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Taguchi Grey Relational Analysis for Multi-Objective FDM Parameter Optimization of PLA Components

Khushbu Patel[a*], Shailee Acharya[b] & G. D. Acharya[c]

[a]*Gujarat Technological University, Ahmedabad, Gujarat, India.*

[b]*SVIT, Gujarat, India.*

[c]*Aatmiy University, Rajkot, Gujarat, India.*

**Corresponding author: khushbutpatel@gmail.com*

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ABSTRACT

Fused Deposition Modelling (FDM) employs Polylactic Acid (PLA), Acrylonitrile Butadiene Styrene (ABS), and other materials to manufacture items from Computer Aided Design (CAD) files in recent era. Process parameter optimization could aid in producing durable products. This article presents multi-objective parametric optimization for the FDM process. The infill density, orientation angle, and layer height characteristics are studied in proposed work. In this task, PLA material is used to create FDM parts. Using Taguchi grey relational analysis, the printing time, surface roughness, dimensional accuracy, and tensile strength are optimised. Analyses of Variance (ANOVA) assesses the importance of process factors relative to response parameters. The recommended method aids decision analysts in comprehending the whole evaluation process and expedites the production of components with exceptional surface finish, dimensional accuracy, and tensile strength with optimum time. The layer height, orientation angle, and infill density have the most effects on surface roughness, according to the data. Finally, the results shows that the orientation angle, layer height, and infill density have the greatest effects on dimensional variance. Grey Relational Grade (GRG) was able to ascertain the ideal values of the parameters layer height (0.3 mm), orientation angle (90°), and infill density (40%) using the Grey Taguchi Method.

Keywords: Fused deposition modelling (FDM); Polylactic Acid (PLA); Taguchi grey relational analysis (TGRA); Analysis of variance (ANOVA).

INTRODUCTION

The manufacturing industry of today is eager to swap out outdated methods for 3D printing wherever it makes sense, thanks to the widespread popularity of the technology in a variety of fields (Abeykoon, Sri-Amphorn & Fernando 2020). Components are built using Additive Manufacturing (AM) by depositing material in successive layers based on a CAD model. This allows for the printing of complicated shapes to be done quickly and easily, unlike traditional production techniques (Patil et al. 2021). The primary benefit of this method is that it eliminates the need to physically mould the product into the correct form in order to achieve near-net shape production. Using the appropriate software, the necessary component or item may be drawn in three dimensions.

In order to print high-quality components, the production-related variables of fused deposition modelling (FDM) have been the subject of a substantial amount of published research. Fused Deposition Modeling for Producing ABS Plastic Components Chemical finishing, in which acetone vapour is combined with hot air, was utilised to enhance the surface finish (Chohan et al. 2020). Taguchi and ANOVA were used to analyze the interplay between the finishing parameters of orientation angle, temperature, and time. Higher temperatures aid in the melting process, hence a greater proportion of surface roughness change is seen as the temperature rises.

The quality of the surface is proportional to the amount of time spent completing it, since more time allows for the layers to re flow and settle. Specifically (Lyu et al. 2021) analyzed the impact of four variables (layer thickness, printing speed, nozzle temperature, and platform temperature). By finding the right combination of factors, we may be able to facilitate more molecule chain diffusion and entanglement between layers. The appropriate values may also lessen the FDM products' anisotropy. Layer thickness, wall print speed, wall thickness, build orientation and extrusion temperature are five process parameters of FDM whose effects on response characteristics are investigated in a study by (Vyavahare, Kumar & Panghal 2020). Surface roughness is heavily influenced by process characteristics such as layer thickness & build orientation. Roughness rises with layer thickness and reduces with build orientation at first, before increasing again. The dimensional accuracy of FDM products is greatly influenced by the thickness of Layer, wall print speed, and build orientation of the manufacturing process. When considering the duration of the manufacturing process, it is discovered that layer thickness \& build orientation are crucial process characteristics.

