Grey relational analysis based optimization of process parameters for efficient performance of fused deposition modelling based 3D printer

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ABSTRACT

Rapid prototyping techniques such as three-dimensional (3D) printing have rapidly gained popularity in industry since material layers are added rather than removed. Additive manufacturing creates objects from 3D CAD model data by layering materials, thus saving time and money. Fused deposition modelling (FDM) is the most often utilized additive manufacturing technology. To find the best parameters simultaneously affecting tensile strength, flexural strength, and wear resistance, this research aims to make use of grey relational analysis (GRA). In this investigation, the effect of different combinations of layer height, extruder temperature, infill percentage and print speed on the three mechanical properties is examined in depth. GRA optimization is used to find the ideal design factor levels for achieving the lowest wear rate while still providing the maximum possible tensile and flexural strength for the data obtained for sixteen experiments as per L16 orthogonal array. It is crucial to do Analysis of Variance (ANOVA) analysis in order to figure out the parameter contribution ratios. The grey relational grade (GRG) for any combination can be predicted quite accurately using regression analysis. The findings of the confirmation experiments demonstrated that the information gleaned from regression analysis is in line with that acquired from the experiments themselves.

Keywords: Analysis of Variance; Grey Relational Analysis; Grey Relational Grade; Regression

Analysis

INTRODUCTION

Rapid prototyping technology has gradually increased in industrial use in recent years. Rapid prototyping, such as 3D printing, builds 3D items by adding material layers rather than removing them. Unlike traditional machining, which requires special tools, additive manufacturing creates items from 3D CAD model data by layering materials. The most extensively used additive manufacturing (AM) technology is fused deposition modelling (FDM) due to the large variety of commercially available materials, low cost, and convenience of use. These methods can save a lot of money by reducing material waste and fabricating complex shapes. The FDM printer builds up layers of material from the bottom up by extruding a heated, semi-melted thermoplastic stream from the heated print head. The deposited material hardens very instantly after leaving the hot print head, resulting in a quick workpiece. In recent years, researchers have been inspired to study the structural performance of items manufactured utilising FDM machines.

The impact of input factors on various mechanical properties has been studied extensively in recent years. A number of input factors have been investigated, including the density of infill, the feed rate, the nozzle diameter, the annealing temperature, the height of the layer, printing velocity, and raster angle and breadth. According to Dhinesh et al.,2021, PLA has superior tensile strength than ABS, and the strength increases even further when an 80/20 PLA/ABS blend is used. When it comes to flexural strength, PLA and ABS both perform better when made up of 50% each. This paves the way for further research into various PLA/ABS percent combinations. The PLA reinforced with chitosan was researched by Singh et al.,2020, who discovered that as the chitosan weight percentage rose, the tensile and flexural strength decreased while the compressive strength increased. For wood PLA composites, layer thickness was found to be the most influential factor (Zandi et al.,2020). Infilled density, according to Gunaya ,2019, was the most important factor affecting PLA+ samples' mechanical properties. 0 or 90-degree orientation produced greater tensile strength, whereas increasing print speed reduced it. Camargo et al.,2019, found that the mechanical characteristics of PLA-graphene improved as the layer height was increased. Layer thickness was shown to be the most important and inversely related characteristic by Rajpurohit et al.,2018. Gebisa et al.,2018, found that the flexural strength of specimens produced using FDM was affected by raster angle and raster width. In order to maximise mechanical qualities like tensile and flexural strength, Chacon et al.,2017, recommended edge orientation. To find the optimum parametric combination for tensile and flexural strength, Sood et al.,2010, used response surface analysis.

