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A Design of Experiment Analysis Approach to Improve Part Quality in 3D Printing

Mostafa Abbas Jabbar (0000-0002-3703-6205)
Department of Mechanical Techniques, Al-Nasiriya Technical Institute, Southern Technical University, Thi-Qar, Al-Nasiriya 64001, Iraq. E-mail: m.jabbar@stu.edu.iq

Fused Deposition Modelling (FDM) is used widely in additive manufacturing technology. The research community is becoming increasingly concerned about FDM products' surface quality and dimensional accuracy. The design of the experimental methodology is based on the analysis of variance (ANOVA) of fractional factorial design. This analysis was used to study the effect of layer thickness, extrusion temperature, speed of deposition, and fill density on dimensional accuracy and surface roughness of the model developed by FDM. Polylactic Acid (PLA) material has been selected as an article-forming material. The results showed that layer thickness has an influential factor in determining surface roughness. Fill density (X and Z dimensions), layer thickness (Y dimension), and speed of deposition (Z dimension) are significant factors affecting dimensional accuracy. The influence of curvature on surface roughness was presented and discussed; however, , the minimum optimization point was not attained, Therefore, further experiments were required to reach it. In terms of optimizing dimensional accuracy, it was observed that lower levels of every factor except for fill density led to greater accuracy in the dimensions along X, Y, and Z. Consequently, fill density was optimized to enhance dimensional accuracy.

Keywords: Fused Deposition Modeling, Polylactic Acid, Design Expert Software, Dimensional Accuracy, Surface Roughness

1 Introduction

Rapid Prototyping (RP) is a beneficial technique in producing physical prototypes, as it involves a crucial element of abbreviating and optimizing the product development process. The aim is to enhance the accuracy and minimize the time required to fabricate the prototypes [1]. Additive Manufacturing (AM) offers a nuanced manufacturing approach that underscores a vital aspect of sustainability. This technique enables the creation of lightweight components and the reduction of the overall number of parts by implementing intricate geometric designs [2].

A 3D modeling software such as Computer-Aided Design (CAD) can be used to generate the desired model of product components. Upon generating a CAD sketch, the AM equipment can read the data from the CAD file and systematically incorporate successive layers of liquid, sheet material, powder, or other materials to form a 3D object in a layer-by-layer manner, ultimately completing the component [3]. Several critical steps of the generic procedure from CAD to the final Specimens can be identified as follows [4]:

- Conceptualization and CAD.
- Transformation to STL file.
- Transfer and manipulation of the STL file to AM machine.
- Machine setups.
- Start to build.
- Product removal and cleanup.
- Post-processing of product.
- Applications.

Fused Deposition Modeling (FDM), depicted in Fig. 1, is an Additive Manufacturing (AM) process that possesses noteworthy features such as cost-effective tooling, the ability to fabricate intricate shapes, minimal material wastage, and user-friendliness [5, 6, 7, 8]. This process has demonstrated its cost and time efficiency superiority over conventional techniques [9, 10, 11]. The quality of the FDM-produced components is regarded as the critical determinant of their performance in specific applications [12, 13]. Therefore, it is imperative to comprehend the interplay between the FDM process parameters and the resultant parts to ensure the reliability of the manufactured components for industrial use.

This work aims to demonstrate the optimal factors contributing in order to improve dimensional accuracy and reduced surface roughness in Fused Deposition Modeling (FDM) using Polylactic Acid (PLA) as the article-forming material. The research methodology employs a fractional factorial design and an analysis of variance (ANOVA). The paper outlines the process of designing the experimental approach based on the ANOVA of fractional factorial design.