Layer thickness is closely connected to surface roughness, with increased layer thickness also increasing surface roughness, as was discovered by (Shirmohammadi, Goushchi & Keshtiban 2021) who worked to reduce surface roughness of FDM-produced PLA material components. High internal density causes a decrease in outflow and higher component strength, which was discovered to be a function of the infill density.

Taguchi Optimization is a powerful optimization method for designing AM process parameters (Dakshinamurthy & Gupta 2018; Kumar, Singh & Ahuja 2015; Ramesh & Panneerselvam 2020; Bhati et al. 2020). Among others, the Taguchi method have been recommended for optimization of the process due to its simplicity, effectiveness, and systematic approach to improve the quality, efficiency, and cost of operations (Singh & Dureja 2019; Camposeco-Negrete 2020). The Taguchi approach, a powerful tool for design optimization for quality, was utilised to find the best process parameters for the FDM rapid prototyping machine used to build an ABS-compliant prototype (Chua et al. 2005). However, it can only be used for an optimization of a singular score. Most modern applications need to be optimised for several possible outcomes at once.

Numerous programmes exist for optimizing several criteria simultaneously. The Grey-based Taguchi method is one of many tools used to address ambiguous, inconclusive, and incomplete simulation issues in fields as diverse as FDM (Boschetto et al. 2020; Venkatasubbareddy, Siddikali & Saleem 2016), composites (Kavimani, Soorya Prakash & Thankachan 2019), casting (Kumari, A. et al., Shilpa, Prakash & Shivakumar 2020; Chate et al. 2018), welding (Acherjee et al. 2011; Balaram Naik & Chennakeshava Reddy 2018; Trembach et al. 2021).

From the in-depth literature review, summarized that majority researchers used TM for the optimization of FDM process parameters. Few tries TGRA but in limited domain. Nobody used proposed combinations of input with responses.

Detailed review of literature and discussion with senior personals of foundry guided towards the selection of input parameters with their ranges, responses and TGRA methodology which yet to be implemented particularly for the multi-objective optimization as per authors knowledge.

METHODOLOGY

SPECIMEN PREPARATION

Polylactic acid (PLA), a widely used material in industrial 3D printing, was employed in this investigation. The filament used to make the components was 1.75 millimeters in diameter.

Solid Works CAD software was used to create the ASTM D 638 compliant 3D test specimens illustrated in Figure 1 (a), and .STL file was then sent to the FDM machine using the CURA programme (Figure 1(b)). For each experimental model, this programme was used to adjust the appropriate process control settings of the specimen. For this project, we utilised a DAMBoy ET-200 FDM 3D Printer (Figure 2(a)). Each specimen was printed using the constant settings as a filament diameter of 1.75 mm, a printing speed of 50 mm/s, and a heating bed temperature of 110°C. All the test pieces were printed in the exact same spot in the middle of the print bed.

DESIGN OF EXPERIMENTS

The trials were devised using the Taguchi method. Specifically, there are 3 factors, each having 2 levels of investigation in this research (Table 1). To do this, a L8 orthogonal array is used. As may be seen in Figure 2(b), eight separate samples are created using FDM with PLA material.

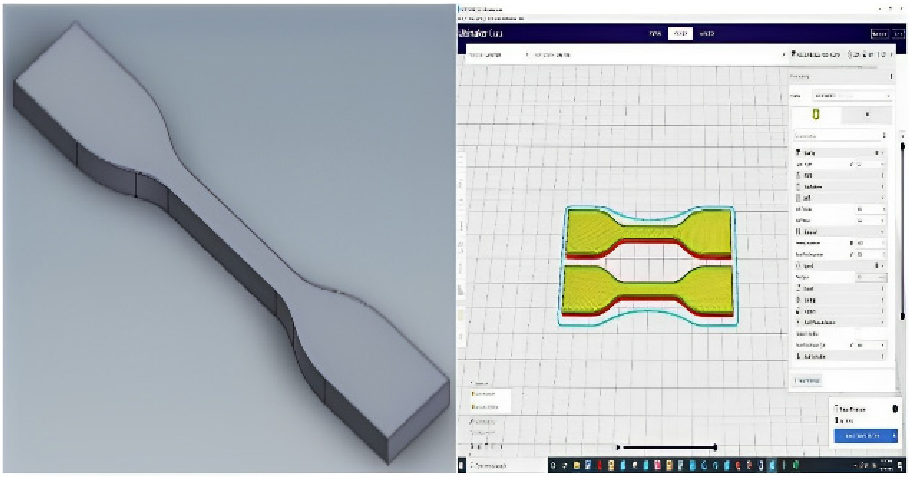

FIGURE 1:(a). 3D CAD image of test specimen, (b). Test specimen image imported to CURA software

