

Optimization of FDM 3D Printing Process Parameters for PLA+ Material using Taguchi Design of Experiments (DOE)

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Abstract: *Abstract: Manufacturing (AM), or 3D printing, creates parts layer by layer from a digital design. Fused Deposition Modeling (FDM) is a widely used method for PLA + Materials due to its low cost and ease of use. This project focuses on improving the quality of PLA + material parts by setting important printing parameters such as layer height, print speed, nozzle temperature, bed temperature, infill percentage, and infill structure. The goal is to find the best combination of these parameters to get strong parts with a good surface finish, while also saving material and reducing printing time. . This project focuses on optimizing these parameters using Taguchi DOE and testing the samples for surface roughness and hardness. Then, an Artificial Neural Network (ANN) was used to study the relationship between the input parameters and the output results. The ANN model helped to predict which parameter combinations would give the best results. It also made it easier to find the best settings without doing too many physical experiments. This project shows that using ANN along with experimental testing is a smart way to improve the 3D printing process. The outcome is a clear method to choose the right settings for printing strong and smooth PLA+ Material efficiently.*

Keywords: Additive Manufacturing, Fused Deposition Machine, PLA+ Material, 3D

I. INTRODUCTION

The PLA+ (Polylactic Acid Plus) is an eco-friendly, biodegradable material derived from renewable resources like corn starch and sugarcane. It is an enhanced version of standard PLA, modified with special additives during the polymerization process to improve its strength, toughness, and thermal properties. Because it offers better layer adhesion, low warping, and a smooth surface finish, it is widely utilized for engineering prototypes, mechanical components, and various consumer products.

II. METHODOLOGY

The suitable material and 3D printing machine are selected based on their compatibility, ease of processing, and ability to produce good quality parts. The selection is made to ensure better performance, reliable results, and smooth printing. The chosen system allows control over important process parameters such as layer height, printing speed, and temperature, which are essential for conducting optimization studies and improving the final output quality.

2.1 Designing of Test Components

The required test specimens are created using Catia software. The designs are usually made according to standard testing dimensions, like ASTM D638 for tensile specimen. Proper design ensures that the printed parts can be tested accurately for strength, deformation, or other output parameters in later stages.



2.2 Selection of Input and Output Parameters

This step focuses on identifying the different printing settings that influence the FDM process. The input parameters include the various printer settings such as layer height, print speed, infill, and temperature, which directly affect how the part is built. The output parameters include the qualities Or Properties Observed After Printing, Such As Strength, Surface Finish, Or Dimensional Accuracy. Understanding these parameters helps in studying how changes in printing settings affect the final performance of the printed component.

2.3 Experimental Plan (Taguchi / DOE)

A systematic plan is created to conduct the experiments in an organized and efficient way. Taguchi or Design of Experiments (DOE) methods are used to arrange the trials so that the effect of each input parameter on the output can be studied with the minimum number of experiments. Instead of testing every possible combination, Taguchi's orthogonal array helps in choosing a smaller set of experiments that still provides meaningful and accurate information. This structured planning ensures that the experiments are carried out logically, reduces time and material usage, and helps in understanding which printing conditions influence the final performance of the parts.

2.4 3D Printing of Samples

The test specimens are printed using the FDM 3D printer according to the experimental plan. The printing is carried out by setting the required input parameters for each trial and preparing the printer with the chosen filament. Proper bed leveling, nozzle cleaning, and calibration are done to ensure smooth printing. Each sample is printed carefully under controlled conditions so that the results remain consistent. Once printed, the specimens are allowed to cool and are then removed from the build plate for further testing and evaluation.

2.5 Optimization of Process Parameters Using ML

Machine Learning (ML) enables prediction and optimization by learning from data to determine the best input conditions for desired outcomes. ML models can evaluate multiple parameter combinations virtually, identify optimal settings, and improve performance efficiently without physical experimentation, saving time, material, and effort.