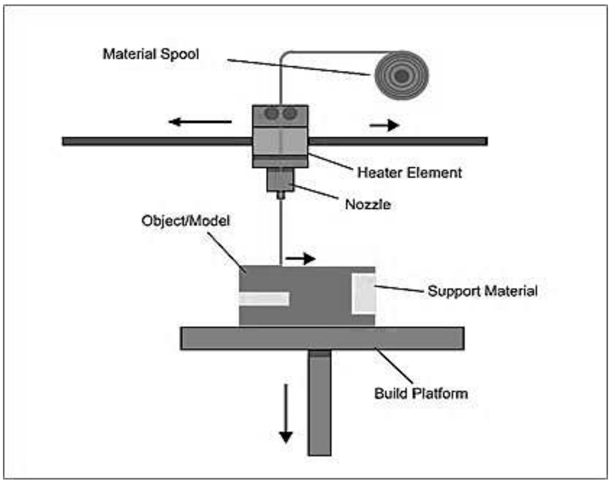

Fig. 1 *FDM-Process*

2 Methodology

A 3D model of the component (tensile part), depicted in Fig. 2(a), was designed using AutoCAD 2020 to fabricate it using a 3D printing machine. Fig. 2(b) displays the dimensions of the tensile part, illustrated via a 2D drawing.

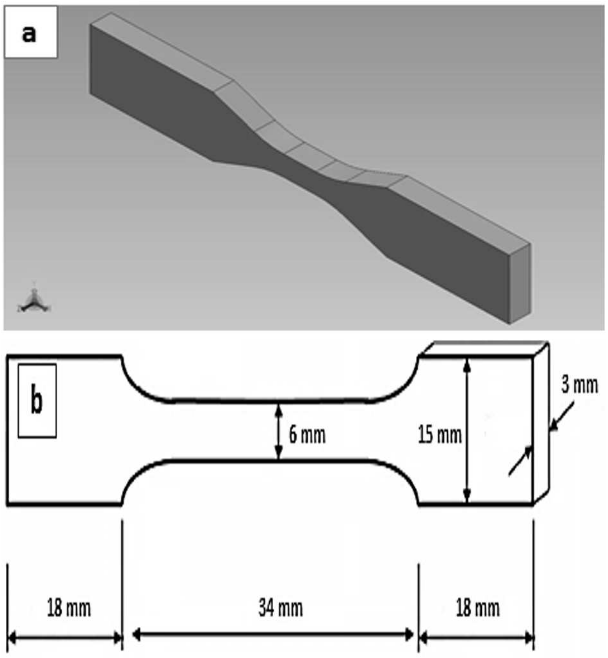

Fig. 2 *3D model (a), 2D drawing (b)*

The STL (stereolithography) file of the model was imported into the FDM software, namely Ultimaker Cura. The FDM software dissects the STL model into distinct slices and generates a G-Code specific to the printer. Prior to each experimental run, the input factors were configured in the software and transferred to the machine via an SD card. The nozzle travel speed was maintained at a constant value of 100mm/s, while a nozzle diameter of 0.4mm was employed. The adhesion type is implemented as a skirt. Fig.3 displays the experimental setup.

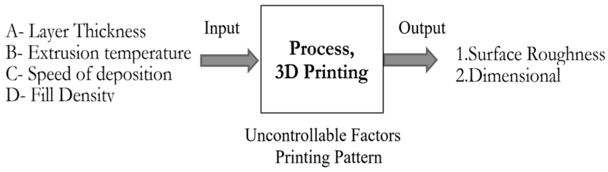

Fig. 3 *Experimental setup*

The selection of the material for this work was based on several analyses and experiments conducted on Polylactic Acid (PLA) utilized in the Fused Deposition Modeling (FDM) process [14, 15]. The FDM printer model M-100, depicted in Fig. 4, was used to construct the model. Bed leveling was performed to ensure the flatness of the bed before commencing the experiments. The article-forming material, Polylactic Acid (PLA), was loaded into the machine's head in the form of a flexible strand composed of solid material. After preheating, the material was extruded semi-solid onto the previously deposited material on the build platform. Consequently, the model was fabricated layer-by-layer, following a predetermined tool path pattern.

