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Original Article

Optimizing Surface Roughness of PLA Printed Parts using Particle Swarm Optimization (PSO)

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Abstract *- Fused Deposition Modelling (FDM) is an additive manufacturing-based rapid prototyping technology that has gained widespread attention due to its ability to produce complex geometries with relatively low cost and fast production time. However, the surface finish of the FDM printed parts can be adversely affected by the selection of input parameters, such as layer height, infill density, print temperature, etc. This study aims to investigate the impact of these parameters on surface roughness and optimize the FDM process to improve surface finish. Two optimization approaches were employed in the study to address this problem, namely the Response Surface Methodology (RSM) and the particle swarm optimization (PSO) method. The impacts of four factors, layer height, printing speed, infill density, and print temperature, on the surface roughness of Polylactic Acid (PLA) printed parts were evaluated. A Face-centred Central Composite Design (FCCD) was used to reduce the number of experiments and to optimize the process. Both RSM and PSO methods were employed to find the best combination of process parameters for minimum surface roughness. The results of the experiment indicated that the optimal settings for minimum surface roughness were a layer height of 0.10 mm, printing speed of 30.36 m/s, infill density of 77.10 %, and print temperature of 195.12 °C, resulting in a surface roughness value of 1.31 µm. From these findings, the PSO optimization method was found to be more effective than the RSM method, showing a significant improvement in surface roughness with a reduction of 13.5 %.*

Keywords *- Fused deposition modelling, Surface roughness, Particle swarm optimisation, Response surface methodology, Face-centred central composite designs.*

1. Introduction

Additive manufacturing, specifically Fused Deposition Modeling (FDM), has significantly impacted manufacturing and prototyping due to its user-friendliness and lower cost compared to conventional techniques such as molding, computer numerical control machining, and forming. FDM is commonly used in rapid prototyping to create intricate geometric components for various industries, including medical device development, lab-on-a-chip technologies, ecological sciences, and natural sciences [1].

Its flexibility allows for quick and efficient production of components with complex structures, unlike traditional processes that can be more challenging and time-consuming [2]. It is crucial to evaluate the FDM process, identify areas for improvement, and make necessary adjustments to enhance part quality to meet the quality standards for FDM printed parts [3-5].

Two key factors for improving the properties of printed parts, including surface finish, tensile strength, wear strength, and compressive strength, are the use of improved materials and the proper configuration of FDM process parameters [6-8]. The development of new materials provides an opportunity to enhance the quality and mechanical characteristics of prototype models, but this depends on using the correct process parameters. Inadequate parameter settings can lead to negative consequences such as reduced mechanical properties, increased material consumption, deteriorated surface finish, prolonged manufacturing time, and higher manufacturing costs [9]. Adjusting the FDM process parameters effectively has been shown to improve the properties of printed models, as the FDM machine's settings influence the model's quality. Selecting the appropriate process parameters can enhance the quality of the printed model, and studying the influence of various parameters on output responses is necessary for determining the optimum settings.

As 3D printing technology and materials continue to advance, it has transitioned from being limited to prototyping to becoming a viable option for final product production. Ensuring that printed models possess the necessary mechanical and quality characteristics is crucial for their performance in large-scale additive manufacturing production [10]. Researchers have employed various advanced optimization techniques to determine the ideal combinations of process parameters for enhancing the mechanical characteristics and surface quality of printed parts. Traditional optimization approaches like full factorial design, Taguchi design approach, and response surface methodology (RSM) have been widely used in optimizing FDM processes. Traditional approaches are often used to optimise FDM process parameters such as printing temperature, infill density, printing speed, layer thickness, component orientation, and infill pattern, which greatly influence surface quality and mechanical qualities.

The Box-Behnken design was used by Vaibhav et al. (2022) to explore the effects of infill percentage, printing speed, and layer thickness on the surface quality, tensile strength, and printing time of PLA samples. The research found that decreasing layer thickness might enhance these properties since it significantly influenced the strength and surface quality of the printed parts [11]. Torres et al. (2016) used the Taguchi approach to investigate the impacts of layer thickness, printing speed, extrusion temperature, part orientation, infill density, and infill direction on the mechanical characteristics and surface quality of PLA printed parts. The results demonstrated that layer height and infill percentage substantially impacted surface finish and tensile strength. It should be noted, however, that decreasing layer thickness may have a detrimental influence on tensile strength [12]. Deswal et al. (2019) used a hybrid technique to increase dimensional accuracy and optimise FDM process parameters, using response surface methodology (RSM), artificial neural networks, and genetic algorithms. The research focused on internal density, layer thickness, line count, and manufacturing orientation to improve accuracy and reduce dimension deviation [13].