TABLE 1. Level of Parameters considered for DOE

Factors	Units	Level 1	Level 2
Infill density (ID)	(%)	20	40
Orientation Angle	(°)	00	90
Layer height (LH)	(mm)	0.2	0.3

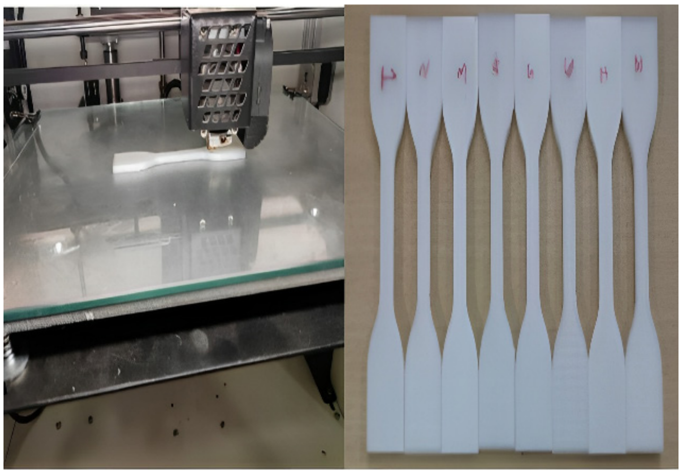

FIGURE 2: (a). 3D printing of Specimen, (b). FDM produced specimen

RESPONSE MEASURED

In this analysis, we look at four distinct measures of output performance: dimensional deviation (DD), surface roughness (SR), tensile strength (TS), and printing time (PT). Place of work Measuring tools included a digital caliper with a range of 0-150 millimeters. At least twenty measurements were collected in various spots on both the top and bottom to determine the range of sizes. The surface roughness was measured using a Mitutoyo SJ-210 Surface Roughness tester. The roughness of a surface was measured by taking the average of its roughness profile (Ra). All the samples were split up into 3 fractions. For each side, three readings of surface roughness were collected (Left, Middle and Right). Both axial and longitudinal measurements were taken, yielding complementary results. The tensile stress of the specimen was measured using Autograph Shimadzu Universal Testing Machines (Reference: CIPET IPT AHMADABAD). The total amount of time required to print an FDM machine component is denoted by PT. When printing experimental models on an FDM machine, CURA software was used to estimate PT. (Shown in Table 2).

TABLE 2. L8 orthogonal array with response variables

Exp. No.	Infill Density	Orientation Angle	Layer Height	PT (min)	Surface Roughness (Ra)	DD in Length (mm)	DD in Width (mm)	DD in Thickness (mm)	TS (N/ mm^2)
1	20	0	0.2	36	1.912	0.012	0.015	0.09	38.446
2	20	0	0.3	33	3.52	0.05	0.034	0.12	36.794
3	20	90	0.2	53	3.11	0.2	0.085	0.01	33.293
4	20	90	0.3	48	4.72	0.33	0.123	0.05	33.123
5	40	0	0.2	43	2.315	0.03	0.026	0.11	42.723
6	40	0	0.3	40	3.91	0.17	0.055	0.14	40.719
7	40	90	0.2	64	3.51	0.22	0.105	0.02	35.791
8	40	90	0.3	60	4.31	0.42	0.141	0.08	33.705

TAGUCHI GREY RELATIONAL ANALYSIS

Orthogonal Array response parameters are optimized using a multi-objective approach that is consistent with Taguchi grey relational analysis.

