Multi-Objective Optimization of Fused Deposition Modeling Process Parameters to Improve Quality of Graphene-Reinforced PC-ABS Composite Part Using Taguchi -Grey Relational Grade

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Abstract: Fused deposition modeling is a most accepted method of additive manufacturing to fabricate complex and customized parts in layer by layer deposition of a material. Several factors affect the mechanical properties, appearance of parts and printing time of parts. Optimization of process parameters of fused deposition modeling (FDM) process is required to improve quality, cost effectiveness, and efficiency of the method to build parts. However, research on optimization of process parameters to improve quality of printed part using PC- ABS with 0.25 % graphene is limited. The main objective of this study is to identify the effect of various process parameters on dimensional accuracy, printing time, and material consumed. This study also determines the optimal setting to achieve better dimensional accuracy with less material consumption in minimum time. Taguchi's "L27 orthogonal array" was implemented as design of experiment to collect the data. Grey Analysis was used to find the optimal setting to achieve desired outputs. Analysis of Variance (ANOVA) shows that layer thickness is most influential factor for all performance parameters. Grey relational analysis (GRA) is utilized to found optimal setting for all performance parameters as 0.2 mm layer thickness, 40 % infill density, line infill style, 240 °C printing temperature, and 80 mm/sec printing speed.

Keywords: *Additive Manufacturing, Fused Deposition Modeling, FDM, Taguchi Analysis, Grey Relational Analysis.*

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I. INTRODUCTION

Additive Manufacturing also known as additive rapid prototyping or 3D printing nowadays very popular and emerging due to its versatility and wide scope in the engineering field such aerospace, automobile, pattern making etc. Fused deposition modeling is most commonly used additive manufacturing technique to produce complex parts which is not possible by conventional subtractive manufacturing methods. FDM Process is able to fabricate the parts accurately and precisely.[1]. The FDM process use 3D model to fabricate the parts. 3D modeling software like solidworks, Catia, Fusion 360 etc. are utilized to create 3D model and .stl file of desired part. A .stl file is imported into a slicing software. Slicing software like CURA, Kisslicer are used to generate cnc code of 3D model to guide the 3D printing machine and deposit the material on printing bed [2]. Material extruded from nozzle has a tendency to shrink and warp after depositing on printing bed that affected the dimensional accuracy. Many other factors are also responsible for dimensional inaccuracy such as layer thickness, infill density, and infill style etc. [3].

In today's competitive scenario, it is required to fabricate light weight product in minimum time without affecting the quality of product. Several factors affect the printing time as well as material consumption. This study considered some process parameters on the basis of literature review and identify the effect of these process parameters on printing time, material consumption, and dimensional accuracy using Taguchi methodology and grey relational grade method.

II. LITERATURE REVIEW

Numerous studies have examined the different process parameters that are primarily responsible for enhancing the mechanical properties, material consumption, printing time of the manufactured part using FDM, etc. A hybrid optimization method was presented by Srivastava et al. to maximize model material volume and build time. After

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optimizing process parameters using response surface methodology and grey relational grade, it was determined that a part with a contour width of 0.654 mm, an air gap of 0.0254 mm, a raster angle of 00, and a part orientation of 00 could be fabricated in the least amount of time.[4] In order to find the ideal configuration that enhances tensile strength, toughness, and surface roughness, Raju et al. used Taguchi's Methodology with grey analysis for multi-objective optimization. The main factor influencing the printed part's toughness and tensile strength was found to be printing speed. At 90 mm/sec printing speed, 15 mg carbon deposition, and two layers, the printed part's tensile strength, toughness, and surface roughness all improved.[5] Arifin et al. used the Taguchi method and grey analysis to optimize the human denture's shrinkage and hardness. They found that a layer thickness of 0.15 mm, a print speed of 25 mm/s, and a print temperature of 210oC were the best settings for achieving both. [6] By using the Taguchi method with Grey analysis, Muhamedagic et al. discovered that layer thickness at 0.1 mm, raster angle at 90 degrees, and printing temperature at 220 degrees Celsius are the ideal settings to achieve maximum flexural strength and compressive strength of parts printed using PLA material.[7] In order to simultaneously improve surface finish, dimensional accuracy, and tensile strength using the grey Taguchi method, Patel et al. proposed a multi-objective parametric optimization for the FDM process and recommended optimal settings as 0.3mm layer thickness, 90^0 orientation angle, and 40% infill density. [8] In order to increase dimensional accuracy, Kumar and Singh looked into the impact of numerous factors. The best settings for producing accurate PLA parts were found to be layer thickness of 0.1 mm, grid infill pattern, line pattern of top and bottom layers, four top and bottom layers, infill density of 50%, flow of 125%, two shells, printing temperature of 200 ºC, bed temperature of 55 ºC, 80 mm/sec, and cooling fan capacity of 50%.[9]

The literature review makes clear that numerous studies were carried out to determine how process parameters affected the mechanical characteristics, printing time, and material consumption of various materials, including PLA, ABS, PC, and PC-ABS. However, very little research has been done to determine how FDM process parameters affect parts printed using PC-ABS with 0.25% graphene. The Taguchi method and ANOVA were used in this study to optimize material consumption, printing time, and dimensional accuracy by taking into account five process parameters: layer thickness, infill density, infill style, printing temperature, and printing speed. The Grey Relation Grade method is used to determine the best configuration for the multi-objective index, which simultaneously improves dimensional accuracy, printing time, and material consumption.