2.6 Verification and Result Analysis

Machine Learning (ML) provides a powerful framework for predicting and optimizing outcomes based on data. After training, ML models can suggest the most effective input parameters for achieving desired results. The reliability of these predictions is verified by comparing the model's forecasts with actual experimental results. Accuracy, error percentage, and consistency are analysed to evaluate the performance of the ML model. This validation process ensures that ML-based optimization is trustworthy and can be confidently used to enhance quality, efficiency, and performance in practical applications, reducing reliance on trial-and-error methods and saving both time and resources.

2.7 Comparison of Experimental Results and ML Results

The actual experimental results are compared with the values predicted by the Machine Learning (ML) model. The differences between predicted and real values are analyzed to assess the accuracy and reliability of the ML model. Error percentages, graphs, or tables are used to visualize how closely the model predictions match experimental outcomes. This comparison helps evaluate the performance of the ML approach and demonstrates its ability to reliably forecast the behavior and quality of 3D- printed parts under different process conditions.

III. SELECTION OF MACHINE AND MATERIAL

Selection of Machine The machine is chosen based on factors such as ease of operation, reliability, availability, and compatibility with the required process parameters. machines are classified based on their working principles and the type of materials used.



- Fused Deposition Modelling (FDM)
- Stereolithography (SLA)
- Selective Laser Sintering (SLS)
- Digital Light Processing (DLP)
- Selective Laser Melting (SLM)
- Electron Beam Melting (EBM)

IV. FDM 3D PRINTING SYSTEM

Fused Deposition Modeling (FDM), also known as Fused Filament Fabrication (FFF), is one of the most widely used 3D printing techniques in additive manufacturing. In this process, three-dimensional objects are created by depositing melted thermoplastic material layer by layer based on a digital model. The process begins with a CAD design, which is converted into thin layers using slicing software, and the printer follows these instructions to build the object from bottom to top.

In FDM, a thermoplastic filament such as PLA, ABS, or PETG is fed into a heated nozzle, where it melts and is extruded onto a build platform. Each deposited layer cools and solidifies, bonding with the previous layer to form the final object. After printing, some post-processing steps like removal of supports or surface finishing may be required. FDM is widely popular due to its simplicity, low cost, and ease of use. It is commonly used for prototyping, product development, and manufacturing functional parts. However, it may produce visible layer lines and comparatively lower surface finish, and the strength of printed parts depends on printing parameters and orientation.



Figure 4.1: Fused Deposition Modelling

4.1 Working Principle of Fused Deposition Modelling

The working of Fused Deposition Modelling (FDM) is based on a simple layer-by-layer manufacturing process. It begins with creating a 3D CAD model of the desired object, which is then converted into a STL file and processed by slicing software. This software divides the model into thin horizontal layers and generates the toolpath that the printer's nozzle will follow during printing. Once the design is prepared, the printer starts building the object on a heated build platform. A thermoplastic filament such as PLA, ABS, or PETG is fed from a spool into a heated extrusion head. Inside the nozzle, the filament is heated to its melting point and extruded in a semi-liquid form. The nozzle moves precisely in the X and Y directions to deposit the material according to the digital design, while the build platform moves vertically (Z-axis) after each layer is completed. As each layer is laid down, it cools and solidifies, bonding with the previous layer to gradually form the final 3D object. In some cases, support structures are printed along with the main part to hold overhanging features or complex geometries. These supports are later removed manually or dissolved after



printing. Once the print is complete, post-processing steps such as sanding, polishing, or painting can be applied to improve the surface finish. Overall, the working of FDM is straightforward yet effective-it transforms a digital model into a physical object by melting and depositing thermoplastic material in successive layers. This process makes FDM one of the most cost-effective, user- friendly, and widely used 3D printing technologies in industries such as prototyping, education, and small-scale manufacturing.