The following are some of the broad procedures involved in GRA:

NORMALIZATION

The experimental findings of each answer are subjected to normalization, and the results are given a rating between 0 and 1. The normalization of the output characteristics is computed based on the requirements, such as the fact that a "lower is better" is preferable for Surface roughness, dimensional accuracy, and printing time, and a "larger is better" is preferable for tensile stress, as seen by the equation below.

If the target values of original sequences are infinite, then it has a characteristic of the "Higher is Better". The original sequences can be normalized a follow: (Equation (1)) (Sutono et al. 2017).

$$y(t)\frac{y_i^o(t)-y_i^o(t)}{y_i^o(t)-y_i^o(t)} \tag{1}$$

When the "Lower is Better" is a characteristic of the original sequence, then the original sequence should be normalized as follows: (Equation (2)) (Sutono et al. 2017).

$$y(t)\frac{max\, y_i^o(t)-y_i^o(t)}{y_i^o(t)-y_i^o(t)} \tag{2}$$

CALCULATION OF GREY RELATIONAL CO-EFFICIENT (GRC)

The GRC may be determined using the simplified formula that is shown in (Equation (3) (Sutono et al. 2017).

$$\zeta_{i\,(k)} = \frac{\Delta + \zeta\Delta max}{\Delta + \zeta\Delta max} \tag{3}$$

ζ = Identification Co-efficient; $0 < \zeta < 1$ Calculation of grey grade (Equation (4)) (Sutono et al. 2017).

$$\gamma_i = \frac{1}{n}\sum_{j=1}^{n} \beta_j \zeta_{i\,(k)} \tag{4}$$

βj = Weight for each process parameter.

RESULT AND DISCUSSION

The analysis of process parameters carried out using the Taguchi technique contributes to the establishment of optimum circumstances and, as a consequence, facilitates the achievement of superior outcomes. The analysis was completed, and the impact that the various parameters had on each answer is addressed in this section.

ANALYSIS OF SIGNAL/NOISE RATIO BASED ON TAGUCHI

The Taguchi approach was used to each individual aspect in order to accomplish optimization of a single target. Tabular representation of the obtained S/N ratio together with response parameters can be seen in Table 3.

TABLE 3. S/N ratio of L8 orthogonal array

EXP. NO.	SNR(PT)	SNR(SR)	SNR(DDL)	SNR(DDW)	SNR(DDT)	SNR(TS)
1	-31.1261	-5.6298	38.4164	36.4782	20.9151	31.6970
2	-30.3703	-10.9309	26.0206	29.3704	18.4164	31.3155
3	-34.4855	-9.8552	13.9794	21.4116	40.0000	30.4471
4	-33.6248	-13.4788	9.6297	18.2019	26.0206	30.4026
5	-32.6694	-7.2910	30.4576	31.7005	19.1721	32.6132
6	-32.0412	-11.8435	15.3910	25.1927	17.0774	32.1959
7	-36.1236	-10.9061	13.1515	19.5762	33.9794	31.0754
8	-35.563	-12.6895	7.5350	17.0156	21.9382	30.5538

Table 3 include the results of calculations that were done to determine the S/N ratios for each parameter of surface roughness, dimensional deviation, tensile strength, and printing time. Greater rankings are provided to the parameters that have a higher delta value in accordance with the criteria of the delta value.

According to Table 4, the parameter that has the greatest impact on the final surface roughness of an FDM specimen is the layer height, followed by the orientation angle. When calculating the S/N ratio, the "smaller is better" feature is used.