Tontowi et al. (2017) studied the effects of printing temperature, part orientation, and layer thickness on printing quality, including tensile strength and dimensional accuracy. Printing samples were analysed using response surfaces and Taguchi methodologies. The goal of the study was to obtain maximum tensile strength while retaining dimensional accuracy. The findings showed that layer thickness most influenced tensile strength [14]. Devicharana and Garg (2019) investigated several 3D printer input factors, such as printing speed, nozzle position, and bed temperature, to address initial layer adhesion and upper layer gaps. Using Pareto analysis, the research intended to enhance the quality of printed parts while lowering material prices and printing time [15]. Khatwani and Srivastava (2019) evaluated the bending and tensile strength of PLA specimens as a function of nozzle diameter, layer thickness, and printing temperature. SEM was utilised to analyse the fracture of the PLA components in the research, and it was discovered that raising the printing plate temperature enhanced both tensile and bending strength. Furthermore, in relation to mechanical properties, it was observed that layer thickness had a dual effect: it increased bending strength while decreasing tensile strength. Additionally, the initial positive impact of nozzle diameter on tensile strength was counterbalanced by a subsequent reduction in bending strength. [16].

Barua et al. (2019) investigated the link between FDM process parameters (layer thickness, raster width, raster angle, part orientation, and air gap) and the printed part's mechanical strength and surface roughness. The Taguchi method and the MOORA optimisation algorithm were used in the investigation. The findings emphasised the significance of part orientation in increasing mechanical strength and surface roughness [17, 18]. Srinivasan et al. (2022) investigated the effects of layer thickness, infill density, and infill pattern on ABS printed parts. The response surface technique with central composite design was used for statistical analysis and optimisation.

The results emphasized that infill density and layer thickness played a crucial role as the primary influential factors impacting the outcomes. [19]. Altan et al. (2018) investigated the effect of several features of the FDM process, namely layer thickness, nozzle temperature, and printing speed, on tensile strength and surface roughness. The Taguchi L16 orthogonal array was used to print PLA parts using various FDM settings. The findings revealed that layer thickness and deposition head velocity substantially impacted the final output. Lower layer thickness values were found to improve both the tensile strength and surface quality of the printed parts [20].

Numerous research studies have been dedicated to optimizing FDM process parameters, including printing temperature, infill density, printing speed, layer thickness, part orientation, and infill pattern, with the aim of significantly improving surface quality and mechanical properties. These investigations have consistently demonstrated the impact of layer thickness and infill percentage on FDM-printed parts' strength and surface quality. However, it is crucial to consider the potential negative effect of reducing layer thickness on the durability of the printed components. To address complex optimization problems, advanced computational techniques such as Particle Swarm Optimization (PSO), Symbiotic Organisms Search (SOS), Genetic Algorithm (GA), Firefly Algorithm (FA), and Artificial Bee Colony (ABC) have been employed and integrated with response surface methodology, factorial design, and Taguchi method experimental designs. These computational optimization techniques have shown promising outcomes when compared to traditional approaches. For instance, Rojek et al. (2018) utilized a Genetic Algorithm (GA) to optimize the 3D-printing process, specifically focusing on features and material selection, to achieve satisfactory tensile strength in a hand exoskeleton component [21]. Fountas et al. (2022) investigated the optimal parameter settings for the FDM process using the Grey Wolf Optimization (GWO) method, aiming to enhance the performance and longevity of printed parts [22]. By optimizing the FDM process, it is possible to enhance both the performance and durability of the printed parts, resulting in higher quality and more reliable components.

The experimental design was performed based on the response surface method with 27 runs of standard samples from ASTM D790 using Polyethylene Terephthalate Glycol (PET-G) material with five input parameters: printing speed, angle, infill density, layer height, and printing temperature. Results demonstrated that the algorithm could recommend a strong combination of parameter settings to maintain good flexural strength with a 15 percent improvement over the highest value achieved from the experimental data [23]. Sai et al. (2020) focused on improving the compressive strength, surface quality, and printing time of biomedical implant components by utilizing an Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Whale Optimization Algorithm (WOA).

The study's results demonstrated that the ANFIS-WOA approach successfully identified optimal FDM parameters that produced parts of better quality [24]. Deshwal et al. (2020) evaluated the efficacy of three hybrid optimization techniques: GA-ANN, GA-RSM, and GA-ANFIS. They found that GA-ANFIS outperformed the other strategies in terms of prediction accuracy and tensile strength, making it the most effective approach for optimizing FDM parameters and improving tensile strength [25]. These studies collectively highlight the importance of utilizing advanced optimization techniques to enhance the quality and reliability of FDM-printed components, resulting in improved performance and durability.

Although metaheuristic algorithms are widely used in FDM optimization research, Particle Swarm Optimisation (PSO) has received limited attention for optimising FDM process parameters to enhance printed component surface roughness. Nevertheless, a number of studies have demonstrated the efficiency of PSO in optimising printed components. In a study by Shirmohammadi et al. (2021), a hybrid technique incorporating artificial neural networks and a particle swarm algorithm was used to determine the optimal FDM process parameter for improving the surface quality of a rectangular sample. The outcomes demonstrated that the metaheuristic algorithm improved the surface imperfection of the printed parts [26]. Similarly, Raju et al. (2019) evaluated the efficacy of the FDM machine in producing specimens with enhanced surface quality and mechanical properties. The study examined the effects of a number of variables, including support material, layer height, part orientation, and internal pattern density. The results indicated that optimal results could be obtained with sparse support material, a layer height of 0.007 mm, a high-density internal pattern, and a part orientation of 60° [27].