4.3 Specifications of FDM Machine

1. Technology: FDM (Fused Deposition Modeling)
2. Build Volume: 250 × 220 × 220 mm
3. Machine Dimensions: 485 × 440 × 440 mm
4. Machine Weight: 7.3 kg
5. Nozzle Diameter: 0.4 mm (replaceable)
6. Maximum Nozzle Temperature: 260°C
7. Maximum Bed Temperature: 110°C
8. Printing Speed: Max: 250 mm/s Typical: 150 mm/s
9. Extruder Type: Direct drive extruder
10. Leveling System: Levi Q 2.0 Auto Bed Leveling (25-point)
11. Printing Platform: PEI magnetic spring steel bed
12. Control Panel: 2.4-inch LCD with knob control
13. Supported Materials: PLA, ABS, PETG, TPU
14. File Transfer: MicroSD card
15. Cooling System: High-speed fan (~7000 RPM)
16. Structure: Modular frame for easy assembly

4.4 PLA+ Material for 3D Printing

PLA+ material is an advanced biodegradable thermoplastic derived from renewable resources such as corn starch or sugarcane. Compared to standard PLA, PLA+ material contains additives that enhance its mechanical strength, toughness, and thermal stability. It exhibits a tensile strength of 55–65 MPa, flexural strength of 90-100 MPa, and elongation at break of 6-12%, offering improved flexibility and impact resistance. PLA+ also has a glass transition temperature of 60-65°C and a melting temperature of 175-185°C, ensuring stability during 3D printing. The material provides low shrinkage, excellent layer adhesion making it suitable for functional components as well as aesthetically detailed parts in FDM 3D printing.



FIG 4.2- PLA+ Material



V. DESIGNING OF TEST COMPONENTS

5.1 Introduction About Catia V5

CATIA is acronym of Computer Aided 3D Interactive Application. It is one of the leading 3D software used by organizations in multiple industries ranging from aerospace automobile to consumer products.

CATIA is a multi-platform 3D software suite developed by Dassault Systems, encompassing CAD, CAM as well as CAE. Dassault is a French engineering giant active in the field of aviation, 3D Design, 3D digital mock-ups, and product lifecycle management (PLM) software. CATIA is a solid modelling tool that unites the 3D parametric features with 2D tools and also addresses every Design-to-manufacturing process. In addition to creating solid models and assemblies, CATIA also provides generating orthographic, section, auxiliary, isometric or detailed 2D drawing views.

5.2 Modelling Procedure of a Tensile Test Specimen

1. Sketching: Initially the profile of the tensile specimen is drawn with the help of the sketcher tool as shown in fig 5.1.

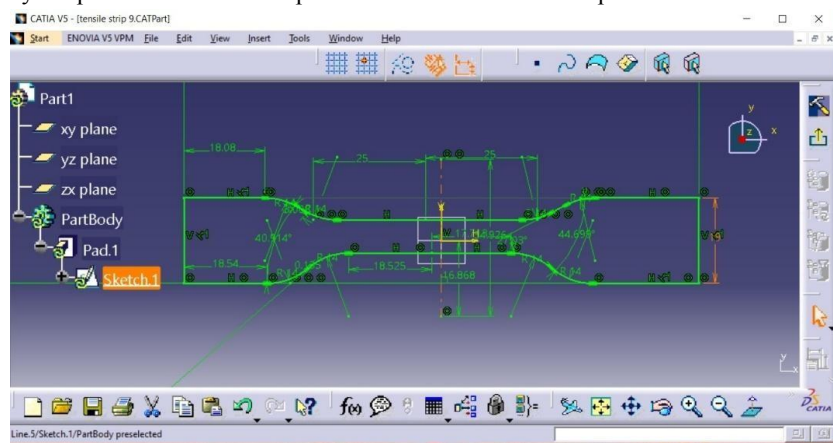


Fig 5.1: Sketch of tensile test specimen

2. PAD:

Creating the pad is extrude a 2D sketch into a 3D solid, adding material normal to the sketch plane, as shown in figure 5.2.