III. EXPERIMENTAL SETUP

On the basis of literature review, five process parameters were considered that are responsible for material consumption, printing time, and dimensional accuracy. Table 1 shows various process parameters with their levels. Polycarbonate blend with ABS with 0.25% graphene is used as material to print the specimen ASTM D638 type IV as shown in figure.

Table 1 Process Parameters and Their Levels

Process Parameters	**Level 1**	**Level 2**	**Level 3**
Layer Thickness (A)	0.1 mm	0.15mm	0.2mm
Infill Density (B)	40 %	70 %	100 %
Infill Style (C)	Line	Triangular	Hexa-triangular
Printing Temp. (D)	235 ºC	240 ºC	245 ºC
Printing Speed (E)	40 mm/sec	60 mm/sec	80 mm/sec

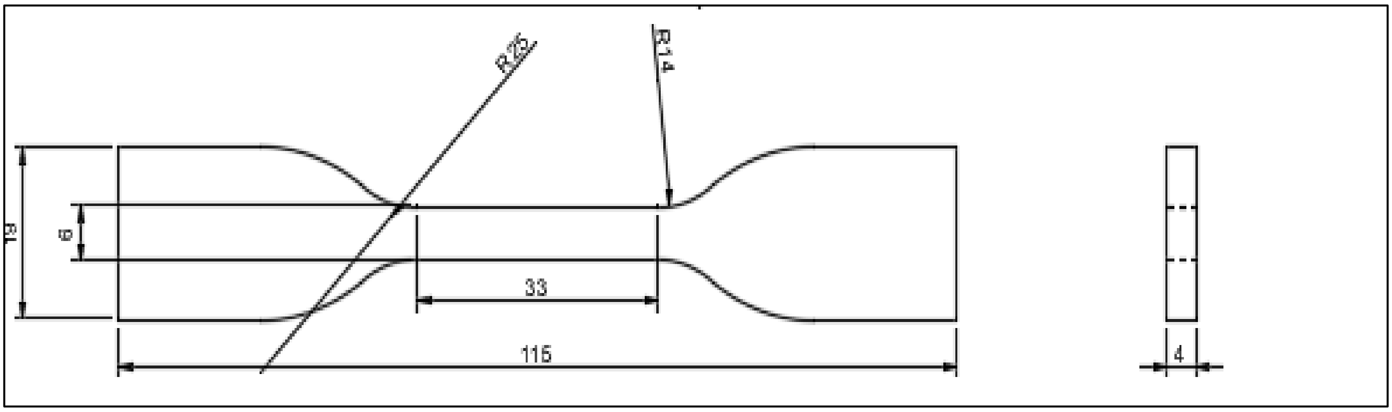

Fig 1 ASTM D638 Type IV

Taguchi's "L27" orthogonal array as shown in table 2 is implemented as design of experiment to print the specimen. Accucraft 250 i plus 3D printer as shown in figure 2(a) is used to print the specimen. Weight of the specimen was measured by weighing machine as shown in figure 2(b). Printing time was measured by stop watch. A vernier caliper was used to measure the dimensions of the printed specimen.