In this particular study, the novelty lies in its integrated approach to optimize the Fused Deposition Modeling (FDM) process parameters for reducing surface roughness in printed components. Unlike traditional approaches, this study combined statistical analysis, specifically Response Surface Methodology (RSM) [28], with the Particle Swarm Optimization (PSO) algorithm, a metaheuristic optimization technique. This integration allowed for a more comprehensive exploration of the relationship between input parameters (layer height, infill density, printing temperature, and printing speed) and their impact on surface roughness.

The objective of this study was to determine the optimal combination of FDM process parameters to minimize surface roughness. This was achieved by employing a combination of Response Surface Methodology (RSM) and the Particle Swarm Optimization (PSO) algorithm. The experimental design utilized the Face-centered Central Composite Design (FCCD), which incorporated four key input parameters: layer height, infill density, printing temperature, and printing speed. Through Analysis of Variance (ANOVA), the effects of these input factors on surface roughness were investigated, providing insights into their individual significance and contribution.

Furthermore, the study aimed to establish the relationship between the selected input components and the resulting output responses, thereby understanding the underlying interactions. Experimental validation was performed to assess the accuracy of the findings, comparing predicted outcomes with physical tests on printed samples using the optimal parameter combination. This integrated approach of statistical analysis, PSO optimization and experimental validation enhanced the credibility and practical applicability of the results, thereby offering valuable insights for practitioners and researchers seeking to improve the surface quality of FDM-printed components.

2. Methodology

2.1. Test Configuration

This study utilized the FDM machine (Model: Ender-3 V2 Pro 3) to print the samples of PLA-type filament material. Figure 1 shows the sample dimensions (ASTM D638). The CAD drawing of the sample was converted into STL format and processed in CURA software to generate G-Code that is readable by the FDM 3D printer. Surface roughness testing was performed on all specimens using a surface roughness tester (Mitutoyo SV-C4500), as shown in Figure 2. The sample data was then statistically analysed using Design Expert software. This software enhanced data exploration and interpretation, allowing for a complete statistical assessment and inference. The study used statistical analysis to obtain important insights into the surface roughness characteristics of the investigated materials and develop relevant inferences based on the findings.

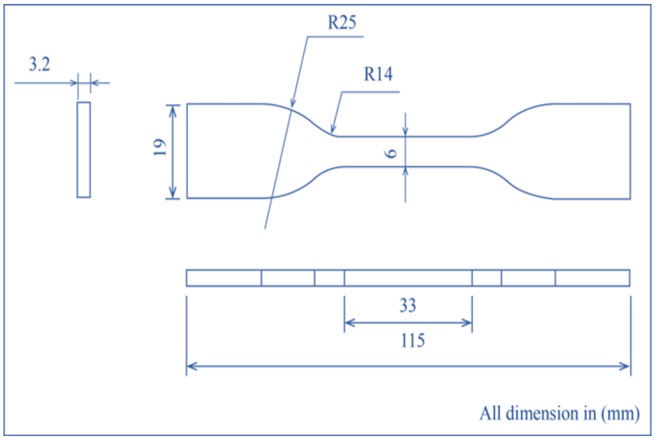

Fig. 1 Sample dimensions

2.2. Experimental Design

The use of experimental design, in general, aims to optimise the testing process while assuring high-quality outcomes by effectively gathering the data needed to build response models. Data was collected in the current investigation utilising the Face-centered Central Composite Design (FCCD) modified with extra centre and axial points, allowing for the estimate of a second-order model.

The experiment focused on four major input parameters: layer height (*A*), printing speed (*B*), infill density (*C*), and printing temperature (*D*), as outlined in Table 1. A total of 46 experimental runs were carried out to collect a thorough dataset, as shown in Table 2. Figure 3 shows the experimental samples produced from 46 different runs.

Fig. 2 SV-C4500 Mitutoyo formtracer

Table 1. FDM parameter levels

Parameter	Unit	Level 1	Level 2	Level 3
Layer height *(A)*	mm	0.06	0.18	0.3
Printing speed *(B)*	mm/s	30	45	60
Infill density *(C)*	%	20	50	80
Printing temperature *(D)*	°C	190	195	200

2.3. PSO Optimization for FDM 3D Printer

Particle Swarm Optimization (PSO) is a computational optimization algorithm modeled after the collective behavior of flocking birds or schooling fish. The algorithm initializes the population of a random particle to search for the best solution in the search space. Unlike traditional optimization methods that rely on the gradient or differential form of the objective function, PSO only requires the specification of the objective function, which is a relatively straightforward optimization technique [29]. In this study, the fitness function for the PSO algorithm was employed by the surface roughness regression model. Figure 4 shows a flowchart demonstrating the FDM 3D printer optimization approach using PSO. The steps involved in optimizing surface roughness in FDM 3D printing using PSO are as follows:

2.3.1. Configuring the Variables

- Set the maximum iterations.
- Set the population size.
- Set the particle velocity and particle position size.
- Determine the range for the input parameters.

2.3.2. Initialization

- Particle velocity and particle position: randomization of input parameters.
- Fitness function: surface roughness regression model.
- Evaluate the fitness function for each particle position.