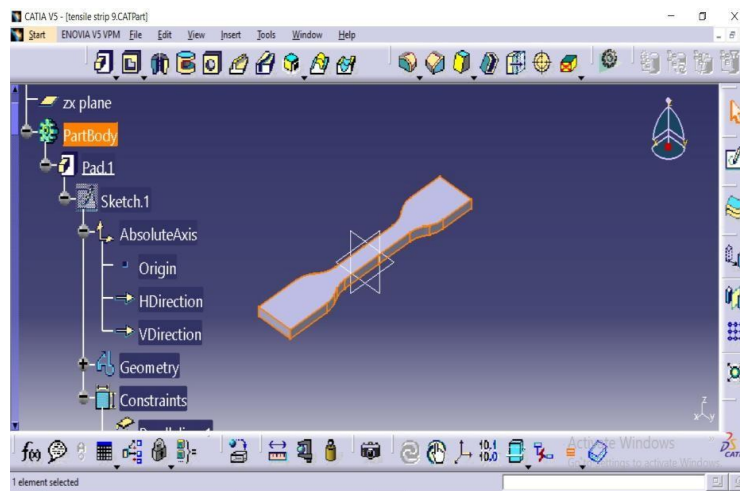


Fig 5.2: 3D modelling of tensile test specimen



3. FILE FORMAT:

These 3D modelling file is saved in STL format and the next step, These file is imported into ULTIMAKER CURA software.

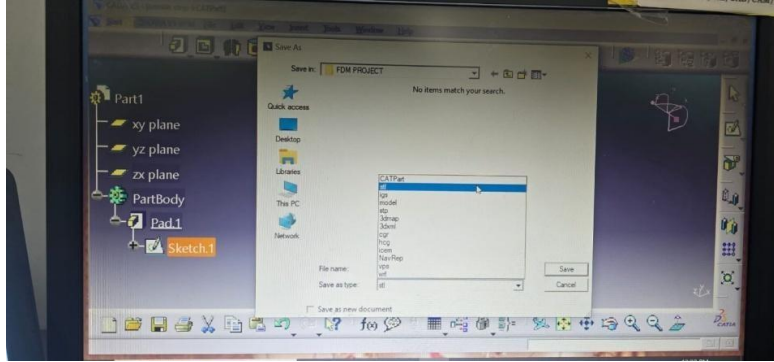


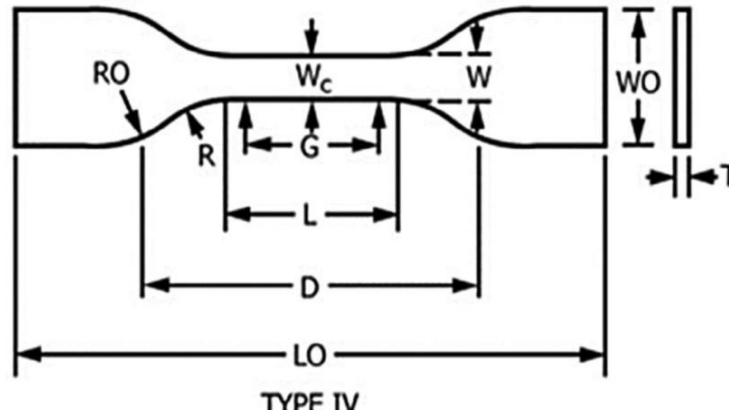
Fig 5.3: Format of file

5.3 Dimension of The Tensile Test Specimen

The tensile test specimen is designed according to standard of ASTM E8/E8M The specimen is a flat type with uniform thickness and a defined gauge section. The dimensions are specified as follows:

Table 5.1 Dimension Of The Component

Specifications	Units
Overall Length (Lo)	50MM
Overall Width (Wo)	15MM
Outer PART RADIUS (Ro)	3MM
CURVED PART RADIUS (R)	3MM
DISTANCE BETWEEN GRIPS(D)	30 MM
GAGE LENGTH (G)	20MM
THICKNESS (T)	2MM



VI .EXPERIMENTAL PLAN [TAGUCHI/DOE]

6.1 Overview

This chapter explains the method followed to design the experiments using the Taguchi Design of Experiments (DOE) approach. It includes the selection of control factors, their levels, and the choice of an appropriate Orthogonal Array (OA) using the Degree of Freedom (DOF) method. The Taguchi method helps in reducing the number of experiments while maintaining the accuracy of results.

6.2 Taguchi Design of Experiments (DOE) Preparation

The following steps will explore and help to prepare the best Design of Experiments:

6.2.1 Selection of Control Factors and Levels

Initially, five factors Insert layer Thickness, Printing Speed, Nozzle Temperature, Bed Temperature, Infill Density were considered. However, including all five would require a Taguchi Orthogonal Array (OA), which provides only less and fixed experimental combinations.

