

Multi Objective Optimization of Fused Deposition Modeling Parameters for PC/ABS Blend Material Parts using GRA

Aamir M. Shaikh, Omkar A. Salokhe

Abstract: In this research, multi objective optimization is done on Fused Deposition Modeling (FDM) printing machine for Polycarbonate/Acrylonitrile Butadiene Styrene (PC/ABS) blend material parts. Reductions in part build time and material consumption without compromising its dimensional accuracy and mechanical properties are the major goals of many industries, because there is need to fulfil one part with multiple qualities. So that in this research, part printed without support structure by controlling five FDM process parameters at three levels such as layer thickness, raster width, extrusion temperature, bed temperature and printing speed by using Taguchi's design of experiments method (L27 Orthogonal Array). This research can save part build time, post processing time on support removal and damages occurred due to removal of support structure in part. For that, in this research effects of parameters are studied on surface roughness, build time, and flatness error of overhang structure of parts. Then Grey Relational Analysis (GRA) methodology is used for multi-objective optimization of FDM parameters to find best set of parameters for three responses. Analysis of Variance (ANOVA) is also used to find out significant parameters for multi responses and then confirmation test of experimental results also performed to verify the optimal settings of FDM parameters. The experimental result showed, layer thickness, raster width and part printing speed have the more significant effects on multiple performance characteristics.

Keywords : FDM, PC/ABS blend material, GRA Method, Build time, Surface finish, Flatness error.

I. INTRODUCTION

Reduction in part manufacturing cycle with required mechanical properties are the major objective of all industries and this helps to make industries competitive in markets. Therefore, focus of all manufacture has been shifted from traditional manufacturing process to Rapid Prototyping (RP) processes. This RP process manufactures parts by addition of material in layered format with the help of Computer Aided Design (CAD) and these processes is known as Additive Manufacturing (AM) and also Three Dimensional (3D) printing processes. These RP processes were introduced in the time of 1980's and these have main four major categories, classified according to their manufacturing process, source of

energy and usage of raw material [1]. Sterolithography (SLA) was the first technique of RP process, introduced in 1986's by Charles W. Hull. The working principle of SLA is based on photopolymerization process, this usage UV laser to convert liquid resin material into solid parts. Next, second is Selective Laser Sintering (SLS), this was introduced in 1989's by Carl R. Deckard. The working principle of SLS is based on sintering of powder (metal) material, this process uses CO₂ laser to scan and sinter a part layers according CAD model to create a solid part. Then, third is Laminated Object Manufacturing (LOM) process, invented by Michael Feygin in 2000's. This process fabricates part by lamination of material on previous layers. In that, material is available in paper format and CO₂ laser is used to manufacture parts by cutting required shape from paper in one layer and laminate to this with previous layer. Fourth is, Fused Deposition Modeling (FDM), introduced by S. Scott Crump in 1990's and he was a co-founder of Stratasys Inc. [2]-[3] and this is second most widely used RP process after SLA technique. Because, FDM have advantages like price of system, maintenance and raw material cost is very less as compared to other techniques [4]. Also, it can fabricate any complex part or model with required mechanical properties. But, Still this FDM process have limitation in printing of blend materials also manufacturing of part with precise dimensional accuracy and surface finish. FDM parts have lower surface finish as compared to other RP processes [14]. Working principle of FDM is shown in following Fig. 1. The working principle of FDM printer is, semi-molten filaments gets extruded from tip of the nozzles (one or two) after heating inside the nozzles. Then, this extruded filament is horizontally deposited on the build plate in layer by layer to create a solid part from lower to top of the part continuously till the part gets completed But, there is limitation to print part in FDM with higher dimensional accuracy and surface finish and obtaining quality in one part is difficult. Because, complex nature of FDM process parameters settings, so multi objective optimization of FDM parameters is very important to obtain multiple quality characteristics in one part. From the previous work of O. A. Salokhe and A. M. Shaikh [5] it is found that Taguchi's method is an effective only for single objective optimization because this method gives different combination of parameters for different responses with minimum number of experiments. Moreover, there is several difficulties to print PC/ABS blend material parts, because of their high Glass Transition Temperature (T_g) 125°C [11]. Hence, there is essential to apply multi

Revised Manuscript Received on January 05, 2020.

* Correspondence Author

Aamir M. Shaikh*, Assistant Professor, Department of Mechanical Engineering, Karmaveer Bhaurao Patil College of Engineering, Satara, India. Email: amir.shaikh@kbpcoes.edu.in

Omkar A. Salokhe, Department of Mechanical-Production Engineering, Shivaji University, Karmaveer Bhaurao Patil College of Engineering, Satara, India. Email: omkarashoksalokhe@gmail.com

objective optimization method in this work to optimize FDM process parameters which gives best combination for multiple responses. This PC/ABS blend material was selected according its mechanical properties such as tensile strength 41Mpa (ASTM D638), Flexural strength 68 Mpa (ASTM D790) and Izod impact 196 J/m (ASTM D256) etc. and industrial application e.g. mobile phone covers, monitor cover, keyboard, console of cars, gears etc. [11]. So, objective of this research is to study and use multi objective optimization method from different literature survey.