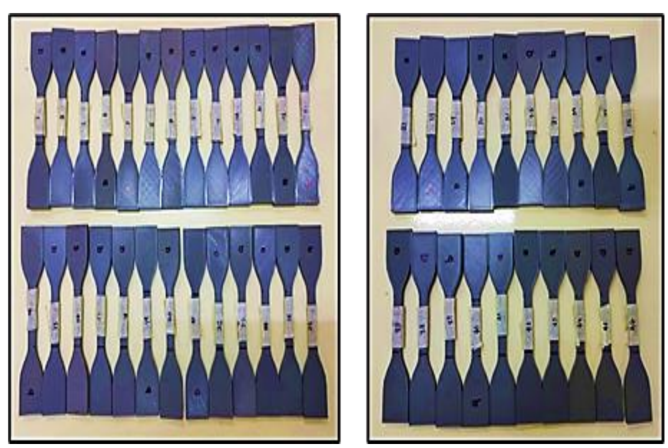

Fig. 3 ASTM D638 standard printed samples

Table 2. Experimental data for surface roughness

Number of samples	Parameter setting				Surface roughness (μm)
	A **(mm)**	***B*** **(mm/s)**	***C*** **(%)**	***D*** **(°C)**	
1	0.30	30.00	20.00	195.00	2.406
2	0.10	60.00	80.00	195.00	1.457
3	0.20	45.00	50.00	205.00	1.743
4	0.30	60.00	20.00	215.00	2.823
5	0.30	60.00	80.00	215.00	2.449
6	0.10	60.00	20.00	215.00	1.698
7	0.30	30.00	80.00	215.00	2.341
8	0.20	45.00	50.00	195.00	1.855
9	0.10	30.00	20.00	195.00	1.107
10	0.20	45.00	50.00	205.00	1.800
11	0.30	45.00	50.00	205.00	2.570
12	0.20	45.00	50.00	205.00	2.056
13	0.30	30.00	20.00	215.00	2.977
14	0.30	30.00	20.00	215.00	3.093
15	0.10	30.00	80.00	195.00	0.942
16	0.10	30.00	20.00	195.00	1.327
17	0.10	30.00	80.00	195.00	1.118
18	0.10	30.00	80.00	215.00	1.673
19	0.10	30.00	80.00	215.00	1.788
20	0.30	30.00	20.00	195.00	3.293
21	0.30	60.00	80.00	215.00	2.614
22	0.30	60.00	20.00	215.00	2.887
23	0.10	30.00	20.00	215.00	1.457
24	0.20	45.00	80.00	205.00	2.173
25	0.20	30.00	50.00	205.00	1.698
26	0.30	60.00	20.00	195.00	3.696
27	0.20	45.00	50.00	205.00	3.232
28	0.20	45.00	20.00	205.00	1.913
29	0.20	45.00	50.00	205.00	2.124
30	0.10	45.00	50.00	205.00	1.072
31	0.20	45.00	50.00	205.00	2.058
32	0.10	30.00	20.00	215.00	1.127
33	0.10	60.00	20.00	215.00	1.994
34	0.30	60.00	20.00	195.00	3.314
35	0.10	60.00	80.00	195.00	1.469
36	0.20	45.00	50.00	215.00	1.719
37	0.20	60.00	50.00	205.00	2.476
38	0.30	60.00	80.00	195.00	3.907
39	0.30	30.00	80.00	195.00	2.793
40	0.30	30.00	80.00	195.00	1.753
41	0.10	60.00	80.00	215.00	1.712
42	0.10	60.00	80.00	215.00	1.837
43	0.30	60.00	80.00	195.00	3.569
44	0.30	30.00	80.00	215.00	1.942
45	0.10	60.00	20.00	195.00	1.188
46	0.10	60.00	20.00	195.00	1.503