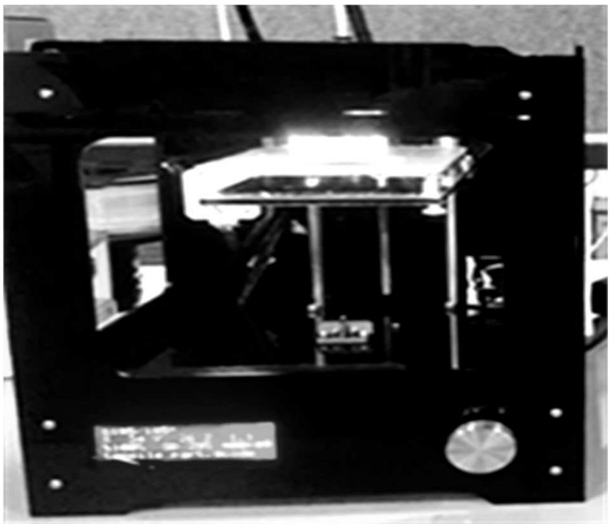

Fig. 4 *M-100 FDM Printer*

The objects' width, length, and thickness were determined using a digital vernier caliper with a least count of 0.01mm. The surface roughness was assessed employing a portable contact-type roughness tester (Mitutoyo Surftest SJ-310 Series 178), as shown in Fig. 5. Two readings were recorded from two distinct locations for each model, and the mean of the two roughness (Ra) values was considered the response variable.

Fig. 5 *Surface Roughness Tester with accuracy 0.001µm*

A full factorial design involving four factors would require us to perform 24, i.e., 16 experiments. In this design, just 4 out of 15 freedom degrees are related to the substantial influence and only 6 freedom degrees are related to two-factor interactions. Assuming that the higher order interactions are negligible, a fractional factorial of 24-1, i.e., 8 experiments was considered. The experiment design was of resolution IV; hence, the main influences were not aligned with any other main influence or two factor dealings. Nevertheless, two-factor interactions are aligned with other two-factor dealings.

Ockham's razor was found to be of great application in this context. To determine the significance of curvature, three further experiments were conducted to obtain the centre points. Each factor's low and high levels were chosen based on the manufacturer's recommended minimum and maximum settings and practical experience, as illustrated in Tab. 1. The level combinations for the half fraction obtained from the randomized design of Design Expert Software are presented in Tab. 2.

Tab. 1 *Value of Process Parameters*

Factors	Name	Low	High
A	Layer Thickness	0.1	0.3
B	Extrusion Temperature	185	215
C	Speed of Deposition	60	80
D	Fill Density	60%	100%

Tab. 2 *Combinations of Level*

RUN	A	B	C	D	Treatment Combination
1	-	-	-	-	(1)
2	+	-	-	+	ad
3	-	+	-	+	bd
4	+	+	-	-	ab
5	-	-	+	+	cd
6	+	-	+	-	ac
7	-	+	+	-	bc
8	+	+	+	+	abcd

3 Results & discussion

An experimental investigation was conducted to evaluate the impact of specific process parameters on the dimensional accuracy and surface roughness of PLA parts fabricated using Fused Deposition Modeling (FDM). The selected parameters were layer thickness (A), extrusion temperature (B), speed of deposition (C), and infill density (D), along with their interactions. To minimize the number of experimental trials required, the analysis of variance was employed as a cost-effective and straightforward approach to investigate the influence of these process parameters and their interactions on the accuracy of the dimensions and surface roughness of the FDM-produced parts. The tensile test samples in the form of a dog bone structure were obtained by conducting eight experiments using the M-100 FDM machine, as illustrated in Fig. 6.