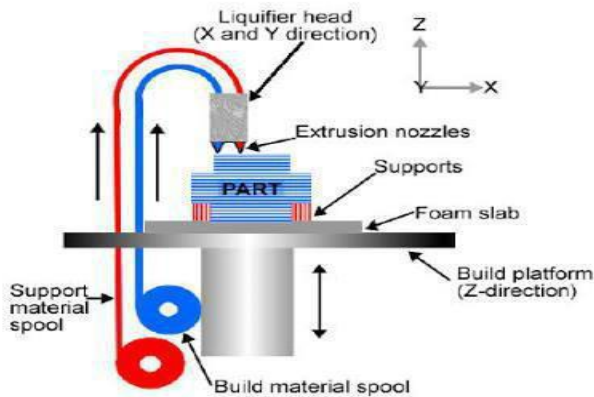


Fig. 1. Working principle of FDM process [11]

II. LITERATURE SURVEY

These section shows, different methodologies used for multi-objective optimization in different research. O. A. Mohamed et al [2] used Q-optimal response surface methodology (RSM) for optimization of FDM parameters for PC/ABS blend material. For that, four levels of layer thickness and six levels of air gap, raster angle, build orientation, road width and numbers of contours parameters were selected and fabricated total 60 samples (60 combinations) on FDM Fortus 400 machine. Material consumption, parts build time and dynamic flexural strength these responses were selected in this wok and ANOVA was selected to find out significant parameters for these responses. In results, optimal combination obtained with thick layers (0.2540mm) and increase in number of contours from 1 to 7, lower levels of raster angle (0°) and build orientation (0°), raster width at 0.484mm and air gap at 0.499mm. S. Vinodh and Priyanka Shinde [6] used multi-objective optimization on the basis of Ratio Analysis (MOORA) methodology for Multi-Criteria Decision making (MCDM) of ABS plus material parts printed on uPrint SE plus FDM printer. For that, total eight samples were fabricated by using two levels of three parameters like layer thickness, build pattern and fill pattern to study their effects on surface roughness and build time of parts. In this research, optimal combination of parameters was obtained at layer thickness with 0.3302mm, solid build pattern and smart fill pattern for minimum build time and surface roughness of the part. This research shows, MOORA method is also able to optimize parameters with minimum number of experiments. O. A. Mohamed et al [7] used fraction factorial Design of Experiments (DOE) to find out optimal FDM (FDM Fortus 400 machine) parametric combination which gives higher dynamic mechanical performance of PC/ABS blend material parts. In this work,

total six parameter were selected at two levels of each parameters, these includes layer thickness, air gap, raster angle, build orientation, road width and number of contours. Total 16 parts were fabricated using fraction factorial DOE created in MINITAB V17 software and tested these parts with storage modulus, loss modulus and mechanical damping properties of parts. The results of this experiments showed, higher dynamic mechanical properties of a part was obtained with higher value of layer thickness (0.3302mm), number of contours (10) and lower level of air gap 0mm, raster angle at 0°, build orientation at 0° and raster width at 0.4572mm. This work shows fraction factorial method is also useful to find out interaction of process parameters for responses and significant parameters for given responses with minimum number of experiments. However, this method uses high (+) and low level (-) of parameters so there is difficult to use when number of levels increases. O. A. Mohamed et al [8] worked with same input and response parameters [7] by using I-optimal response surface methodology. However, the difference between them was the use of optimization method and different levels of process parameters (4 levels of layer thickness and 6 levels of air gap, number of contours, raster angle, part build orientation and road width) were selected. Result of these two experiments was also same. This work shows fraction factorial DOE (16 parts) was more efficient than I-optimal response surface methodology (60 parts) with number of experiments. O. Y. Venkatasubbareddy et al [9] implemented Grey Relational Analysis (GRA) multi-objective optimization method with Taguchi's DOE method to find out optimal combination of FDM (Vantage SE machine) process parameters for ABS M30 materials parts, which gives higher surface finish and dimensional accuracy of the parts with respect to its length, thickness and diameter. For this experimentation, L27 Orthogonal Array (OA) was selected using Taguchi's DOE with five parameters at three levels of each parameter. For setting of FDM parameters Insight software was used in fabrication of parts. Optimum combination of parameters was obtained using GRA at layer thickness with 0.254mm, part orientation and raster angle at 0°, raster width at 0.4564mm and zero air gaps to enhance surface finish and dimensional accuracy of the parts. Nitesh Kumar Dixit et al [3] also used Taguchi method with GRA to find out optimal combination of FDM process parameters for minimum variation of parts dimensions (length, width and height) printed on FDM and low cost open source 3D printer. For this experimentation, DOE was done in MINITAB 17 software using Taguchi's method with two levels of three parameters. In that, 2³ full factorial design of experiments were selected to compare parts printed between these two printers. In the results, maximum GRA was obtained for low cost open source 3D printer at slice height 0.50mm, raster width 0.45mm and path speed 10mm/s parametric combination. Also, optimal combination for FDM parts obtained with slice height at 0.254mm, raster width 0.304mm and tip dimension was at 0.254mm. Experimental result of this work revels that 3D open source printer have more dimensional accuracy in part fabrication than FDM. S. R. Jadhav and A. M. Shaikh [10] used GRA in optimization of