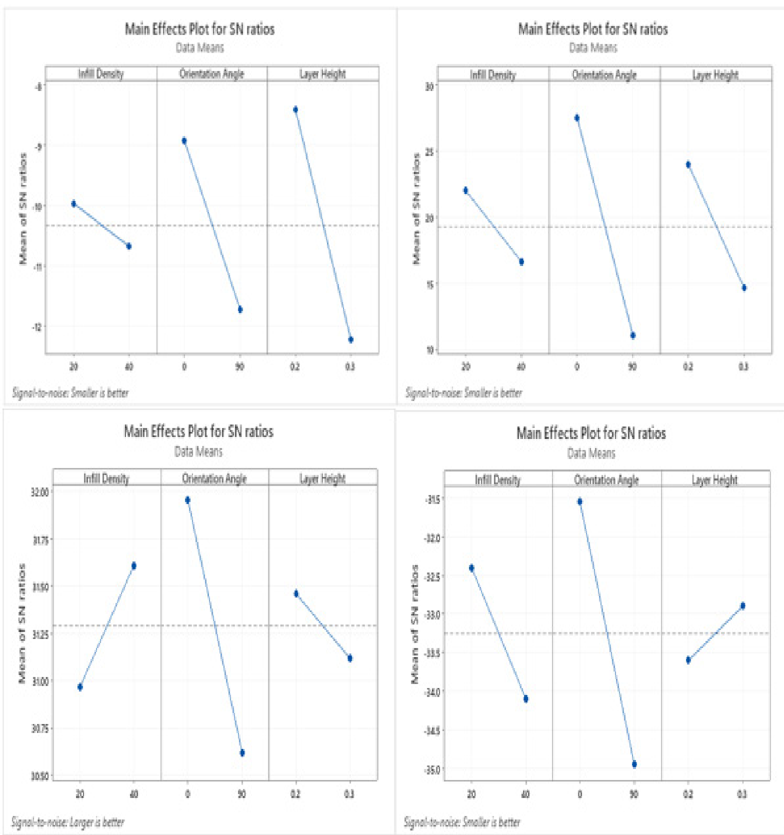

FIGURE 3: (a). Mean effect response plot for Surface roughness, (b). Mean effect response plot for dimensional deviation, (c). Mean effect response plot for Tensile Strength, (d). Mean effect response plot for Printing Time.

Figure 3(a) depicts the main-effects graph for S/N-ratios of surface roughness. The layer height is the most significant parameter that impacts the surface roughness. Surface roughness tends to become more pronounced with an increase in layer height. The surface roughness of FDM components is not significantly affected by the infill density of the parts. The part with the best surface polish was produced with a layer height of 0.2 millimeters, an orientation angle of 0 degrees, and a 20% infill density.

TABLE 4. Response Table for S/N ratio for Surface Roughness

Level	Infill Density	Orientation Angle	Layer Height
1	-9.974	-8.924	-8.421
2	-10.683	-11.732	-12.236
Delta	0.709	2.809	3.815
Rank	3	2	1

TABLE 5. Response Table for S/N ratio for Dimensional Deviation (Length)

Level	Infill Density	Orientation Angle	Layer Height
1	22.01	27.57	24.00
2	16.63	11.07	14.64
Delta	5.38	16.50	9.36
Rank	3	1	2

TABLE 6. Response Table for S/N ratio for Dimensional Deviation (Width)

Level	Infill Density	Orientation Angle	Layer Height
1	26.37	30.69	27.29
2	23.37	19.05	22.45
Delta	2.99	11.63	4.85
Rank	3	1	2

TABLE 7. Response Table for S/N ratio for Dimensional Deviation (Thickness)

Level	Infill Density	Orientation Angle	Layer Height
1	26.34	18.90	28.52
2	23.04	30.48	2086
Delta	3.30	11.59	7.65
Rank	3	1	2

TABLE 8. Response Table for S/N ratio for Tensile Strength.

Level	Infill Density	Orientation Angle	Layer Height
1	30.97	31.96	31.46
2	31.61	30.62	31.12
Delta	0.64	1.34	0.34
Rank	2	1	3

TABLE 9. Response Table for S/N ratio for Printing Time.

Level	Infill Density	Orientation Angle	Layer Height
1	-32.40	-31.55	-33.60
2	-34.10	-34.95	-32.90
Delta	1.70	3.40	0.70
Rank	2	1	3

Table 5, 6 and 7 gives results of response table for S/N ratio of dimensional deviation in length, width, and thickness respectively. The orientation angle is the factor that has the greatest influence on the dimensional variation of the FDM specimen that is created, followed by the Layer height. When calculating the S/N ratio, the "smaller is better" feature is used.