Process parameters have been investigated by a number of scientists for their impact on wear properties. Parameters such as layer thickness, air gap as well as build orientation, road width and the number of contours have been examined to determine how specimens printed using FDM wear over time. According to the findings of Norani et al.,2020, when layer thickness and orientation rise, so does wear rate, while raster angle and air gap have inverse effect on wear rate while Fibres oriented at 90^0 had a higher coefficient of friction (Boparai et al.,2015). Layer height had the greatest influence on wear behaviour, followed by nozzle temperature and pattern. Singh and Bharti, 2021, applied regression and Artificial Neural Network (ANN) and suggested that infill density and layer height have more effect on wear as compared to other variables

METHODOLOGY

The proposed methodology is portrayed in Figure 1. The first step is to choose the process parameters, equipment, and material. Taguchi's L16 design has been selected for the experiment and specimens have been printed in accordance with that, followed by post-processing and measurement of mechanical characteristics. After that, the information has been put to use through the process of analysis. In this case, regression has been used to create mathematical models after doing a grey relational analysis. These analyses have been performed using the experimental data.

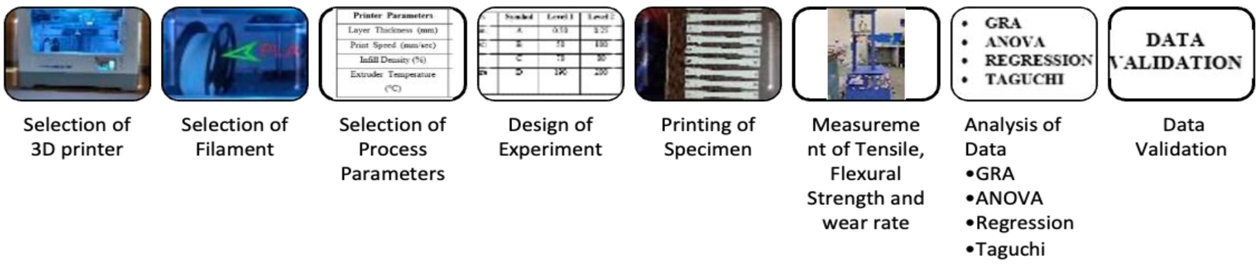

Figure 1. Proposed Methodology

MATERIALS AND PROCEDURES

The ASTM D638, D790, and G99 standards have been followed in the production of the 3D printed specimens of PLA for tensile, flexural, and wear tests. The 3D model has been created in Autodesk Inventor and then converted to an. STL (Stereolithography) file type for printing. The machine parameters of the Flash forge Dreamer NX printer have been controlled and slicing is performed using the Flash Print software. There are four degrees of adjustment for the four input parameters under study, which include extruder temperature, infill density, print speed, and layer thickness (Table 1).

FABRICATION AND EVALUATION

Three specimens have been printed in accordance with the experiment's design for each combination of the L16 orthogonal array. The specimens were tested for tensile and flexural strength using an NTF Tensile, Compression and Flexural Strength Tester, and wear has been measured using a Ducom pin on disc equipment. The maximum force, maximum elongation, and maximum strength were measured for each tensile and flexural test. Similarly, wear rate has been calculated for all the samples (Singh and Bharti,2021). Table 1 shows the average value of the tensile, flexural, and wear rates.

Table 1. *Test results of all specimens*

Specimen No.	Layer Thickness (mm) LT	Print Speed (mm/sec) PS	Infill Density (%) ID	Extruder Temp. (°C) ET	Tensile Strength (Kg/mm^2) TS	Flexural Strength (Kg/mm^2) FS	Wear Rate(×10^{-2}) mm^3/m WR
1	0.2	50	70	190	3.735	14.632	1.721
2	0.2	100	80	200	4.025	11.836	1.834
3	0.2	150	90	210	3.988	15.146	1.837
4	0.2	200	100	220	3.400	16.113	2.338
5	0.25	50	80	210	3.688	15.962	1.575
6	0.25	100	70	220	3.366	14.978	1.638
7	0.25	150	100	190	1.615	3.193	1.883
8	0.25	200	90	200	2.452	1.729	1.741
9	0.3	50	90	220	4.576	17.051	1.868
10	0.3	100	100	210	3.567	12.187	1.878
11	0.3	150	70	200	1.904	6.006	1.387
12	0.3	200	80	190	1.291	2.988	1.599
13	0.35	50	100	200	3.585	14.039	1.819
14	0.35	100	90	190	1.558	2.754	1.482
15	0.35	150	80	220	2.945	9.906	1.580
16	0.35	200	70	210	1.751	4.629	1.624