CNC turning machining parameters for EN24 alloy steel with Taguchi DOE. For that, two different inserts were used, one was PVD coated TiAlN insert and second was uncoated carbide insert with dry machining condition. Results of these works were compared by measuring the surface roughness and material removal rate values after machining. In that, optimal combination of parameters obtained for both case using GRA and result showed PVD coated insert gives better results in dry condition with higher GRG value. K. Krishnaprasad et al [15] optimized face milling process parameters such as cutting depth, spindle speed and feed at three levels by using RSM statistical method for AISI 304 steel. Total 20 samples were machined for simulation of responses. Optimal combination of parameters was obtained to minimize cutting forces, PEEQ and enhance flatness with material removal rate at depth of cut 0.8636mm, feed at 200 mm/min and cutting speed at 1000 rpm.

On the basis of above survey, it is found that GRA is very simple, efficient and cost effective than other methods like Q and I-optimal response surface methodology, MOORA and fraction factorial design etc. because, this method can be directly implemented with Taguchi method and this method usages results of Taguchi method to find out optimum combination of parameters for multiple response. And the levels obtained in results using RSM were difficult to set in some case of parameters because of physical constraints of parameters settings in FDM. So, in this work GRA was used for multi-objective optimization of FDM parameters for PC/ABS blend with ANOVA.

III. EXPERIMENTAL DETAILS AND RESULTS OF TAGUCHI METHOD (L27 OA)

In this experimentation, rectangular specimens are manufactured on Lulzbot Taz 6 printer shown in following Fig. 2, with dimension of 40mm×20mm×10mm (with pocket of 30mm×10mm×8mm from bottom side) [11], for finding of optimal setting for overhang structure.

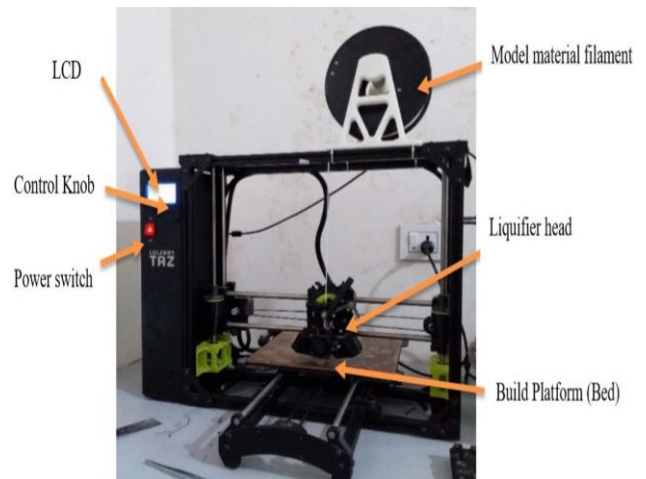


Fig. 2. Photograph of LulzBot TAZ 6 Printer

Because this research can save material consumption as well as build time of the parts. Then Ultimaker Cura 3.4.1 software is used for setting of FDM parameters. This printer fabricates 3D models by extruding thermoplastic material from single nozzle by using CAD models. This printer was selected according its ability to print PC/ABS material and from pilot experimentation [11]. Then, new levels of process parameters for L27 (layer thickness mm (A), raster width mm (B), extrusion temperature °C (C), bed temperature °C (D) and printing speed mm/s (E)) were selected according pilot experimentation and setting range of parameters. Following Table 1. shows levels of parameters selected for L27 OA from previous work [5].

After manufacturing of parts, Build Time (BT) of parts are noted from software for every part then average value of surface roughness measured on top (2 reading for x-axis and 2 for y-axis) and side surfaces (2 readings) were taken using Mitutoyo SJ210 surface roughness tester. Cut-off value λ_c 0.8mm with tip radius of 5 μ m were selected to measure R_a values of the parts. Then, total 13 points were measured for overhang structure (Top surface) to measure flatness (F) error using Co-ordinate Measuring Machine (CMM) [5, 11].

Table-I: FDM process parameters and levels for L27 OA [11]

Levels	Input parameters				
	Layer thickness mm (A)	Raster width mm (B)	Extrusion temperature °C (C)	Bed temperature °C (D)	Printing speed mm/s (E)
1	0.1	0.45	260	100	20
2	0.2	0.50	270	105	30
3	0.3	0.55	280	110	40

Following Table 2. Shows the results of L27 OA performed using Taguchi’s method designed in MINITAB

V17 software and optimal combination of parameters in Table 3 for Build time in min (BT), Surface roughness in μ m (R_a) and Flatness (F) error in mm [5].