Figure-3(b) depicts the main-effects graph for S/N-ratios of dimensional deviation. The orientation angle is the most significant parameter that impacts the dimensional deviation, followed by layer height as the next most significant component. When it comes to FDM components, the infill density does not have a significant influence on the dimensional deviance. Fabricated component with a 0° orientation angle, with a 20% infill density and a 0.2 mm layer height gives the best dimensional accuracy.

According to Table 8, the orientation angle is the aspect that has the greatest influence on the tensile strength of the parts. When calculating the S/N ratio, the "larger is better" principle is used as a guide.

Figure 3 (c) depicts the main-effects graph for S/N-ratios of tensile strength. The orientation angle is the most significant parameter that impacts the tensile strength, followed by the infill density. The tensile strength of FDM components is not significantly affected by the layer height of the parts. The component with the highest tensile strength is the one that was built with a 40% infill density, a 0° orientation angle, and a 0.2 mm layer height.

According to Table 9, the orientation angle is the factor that has the greatest impact on the amount of time required to print FDM components. When calculating the S/N ratio, the "smaller is better" feature is used.

Figure 3 (d) depicts the main-effects graph for S/N-ratios of printing time. The orientation angle is the most significant parameter that impacts the printing time, followed by infill density. The layer height of FDM components does not have a significant influence on the amount of time required for printing. The optimum printing time is achieved when the part is made with a 20% infill density, a 0° orientation angle, and a 0.3 mm layer height.

RESULTS OF TAGUCHI GREY RELATIONAL ANALYSIS

Taguchi grey relational analysis was used to determine how control parameters impacted the performance of optimizations with numerous objectives. After utilizing GRA to reduce the number of goals to a single number, the data may be analyzed using a response table and an ANOVA. The "smaller is better" principle was used to the computation of SR, DD, and PT, whereas the "larger is better" principle was applied to the computation of TS. For the simple reason that increasing the S/N ratio always results in improved performance. Because a greater S/N ratio displays only minute mistakes, it is used to determine the "larger is better" aspect of the GRG value (Boschetto et al. 2020). Table 8 displays the results of the GRA analysis, which was performed using equations Equation (1) through Equation (3). In order to use Equation (4) to determine GRG, it is assumed that the distinguishing coefficient ζ is equal to 0.5. The many objective output answers are standardized into a single objective value in GRG form in GRA. When determining a rank, the GRG value closest to 1 is given priority.

Table 10 is the representation of the response table for the GRG. If there are more variations in GRG, this indicates that the component has a higher degree of importance in comparison to the other variables. When the other two parameters are taken into consideration, Infill density emerges as the most important of the three. In addition to this, the Layer Height is far more important than the Orientation Angle.

TABLE 10. Response Table for S/N Ratios for GRG.

Normalized Values						Deviation Sequences						Grey Relational Coefficient						GRG	Rank
PT	SR	DD_L	DD_W	DD_T	TS	PT	SR	DD_L	DD_W	DD_T	TS	PT	SR	DD_L	DD_W	DD_T	TS		
0.1	0.0	0.0	0.0	0.8	0.6	0.9	1.0	1.0	1.0	0.2	0.4	0.4	0.3	0.3	0.3	0.7	0.5	0.4	8
0.0	0.7	0.4	0.4	0.9	0.4	1.0	0.3	0.6	0.6	0.1	0.6	0.3	0.6	0.5	0.4	0.9	0.5	0.5	7
0.7	0.5	0.8	0.8	0.0	0.0	0.3	0.5	0.2	0.2	1.0	1.0	0.6	0.5	0.7	0.7	0.3	0.3	0.5	6
0.6	1.0	0.9	0.9	0.6	0.0	0.4	0.0	0.1	0.1	0.4	1.0	0.5	1.0	0.9	0.9	0.6	0.3	0.7	2
0.4	0.2	0.3	0.2	0.9	1.0	0.6	0.8	0.7	0.8	0.1	0.0	0.5	0.4	0.4	0.4	0.8	1.0	0.6	5
0.3	0.8	0.7	0.6	1.0	0.8	0.7	0.2	0.3	0.4	0.0	0.2	0.4	0.7	0.7	0.5	1.0	0.7	0.7	3
1.0	0.7	0.8	0.9	0.3	0.3	0.0	0.3	0.2	0.1	0.7	0.7	1.0	0.6	0.7	0.8	0.4	0.4	0.7	4
0.9	0.9	1.0	1.0	0.8	0.1	0.1	0.1	0.0	0.0	0.2	0.9	0.8	0.8	1.0	1.0	0.7	0.3	0.8	1