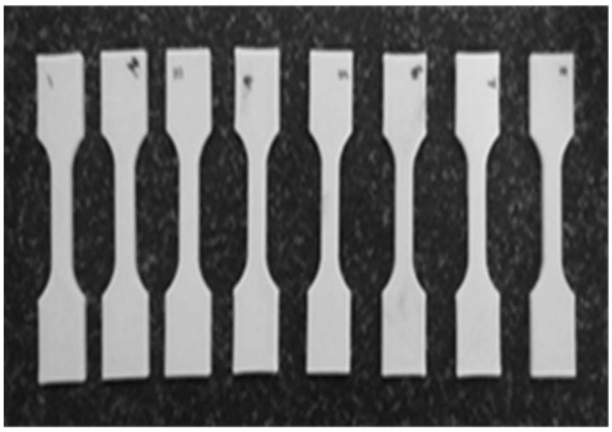

Fig.6 *Tensile Test Specimens*

The mean responses are representative values for surface roughness and dimensions. The obtained values and the added center points are given in Tab. 3.

Tab. 3 *Data of Responses for Each Run*

Run	A	B	C	D	Ra	△x	△y	△z
1	0.1	185	60	60	15.60	0.44	0.04	0.18
2	0.3	185	60	100	32.90	0.63	0.03	0.03
3	0.1	215	60	100	8.30	0.40	0.15	0.02
4	0.3	215	60	60	24.19	0.44	0.23	0.02
5	0.1	185	80	100	6.44	0.10	0.16	0.09
6	0.3	185	80	60	33.21	0.15	0.13	0.14
7	0.1	215	80	60	18.21	0.18	0.27	0.07
8	0.3	215	80	100	31.30	0.61	0.07	0.00
9	0.2	200	70	80	28.24	0.29	0.18	0.02
10	0.2	200	70	80	25.67	0.20	0.07	0.01
11	0.2	200	70	80	31.38	0.25	0.11	0.05

3.1 Surface roughness analysis and optimization

The Design Expert 7.0 software was utilized to perform the Analysis of Variance (ANOVA) on the resolution IV design under consideration. The resulting ANOVA Tab. 4 was evaluated to assess the significance of the remaining factors. The main and interaction effect plots for the surface roughness of the tensile components are depicted in Fig. 7 (a, b).

Tab. 4 *ANOVA Table for surface roughness*

Source	SS	DF	MS	F	P-Value
Model	769.51	3	256.50	24.25	0.0009 Sig.
A	667.04	1	667.04	63.07	0.0002
D	18.82	1	18.82	1.78	0.2306
A-D	83.66	1	83.66	7.91	0.0307
Curv.	111.89	1	111.89	10.58	0.0174 Sig.
Resi.	63.45	6	10.58		
Leck of Fit	47.10	4	11.77	1.44	0.4491 Not Sig.
Pure Error	16.36	2	8.18		
Total	944.86	10			