FINDINGS AND ANALYSIS

Grey Relational Analysis

GRA is a decision-making approach which has been derived from Deng's grey system theory (GST) which uses the terms black and white to denote systems with incomplete data and systems with complete data (Deng Julong,1989). The partial information is used to represent the grade of association between two sequences, a grey relation is utilised to characterise the distance between two components. Gradient augmentation compensates for a lack of statistical regression when the experiment is ambiguous or the experimental procedure is incorrect. To address the disadvantages of statistical methods, GRA is an excellent way to investigate relationships between sequences with fewer data (Acir et al., 2017) as the Taguchi technique is not ideal for optimising many responses. To solve this problem, we can use grey relational analysis (GRA). Derived from Taguchi's method, grey relational analysis can be used to optimise numerous attribute features and investigate relationships (Aslani et al., 2017).

The Taguchi method is used for one response optimization. Only experimental data response tables and graphs are used to analyse this procedure. Using the Taguchi, Gray Relational Analysis, and Principal Component Analysis approaches, we can do optimization of multiple responses (Sudhir et al.,2020). To evaluate large numbers of responses, GRA calculates the Gray Relational Grade (GRG). Since Principal Component Analysis (PCA) selects a small number of components to reflect the variance of several original replies, it is possible to optimize several responses by optimizing a single GRG (Jain et al.,2020). The various steps involved are explained further.

Normalization of experimental results

Normalization is the process of converting experimental data into a value between 0 and 1. Each response has been evaluated for quality attributes before the normalization procedure begins. The normalization method relies on the response variable's qualities, such as the larger the better (Larger is Better) for tensile and flexural strength and is given by equation 1. the smaller, the better (Smaller is Better) as in wear is shown in equation 2.

$$X_i(k) = \frac{x_i(k) - x_i(k)}{x_i(k) - x_i(k)} \quad (1)$$

$$X_i(k) = \frac{max\ x_i(k) - x_i(k)}{x_i(k) - x_i(k)} \quad (2)$$

Where $max\ x_i(k) = maximum\ value\ of\ x_i(k)$ and $min\ x_i(k) = minimum\ value\ of\ x_i(k)$

Calculation of Deviation Sequence

The absolute difference between the highest normalised values for each response is represented by the deviation sequence $\Delta O_i(k)$ and is given by equation 3.

$$\Delta O_i(k) = \left| X_o(k) - X_i(k) \right| \quad (3)$$

Where, $X_o(k) = Largest\ Normalised\ value\ of\ output$ and

$$X_i(k) = Normalised\ value\ of\ output\ variable\ in\ i^{th}\ experiment$$

Calculation of Gray Relational Coefficient (GRC)

The GRC value for each variable is derived from the response's $\Delta O_i(k)$ value as per equation 4. In other words, the Grey Relation Coefficient (GRC) is a measure of how well the experiment performed under different experimental settings.

$$\gamma_i(k) = \frac{\Delta + \ \zeta\Delta max}{\Delta O_i(k) + \zeta\Delta max} \tag{4}$$

Where, $\Delta =$ $the\ series\ of\ deviations\ with\ the\ smallest\ value$,

$\Delta =$ $the\ series\ of\ deviations\ with\ the\ highest\ value$

$\zeta =$ $distinguishing\ coefficient$ *having value between 0 and 1. In most cases, a Distinguishing Coefficient of 0.5 is employed.*

$\Delta O_i(k) =$ $Deviation\ sequence\ of$ i^{th} $experiment$

In case of smaller the better, the lower the Gray Relational Coefficient (GRC), the more closely the experimental results match the optimal normalised response value while for higher the better higher values of GRC are expected. The Gray Relational Grade (GRG) for each response is combined using the Principal Component Analysis (PCA) method in the Minitab 17 software to get a single multi-response score. In order to correctly and objectively explain a number of relatively relevant traits, Principal Component Analysis is performed. Response characteristic k-weight is represented by β_k, and its weight is calculated by using eigenvector's squared value. The PCA value PC1 has been selected because it matched the criteria for picking the primary component with an eigenvalue greater than or equal to 2.2312. The values of PC1 for tensile strength, flexural strength and wear are 0.631, 0.629 and 0.454 respectively. The respective squared values, which have been used us weights for tensile strength, flexural strength and wear are 0.398161, 0.395641 and 0.206116 respectively. The Gray Relational Grade (GRG), which is weighted sum of GRC, has been calculated using the equation number 5.