The S/N-ratios of GRG are shown graphically in the main-effects graph in Figure 4. The infill density is the most influential characteristic on the quality of the component as a whole, followed by the layer height. When taking into account all response factors, the optimal parameters for achieving the best quality of part are 40% infill density, 90° orientation angle, and 0.3 mm layer height. This allows for the lowest possible printing time without sacrificing surface roughness, dimensional accuracy, or tensile strength.

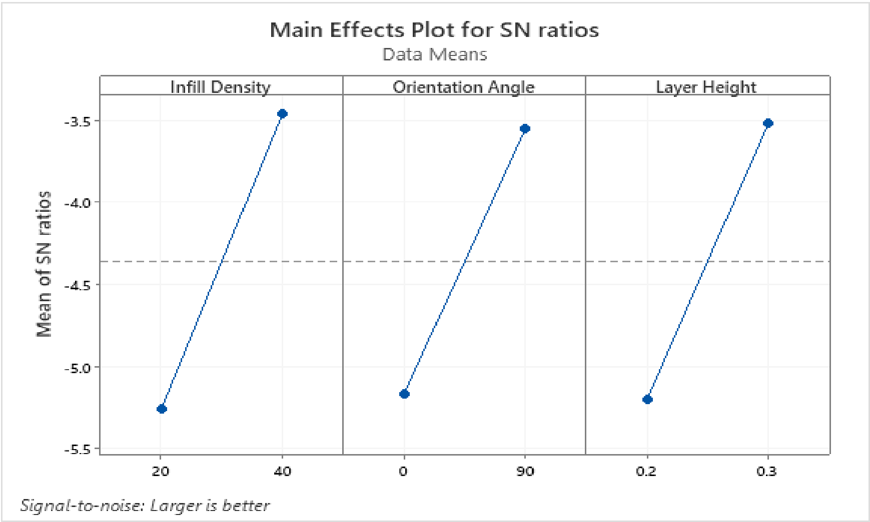

FIGURE 4. Mean effect response plot for GRG

ANALYSIS OF VARIANCE FOR GRG

In this study of multi-objective optimization, analysis of variance (ANOVA) is performed to determine the relative importance of each control factor. Determining if the control factor significantly influenced the various responses is also included. Results of the ANOVA for GRG in presented in Table 12. Based on the analysis of variance, it has been shown that the most influential control element in the Grey-based Taguchi technique that influence multiple responses is infill density.

To illustrate how ANOVA determines the relative importance of each component in determining GRG, see Figure 5 (a). It demonstrates that the GRG is jointly affected by the layer height (34%), the orientation angle (30%), and the infill density (36%).

TABLE 11. Results for S/N Ratio for GRG

Level	Infill Density	Orientation Angle	Layer Height
1	-5.260	-5.167	-5.199
2	-3.548	-3.551	-3.516
Delta	1.802	1.616	1.681
Rank	1	3	2

TABLE 12. Analysis of variance for GRG.