The DOE was designed using the following five input parameters and their levels as show in the Table 7.1.

Table 7.1: Control Factors and Their Level

Control Factor	Level 1	Level 2	Level 3
Layer Thickness (mm)	0.1	0.2	0.3
Print speed (mm/sec)	30	40	50
Nozzle Temperature (oc)	195	205	215
Bed temperature(oc)	50	57.5	65
Infill density (%)	50	75	100

Selection of OA in Taguchi Available Designs using DOF Method

The next step is to find the DOF (degree of freedom) to select an appropriate OA from the Taguchi Designs (with no.of factors). To calculate the total Degrees of Freedom (DOF), using the following formula.

$$\text{Total DOF} = \sum_{i=1}^k (L_i - 1)$$

Where:

k = number of control factors

Li= number of levels for the ith factor

Explanation:

Each factor with L levels contributes (L-1) degrees of freedom.

The minimum number of experimental runs (N) must be \geq total DOF + 1 (to include at least 1 DOF for error).

We should then select a Taguchi Orthogonal Array that has at least $N \geq$ Total DOF + 1 rows.

For our Case:

$$\text{Total DOF} = (3-1) = 2$$

For 5 factors:

$$2 + 2 + 2 + 2 + 2 = 10$$

Add 1 DOF for error:

$$\text{Total DOF} = 10 + 1 = 11$$

Hence, we should select the Orthogonal Array, which has greater value of OA than DOF (11) from available Taguchi Designs which is L27 Array, and is sufficient for 2 to 6 control factors with 3 level DOE preparation.

•Select the “Design...” and make sure that the “L27 – 3 ^ 5” is selected.



•Select “Factors...”, and enter the control factor names and their corresponding four levels in the “Taguchi Design: Factors” during the setup of L27Taguchi OA design.

Table 7.2: Prepared DOE for Conducting the Experimentation

List of L27 experiments					
S.No	Nozzle Temperature	Layer Thickness	Print Speed	Infill Density	Bed Temperature
1	195	0.1	30	50	50
2	195	0.1	30	50	57.5
3	195	0.1	30	50	65
4	195	0.2	40	75	50
5	195	0.2	40	75	57.5
6	195	0.2	40	75	65
7	195	0.3	50	100	50
8	195	0.3	50	100	57.5
9	195	0.3	50	100	65
10	205	0.1	40	100	50
11	205	0.1	40	100	57.5
12	205	0.1	40	100	65
13	205	0.2	50	50	50
14	205	0.2	50	50	57.5
15	205	0.2	50	50	65
16	205	0.3	30	75	50
17	205	0.3	30	75	57.5
18	205	0.3	30	75	65
19	215	0.1	50	75	50
20	215	0.1	50	75	57.5
21	215	0.1	50	75	65
22	215	0.2	30	100	50
23	215	0.2	30	100	57.5
24	215	0.2	30	100	65
25	215	0.3	40	50	50
26	215	0.3	40	50	57.5
27	215	0.3	40	50	65

VII. TESTING OF THE SAMPLES

8.1 Overview

The testing of printed samples is performed to evaluate the quality and performance of the fabricated parts, with surface roughness taken as the primary output parameter. Surface roughness represents the surface irregularities present on the printed components and plays a crucial role in determining the surface finish, functional performance, and overall quality of the product. In this study, surface roughness values are measured for each sample using appropriate testing equipment to understand the influence of various process parameters such as layer height, nozzle temperature, and print speed. Consistent testing conditions are maintained to ensure accuracy and reliability of results. The collected data is



then used for further analysis, comparison, and optimization to achieve improved surface finish and better printing performance.

- Surface Roughness Measurement
- Contact-Type Profilometer Method

8.2 Recording Data

During the experimentation, the input parameters such as nozzle temperature, layer thickness, print speed, infill density, and bed temperature are recorded for each trial based on the Taguchi design. After machining, the output responses including surface roughness (Ra) measured using a profilometer are noted. For surface roughness, multiple readings are taken at different locations of the specimen, and the average value is calculated to ensure accuracy. All the observed data is systematically tabulated for further analysis and optimization using machine learning techniques.

