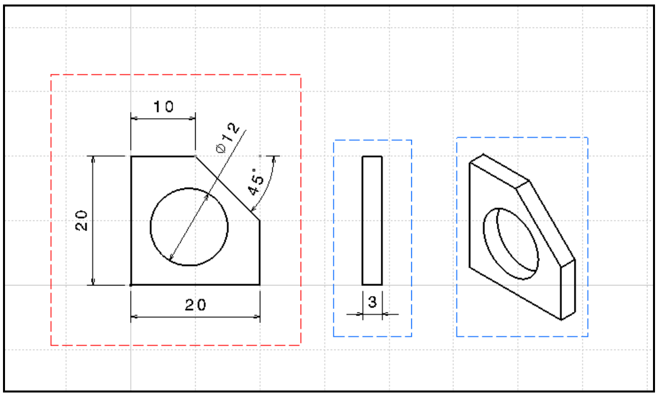

Figure 2: Dimension of the specimen (mm)

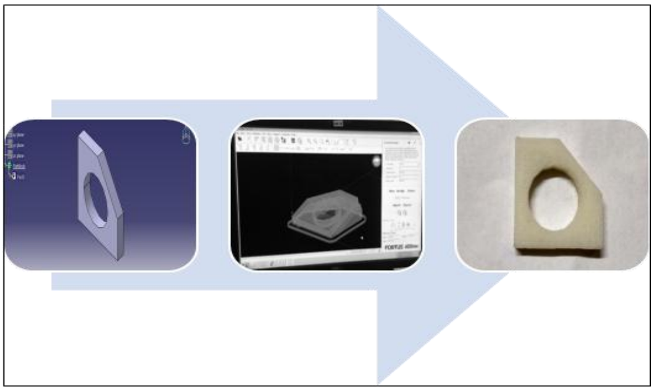

Figure 3: Fabrication of FDM processed part

Design of Experiments

FDM process has large number of process related parameters which are defined in Table 2 and 3. Here, five parameters namely, layer thickness, orientation, raster angle, raster width, and air gap are identified as significant factors and hence are selected to study their influence on output responses. The levels of factors are selected in accordance with the permissible minimum and maximum settings recommended by the equipment manufacturer, experience, and real industrial applications. Fixed parameters and control parameters are provided in Table 2 and Table 3 respectively.

Table 2: Fixed Parameters [1-7]

Parameter	Value
Part fill style	Perimeter/raster
Counter width	0.4064 mm
Part interior style	Solid normal
Visible surface	Normal raster
X Y & Z shrink Factor	1.0038
Perimeter to raster air gap	0.0000 mm

Table 3: Control Parameters & their levels [1-7]

Parameters	Symbol	Levels		
		1	2	3
Layer thickness	A	0.127 mm	0.178 mm	0.254 mm
Orientation	B	0^0	15^0	30^0
Raster angle	C	0^0	30^0	60^0
Raster width	D	0.4064 mm	0.4654 mm	0.5064 mm
Air Gap	E	0.000 mm	0.004 mm	0.008 mm

The surface roughness was measured using a Mitutoyo Surftest SJ-410 surface roughness meter. Three surfaces were chosen for measuring the surface roughness i.e. the top surface, bottom surface and the side surface along a particular direction as shown in figure 4.

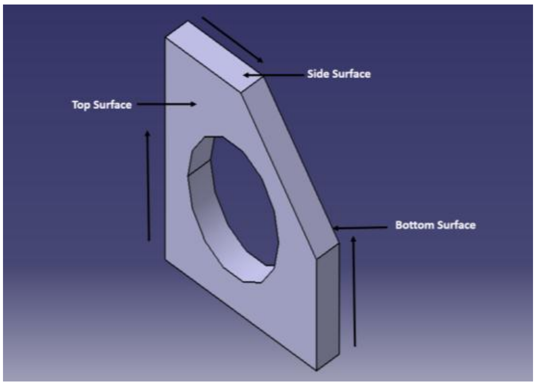

Figure 4: Test specimen model where arrows show direction of measurement of surface roughness