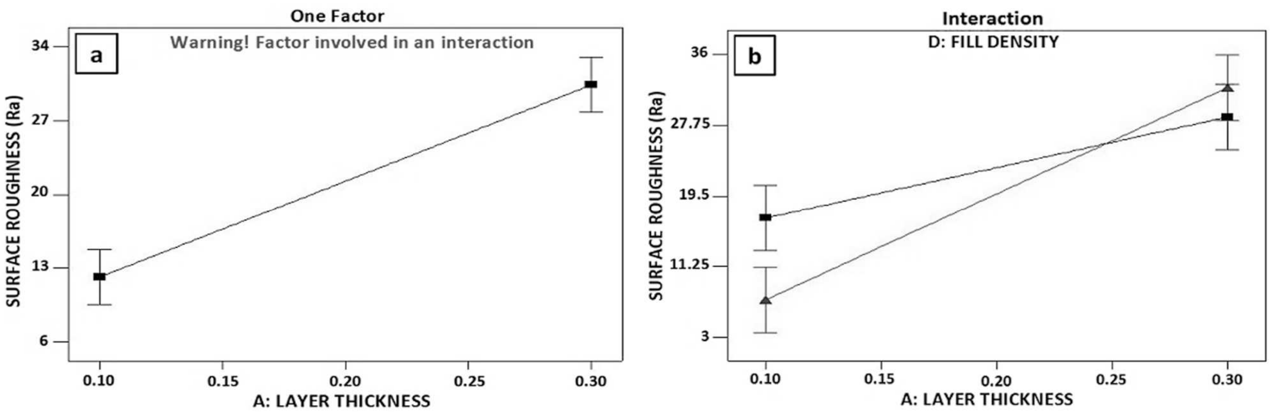

Fig. 7 *Main (a), and interaction, (b) Effect plots for Surface Roughness*

The ANOVA Tab. 3 revealed that the layer thickness (A) and the interaction between layer thickness and infill density (AD) significantly influenced the surface roughness of the FDM-produced parts, with percentage contributions of 70.60 and 8.85, respectively. Although the interaction of AD is confounded with the interaction of BC, the principle of Ockham's Razor justifies the conclusion that AD is the significant interaction between AD and BC. The surface roughness was observed to increase with an increase in layer thickness. Based on the interaction plot, using a low-thickness layer and a high fill density is recommended to minimize the surface roughness of the fabricated part.

Figure 8 (a, b) shows the normal probability plot for residuals and the residuals versus the predicted response plot. The plot analysis in Fig. 8 (a) reveals that the residuals are generally distributed along a straight line, indicating a normal distribution of errors. Furthermore, the plot in Fig. 8 (b) confirms the suitability of the proposed model, with no indication of a consistent violation of variance.

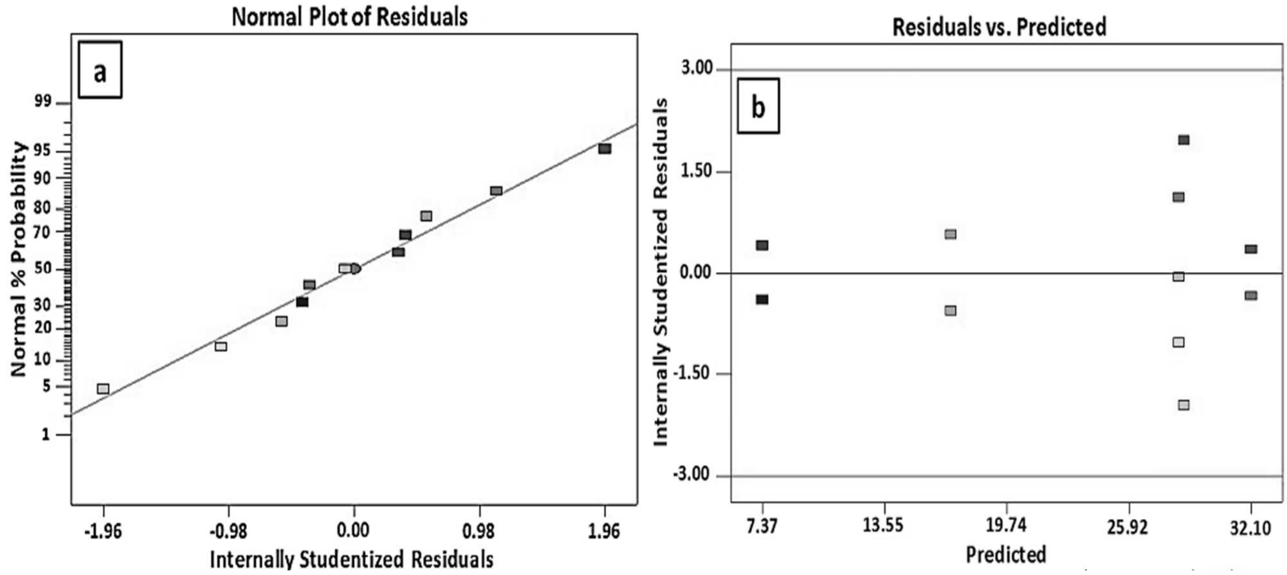

Fig. 8 *Normal Probability (a), Residual v/s Predicted Plot (b)*

The Analysis of Variance (ANOVA) conducted on the model demonstrated a significant curvature. This was confirmed by the contour and 3D plots presented in Fig. 9 (a, b), which provided a suitable direction to optimize the surface roughness of the produced components. However, it should be noted that the minimum surface roughness was not achieved in this work, indicating that further adjustments in a perpendicular direction are necessary to achieve the minimum value. Numerical optimization determined the minimum achievable surface roughness within the selected parameter range. The optimized result indicated a minimum value of approximately 7.4.