TABLE 8.1- INPUT PARAMETERS WITH OUT PUT PARMATERS [RA]

List of L27 experiments						
S.No	Nozzle Temperature	Layer thickness	Print speed	Infill Density	Bed Temperature	Ra (µm)
1	195	0.1	30	50	50	5.553
2	195	0.1	30	50	57.5	13.709
3	195	0.1	30	50	65	16.7
4	195	0.2	40	75	50	8.934
5	195	0.2	40	75	57.5	8.516
6	195	0.2	40	75	65	13.527
7	195	0.3	50	100	50	15.128
8	195	0.3	50	100	57.5	15.455
9	195	0.3	50	100	65	14.302
10	205	0.1	40	100	50	9.692
11	205	0.1	40	100	57.5	8.557
12	205	0.1	40	100	65	5.583
13	205	0.2	50	50	50	5.509
14	205	0.2	50	50	57.5	15.533
15	205	0.2	50	50	65	15.059
16	205	0.3	30	75	50	16.204
17	205	0.3	30	75	57.5	14.155
18	205	0.3	30	75	65	13.527
19	215	0.1	50	75	50	15.044
20	215	0.1	50	75	57.5	15.935
21	215	0.1	50	75	65	8.249
22	215	0.2	30	100	50	8.995
23	215	0.2	30	100	57.5	16.049
24	215	0.2	30	100	65	11.93
25	215	0.3	40	50	50	14.574



26	215	0.3	40	50	57.5	14.74
27	215	0.3	40	50	65	16.091

IX. DATA COLLECTION & PREPROCESSING

9.1 Overview

The data used in this study is collected from experimental trials conducted on 3D printing FDM based on the Taguchi design of experiments. The input parameters such as nozzle temperature, layer thickness, print speed, infill density, and bed temperature are systematically varied according to the experimental plan. The corresponding output responses, including surface roughness (Ra) measured using a profilometer.

Before applying machine learning techniques, the collected data is preprocessed to ensure accuracy and consistency. This includes checking for missing or inconsistent values, removing any experimental errors, and organizing the data in a structured format. If multiple readings are taken, average values are calculated to improve reliability. The dataset is then normalized or scaled if required to enhance model performance. Finally, the processed data is divided into training and testing sets for building and evaluating the machine learning models.

9.2 Taguchi Analysis of Surface Roughness (Ra)

9.2.1 Procedure of S/N Ratio Analysis for Surface Roughness

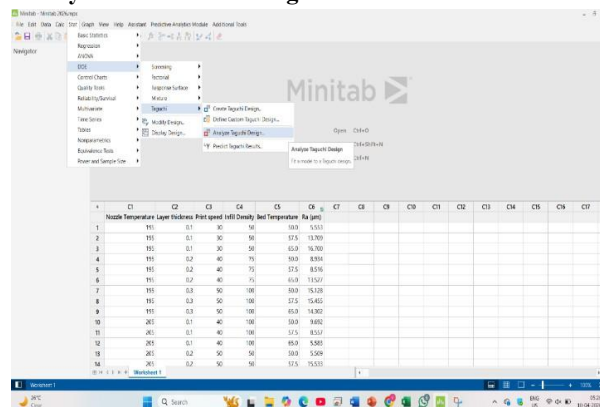
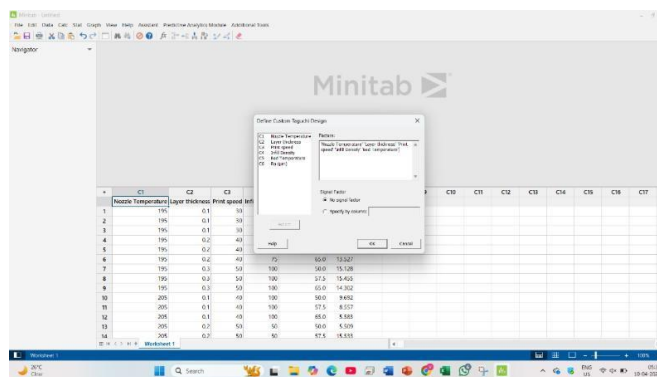
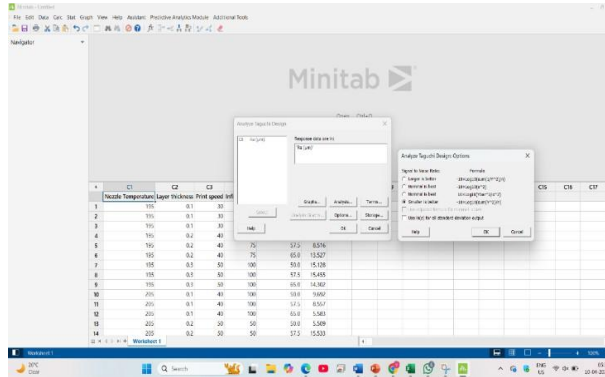