Multi objective optimization on the basis of the ratio analysis method (MOORA)

The MOORA method (Multi objective optimization on the basis of the ratio analysis) has been used to disregard unsuitable substitutions by selecting the most appropriates an also by collation the selection parameter. It is a decision making method, where the objectives were restrained for every pronouncement of outcomes from a set of available alternatives. The MOORA method can be functional in numerous forms of complex multi objective optimization problems. In MOORA method the recital of the diverse output responses is arranged in a decision matrix as specified in Equation (i) [10, 11].

$$X = \begin{bmatrix} x_{11} & x_{12} & .. & .. & x_{1n} \\ x_{21} & x_{22} & .. & .. & x_{2n} \\ :: & :: & :: & :: & :: \\ x_{m1} & x_{m1} & .. & .. & x_{mn} \end{bmatrix} \qquad \text{(i)}$$

Where, x_{ij} is the performance measure of the i^{th} alternative on j^{th} attribute, m is the number of alternatives, and n is the number of attributes.

A ratio system will be formed by normalizing the data of decision matrix which can be calculated by using the equation (ii).

$$x_{ij}^{*} = x_{ij} / \left[\sum_{i=1}^{m} x_{ij}^{2}\right]^{\frac{1}{2}} \qquad (j = 1, 2, \ldots\ldots n) \qquad \text{(ii)}$$

Where, x_{ij}^{*} represents the normalized value x which is a dimensionless number which lies between 0 and 1 i^{th} alternative on j^{th} attribute.

After that, the normalized value will be added for maximization problem or subtracted in case of minimization problems. In some cases, some of the attributes have more importance than others, and to deliver even more importance to these attributes, they are multiplied by their corresponding weight. After the consideration of weight, the equation will be:

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^{*} - \sum_{j=g+1}^{g} w_j x_{ij}^{*} \qquad \text{(iii)}$$

where, g is the maximized number of attribute, (n-g) is the attributes to be minimized and w_i is the weight of j^{th} attribute.

y_i is the normalized assessment value of the i^{th} alternative relating to all the attributes. After calculation of normalized assessment value, ranking of y_i is done from highest to lowest value to know the best alternate among the entire attributes. Thus, highest y_i value is the best alternative among all since ranking of the y_i is the final preference. [10, 11].

Desirability Function Analysis

Here, the first step is to convert each response into the corresponding desirability value. The desirability value varies within zero to unity which be subject to the preferred range of the responses and the target value to be achieved. If the response touches its target value, which is the most desired condition, its desirability is consigned as unity. If the value of the response falls outside the prescribed tolerance rage, which is not desired, its desirability value is implicit as zero. Consequently, desirability value may vary within zero to unity. Derringer and Suich in 1980 proposed the formulae to calculate the desirability of each response depending upon the requirement of the target value. To calculate the individual desirability index (d_i) for the corresponding responses using two forms of the desirability functions according to the response characteristics [10].

Smaller-the better

Smaller the better characteristic is functional to regulate the individual desirability values when the objective is to minimize the response. The value of $\hat{y}$ is predictable to be the smaller the better. When the $\hat{y}$ is less than a precise criteria value, the desirability value equals to 1; if the $\hat{y}$ surpasses a certain criteria value, the desirability value equals to 0. The desirability function of the-smaller-the-better can be defined as specified in Equation (iv) [10]:

$$d_i = \begin{cases} 1 & \hat{y} \le y_{min} \\ \left(\frac{\hat{y} - y_{max}}{y_{min} - y_{max}}\right)^{r}, y_{min} \le y \le y_{max}, r \ge 0 & r \ge 0 \\ 0 & \hat{y} \ge y_{max} \end{cases} \qquad \text{(iv)}$$

Where the y_{min} signifies the lower tolerance limit of $\hat{y}$, the y_{max} signifies the upper tolerance limit of $\hat{y}$, and r denotes the weight. If the corresponding response is predictable to be closer to the target, the weight can be set to the larger value; otherwise, the weight can be set to the smaller value.