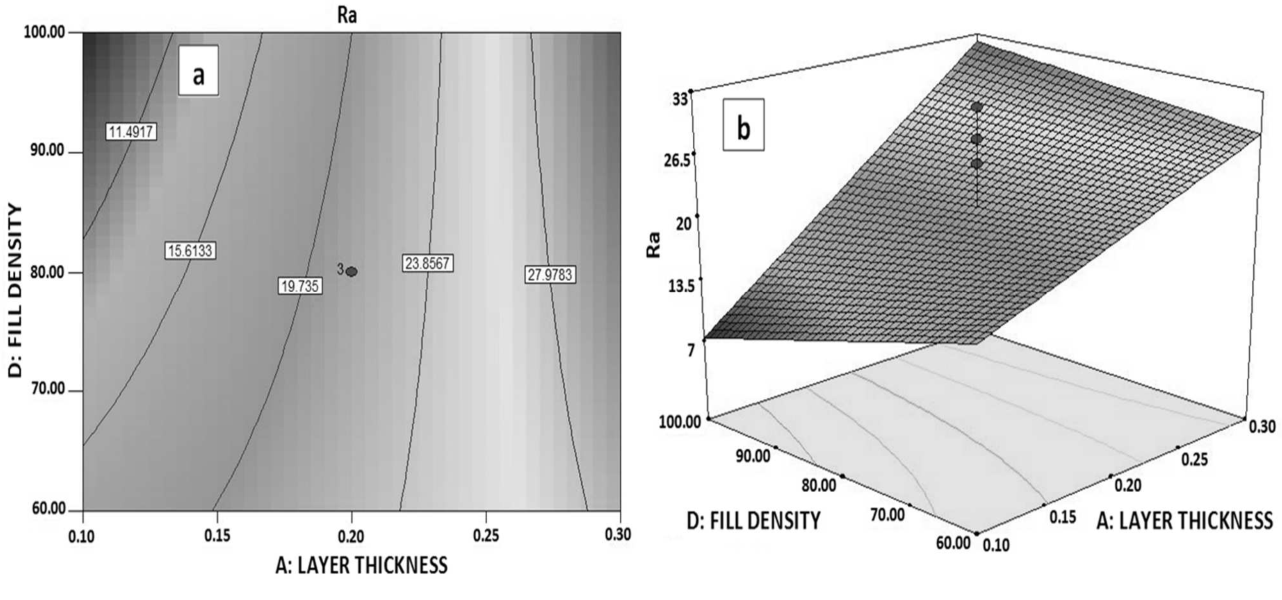

Fig. 9 *Contour (a), 3D surface roughness (b)*

3.2 Dimensional accuracy analysis and optimization

The measurements of the dimensions were conducted in the X, Y, and Z directions at various locations to compute the relative changes in length (ΔL), width (ΔW), and thickness (ΔT) of the parts. The measured values demonstrated that the length and width of the part exceeded the specified values, while the thickness fluctuated around the given value, with both decreases and increases observed. The data obtained from these measurements are presented in Tab. 5. To identify the significant factors, half-normal probability plots, and ANOVA tables were employed. The resulting ANOVA tables and the main and interaction effect plots are presented below for the dimensional accuracy of the tensile component.