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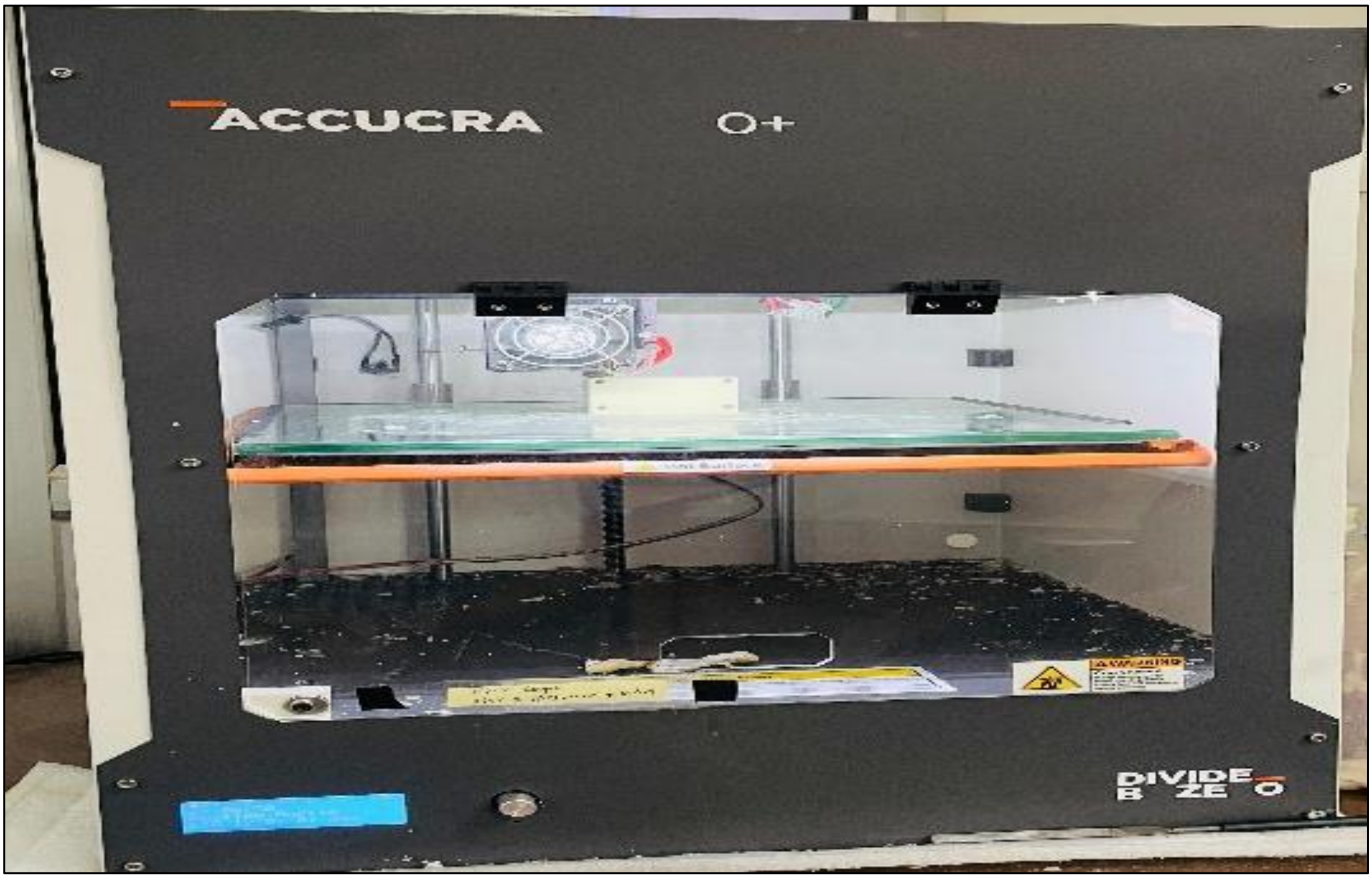