Source	DF	Seq. SS	Contribution	Adj. SS	Adj. MS	F-Value	P-Value
ID	1	0.029927	34.86%	0.029927	0.029927	48.12	0.002
OA	1	0.025397	29.59%	0.025397	0.025397	40.84	0.003
LH	1	0.028025	32.65%	0.028025	0.028025	45.06	0.003
Error	4	0.002488	2.90%	0.002488	0.000622		
Total	7	0.085837	100.00%				

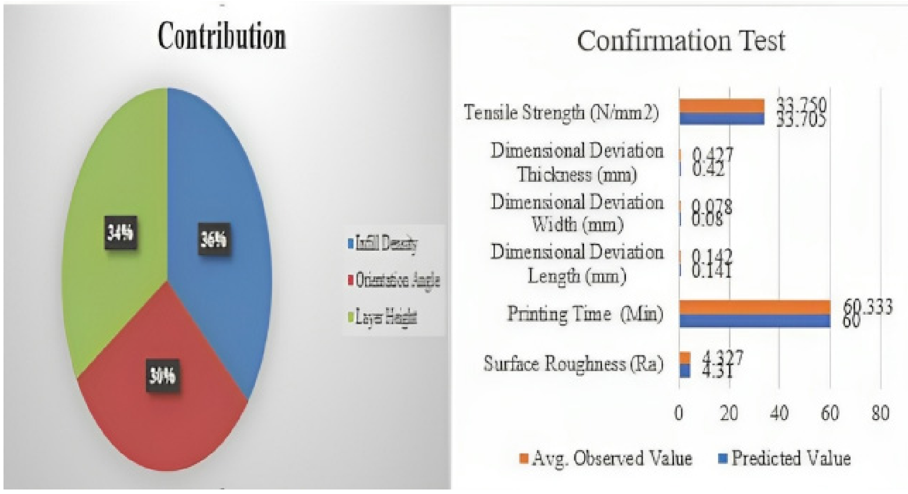

FIGURE 5: (a). Percentage contribution of factors considering multiple response, 5 (b). Confirmation Test Result

CONFIRMATION TEST

Confirmation tests are done to verify the results of the studies phase's findings. By performing the test with particular combination of variables and amounts previously assessed, the confirmation tests are carried out. Three confirmatory experiments were carried out in this research using the ideal values of the ideal process parameters. Using the gathered collection of optimal component values, confirmatory tests were run. The outcomes are displayed in Table 13 below. The findings are discovered to be fairly close to the values anticipated. (Figure 5 (b))

TABLE 13. Result of Confirmation Test

Response	Predicted Value	Avg. Observed Value
Surface Roughness (Ra)	4.31	4.327
Printing Time (min)	60	60.333
Dimensional Deviation Length (mm)	0.141	0.142
Dimensional Width (mm)	0.08	0.078
Dimensional Deviation Thickness (mm)	0.42	0.427
Tensile Strength (N/mm^2)	33.705	33.750

CONCLUSION

This study utilized a multi-objective optimization paradigm to improve the FDM process parameters for PLA parts. The parameters of interest are the infill density, the orientation angle, and the layer height. Surface roughness, dimensional accuracy, printing time, and tensile strength are all analyzed using Taguchi Grey relational analysis as replies. The results of a study lead to these inferences.

1. The Taguchi technique is also used to optimize each process parameter separately. The results show that layer height has the greatest impact on surface roughness, followed by orientation angle and infill density. Dimensional variation is most sensitive to the orientation angle, then to layer height, and finally to the infill density. The tensile strength depends on the orientation angle, followed by the infill density and the layer height. The printing time depends on the orientation angle, the infill density, and the layer height in that order.
2. Using the Grey Taguchi Method, GRG was able to determine that the optimal levels of the factors layer height (0.3 mm), orientation angle (90°), and infill density were (40%).
3. Analysis of variance shows that infill density is more important than any other process parameter in enhancing the efficiency of multiple responses.

Consequently, these optimization strategies may facilitate the production of high-quality FDM components with less wastage. Future applications of the optimization method will include real-time components in the automotive, aerospace, electrical, biomedical, concrete technology, food processing, and other industries.

Summarized the above results, the proposed results claim same results with L8 OA, instead of L16 OA, that claimed by other researchers. Also, combinations for the optimization of proposed input parameters and responses with TGRA never used before. That shows the novelty in proposed research.

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DECLARATION OF COMPETING INTEREST

None

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