Larger-the better

Larger the better characteristic is applied to determine the individual desirability values for tool life since objective is to maximize the tool life. The value of $\hat{y}$ is predictable to be the larger the better. When the $\hat{y}$ outdoes a particular criteria value, which can be viewed as the obligation, the desirability value equals to 1; if the $\hat{y}$ is less than a particular criteria value, which is deplorable, the desirability value equals to 0. The desirability function of the larger-the better can be written as given in Equation (v) [12, 13]:

$$d_i = \begin{cases} 0 & \hat{y} \le y_{min} \\ \left(\frac{\hat{y} - y_{min}}{y_{max} - y_{min}}\right)^{r}, y_{min} \le \hat{y} \le y_{max}, r \ge 0 \\ 1 & \hat{y} \ge y_{min} \end{cases} \qquad \text{(v)}$$

where the y_{min} represents the lower tolerance limit of $\hat{y}$, the y_{max} represents the upper tolerance limit of $\hat{y}$ and r represents the weight.

In the next step, calculate the overall desirability value D_0. The individual desirability index of all the responses can be combined to form a single value called composite desirability D_0 by the following Equation (vi):

$$D_0 = (d_1^{w1} d_2^{w2} \dots d_n^{wn})^{\frac{1}{w}} \qquad \text{(vi)}$$

where d_i is the individual desirability of the property y_i, w_i is the weight of the property y_i in the composite desirability and W is the sum of the individual weights.

Results and Discussions

Samples are prepared by using Taguchi's experimental design which is shown in Table 4. As per design of experiment, 27 experimental runs are carried out in FDM setup. After experimentation the Roughness for top, bottom and side surfaces are recorded in Table 4 along with the L27 orthogonal array of input parameters.

Table 4: Orthogonal array L27 of the experimental runs and responses

Expt. No.	A	B	C	D	E	Top (μm)	Bottom (μm)	Side (μm)
1.	0.127	0	0	0.4064	0	4.4941	5.3454	1.1013
2.	0.127	0	0	0.4064	0.004	4.2173	5.4310	1.1408
3.	0.127	0	0	0.4064	0.008	4.7436	6.9856	0.9433
4.	0.127	15	30	0.4654	0	5.6151	4.2967	0.6541
5.	0.127	15	30	0.4654	0.004	5.3383	4.3823	0.6937
6.	0.127	15	30	0.4654	0.008	5.8646	5.9369	0.4962
7.	0.127	30	60	0.5064	0	3.4037	4.4528	0.7526
8.	0.127	30	60	0.5064	0.004	3.1269	4.5384	0.7922
9.	0.127	30	60	0.5064	0.008	3.6532	6.0930	0.5946
10.	0.178	0	30	0.5064	0	5.8285	6.3384	0.8099
11.	0.178	0	30	0.5064	0.004	5.5517	6.4240	0.8495
12.	0.178	0	30	0.5064	0.008	6.0780	7.9786	0.6519
13.	0.178	15	60	0.4064	0	5.5295	5.6985	0.6598
14.	0.178	15	60	0.4064	0.004	5.2527	5.7841	0.6994
15.	0.178	15	60	0.4064	0.008	5.7790	7.3387	0.5018
16.	0.178	30	0	0.4654	0	4.5377	5.1381	0.5940
17.	0.178	30	0	0.4654	0.004	4.2609	5.2237	0.6336
18.	0.178	30	0	0.4654	0.008	4.7872	6.7783	0.4361
19.	0.254	0	60	0.4654	0	4.6943	5.5056	0.4039
20.	0.254	0	60	0.4654	0.004	4.4175	5.5912	0.4434
21.	0.254	0	60	0.4654	0.008	4.9438	7.1458	0.2459
22.	0.254	15	0	0.5064	0	4.3630	4.7811	0.6684
23.	0.254	15	0	0.5064	0.004	4.0862	4.8667	0.7080
24.	0.254	15	0	0.5064	0.008	4.6124	6.4213	0.5105
25.	0.254	30	30	0.4064	0	3.2138	4.1407	0.8564
26.	0.254	30	30	0.4064	0.004	2.9370	4.2263	0.8959
27.	0.254	30	30	0.4064	0.008	3.4632	5.7809	0.6984