Figure 2(a) Accucraft 250i plus 3D printer

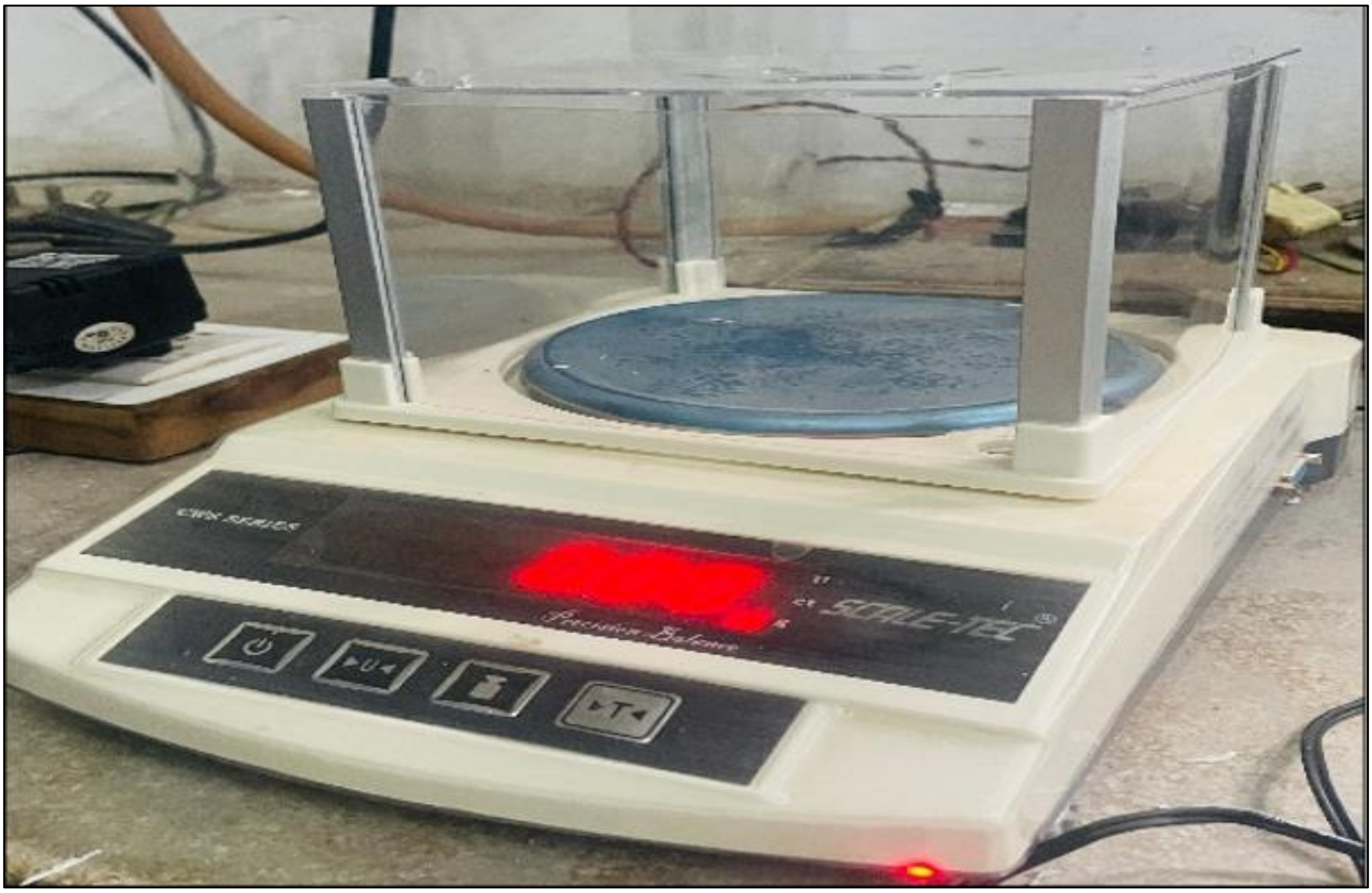

Figure 2(b): Weighing Machine

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Table 2 Design of Experiments in Coded Form

Process parameters of Fused Deposition Modeling					Performance Parameters		
Layer thickness (mm)	Infill density	Infill pattern	Print temp (°C)	Printing speed (mm/sec)	Printing time (minutes)	Weight of specimen (grams)	Overall Dimensional Difference (mm)
A	B	C	D	E	P_T	W_S	O_d
1	1	1	1	1	95	4.473333	0.98
1	1	1	1	2	77	4.51	0.62
1	1	1	1	3	71	4.513333	1.02
1	2	2	2	1	108	5.34	0.98
1	2	2	2	2	89	5.353333	0.64
1	2	2	2	3	82	5.36	0.86
1	3	3	3	1	110	5.95	0.64
1	3	3	3	2	89	5.97	0.88
1	3	3	3	3	82	5.98	1.04
2	1	2	3	1	65	4.69	0.98
2	1	2	3	2	61	4.68	0.90
2	1	2	3	3	57	4.67	1.02
2	2	3	1	1	76	5.48	1.02
2	2	3	1	2	65	5.49	1.06
2	2	3	1	3	62	5.52	1.12
2	3	1	2	1	90	6.366667	0.84
2	3	1	2	2	67	6.36	1.10
2	3	1	2	3	61	6.316667	0.96
3	1	3	2	1	42	4.37	0.98
3	1	3	2	2	32	4.39	1.04
3	1	3	2	3	28	4.403333	1.02
3	2	1	3	1	49	5.32	1.02
3	2	1	3	2	38	5.356667	0.94
3	2	1	3	3	33	5.363333	1.08
3	3	2	1	1	67	6.07	0.80
3	3	2	1	2	48	6.14	0.90
3	3	2	1	3	42	6.176667	0.98

IV. RESULTS AND DISCUSSIONS

According to design of experiments, specimens were printed. Time consumption, material consumed and dimensional difference were recorded for printed specimen. Analysis of variance was implemented to identify the effect of various process parameters on performance parameters. Grey Relational Grade (GRG) was implemented to determine the optimal setting to achieve light weight specimen with high dimensional accuracy in less time. The effect of various parameters on printing time, material consumption, and overall dimensional difference are as follows:

- *Effect of Process Parameters on Printing Time:*

ANOVA analysis for printing time (Table 3) indicates that layer thickness is the most significant factor affecting the printing time of the specimen. As layer thickness increases, the number of layers decreases, which in turn reduces the printing time. Following layer thickness, printing speed has the next greatest impact, although it also affects dimensional accuracy as printing speed increases. Infill density also influences printing time. As infill density increases, the material deposited on the build platform increases, which in turn raises the printing time. Infill pattern and printing temperature have minimal impact on printing time.

Table 3 Analysis of Variance for Means for Printing Time

Factors	Degree of freedom	Seq SS	Adj SS	Adj MS	F	P
Layer thickness (A)	2	10000.1	10000.1	5000.04	304.91	0.000
Infill Density (B)	2	917.6	917.6	458.81	27.98	0.000
Infill Pattern (C)	2	94.7	94.7	47.37	2.89	0.085
Printing Temperature (D)	2	22.3	22.3	11.15	0.68	0.521
Printing Speed (E)	2	2024.3	2024.3	1012.15	61.72	0.000
Residual Error	16	262.4	262.4	16.40		
Total	26	13321.4				

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Based on the main effect plots (figure 3), it has been observed that the specimen can be printed in less time with the following settings: 0.2 mm layer thickness, 40% infill density, tri-hexagonal infill pattern, 245°C printing temperature, and 80 mm/sec printing speed.