Tab. 5 *ANOVA Tables for x, y and z errors*

Response 1 x error
ANOVA for selected factorial model
Analysis of variance table (Partial sum of squares – Type III)

Source	Sum of Squares	DF	Mean Square	F-Value	P-Value Prob>F	
Model	0.18	1	0.18	12.80	0.0072	Significant
D-Fill Density	0.18	1	0.18	12.80	0.0072	
Curvature	0.033	1	0.033	2.28	0.1699	Not Significant
Residual	0.11	8	0.014			
Leck of Fit	0.11	6	0.018	9.04	0.1029	Not Significant
Pure Error	4.067E-003	2	2.033E-003			
Cor Total	0.33	10				

Response 2 y error
ANOVA for selected factorial model
Analysis of variance table (Partial sum of squares – Type III)

Source	Sum of Squares	DF	Mean Square	F-Value	P-Value Prob>F	
Model	0.042	3	0.014	5.28	0.0404	Significant
A-Layer Thickness	0.029	1	0.029	10.73	0.0169	
B- Extrusion Temperture	2.450E-003	1	2.450E-003	0.91	0.3762	
AB	0.011	1	0.011	4.19	0.0865	
Curvature	4.909E-004	1	4.909E-004	0.18	0.6838	Not Significant
Residual	0.016	6	2.683E-003			
Leck of Fit	9.900E-003	4	2.475E-003	0.80	0.6219	Not Significant
Pure Error	6.200E-003	2	3.100E-003			
Cor Total	0.059	10				

Response 3 z error
ANOVA for selected factorial model
Analysis of variance table (Partial sum of squares – Type III)

Source	Sum of Squares	DF	Mean Square	F-Value	P-Value Prob>F	
Model	0.028	5	5.953E-003	12.49	0.0149	Significant
A-Layer Thickness	3.125E-004	1	3.125E-004	0.70	0.4506	
B–Extrusion Temperture	1.250E-005	1	1.450E-005	0.028	0.8754	
C-Speed of extrusion	4.513E-003	1	4.513E-003	10.07	0.0337	
D-Fill Density	0.021	1	0.021	46.91	0.0024	
AB	2.113E-003	1	2.113E-003	4.72	0.0956	
Curvature	3.864E-003	1	3.864E-003	8.63	0.0425	Significant
Residual	1.792E-003	4	4.479E-004			
Leck of Fit	9.250E-004	2	4.625E-004	1.07	0.4837	Not Significant
Pure Error	8.667E-004	2	4.333E-004			
Cor Total	0.034	10				

The fill density (D) was established as a significant factor for the dimensions along the x-axis, accounting for a 55.48% contribution, as per the ANOVA analysis, for the dimensions along the y-axis, layer thickness (A) was recognized as the significant factor, with a 63.56% contribution. The main factors influencing the dimensions along the z-axis were identified as the speed of extrusion (C) and the fill density (D), with percentage contributions of 13.42% and 62.50%, respectively.

The main effects plots indicated that an increase in fill density caused a rise in dimensional error along the x-axis. In contrast, an increase in the layer thickness and extrusion temperature resulted in a surge in dimensional error along the y-axis. Therefore, a lower fill density, layer thickness, and extrusion temperature would yield a lower dimensional error along the x and y-axes. However, a higher fill density (D) reduced the dimensional error along the z-axis. Using point prediction, an optimal fill density to minimize the dimensional error along the x, y, and z-axes was determined and presented in Fig. 10.

The dimensional accuracy along the y-axis was influenced by the layer thickness and extrusion temperature, with a decrease in dimensional accuracy observed at lower values of these factors. Conversely, the fill density was identified as the primary factor impacting the dimensional accuracy along the x and z axes. The numerical optimization approach revealed that minimizing all factors and setting the fill density to an optimal value of 69.15 would improve dimensional accuracy.