Table-II: Experimental chart of L27 OA and results using Taguchi's method [5]

Exp. No.	Input parameters					Performance parameters		
	A (mm)	B (mm)	C (°C)	D (°C)	E (mm/s)	BT (min)	Ra (µm)	F (mm)
1	0.1	0.45	260	100	20	138	5.3994	0.2125
2	0.1	0.45	270	105	30	95	5.649	0.2045
3	0.1	0.45	280	110	40	73	6.2598	0.2099
4	0.1	0.50	260	105	30	89	6.5136	0.2392
5	0.1	0.50	270	110	40	69	6.8864	0.2199
6	0.1	0.50	280	100	20	129	6.1621	0.2502
7	0.1	0.55	260	110	40	63	7.682	0.1758
8	0.1	0.55	270	100	20	120	6.5906	0.1799
9	0.1	0.55	280	105	30	82	6.8048	0.1763
10	0.2	0.55	260	100	30	43	9.376	0.1163
11	0.2	0.55	270	105	40	33	11.0435	0.1052
12	0.2	0.55	280	110	20	63	10.1846	0.1392
13	0.2	0.45	260	105	40	38	11.849	0.1765
14	0.2	0.45	270	110	20	72	8.4307	0.1943
15	0.2	0.45	280	100	30	49	8.6454	0.2001
16	0.2	0.50	260	110	20	68	8.6943	0.2130
17	0.2	0.50	270	100	30	46	9.156	0.1440
18	0.2	0.50	280	105	40	36	10.5865	0.1263
19	0.3	0.50	260	100	40	25	14.4853	0.2702
20	0.3	0.50	270	105	20	47	12.7354	0.3380
21	0.3	0.50	280	110	30	32	13.6375	0.3203
22	0.3	0.55	260	105	20	44	14.1014	0.2740
23	0.3	0.55	270	110	30	30	14.2952	0.2662
24	0.3	0.55	280	100	40	23	14.6061	0.2531
25	0.3	0.45	260	110	30	35	13.8359	0.3512
26	0.3	0.45	270	100	40	27	13.9623	0.2756
27	0.3	0.45	280	105	20	51	12.6465	0.3711

Table-III: Optimal combination obtained using Taguchi's method [5]

Performance Measures	Required Quality Characteristics	Input parameters				
		A (mm)	B (mm)	C (°C)	D (°C)	E (mm/s)
Surface roughness	Smaller the better	0.1	0.45	270	100	20
Build time	Smaller the better	0.3	0.55	280	100	40
Flatness error	Smaller the better	0.2	0.55	270	100	40

This Table 3 shows different parametric combination for different response. It is found from this table, optimal parametric combination for minimum build time shows higher value of surface roughness to the part and optimal combination for minimum Ra values shows increased part build time as well as flatness error values shown in above Table 2 [11]. For that, reason in this research multi-objective Grey Relational Analysis was used to find out optimal parametric combination which gives optimal values of these three responses.

IV. GREY RELATIONAL ANALYSIS (GRA)

This research focuses an approach to use of GRA methodology for multi-objective optimization with Taguchi

single objective optimization method, this GRA methodology was developed in 1989's by Deng [12]. GRA is useful for multi-objective optimization, because manufacturing of part with multiple quality characteristics is critical and Taguchi method is unable to give multi objective optimization for number of responses. For that, GRA was used in this research for multi objective optimization of previous work results [5]. Lower the better quality characteristic was selected for all the responses in this work and higher the better of Grey Relational Grade (GRG) value is selected in GRA. In GRA, first step is to normalization of all (three) responses in unit less data, then in second step deviation of sequence is calculated using normalized

value and this is a difference between reference sequence and normalized value. Then in third step, Grey relation coefficient (GRC) is calculated to find relation between ideal and actual normalized value. Then in fourth step, GRG is calculated by averaging GRC values of three responses. In that, higher value of GRG shows best combination of parameters for this work. Then lastly results are predicted and tested for confirmation of experimental results. Steps in GRA are explained in details below

A. Normalization

In GRA, first step is normalization in that all three responses are first normalized in the range from zero to one (0 to 1) by using following Eq. (1) [3, 10, 12]. In this step, all three different responses are converted into dimensionless parameters (unit) and these values are shown in following Table 4.

$$X_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \quad (1)$$

Here, $\min y_i(k)$ is smallest value of y_i and $\max y_i(k)$ is largest value of y_i for response. $X_i(k)$ is a normalized value. k is response value ($k=1,2,3,\dots,n$) and i is an experiment number.