Fig 3 Analysis of Variance for Means for Printing Time

- *Effect of Process Parameters on Material Consumption:*

ANOVA analysis reveals that infill density is the most influential factor affecting the specimen's weight, with weight increasing as infill density rises. Layer thickness also plays a role in weight, as shown in the mean effect plot: the lightest specimen was printed at 0.1 mm layer thickness, followed by 0.2 mm and 0.15 mm layer thicknesses. The infill pattern also impacts the weight, with specimens printed using the tri-hexagonal pattern being lighter than those printed with the line or triangular patterns. Printing temperature and speed have minimal effects on the weight of the printed part.

Table 4 Analysis of Variance for Means for Weight of Specimen

Factors	Degree of freedom	Seq SS	Adj SS	Adj MS	F	P
Layer thickness (A)	2	0.3134	0.3134	0.15670	309.89	0.000
Infill Density (B)	2	11.9149	11.9149	5.95743	11781.53	0.000
Infill Pattern (C)	2	0.0712	0.0712	0.03561	70.42	0.000
Printing Temperature (D)	2	0.0091	0.0091	0.00455	9.01	0.002
Printing Speed (E)	2	0.0036	0.0036	0.00182	3.59	0.051
Residual Error	16	0.0081	0.0081	0.00051		
Total	26	12.3203				

Based on the main effect plots (Figure 4), it has been observed that the lightest part can be printed with the following settings: 0.1 mm layer thickness, 40% infill density, tri-hexagonal infill pattern, 245°C printing temperature, and 40 mm/sec printing speed.

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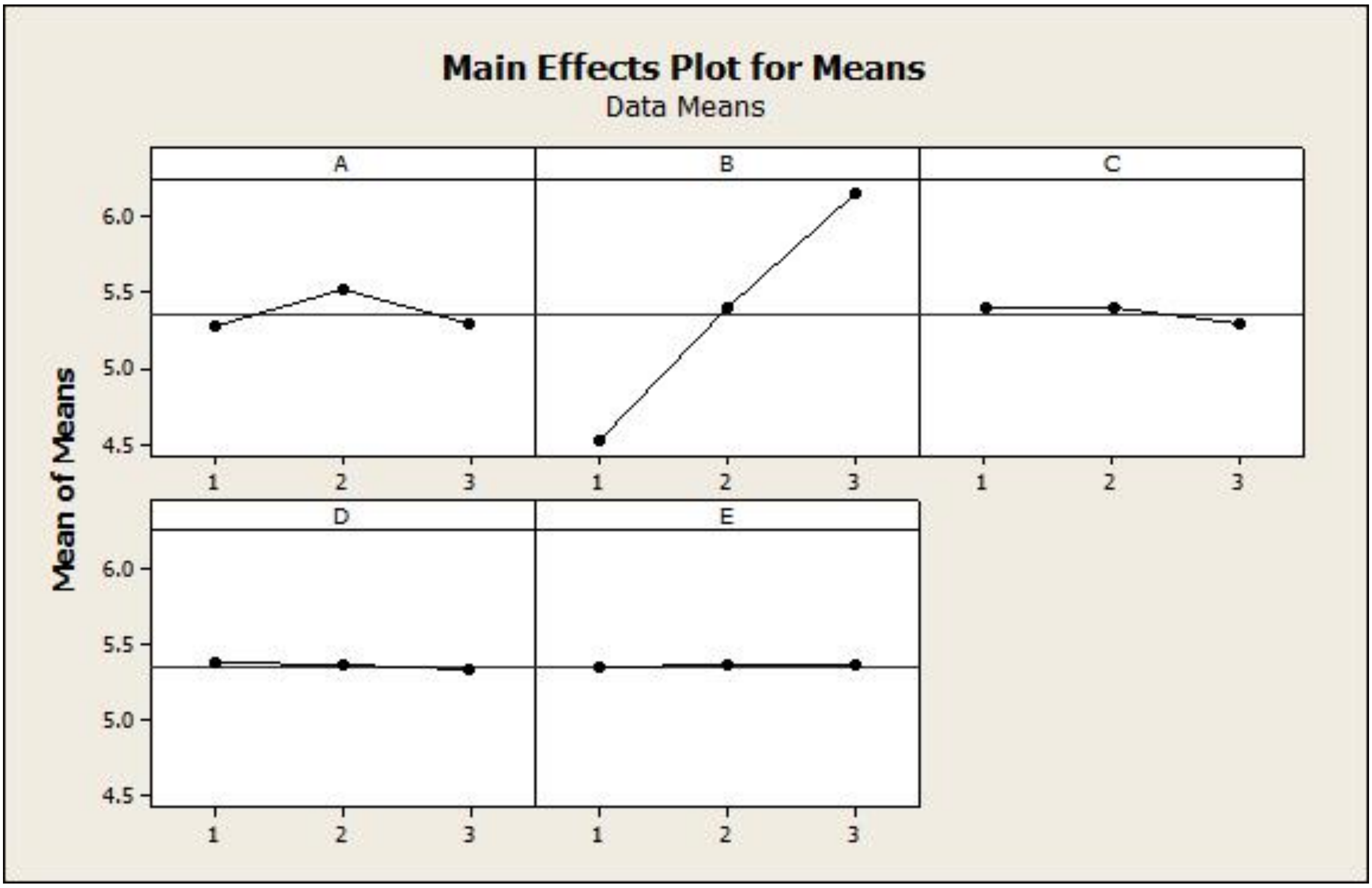