Optimization using MOORA Technique

Now, MOORA optimization method is applied to find out the optimal parameters for FDM process. The normalization of the output responses is done conferring to Equation (ii). After that the normalized assessment values were calculated. Equal percentage of weight is considered for roughness of top, bottom and side surface and the sum of all the weights will be 1. The MOORA overall assessment value is calculated using equation (iii) and ranked according to the highest value of the overall assessment value. Table 5 shows the shows the normalized assessment values of the responses and overall assessment value and their ranking according to the highest value.

Table 5: Normalized Individual Assessment Values and Overall Assessment Value

Run No.	Top	Bottom	Side	y_i	Rank
1.	0.1837	0.1791	0.2984	-0.1000	3
2.	0.1724	0.1820	0.3092	-0.1083	1
3.	0.1939	0.2341	0.2556	-0.1002	2
4.	0.2296	0.1440	0.1773	-0.0320	27
5.	0.2182	0.1469	0.1880	-0.0404	23
6.	0.2398	0.1990	0.1345	-0.0323	26
7.	0.1392	0.1492	0.2040	-0.0727	10
8.	0.1278	0.1521	0.2147	-0.0810	7
9.	0.1494	0.2042	0.1611	-0.0729	9
10.	0.2383	0.2124	0.2195	-0.0661	12
11.	0.2270	0.2153	0.2302	-0.0744	8

12.	0.2485	0.2674	0.1767	-0.0663	11
13.	0.2261	0.1910	0.1788	-0.0492	21
14.	0.2147	0.1938	0.1895	-0.0575	15
15.	0.2363	0.2459	0.1360	-0.0494	20
16.	0.1855	0.1722	0.1610	-0.0503	19
17.	0.1742	0.1751	0.1717	-0.0587	14
18.	0.1957	0.2272	0.1182	-0.0506	18
19.	0.1919	0.1845	0.1094	-0.0348	25
20.	0.1806	0.1874	0.1202	-0.0431	22
21.	0.2021	0.2395	0.0666	-0.0350	24
22.	0.1784	0.1602	0.1811	-0.0556	17
23.	0.1671	0.1631	0.1919	-0.0639	13
24.	0.1886	0.2152	0.1383	-0.0558	16
25.	0.1314	0.1388	0.2321	-0.0813	6
26.	0.1201	0.1416	0.2428	-0.0897	4
27.	0.1416	0.1937	0.1893	-0.0816	5

In the above table, it can be seen that by using the MOORA method for a particular values of input parameter in experiment no. 2 has the highest overall assessment value. Therefore, experiment no. 2 is an optimal parameter combination for FDM build part. Hence, factor setting with Layer thickness (A), part orientation (B), Raster angle (C), raster width (D), air gap (E) should be maintained at 0.127 mm, 0^0, 0^0, 0.4064 mm and 0.004 mm respectively can be recommended for improving the surface roughness of the FDM build part according to MOORA technique optimization.

Optimization using Desirability Function Analysis

In this study, the smaller-the-better characteristic is applied to determine the individual desirability values (d_i) for max. stress, max. deformation, max. strain using equation (iv) since all are to be minimized. After calculating individual desirability, the composite desirability (d_0) is calculated using equation (vi) is shown in table 6.