Calculations for experiment number 1,

Table-IV: Normalized value and deviation sequence using GRA

Exp. No.	Normalized value			Deviation sequence		
	Surface Roughness (µm)	Build time (min)	Flatness error (mm)	Surface Roughness (µm)	Build time (min)	Flatness error (mm)
1	1.0000	0.0000	0.5965	0.0000	1.0000	0.4035
2	0.9729	0.3739	0.6266	0.0271	0.6261	0.3734
3	0.9065	0.5652	0.6062	0.0935	0.4348	0.3938
4	0.8790	0.4261	0.4961	0.1210	0.5739	0.5039
5	0.8385	0.6000	0.5686	0.1615	0.4000	0.4314
6	0.9172	0.0783	0.4547	0.0828	0.9217	0.5453
7	0.7521	0.6522	0.7345	0.2479	0.3478	0.2655
8	0.8706	0.1565	0.7191	0.1294	0.8435	0.2809
9	0.8474	0.4870	0.7326	0.1526	0.5130	0.2674
10	0.5681	0.8261	0.9583	0.4319	0.1739	0.0417
11	0.3870	0.9130	1.0000	0.6130	0.0870	0.0000
12	0.4802	0.6522	0.8721	0.5198	0.3478	0.1279
13	0.2995	0.8696	0.7319	0.7005	0.1304	0.2681
14	0.6708	0.5739	0.6649	0.3292	0.4261	0.3351
15	0.6474	0.7739	0.6431	0.3526	0.2261	0.3569
16	0.6421	0.6087	0.5946	0.3579	0.3913	0.4054
17	0.5920	0.8000	0.8541	0.4080	0.2000	0.1459
18	0.4366	0.8870	0.9206	0.5634	0.1130	0.0794
19	0.0131	0.9826	0.3795	0.9869	0.0174	0.6205
20	0.2032	0.7913	0.1245	0.7968	0.2087	0.8755
21	0.1052	0.9217	0.1910	0.8948	0.0783	0.8090
22	0.0548	0.8174	0.3652	0.9452	0.1826	0.6348
23	0.0338	0.9391	0.3945	0.9662	0.0609	0.6055
24	0.0000	1.0000	0.4438	1.0000	0.0000	0.5562

For Surface roughness: Minimum value =5.3994, Maximum value=14.6061

$$X_i(k) = \frac{14.6061 - 5.3994}{14.6061 - 5.3994} = 1$$

For Build time: Minimum value =23, Maximum value=138

$$X_i(k) = \frac{138 - 138}{138 - 23} = 0$$

For Flatness: Minimum value =0.1054, Maximum value=0.3711

$$X_i(k) = \frac{0.3711 - 0.2125}{0.3711 - 0.1052} = 0.5965$$

B. Deviation sequence

Then, second step is determination of deviation sequence values $\Delta_{0i}(k)$ from Eq. (2), [10, 12]

$$\Delta_{0i}(k) = \|X_0(k) - X_i(k)\| \quad (2)$$

Here, $X_0(k)$ value is taken as 1 and $\Delta_{0i}(k)$ values of all experiments shown in following Table 4.

Calculations for experiment number 1,

For, Surface roughness (Ra), $\Delta_{0i}(k) = \|1 - 1\| = 0$

For, Build time (BT), $\Delta_{0i}(k) = \|1 - 0\| = 1$

For, Flatness (F), $\Delta_{0i}(k) = \|1 - 0.5965\| = 0.4035$

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Exp. No.	Normalized value			Deviation sequence		
	Surface Roughness (μm)	Build time (min)	Flatness error (mm)	Surface Roughness (μm)	Build time (min)	Flatness error (mm)
25	0.0837	0.8957	0.0748	0.9163	0.1043	0.9252
26	0.0699	0.9652	0.3592	0.9301	0.0348	0.6408
27	0.2128	0.7565	0.0000	0.7872	0.2435	1.0000

C. Grey Relational Coefficient (GRC)

Next, in third step, calculation of GRC ($\xi_i(k)$) from deviation sequence values by using following Eq. (3) [10, 12]

$$\xi_i(k) = \frac{\Delta_{\min} + \mu\Delta_{\max}}{\Delta_{0i}(k) + \mu\Delta_{\max}} \quad (3)$$

Here, Δ_{\min} is minimum and Δ_{\max} is maximum values of Δ_{0i} and value of μ is taken as 0.5.

Calculations for experiment number 1,

For Surface roughness: $\xi_i(k) = \frac{0 + 0.5 \times 1}{0 + 0.5 \times 1} = 1$

For Build time: $\xi_i(k) = \frac{0 + 0.5 \times 1}{1 + 0.5 \times 1} = 0.3333$

For Flatness: $\xi_i(k) = \frac{0 + 0.5 \times 1}{0.4035 + 0.5 \times 1} = 0.5534$

D. Grey Relational Grade (GRG)

The overall evaluation of the multi-response characteristics is based on the GRG (y_i) and it is defined as an average sum

of the GRC of responses which is calculated following Eq. (4) [10,12]

$$Y_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \quad (4)$$

Where Y_i is grey relational grade, n is the number of performance characteristics. The GRC and corresponding GRG for each experiment for FDM are calculated. The value of GRG is near to one it shows the optimum process parameters for product quality.