Fig 4 Analysis of Variance for Means for Weight of Specimen

- *Effect of Process Parameters on Overall Dimensional Difference:*

ANOVA analysis of overall dimensional variation shows that layer thickness is the most significant factor affecting dimensional accuracy. According to the main effect plot, a lower layer thickness leads to better dimensional accuracy. Printing speed also influences dimensional accuracy. As printing speed increases beyond a certain threshold, machine vibration increases, which in turn causes greater dimensional inaccuracy. Printing temperature also impacts dimensional accuracy. As temperature increases, material flow increases, leading to faster deposition rates. This results in obstruction upon deposition on the build platform or previous layer, causing machine vibrations and further increasing dimensional inaccuracy.

Table 5 Analysis of Variance for Dimensional Accuracy

Factors	**Degree of freedom**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
Layer thickness (A)	2	0.113452	0.113452	0.056726	3.70	0.048
Infill Density (B)	2	0.019941	0.019941	0.009970	0.65	0.535
Infill Pattern (C)	2	0.031674	0.031674	0.015837	1.03	0.378
Printing Temperature (D)	2	0.000474	0.000474	0.000237	0.02	0.985
Printing Speed (E)	2	0.066874	0.066874	0.033437	2.18	0.145
Residual Error	16	0.245126	0.245126	0.015320		
Total	26	0.477541				

Based on main effect plot for overall dimensional difference figure (5), part with high accuracy can printed with the following setting: 0.1 mm layer thickness, 100% infill density, triangular infill style, 235 ºC, and 60 mm/sec printing speed.

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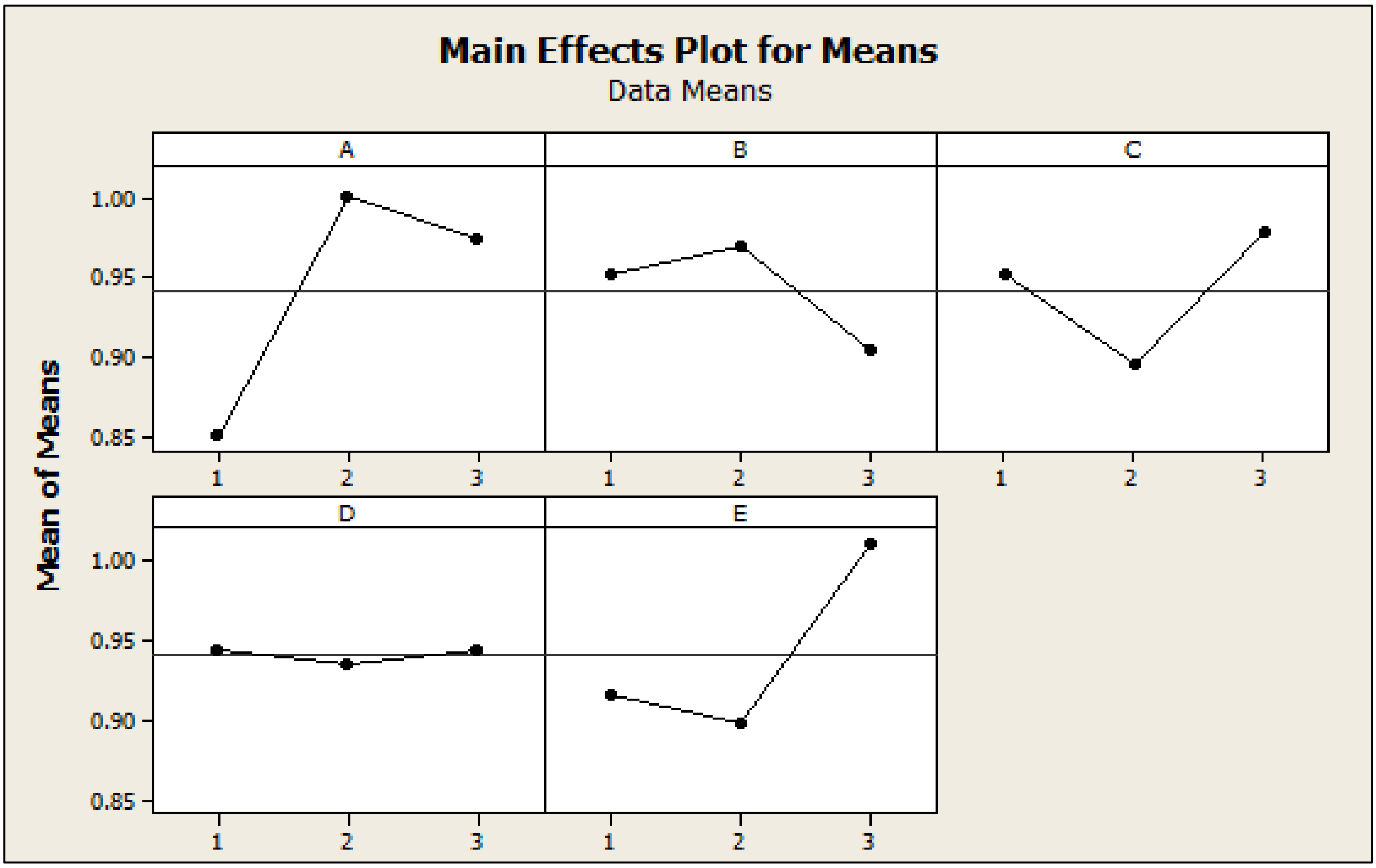