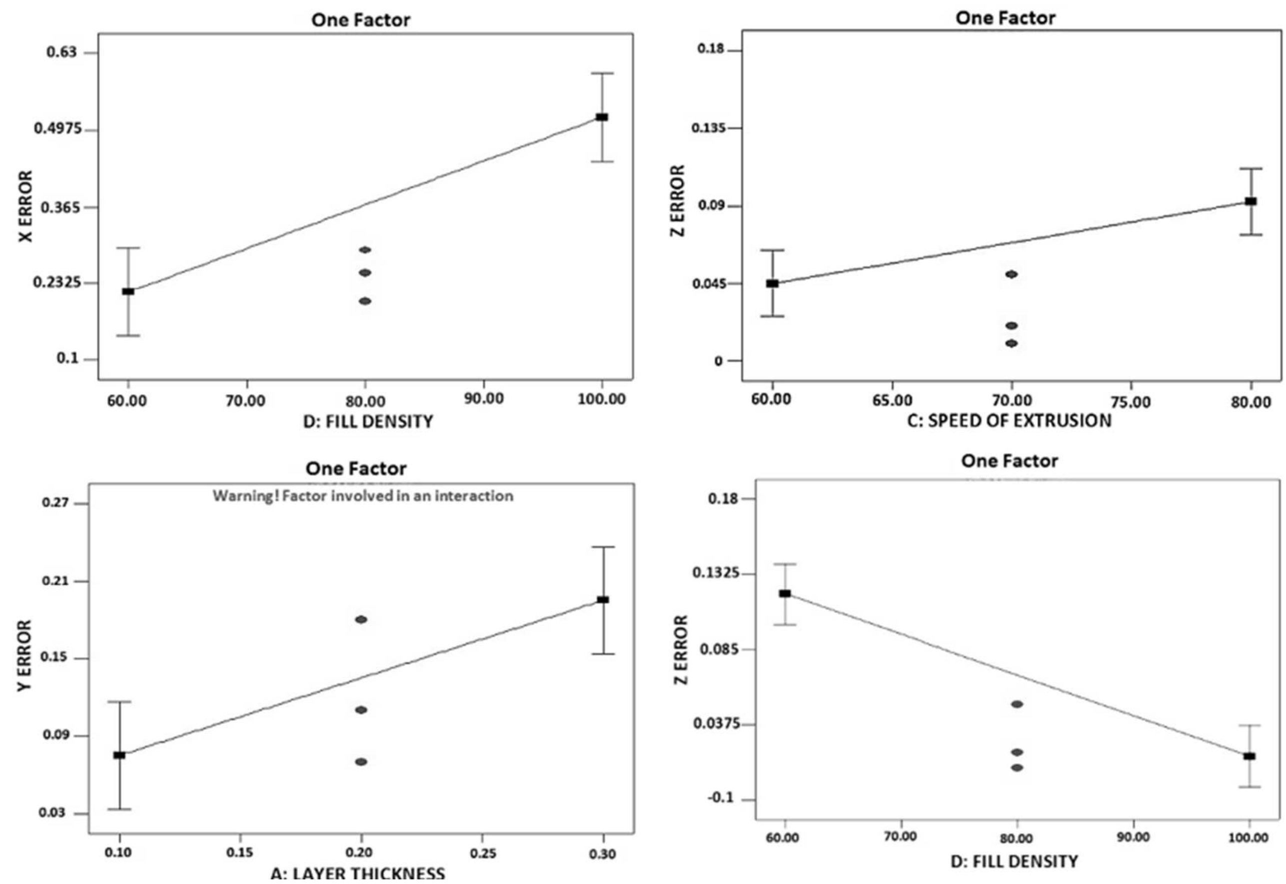

Fig. 10 *Effects Plots for X,Y, and Z Errors*

4 Conclusion

This study emphasizes enhancing the quality of the manufactured parts by controlling the process parameters. The influence of layer thickness (A), extrusion temperature (B), speed of deposition (C), and fill density (D) on the dimensional accuracy and surface roughness of the fabricated parts were examined and discussed. The analysis of variance was utilized to optimize the selected process factors. The results indicated that the best levels for improving surface roughness were a lower layer thickness of 0.1μm and a high fill density of 100%.

The results obtained from the numerical optimization showed a minimum surface value around 7.4μm. In dimensional accuracy optimization, lower levels of each factor, except for fill density (D), produced more accurate dimensions along the X, Y, and Z axes. Both layer thickness and extrusion temperature impacted the dimensional accuracy along the Y-axis. At the same time, the fill density was identified as the dominant factor affecting the dimensional accuracy along the X and Z axes.

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