Following Table 5 shows GRC and GRG values and Fig. 3 shows optimum combination for minimum surface roughness, build time and flatness error of FDM parts for PC/ABS blend material.

Calculations for experiment number 1,

$$Y_i = \frac{1 + 0.3333 + 0.5534}{3} = 0.6289$$

Table-V: Grey relational coefficient and grey relational grades

Expt. No.	Grey Relational Coefficient (GRC)			Grey Relational Grades (GRG)	Rank
	Surface Roughness (μm)	Build time (min)	Flatness error (mm)		
1	1.0000	0.3333	0.5534	0.6289	9
2	0.9486	0.4440	0.5724	0.6550	5
3	0.8425	0.5349	0.5594	0.6456	6
4	0.8051	0.4656	0.4980	0.5896	16
5	0.7558	0.5556	0.5368	0.6161	13
6	0.8579	0.3517	0.4783	0.5626	21
7	0.6685	0.5897	0.6532	0.6371	7
8	0.7944	0.3722	0.6403	0.6023	14
9	0.7661	0.4936	0.6516	0.6371	8
10	0.5365	0.7419	0.9229	0.7338	2
11	0.4492	0.8519	1.0000	0.7670	1
12	0.4903	0.5897	0.7963	0.6255	10
13	0.4165	0.7931	0.6509	0.6202	11
14	0.6030	0.5399	0.5987	0.5805	18
15	0.5865	0.6886	0.5835	0.6195	12
16	0.5828	0.5610	0.5522	0.5653	20
17	0.5506	0.7143	0.7741	0.6797	4
18	0.4702	0.8156	0.8630	0.7163	3
19	0.3363	0.9664	0.4462	0.5830	17
20	0.3856	0.7055	0.3635	0.4849	26
21	0.3585	0.8647	0.3820	0.5350	23
22	0.3460	0.7325	0.4406	0.5064	25



Expt. No.	Grey Relational Coefficient (GRC)			Grey Relational Grades (GRG)	Rank
	Surface Roughness (μm)	Build time (min)	Flatness error (mm)		
23	0.3410	0.8915	0.4523	0.5616	22
24	0.3333	1.0000	0.4734	0.6022	15
25	0.3530	0.8273	0.3508	0.5104	24
26	0.3496	0.9350	0.4383	0.5743	19
27	0.3885	0.6725	0.3333	0.4648	27

V. DETERMINATION OF OPTIMAL COMBINATION OF PROCESS PARAMETERS

For optimization of optimal combination of FDM parameters, larger the better quality characteristic is used for analyzing the GRG. In that, higher value of GRG indicates the better performance of the process and optimal combination of process parameters. For that, GRG is calculated for all the experiments using Eq. (4) and it is taken as a response for the further analysis, values of GRG are shown in above Table 5.

GRG for optimal levels of FDM process parameters are predicted from these results. Optimal condition for responses are predicted from the Fig. 3. The larger the better quality characteristics for GRG is obtained at A2, B3, C2, D1 and E3 levels of process parameters.

Response table of means for GRG is shown in following Table 6. This table shows importance of parameters by using rank. This shows 1st for Layer thickness, 2nd for printing speed, 3rd for raster width, 4th for bed temperature and 5th for extrusion temperature.

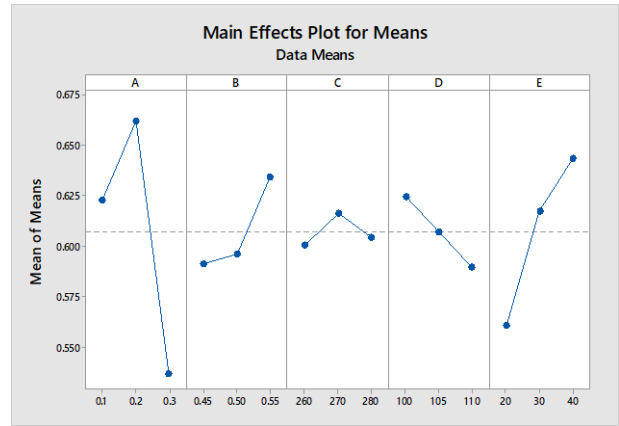


Fig. 3. Main effects plot for means of GRG

In addition, it shows, layer thickness, printing speed and raster width are directly related to improve the all responses. The combination of Layer thickness at 0.2 mm, printing speed at 40mm/s, raster width at 0.55mm, extrusion temperature at 270°C and lower bed temperature 100°C gives maximum GRG and this is optimal combination.