Fig 5 Analysis of Variance for Dimensional Accuracy

- *Multiple Objective Optimization Using Grey Relational Grade (GRG):*

GRG implemented to solve multi response design problems. GRA optimization is based on multi- response decision making. Deng introduced GRA in 1982 that converts the multi-response problem into a single objective problem [10]. It combine all the responses of performance matrices into a single objective [11]. Taguchi method is implemented in this study to perform experimentation. ANOVA revels the optimized results for each response. GRG analysis is applied in the following steps for multi-objective optimization.

Step 1: Preprocessing of each responses in the original sequence: GRG analysis begin with preprocessing of each response that is calculation of S/N ratio for each response for each experiment or specimen. In this study S/N ratio is calculated on the basis of “smaller is best” as shown in table 6. Following formula is applied to calculate S/N ratio.

$$S/N = -10 * \log(\Sigma(y^2)/n)$$

Where y represents the response value and n is the number of experiments.

Step 2: Normalization of S/N ratio data for each response and each experiment: In this step S/N ratio of each response for each experiment was normalized using following formula

$$y_j^*(t) = \frac{y_j^0 - min y_j^0\,(t)}{max y_j^0 - min y_j^0\,(t)}$$

Where $y_j^*(t)$ is the normalized value of t^{th} response for each response and y_j^0 (t) is the S/N ratio of t^{th} response for each experiment. Table 6 shows the normalized data of various responses for each experiment.

Table 6 Results of S/N Ratio and Normalization of Various Experiments

Exp	**S/N Ratio (y_j^0 (t))**			**Normalized data($y_j^*(t)$)**		
	P_T	**W_S**	**O_d**	**P_T**	**W_S**	**O_d**
1	-39.5545	-13.0126	0.175478	0.107145	0.937895	0.225802
2	-37.7298	-13.0835	4.152166	0.260675	0.916202	1
3	-37.0252	-13.0899	-0.172	0.319965	0.914239	0.158153
4	-40.6685	-14.5508	0.175478	0.01341	0.467298	0.225802
5	-38.9878	-14.5725	3.876401	0.154826	0.460672	0.946313
6	-38.2763	-14.5833	1.310031	0.214694	0.457364	0.446681
7	-40.8279	-15.4903	3.876401	0	0.179863	0.946313
8	-38.9878	-15.5195	1.110347	0.154826	0.170946	0.407806

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9	-38.2763	-15.534	-0.34067	0.214694	0.166498	0.125317
10	-36.2583	-13.4235	0.175478	0.384493	0.812205	0.225802
11	-35.7066	-13.4049	0.91515	0.430912	0.817877	0.369804
12	-35.1175	-13.3863	-0.172	0.48048	0.823562	0.158153
13	-37.6163	-14.7756	-0.172	0.270228	0.398527	0.158153
14	-36.2583	-14.7914	-0.50612	0.384493	0.393682	0.093106
15	-35.8478	-14.8388	-0.98436	0.419028	0.379201	0
16	-39.0849	-16.0782	1.514414	0.14666	0	0.486472
17	-36.5215	-16.0691	-0.82785	0.362345	0.002784	0.030469
18	-35.7066	-16.0098	0.354575	0.430912	0.020952	0.260669
19	-32.465	-12.8096	0.175478	0.703667	1	0.225802
20	-30.103	-12.8493	-0.34067	0.902409	0.987866	0.125317
21	-28.9432	-12.8756	-0.172	1	0.979807	0.158153
22	-33.8039	-14.5182	-0.172	0.591007	0.47727	0.158153
23	-31.5957	-14.5779	0.537443	0.776813	0.459017	0.296271
24	-30.3703	-14.5887	-0.66848	0.87992	0.455712	0.061498
25	-36.5215	-15.6638	1.9382	0.362345	0.126803	0.568976
26	-33.6248	-15.7634	0.91515	0.606076	0.096333	0.369804
27	-32.465	-15.8151	0.175478	0.703667	0.080511	0.225802

Step 3: Calculation of Grey Relational coefficient: In this step grey relational coefficient is calculated on the basis of following formula. Table 7 shows the grey relational coefficient for each response and experiment.

$$\varepsilon_i(t) = \frac{\Delta_{min} - \delta\Delta_{max}}{\Delta_{oi}(t) - \delta\Delta_{max}}$$

Where $\varepsilon_i(t)$ is the grey relational coefficient for t[th] response and i[th] experiment and δ is the grey index i.e. 0.33 in this study.