$$\Gamma(x_0 \cdot x_i) = \sum_{k=i}^{n} \beta_k .\ \gamma\ (x_0(k) \cdot x_i\ (k)) \qquad (5)$$

Where, $\sum_{k=i}^{n} \beta_k = 1$

The Grey Relational Grade and ranks have been calculated as per above steps and the results are shown in table 2. The Optimal combination is the one with the highest GRG, which is for experiment number 9. The values for extruder temperature is 220^0C, layer height is 0.3 mm, infill density is 90 percent and print speed is 50 mm/s.

Table 2. Grey Relational Grade and Ranks.

Specimen No.	NORMALISED VALUES			DEVIATION SEQUENCES			GREY RELATION COEFFICIENT			GREY RELATION GRADE	
	TS	**FS**	**WR**	**TS**	**FS**	**WR**	**TS**	**FS**	**WR**	**GRG**	**RANK**
1	0.743988	0.842122	0.648686	0.256012	0.157878	0.351314	0.661365	0.76002	0.587327	0.685082	4
2	0.832268	0.65964	0.529968	0.167732	0.34036	0.470032	0.748803	0.594983	0.515447	0.639786	8
3	0.821005	0.875669	0.526814	0.178995	0.124331	0.473186	0.736382	0.800857	0.513776	0.715948	3
4	0.642009	0.938781	0	0.357991	0.061219	1	0.582757	0.890918	0.333333	0.65322	6
5	0.72968	0.928926	0.802313	0.27032	0.071074	0.197687	0.649081	0.875543	0.716654	0.752553	2
6	0.631659	0.864704	0.736067	0.368341	0.135296	0.263933	0.575811	0.787035	0.654508	0.675553	5
7	0.09863	0.095549	0.478444	0.90137	0.904451	0.521556	0.356794	0.356011	0.489449	0.383797	16
8	0.353425	0	0.62776	0.646575	1	0.37224	0.436081	0.333333	0.573237	0.423664	14
9	1	1	0.494217	0	0	0.505783	1	1	0.497125	0.896267	1
10	0.692846	0.682548	0.483701	0.307154	0.317452	0.516299	0.619461	0.611657	0.491981	0.590047	9
11	0.186606	0.279141	1	0.813394	0.720859	0	0.380693	0.409548	1	0.519727	11
12	0	0.082169	0.777077	1	0.917831	0.222923	0.333333	0.352651	0.691636	0.414801	15
13	0.698326	0.80342	0.545741	0.301674	0.19658	0.454259	0.623695	0.717793	0.523967	0.640317	7
14	0.081279	0.066897	0.900105	0.918721	0.933103	0.099895	0.35243	0.348893	0.833479	0.450154	12
15	0.503501	0.533677	0.797056	0.496499	0.466323	0.202944	0.501757	0.517425	0.711294	0.551104	10

16	0.14003	0.18927	0.750789	0.85997	0.81073	0.249211	0.367655	0.381467	0.667368	0.434865	13

Analysis of Variance (ANOVA)

When examining the impact of several parameters on a result, one analysis method which is widely used is the Analysis of Variance (ANOVA). To find out how much a certain parameter affects output value, we have used ANOVA to compute its contribution value in terms of percentage. Significant and insignificant factors can be separated, allowing for effective assessment. Results of ANOVA has been shown in table 3. Here LT is layer thickness in mm, PS is print speed in mm/s, ID is infill density in percentage and ET is extruder temperature in degree Celsius. As evident from the p value and percentage contribution, the most significant variable is print speed followed by extruder temperature and layer thickness. It can also be concluded that infill density is insignificant variable as far as it's effect on GRG is concerned. The value of R-square for the model is 86.74 percent and corresponding regression equation has been shown in equation 6. The normal probability plot for GRG is shown in figure 2. It can be seen clearly that the data is evenly distributed.