Table-VI: Response table of means for GRG

Level	Input parameters				
	Layer thickness mm (A)	Raster width mm (B)	Extrusion temperature $^{\circ}\text{C}$ (C)	Bed temperature $^{\circ}\text{C}$ (D)	Printing speed mm/s (E)
1	0.6194	0.5888	0.5972	0.6207	0.5579
2	0.6564	0.5925	0.6135	0.6046	0.6135
3	0.5358	0.6303	0.6010	0.5864	0.6402
Delta	0.1206	0.0415	0.0163	0.0343	0.0823
rank	1	3	5	4	2

Analysis of Variance of GRG is shown in following Table 7, performed to find out most significant parameters to reduce surface roughness, build time of parts and flatness error of overhang structure for FDM parts. Based on ANOVA results it conclude that layer thickness is the most significant parameter with 52.35 % contribution also printing speed

shows 23.76% contribution and raster width with 7.11% contribution. In that p-value, indicate significant parameters for GRG with P-value less than 0.05. Extrusion temperature and bed temperature shows no significance for this work because of their P-values more than 0.05 and due to physical constraints of parameter range and material Tg.

Table-VII: Analysis of variance for GRG

Source	DOF	Adj SS	Adj MS	F- Value	P- Value	% Contribution
A	2	0.068664	0.034332	31.96	0.000	52.35 %
B	2	0.009510	0.004755	4.43	0.030	7.11 %
C	2	0.001311	0.000655	0.61	0.556	0.97 %
D	2	0.005318	0.002659	2.47	0.116	3.97 %
E	2	0.031727	0.015864	14.77	0.000	23.76 %
Error	16	0.017189	0.001074			
Total	26	0.133720				



VI. CONFIRMATION OF EXPERIMENT

After obtaining the optimum levels of FDM process parameters, then the final step of GRA is predict and verify the performance quality characteristics by using optimum levels of FDM process parameters. Then the value of predicted GRG ($Y_{predicted}$) for optimum level of the FDM parameter can be calculated by using the following Eq. (5)

$$Y_{predicted} = y_m + \sum_{i=1}^n (y_i - y_m) \quad (5)$$

Where, Y_m is total mean of the GRG, Y_i is the mean of GRG at the optimum level of i^{th} parameter and n is the number (5 parameters) of FDM process parameters.

$$Y_m = \frac{16.3046}{27} = 0.6039$$

Table-VIII: GRA for confirmation of experimental set

Input parameters					Performance Parameters		
A (mm)	B (mm)	C (°C)	D (°C)	E (mm/s)	BT (min)	Ra (µm)	F (mm)
0.2	0.55	270	100	40	33	10.316	0.0494



A. Top view



B. Bottom View

Fig. 4. GRA part (confirmation)

B. Determine S/N ratio for GRG experimental set

For this work smaller value of Ra, BT and F error are required, therefore the lower the better methodology of S/N ratio is employed for the all three responses. Values of S/N ratio is calculated using following Eq. (6) [13]. Higher value of S/N ratio shows optimum levels of parameters for response [16].

$$\frac{s}{n} = -10 \log \left[\frac{1}{n} \sum_{i=1}^n y_i^2 \right] \quad (6)$$

Where, n is number of experiment in row, y_i is the i^{th} value of response in row

For Surface roughness, $\frac{s}{n} = -10 \log \left[\frac{1}{1} (10.316)^2 \right] = -20.27$

For Build time, $\frac{s}{n} = -10 \log \left[\frac{1}{1} (33)^2 \right] = -30.37$

$$Y_{predicted} = (0.6039) + [(0.6539-0.6039) + (0.6303-0.6039) + (0.6135-0.6039) + (0.6207-0.6039) + (0.6402-0.6039)] = 0.7456$$

A. Grey Relational Analysis for experimental set

Part fabricated for GRA is shown in following Fig. 4. (A. shows Top view of part and B. shows Bottom view of part) by using Table 8. By using results of this Table 8, experimental GRG is calculated using GRA for confirmation of results and parameters settings. Part fabricated for confirmation shows reduction in flatness error with optimum value of Ra and build time value. Next step after calculation of experimental GRG is to calculate the percentage error between this work and improvement in GRG.

For Flatness error, $\frac{s}{n} = -10 \log \left[\frac{1}{1} (0.0494)^2 \right] = -26.12$

C. Determine normalization for GRG experimental set:

Normalization value for experimental GRG is calculated by using Eq. (7)

$$X_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \quad (7)$$

For Surface roughness, $X_i(k) = \frac{14.6061 - 10.316}{14.6061 - 5.3994} = 0.4660$

For Build time, $X_i(k) = \frac{138 - 33}{138 - 23} = 0.9130$

For Flatness error, $X_i(k) = \frac{0.3711 - 0.0494}{0.3711 - 0.0494} = 1$

D. Determination of deviation sequence for GRG experimental run:

Determination of deviation sequence is calculated using Eq. (8) for all response

$$\Delta_{0i}(k) = \|X_0(K) - X_i(K)\| \quad (8)$$

For Surface roughness, $\Delta_{0i}(k) = \|1 - 0.4660\| = 0.5340$

For Build time, $\Delta_{0i}(k) = \|1 - 0.9130\| = 0.0870$

For Flatness error, $\Delta_{0i}(k) = \|1 - 1\| = 0$

Values of GRG experimental set (confirmation) shown in following Table 9.