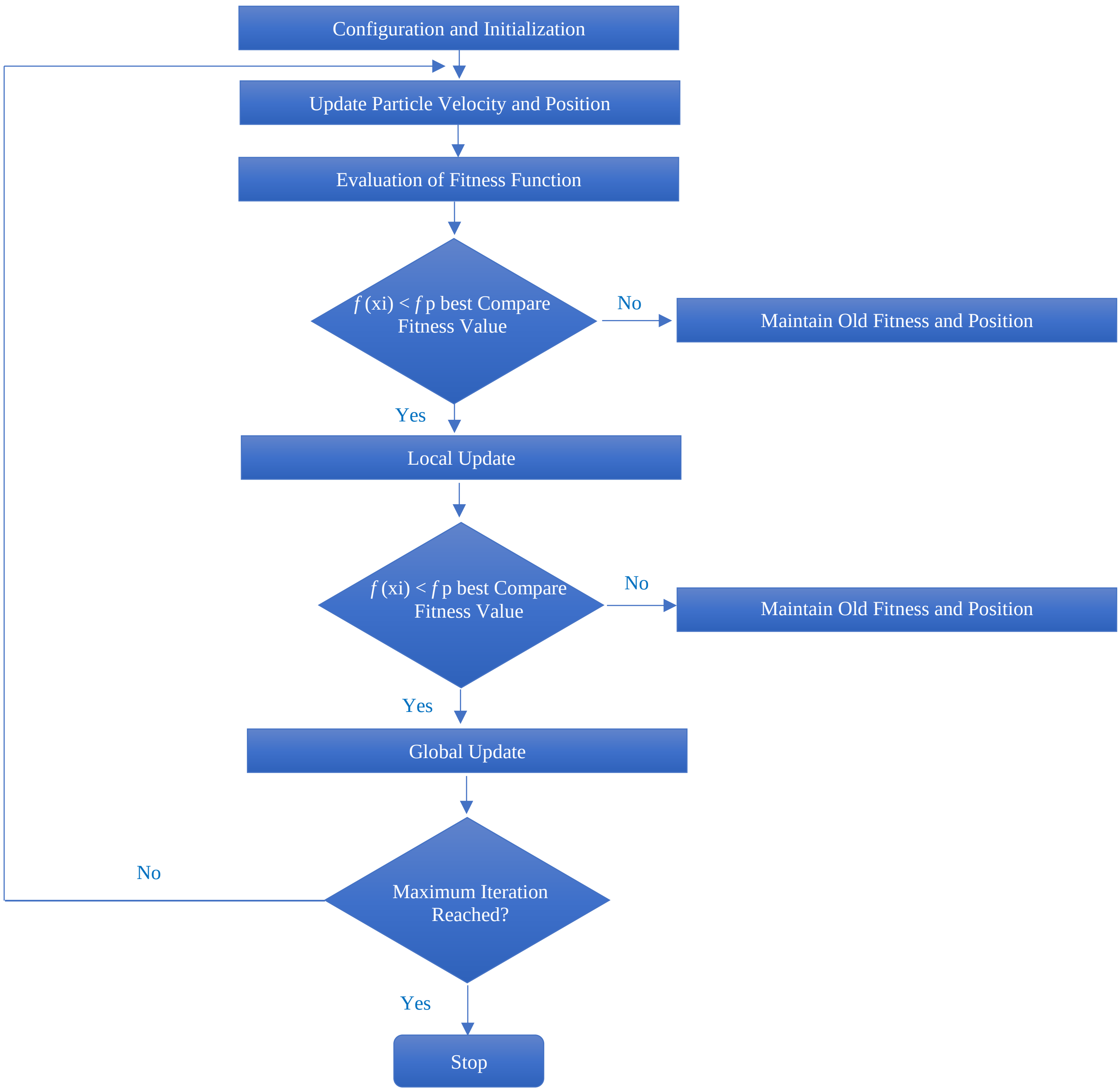

Fig. 4 PSO algorithm process for surface roughness

2.3.3. Main Program

Updating particle velocity and particle position.

Particle Velocity

$$v_i(k+1) = w.v_i(k) + c_1.rnd_1(x_{pbest} - x_i) + c_2.rnd_2(x_{gbest} - x_i) \quad (1)$$

Particle Position

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (2)$$

Where i represents the particle number, k denotes the iteration count, v_i denotes the velocity of the i-th particle, x_i is the position of the i-th particle, rnd_1 and rnd_2 are random values, w denotes weight inertia, c_1 represents the cognitive parameter, and c_2 represents the social parameter.

- Evaluation of particle position.
- Updating local best (*pbest*) and global best (*gbest*):
  - Compare the new fitness value (surface roughness value) with the old local fitness value. If the new fitness value outperforms the old fitness value, the new fitness value will substitute the old fitness value, and its particle position becomes the local best (*pbest*).
  - Compare the new fitness value (surface roughness value) with the old global fitness value. If the new

fitness value outperforms the old fitness value, the new fitness value will substitute the old global fitness to be the global best (*gbest*).

- Repeat steps a-c until the maximum iteration is reached.

Identification of optimal input parameter setting: After completing all iterations, the input parameter setting that results in the lowest surface roughness will be identified.

3. Results and Discussion

3.1. Analysis of Variance (ANOVA)

Analysis of variance (ANOVA), a statistical analysis method, was employed to investigate the impact of layer height, printing speed, infill density, and print temperature on the surface roughness of the printed parts. This study facilitated the identification of significant factors influencing surface roughness, enabling informed decision-making for process optimization and achieving improved results. The findings from the ANOVA study are summarized in Table 3.

The ANOVA test revealed a *p*-value of less than 0.0001, indicating that layer height had the most pronounced effect on surface roughness. Following layer height, printing speed, infill density, and printing temperature also exerted significant influences.

Furthermore, the interaction effects of specific parameter combinations, such as layer height and infill density (*AC*), layer height and printing temperature (*AD*), printing speed and printing temperature (*BD*), and the combination of printing speed, infill density, and printing temperature (*BCD*), were found to have substantial impacts on surface roughness.

Using Design Expert tools, further investigation was conducted to determine the variable terms and coefficients of the quadratic model. The model's validity was assessed through ANOVA, considering factors such as model significance, lack of fit, and the *R*-squared value. The *p*-value of the model was found to be less than 0.0001, indicating its importance and excellent fit to the experimental data. Terms with *p*-values exceeding 0.05 were considered non-significant. The significant model term confirmed the appropriateness of the chosen model for the experimental data. Additionally, the lack of fit, which measures the model's fitness to the data, was determined to be minimal (0.3433) compared to the pure error, indicating a good fit between the model and the actual data.

The coefficient of determination, often known as *R*-squared, was calculated to assess how well the model explains variance in the response variable. The model performed effectively, demonstrating an *R*-squared value of 85.55 % for surface roughness and an adjusted *R*-squared value of 80.29 %. The adjusted *R*-squared factor considers the number of predictors in the model. It increases only when adding a new term significantly improves the model beyond chance.