FIG 9.1- NAVIGATING TO THE S/N RATIO ANALYSIS



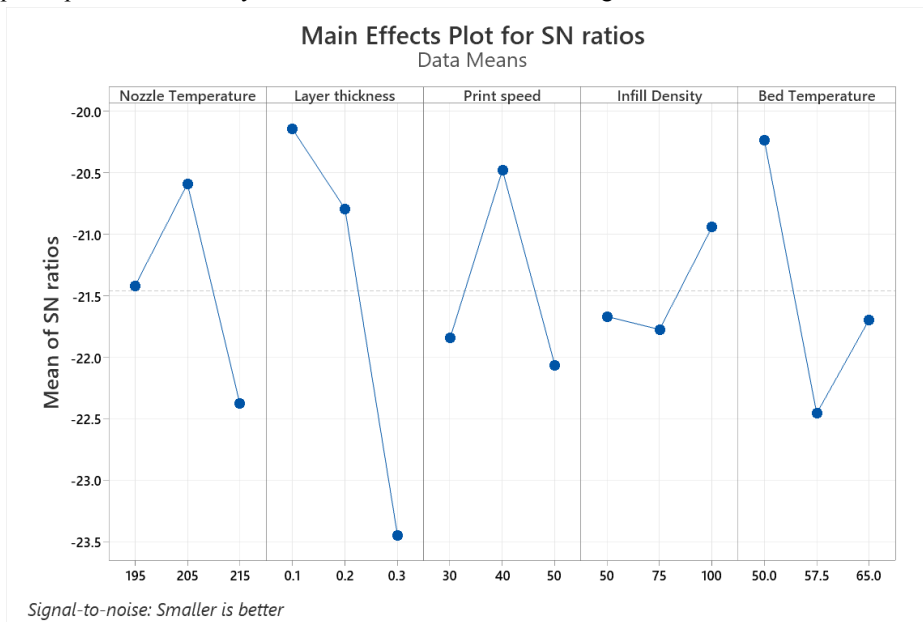


9.2.3 S/N Ratio Analysis for Surface Roughness

Surface Roughness (Ra) was analyzed using the “Smaller-the-Better” quality characteristic, aiming to minimize roughness.

Level	Nozzle Temperature	Layer thickness	Print speed	Infill Density	Bed Temperature
1	-21.42	-20.15	-21.85	-21.67	-20.24
2	-20.59	-20.80	-20.48	-21.78	-22.46
3	-22.38	-23.45	-22.07	-20.95	-21.70
Delta	1.79	3.31	1.59	0.83	2.22
Rank	3	1	4	5	2