Table-IX: Normalized and deviation sequence values for GRG experimental set

Normalized value			Deviation sequence		
Surface Roughness (µm)	Build time (min)	Flatness error (mm)	Surface Roughness (µm)	Build time (min)	Flatness error (mm)
0.4660	0.9130	1	0.5340	0.0870	0



E. Determination of GRG for GRG experimental set:

The GRG for GRG experiment set can be calculated by following Eq. (9)

$$\xi_i(k) = \frac{\Delta_{\min} + \mu\Delta_{\max}}{\Delta_{0i}(k) + \mu\Delta_{\max}} \quad (9)$$

For Surface roughness, $\xi_i(k) = \frac{0+0.5 \times 1}{0.5340+0.5 \times 1} = 0.4835$

For Build time, $\xi_i(k) = \frac{0+0.5 \times 1}{0.0870+0.5 \times 1} = 0.8519$

For Flatness error, $\xi_i(k) = \frac{0+0.5 \times 1}{0+0.5 \times 1} = 1$

F. Determination of GRG for Experimental set:

GRG for experiment set is calculated by using Eq. (10)

$$Y_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \quad (10)$$

$$Y_i = \frac{0.4835 + 0.8519 + 1}{3} = 0.7785$$

Results of initial, predicted and experimental GRG is shown in following Table 10.

Then percentage error and improvement grade is calculated using Eq. (7) and Eq. (8) respectively [10].

Table-X: Result of performance measure for initial and optimal process parameters

	Initial Condition	Optimal Process Parameters	
		Prediction	Experimental
Surface roughness (µm)	11.0435		10.3160
Build time (min)	33		33
Flatness error (mm)	0.1052		0.0494
Grey Relational Grade (GRG)	0.7660	0.7456	0.7785

$$\text{Percentage Error} = 100 - \left[\frac{GRG_{\text{predicted}}}{GRG_{\text{Experimental}}} \times 100 \right] \quad (11)$$

$$= 100 - \left[\frac{0.7756}{0.7785} \times 100 \right] = 4.22\%$$

$$\text{Improvement of grade} = \text{Experimental GRG} - \text{Initial condition GRG} \quad (12)$$

$$= 0.7785 - 0.7670 = 0.0114$$

VII. CONCLUSION

In this research, multi-objective optimization is done using GRA, to find out optimal combination of FDM process parameters for minimal surface roughness, build time and lower flatness error of overhang structure for PC/ABS material parts.

From the above experimentation, it is concluded that results obtained in Taguchi’s experimentation shows, best setting of parameters for higher surface finish which is not suitable to reduce build time and flatness error, while as best parameters setting obtained in GRA i.e GRG shows optimal condition to print part with minimum build time, surface roughness with more accuracy in flatness of overhang structure. Also, following conclusions are made from this work,

- In GRA, it is found that layer thickness, printing speed and raster width are the most significant parameter to control surface roughness, part build time and flatness of the parts.
- ANOVA for GRA shows that, layer thickness have more percentage (%) of contribution 52.35%, printing speed with 23.76% and raster width with 7.11%. Also, this table shows that the selected levels of extrusion temperature and bed temperature are the insignificant for this work.
- Optimum combination of FDM process parameters for PC/ABS blend material parts is obtained at medium levels of layer thickness (0.2mm) and extrusion temperature (270°C), higher levels of raster width (0.55mm) and printing speed (40mm/s) and lower level of bed temperature (100°C). So, larger the better quality

characteristics for GRG is obtained at combination of A2, B3, C2, D1 and E3 levels of parameters.

- Grey Relational Grade shows that, highest GRG 0.7670 is obtained for experiment number 11 and for that surface roughness value is 11.0435 µm, build time 33min and flatness error is 0.1052mm. Results of this experimentation are validated by confirmation of results. Experimental value of GRG is 0.7785 obtained and then improvement in grade is 0.0114 observed from initial GRG and experimental GRG values. The percentage error between predicted and experimental GRG is 4.22 %, which represents good agreement results.
- From this work, it is concluded that GRA is very useful and easy method for multi-objective optimization and to improve efficiency of process with Taguchi’s method.

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AUTHORS PROFILE



Aamir M. Shaikh is currently working as Assistant Professor in Mechanical Engineering Department, Karmaveer Bhaurao Patil College of Engineering, Satara, India and has teaching experience of 11 years and industrial experience of 1.5 year. He has completed M.E.(Mechanical-Heat Power Engineering) from Government College of Engineering, Karad. His area of interest is in additive manufacturing, CAD/CAM, Finite Element Analysis, casting. He is guiding 05 P.G. students. He has published 12 papers. He has life member of ISTE, Associate member of IEI and IAENG.



Omkar A. Salokhe PG Student in Mechanical-Production Engineering Department at Karmaveer Bhaurao Patil College of Engineering, Satara, Shivaji University, India. He has previously published 04 papers.