Step 4: Calculation of Grey Relational Grade: This steps calculates the GRG for each experiment or run on the basis of following formula:

$$GRG_i = \frac{1}{N}\sum_{t=1}^{N} \varepsilon_i(t)$$

Where GRG_i is grey relational grade for i[th] experiment and N is the number of experiment or run.

Step 5: Rank based on Grey Relational Grade: In this step, the highest rank is assigned to the experiment with the maximum GRG. Highest rank experiment is best suited to achieve the performance parameters.

Table 7 Results of Grey Relational Grade

Exp.	**Deviation ($\Delta_{oi}(t)$)**			**Grey Relational Coefficient ($\varepsilon_i(t)$)**			**GRG_i**	**Rank**
	P_T	**W_S**	**O_d**	**P_T**	**W_S**	**O_d**		
1	0.892855	0.062105	0.774198	0.26986	0.841612	0.298859	0.470111	6
2	0.739325	0.083798	0	0.308606	0.797491	1	0.702032	2
3	0.680035	0.085761	0.841847	0.326721	0.793726	0.281607	0.467351	7
4	0.98659	0.532702	0.774198	0.250648	0.382519	0.298859	0.310675	22
5	0.845174	0.539328	0.053687	0.280809	0.379603	0.860076	0.506829	5
6	0.785306	0.542636	0.553319	0.295883	0.378165	0.373591	0.349213	18
7	1	0.820137	0.053687	0.24812	0.286922	0.860076	0.465039	8
8	0.845174	0.829054	0.592194	0.280809	0.284715	0.357842	0.307789	24
9	0.785306	0.833502	0.874683	0.295883	0.283627	0.273931	0.28448	26
10	0.615507	0.187795	0.774198	0.349019	0.637318	0.298859	0.428399	13
11	0.569088	0.182123	0.630196	0.367039	0.644377	0.34368	0.451699	10
12	0.51952	0.176438	0.841847	0.388455	0.651609	0.281607	0.440557	11
13	0.729772	0.601473	0.841847	0.311388	0.354278	0.281607	0.315757	21
14	0.615507	0.606318	0.906894	0.349019	0.352445	0.266797	0.322754	19
15	0.580972	0.620799	1	0.36225	0.347076	0.24812	0.319149	20
16	0.85334	1	0.513528	0.278872	0.24812	0.391214	0.306069	25
17	0.637655	0.997216	0.969531	0.341031	0.248641	0.253938	0.281203	27
18	0.569088	0.979048	0.739331	0.367039	0.252092	0.308604	0.309245	23
19	0.296333	0	0.774198	0.526876	1	0.298859	0.608579	4

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20	0.097591	0.012134	0.874683	0.771766	0.964534	0.273931	0.670077	3
21	0	0.020193	0.841847	1	0.942339	0.281607	0.741315	1
22	0.408993	0.52273	0.841847	0.446553	0.386992	0.281607	0.371717	14
23	0.223187	0.540983	0.703729	0.596543	0.378882	0.319233	0.431553	12
24	0.12008	0.544288	0.938502	0.733202	0.37745	0.260149	0.456934	9
25	0.637655	0.873197	0.431024	0.341031	0.274269	0.433626	0.349642	17
26	0.393924	0.903667	0.630196	0.455849	0.267495	0.34368	0.355675	16
27	0.296333	0.919489	0.774198	0.526876	0.264108	0.298859	0.363281	15

The specimen printed with the settings from 21 experiments, 0.2mm layer thickness, 40% infill density, tri-hexagonal infill style, 240°C printing temperature, and 80 mm/sec printing speed gives the best results for printing time, specimen weight, and dimensional accuracy.

V. CONCLUSION

This study explored how different 3D printing parameters, such as layer thickness, infill density, infill pattern, extrusion temperature, and printing speed—affect printing time, material consumption, and dimensional accuracy. The shortest printing time was achieved using a configuration with a 0.2 mm layer thickness, 40% infill density, line infill pattern, a printing temperature of 245 °C, and a speed of 80 mm/s. In contrast, the lowest material consumption was observed when the specimen was printed with a 0.1 mm layer thickness, 40% infill density, a tri-hexagonal infill pattern, a temperature of 245 °C, and a speed of 40 mm/s. For dimensional accuracy, the most precise results (minimum deviation) were obtained using a 0.1 mm layer thickness, 100% infill density, triangle infill pattern, a printing temperature of 240 °C, and a speed of 60 mm/s. To determine the most balanced set of parameters, a multi-objective optimization approach based on Grey Relational Analysis (GRA) was applied. The optimal combination identified for achieving reduced print time, minimal material usage, and improved dimensional accuracy included a layer thickness of 0.2 mm, 40% infill density, a tri-hexagonal infill pattern, a printing temperature of 240 °C, and a printing speed of 80 mm/s.

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➢ *Competing Interests:*

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