However, it was lower than the R-squared value, indicating that the model's accuracy was overestimated. In brief, the statistical analysis utilising ANOVA and the evaluation of model significance, lack of fit, and the R-squared value provided a complete picture of the connection between input parameters and surface roughness. These discoveries significantly enhance the FDM process, resulting in a superior surface in the end.

Table 3. ANOVA analysis for surface roughness

Source	Sum of squares	*df*	Mean square	*p*-value	Comment
Model	118.00	15	7.87	< 0.0001	Significant
Model	0.66	12	0.055	< 0.0001	Significant
A	0.51	1	0.51	< 0.0001	-
B	0.056	1	0.056	0.0003	-
C	1.567×10^{-3}	1	1.567×10^{-3}	0.5016	-
D	4.059×10^{-4}	1	4.059×10^{-4}	0.7316	-
AC	9.993×10^{-3}	1	9.993×10^{-3}	0.0955	-
AD	0.046	1	0.046	0.0008	-
BC	2.860×10^{-3}	1	2.860×10^{-3}	0.3652	-
BD	6.634×10^{-3}	1	6.634×10^{-3}	0.1713	-
CD	5.099×10^{-4}	1	5.099×10^{-4}	0.7008	-
A^2	4.187×10^{-3}	1	4.187×10^{-3}	0.2747	-
BCD	9.662×10^{-3}	1	9.662×10^{-3}	0.1009	-
A^2D	2.072×10^{-3}	1	2.072×10^{-3}	0.4401	-
Residual	0.11	33	3.393×10^{-3}	-	-
Lack of Fit	0.046	12	3.799×10^{-3}	0.3433	Not Significant
R-squared				0.8555	Adequate
Adj R-Squared				0.8029	Adequate

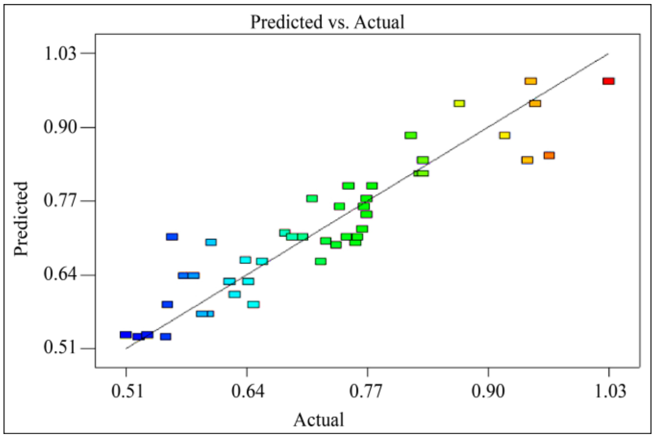

Fig. 5 Comparison of experimental and predicted surface roughness values

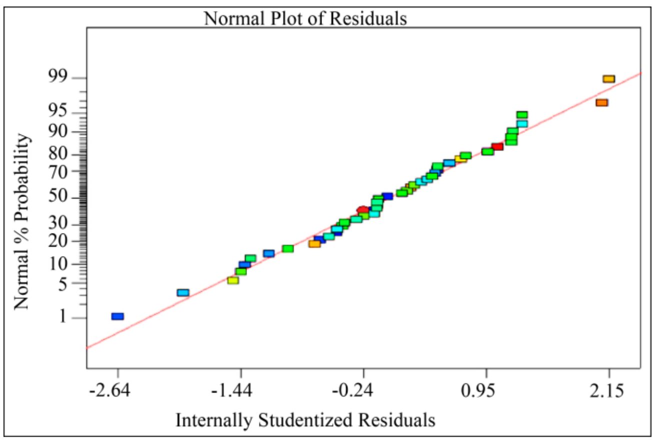

Fig. 6 Normal probability plot of residuals for surface roughness

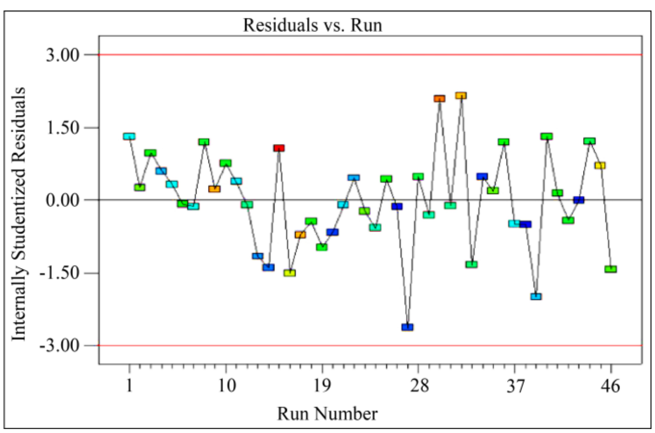

Fig. 7 Residuals vs Run Plot for surface roughness

The comparison of the experimental and predicted values of the RSM model for surface roughness is depicted in Figure 5. An ideal fit should have points clustered around the fitted line. The points on either side of the plot, farthest from the mean, have a great influence and can significantly affect the position of the fitted line. The graph indicates that the majority of the plotted points are near the fitted line, suggesting that the quadratic model developed provided accurate predictions for estimating the predicted surface roughness values.