$$GRG = -0.404 - 0.835 * LT - 0.00166 * PS - 0.00004 * ID + 0.00699 * ET \quad (6)$$

Table 3. *Table for ANOVA*

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Percent Contribution
Regression	4	0.27098	0.06775	17.99	0	46.45
LT	1	0.03476	0.03476	9.23	0.011	5.96
PS	1	0.13844	0.13844	36.77	0	23.73
ID	1	3E-06	3E-06	0	0.978	0.00
ET	1	0.09778	0.09778	25.97	0	16.76
Error	11	0.04142	0.00377			7.10

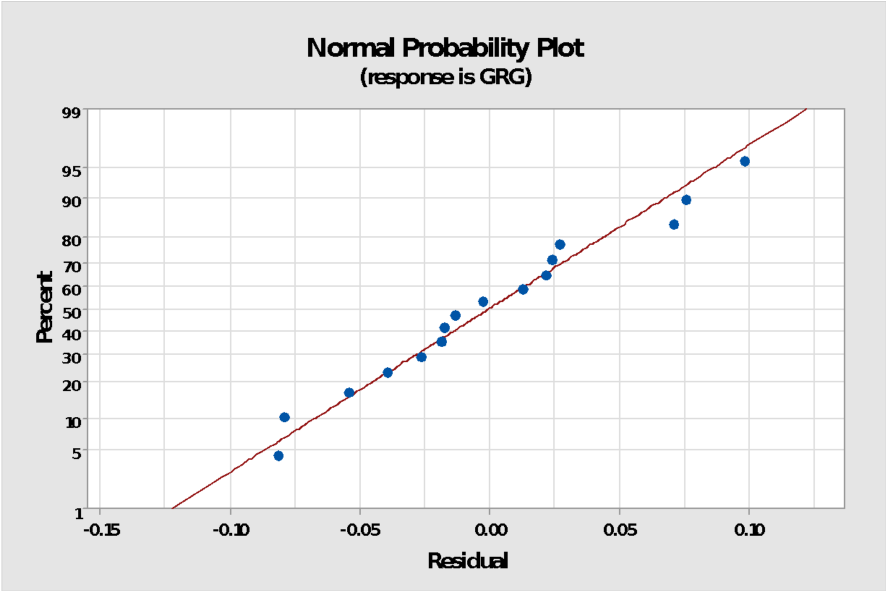

Figure 2. *Normal Probability plot*

Taguchi Analysis for S/N ratios

This experiment's goal is to find the best 3D Printing process parameter settings for the final product production process. where the "greater is better" condition is utilised for the GRG response SN Ratio because a higher GRG value suggests better results in the test. Repetitive data is transformed into one value that measures the variances that happen using the SN Ratio design (Bharti et al.,2011). The SN ratio is determined by the quality of each response and the type of quality characteristic it possesses. When the value is greater, the better; this is demonstrated by equation 7.

$$\frac{S}{N} = -10\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{{y_i}^2}\right) \qquad (7)$$

Response table of signal to noise ratio for GRG is depicted in figure 3 and table 4. The order of significance based upon the rank is print speed (PS) followed by extruder temperature (ET), layer height (LT) and infill density (ID). It is observed that the optimum value of GRG can be obtained at print speed of 50 mm/sec, extruder temperature of 220^{0}C, infill density of 90 % and layer thickness of 0.2 mm. Since this combination is not there in the sixteen sets for which experiments have been performed, hence validation experiments for this combination have been performed with three samples each. The average experimental value of three samples for tensile strength is 4.916 kg/mm^2, flexural strength is 19.769 kg/mm^2 and wear rate is 1.898 X 10^{-2} mm^3/m.