Table 6: Evaluated Individual Desirability and Composite Desirability

Sl. No.	**Individual Desirability (d_i)**			**Composite Desirability (d_0)**
	Top	**Bottom**	**Side**	
1.	0.5042	0.6861	0.0442	0.2440
2.	0.5924	0.6638	0.0000	0.0000
3.	0.4248	0.2587	0.2207	0.2887
4.	0.1474	0.9594	0.5438	0.4263
5.	0.2355	0.9370	0.4996	0.4797
6.	0.0679	0.5320	0.7204	0.3234
7.	0.8514	0.9187	0.4338	0.6838
8.	0.9395	0.8964	0.3896	0.7238
9.	0.7720	0.4913	0.6103	0.6140
10.	0.0794	0.4274	0.3698	0.2335
11.	0.1676	0.4051	0.3256	0.2810
12.	0.0000	0.0000	0.5463	0.0000
13.	0.1746	0.5941	0.5375	0.3833
14.	0.2627	0.5718	0.4933	0.4207
15.	0.0952	0.1667	0.7140	0.2651
16.	0.4904	0.7401	0.6110	0.5874
17.	0.5785	0.7178	0.5668	0.6210
18.	0.4109	0.3128	0.7875	0.4823
19.	0.4405	0.6444	0.8235	0.5857
20.	0.5286	0.6221	0.7793	0.6365
21.	0.3611	0.2170	1.0000	0.4726
22.	0.5460	0.8332	0.5279	0.6027
23.	0.6341	0.8108	0.4836	0.6484
24.	0.4666	0.4058	0.7044	0.5092
25.	0.9119	1.0000	0.3179	0.6533
26.	1.0000	0.9777	0.2737	0.6990
27.	0.8324	0.5726	0.4944	0.5598

Figure 5 shows the SN-ratio plot for the composite desirability value for the levels of the roughness of top, bottom and side surface. Essentially, the smaller the composite desirability, the better is the multiple performance characteristics. In Table 7 and Fig. 5, the combination of A3, B3, C3, D2 and E2 shows the smallest value of the SN ratio for the factors A, B, C, D and E respectively. Therefore, A3 B3 C3 D2 E2 i.e. Layer thickness of 0.254mm, part orientation of 30^0, Raster angle of 60^0, raster width of 0.4654mm and air gap of 0.004mm is the optimal parameter combination for improving surface roughness of the FDM build part.

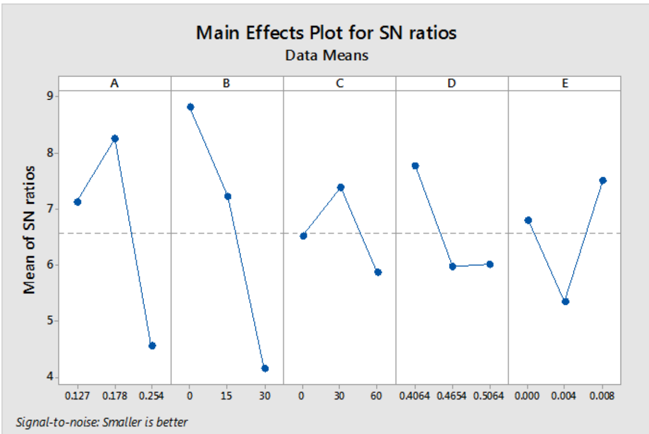

Figure 5: SN-ratio graph with factors and their levels

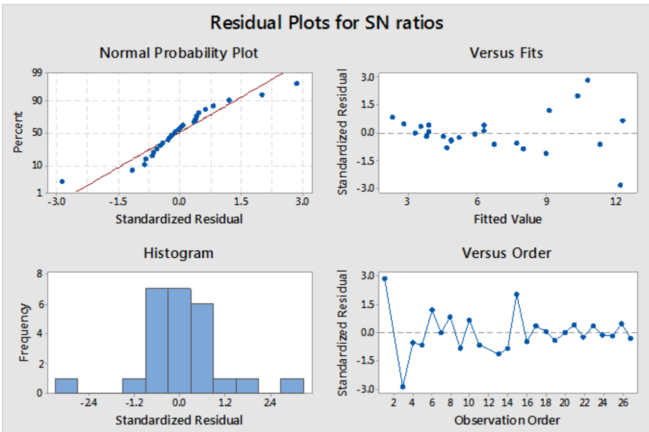

Figure 6: Residual Plots for SN ratio

Table 7: The Response Table for Composite Desirability

Level	A	B	C	D	E
1	7.123	8.826	6.520	7.784	6.810
2	8.267	7.222	7.388	5.974	5.334
3	4.550	4.143	5.868	6.004	7.514
Delta	3.717	4.683	1.520	1.810	2.181
Rank	2	1	5	4	3

Most Influential Factor

Table 8 gives the results of the analysis of variance (ANOVA) for the calculated values of Composite Desirability of surface roughness of 3 surfaces. According to Table 8, factor B, part orientation with contribution of 48.42 % is the most significant controlled parameters for fabrication of FDM processed part followed by factor A, Layer thickness with 34.86%, factor E, air gap with 9.12%, factor C, Raster angle with 8.72% and factor D, raster width with 7.32% of contribution if the minimization of roughness for top, bottom and side surfaces are simultaneously considered.