It is imperative to perform a suitable statistical analysis to confirm the adequacy of any model before accepting it. A normal probability distribution was employed to verify whether the residuals are normally distributed, which should yield a straight line. Figure 6 displays that most of the data points fall close to the line, indicating that the model fits the data well and that there are no substantial problems with response normality or transformation.

The run residual plot is a type of scatter plot in which each residual is plotted against an index that shows the data collection run number (in time). The goal of this plot is to see if there is any process drift. From the residual plot shown in Figure 7, there are no obvious patterns, negative or positive. The point of each run is between the minimum and maximum limits, indicating no drift in this experimental result. This outcome supports the accuracy of the regression model in predicting surface roughness based on the selected process parameters. Based on this experimental result, the surface roughness regression model is given by Equation 3.

$$1/\sqrt{R_a} = 4.11565 - 37.40326A + 0.018253B + 0.038343C - 0.014428D + 5.89038 \times 10^{-3}AC + 0.17078AD - 8.12606 \times 10^{-4}BC - 9.70798 \times 10^{-5}BD - 1.87071 \times 10^{-4}CD + 70.18228A^2 + 3.86145 \times 10^{-6}BCD - 0.33175A^2D \quad (3)$$

3.2. *Interaction Effect Analysis*

The presence of interaction effects is of utmost importance as it reveals how the combination of FDM process parameters influences the output response, specifically the surface roughness of the printed sample. In this study, the focus lies on three significant interactions, namely the interactions between layer height and infill density (*AC*), layer height and print temperature (*AD*), and print speed and print temperature (*BD*), as determined by the ANOVA data.

Figure 8 illustrates the interaction effect of layer height and infill density on surface roughness. It demonstrates that while the surface roughness increases with higher layer heights, the variation in infill density has no discernible impact on surface roughness, even at lower layer heights. Consequently, infill density can be considered to have a negligible effect on surface roughness in this particular interaction.

Notably, the maximum surface roughness occurs when the layer height is at its highest value of 0.30 mm, coupled with the lowest infill density of 20.00 %. According to the ANOVA analysis, the interaction effect between layer height and infill density is statistically significant, as indicated by a *p*-value of 0.0955.

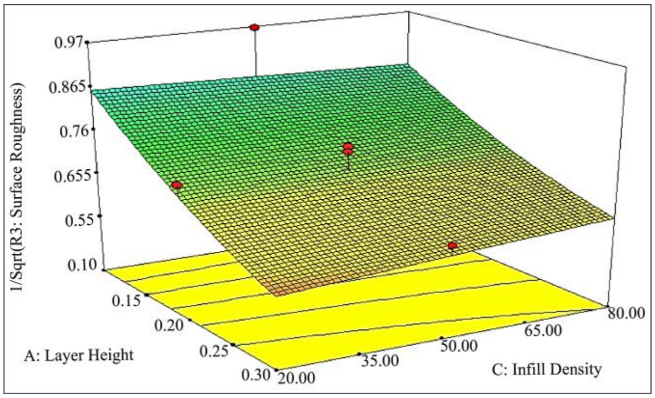

Fig. 8 Surface roughness interaction plot of layer height and infill density

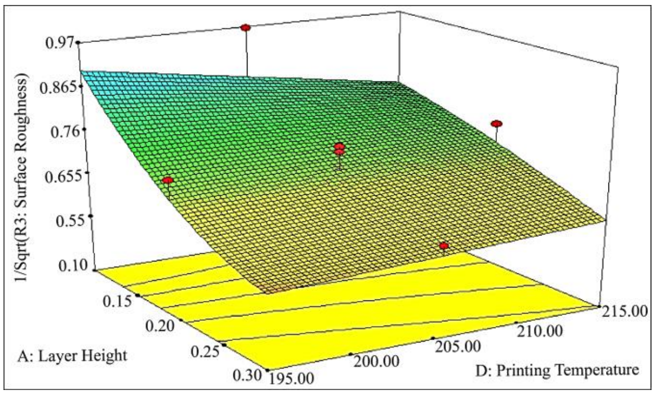

Fig. 9 Surface roughness interaction plot of layer height and print temperature

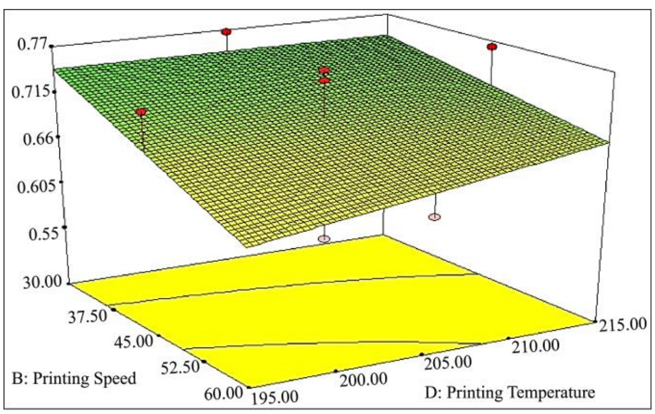

Fig. 10 Surface roughness interaction plot of print speed and print temperature

Furthermore, Figure 9 illustrates the interaction effect between layer height and print temperature on surface roughness. Optimal surface roughness is achieved at the maximum layer height of 0.30 mm and the minimum print temperature of 195.00 °C. Notably, reducing the print temperature does not impact surface roughness at higher layer heights; the same applies to lower layer heights. Hence, in this particular scenario, it can be deduced that print temperature has a minor impact on surface roughness. Conversely, optimizing the layer height results in an enhanced surface roughness. The ANOVA analysis confirms the statistical significance of the interaction effect between layer height and print temperature, as denoted by a *p*-value of 0.0008.