Table 4. Response table of GRG for Signal to Noise Ratio

Level	LT	PS	ID	ET
1	-3.441	-2.644	-4.902	-6.545
2	-5.413	-4.7	-4.792	-5.224
3	-4.715	-5.52	-4.561	-4.297
4	-5.803	-6.509	-5.118	-3.308
Delta	2.362	3.864	0.556	3.237
Rank	3	1	4	2

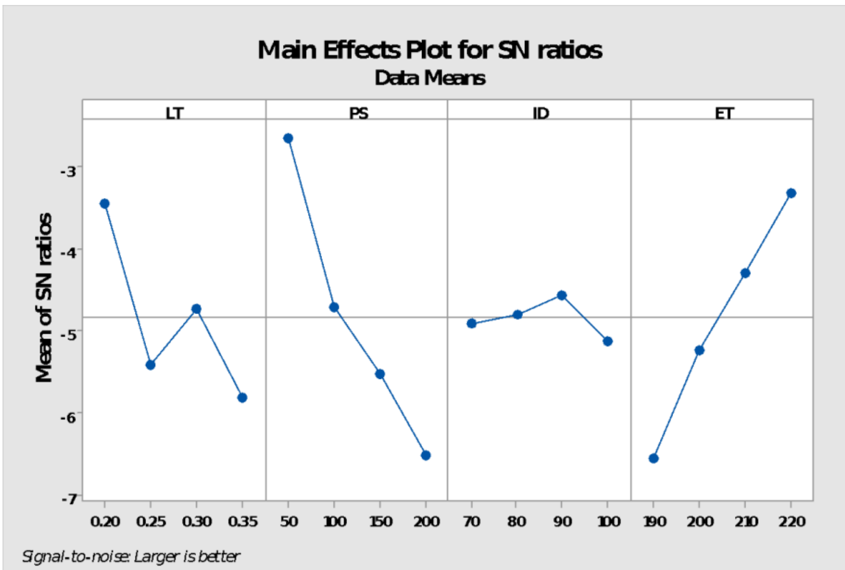

Figure 3. *Main Effect plot for SN ratios*

RESULTS AND DISCUSSION

For the purpose of estimating the GRG for each given combination of components, we have developed a mathematical model that is based on linear regression analysis. The major effect plot (Figure 3) for GRG has been constructed in order to better understand the impact of numerous elements on the final result, including the tensile strength, flexural strength, and wear rate. When layer print speed was raised, it resulted in a fall in GRG, however raising extruder temperature resulted in increase in GRG. In case of layer thickness, the value of GRG decreased with an exception at 0.30 mm height. The output also linearly increased up to infill density of 90 percent and then there was sudden decrease at 100 percent density. The layer thickness directly influences the number of layers required and thus printing time. To improve the bonding between layers, a higher extrusion pressure is required to deposit a thin layer. Less layer thickness means more layers, more ductility, and more strength. As print speed increases, less time is left for solidification, and the bonding between successive layers degrades. Increasing the infill density of the specimen results in increase in mass thus increasing its strength. Proper melting of the filament results in a smoother flow and better adhesion qualities, enhancing the strength.

From Taguchi analysis, it is observed that the optimum value of GRG can be obtained at print speed of 50 mm/sec, extruder temperature of 220^0C, infill density of 90 % and layer thickness of 0.2 mm. This has been validated by performing experiments for the above combinations.

CONCLUSIONS

This research aims to find out the optimized printer parameters simultaneously affecting tensile strength, flexural strength, and wear resistance, using grey relational analysis (GRA) and Taguchi. The observations and conclusions have been summarized below

1. The Grey Relational Grade and ranks have been calculated for the experimental data of sixteen experiments. The Optimal combination is the one with the highest GRG, which is obtained for extruder temperature of 220^0C, layer height of 0.3 mm, infill density at 90 percent and at print speed of 50 mm/s.
2. The most significant variable as per ANOVA is print speed followed by extruder temperature and layer thickness. It can also be concluded that infill density is insignificant variable as far as its effect on GRG is concerned.

3. The value of R-square for the model is 86.74 percent and corresponding regression equation has been generated for prediction of GRG for any set of input variables.
4. Taguchi analysis reveals that the optimum (maximum) value of GRG can be obtained at print speed of 50 mm/sec, extruder temperature of 220^0C, infill density of 90 % and layer thickness of 0.2 mm.
5. The validation result shows that the obtained values of Tensile and flexural strength is maximum for the parameters obtained from Taguchi analysis while that of wear rate is significantly lower.

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