S = 0.7487 R-Sq = 96.6% R-Sq(adj) = 94.2%

Table 8: ANOVA Result for Composite Desirability

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%
A	2	81.22	40.61	72.44	0.000	34.86
B	2	112.81	56.40	100.62	0.000	48.42
C	2	20.31	10.15	18.12	0.000	8.72
D	2	17.11	8.55	15.26	0.000	7.34
E	2	21.25	10.62	18.96	0.000	9.12
Error	14	7.84	0.56			3.37
Total	24	232.98				

Confirmation Experiment

The confirmation experiments were conducted using the optimum combination of the FDM process parameters obtained from Taguchi analysis. These confirmation experiments were used to predict and validate the improvement in the quality characteristics for FDM build part. The optimal conditions using Desirability function analysis is A3 B3 C3 D2 E2 respectively. The final phase is to verify the predicted results by conducting the confirmation test. The estimated composite desirability can be determined by using the optimum parameters as

$$\mu_{predicted} = a_{2m} + b_{1m} - 3\mu_{mean} \quad (16)$$

where a_{2m} and b_{1m} are the individual mean values of the composite desirability with optimum level values of each parameters and μ_{mean} is the overall mean of composite desirability. The predicted mean ($\mu_{predicted}$) at optimal setting is found to be 0.8906.

Table 9: Confirmatory test results

Optimization technique	Optimal setting	Predicted Optimal S/N ratio	Experimental Optimal S/N ratio
Desirability Function Analysis	A3 B3 C3 D2 E2	0.8906	0.7998

From the confirmation experiment performed with the same experimental setup, it may be noted that there is good agreement between the estimated value and the experimental value for Desirability Function Analysis approach. Hence, the obtained parameter setting of FDM process can be treated as optimal. Here, it can be found that the part orientation is influencing on the surface roughness of FDM processed part.

Conclusions

In this study, the FDM process was used to fabricate acrylonitrile-butadiene-styrene (ABS M30) parts. The process parameters were optimized at a common level setting using MOORA technique and Desirability Function Analysis. purposeful relationship between process parameters and three responses (top, bottom, and side surface roughness) for FDM built parts has been established using both the optimization techniques. Based on experiment studies carried out for selecting optimum combination of process parameters for FDM part, some of the important conclusions are as follows.

1. The optimal levels of process parameters for minimum roughness for top, bottom and side surface for FDM processed part are shown in table 10.

Table 10: Optimal Parameters Using Two Optimization Methods

	MOORA Technique	Desirability Function Analysis
Layer thickness	0.127 mm	0.254 mm
Orientation	0^0	30^0
Raster angle	0^0	60^0
Raster width	0.4064 mm	0.4654 mm
Air Gap	0.004 mm	0.004 mm

2. To control the surface roughness of the FDM built part, the contribution of part orientation is largest in comparison with other process parameters.
3. The equation for predicting multi-response performance index is validated by conducting confirmation experiment.

The present study has perceived that part orientation is the chief controlling factor for attaining better surface roughness. Thus, this study opens up further scope of optimization of the Fused Deposition Modelling characteristics with a larger number of process parameters, along with their influences on convoluted geometrical parts, for attaining a better part fabrication superiority more rapidly.

Acknowledgments
This research work is jointly supported by Department of Industrial Design, National Institute of Technology, Rourkela, India and Department of Mechanical Engineering, Government College of Engineering Kalahandi, Bhawanipatna, Odisha, India.

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