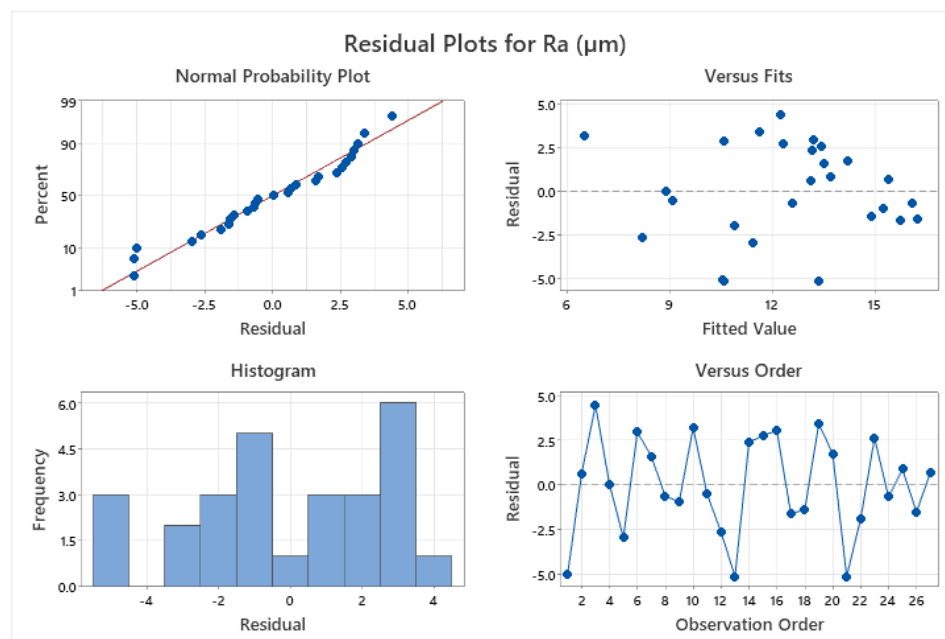
The layer thickness and bed temperature had the most dominant influence on surface roughness, followed by nozzle temperature, print speed. Infill density had the least effect as shown in Figure 6.1.



8.2.2 ANOVA Analysis for Surface Roughness

ANOVA was conducted on the S/N ratios to quantify the statistical significance of each input factor. The results are:
Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Nozzle Temperature	2	17.637	8.819	0.74	0.493
Layer thickness	2	80.317	40.159	3.36	0.060
Print speed	2	25.457	12.728	1.07	0.367
Infill Density	2	8.173	4.086	0.34	0.715
Bed Temperature	2	30.515	15.257	1.28	0.305
Error	16	190.965	11.935		
Total	26	353.063			



The P-value < 0.05 for layer thickness indicates strong statistical influence. Bed temperature is moderately significant, while infill density shows negligible effect.

8.2.4 Model Summary and Fit

R-squared (R^2): 81.91%

Adjusted R^2 : 12.11%

Standard error (S): 3.45475

Although the predictive capability from the Taguchi regression model is limited ($R^2 < 60\%$), the significance results justify that the dataset has meaningful patterns.

Result

The analysis of variance (ANOVA) results indicate that layer thickness has the most noticeable effect on the response, with the highest F-value (3.36) and a P-value of 0.060, making it nearly significant at the 90% confidence level, whereas nozzle temperature, print speed, infill density, and bed temperature show higher P-values (>0.05), indicating



that their individual effects are not statistically significant within the studied range, although they may still contribute to overall trends. The model summary shows a relatively high R-squared (R^2) value of 81.91%, suggesting that the model explains a large portion of the variability in the response; however, the adjusted R^2 is much lower at 12.11%, indicating possible overfitting and that many factors do not significantly contribute to the model. This large difference between R^2 and adjusted R^2 implies poor generalization and limited predictive capability. Additionally, the standard error (S) of 3.45475 reflects moderate variability in the residuals. Overall, while the Taguchi regression model is not suitable for prediction, it effectively captures underlying patterns and factor influences in the dataset, thereby validating its suitability for further analysis and machine learning applications.

Conclusion

the optimization of 3D printing process parameters for PLA+ material was carried out using the Taguchi method to evaluate the influence of key factors such as nozzle temperature, layer thickness, print speed, infill density, and bed temperature. The results from ANOVA indicated that layer thickness has the most significant effect on the response, while other parameters showed comparatively lesser influence within the selected range. The model summary revealed a high R-squared value (81.91%), suggesting good data fitting; however, the low adjusted R-squared (12.11%) indicated overfitting and limited predictive capability of the model. Despite this limitation, the Taguchi approach successfully identified meaningful parameter trends and their relative contributions. Therefore, the study concludes that while the developed regression model is not suitable for accurate prediction, it is effective for parameter analysis and optimization insights, and the dataset can be reliably used for further advanced techniques such as machine learning to improve prediction accuracy and process performance.

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