Additionally, Figure 10 demonstrates the interaction effect of print speed and print temperature on surface roughness. Decreasing the print temperature significantly affects surface roughness at higher print speeds, and the same trend is observed at lower print speeds. Thus, in this interaction, lowering the print temperature and increasing the print speed have a notable impact on surface roughness. Furthermore, the maximum surface roughness in this interaction occurs at the highest print speed of 60 mm/s and the lowest print temperature of 195.00 °C. However, the ANOVA analysis indicates that the interaction effect between print speed and print temperature is not statistically significant, with a *p*-value of 0.1713.

3.3. RSM Optimization Result

Optimizing the FDM process to achieve the lowest surface roughness involved employing Response Surface Methodology (RSM) with the assistance of Design Expert software. Before conducting the optimization, it was necessary to define the range of input parameters and output response. The results, presented in Table 4, demonstrated that the lowest surface roughness of 1.077 µm could be attained by setting the layer height, printing speed, print temperature, and infill density to 0.10 mm, 30.00 mm/s, 196.73 °C, and 79.4 %, respectively. These findings indicate that better surface roughness can be achieved by minimizing the layer height, printing speed, and print temperature while maximizing the infill density. According to the ANOVA analysis, the factors with the most significant impact on surface roughness were layer height and printing speed. Fine-tuning these parameters has the potential to yield a substantial improvement in the surface roughness of printed parts.

Table 4. RSM optimization result for surface roughness

Process parameter	Unit	Values
Layer height (*A*)	mm	0.10
Printing speed (*B*)	mm/s	30.00
Infill density (*C*)	%	79.41
Printing temperature (*D*)	°C	196.73
Optimum surface roughness (R_a)	µm	1.077

3.4. PSO Optimization Result

The objective of employing the Particle Swarm Optimization (PSO) algorithm was to identify the optimal combinations of parameters that would yield the lowest surface roughness. The search for the optimal value of surface roughness was conducted within the specified parameter constraints outlined in Table 1. The PSO algorithm utilized Equation (3) as the objective function for evaluating surface roughness. In this algorithm, the fitness value represented the surface roughness, while the position and velocity of particles in the population represented the input parameters. The initial configuration of the PSO constant parameters can be found in Table 5.

Table 5. PSO algorithm initial setting

Parameter	Setting value
No. of particles (No. of population)	300
Particles steps (No. of iteration)	500
No. of process parameter (Dimension)	4
Cognitive acceleration constant, c_1	1.5
Social acceleration constant, c_2	1.5
Weight inertia, w	0.4

The outcomes of applying the Particle Swarm Optimization (PSO) algorithm to identify the optimal FDM input parameters for achieving minimal surface roughness are illustrated in Figure 11. The convergence profile reveals that the optimal solution was attained after 200 iterations, with a rapid decrease in the fitness value. Table 6 displays the optimal parameters, which were determined to be a layer height of 0.1002 mm, a print speed of 30.36 mm/s, an infill density of 77.11 %, and a print temperature of 195.12 °C. The results indicate that reducing the layer height and increasing the printing speed can contribute to an enhancement in surface quality.

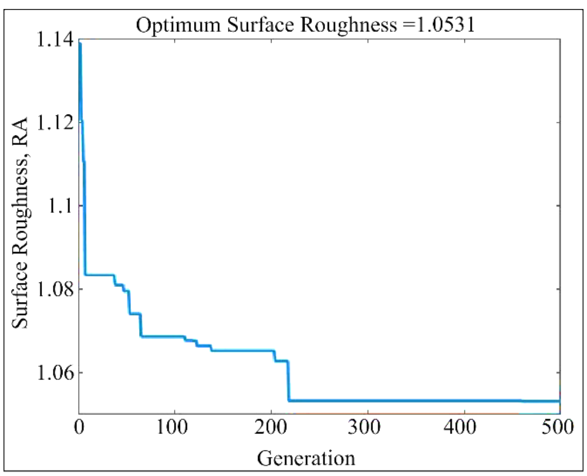

Fig. 11 Convergence profile of surface roughness

Table 6. Optimization result by using PSO.

Process parameter	Values
Layer height (mm)	0.10
Print speed (mm/s)	30.36
Infill density (%)	77.11
Print temperature (°C)	195.12
Optimum surface roughness (R_a)	1.0531

3.4. Experimental Confirmation Test

In this study, the Particle Swarm Optimization (PSO) method was experimentally validated to determine the optimal process parameters for reducing surface roughness in fused deposition modeling. The results, as presented in Table 7, clearly demonstrate the superior performance of the PSO method in identifying process parameters that lead to reduced surface roughness. The predicted improvement was 2.26 %, while the observed experimental improvement was 13.5 %. The experimental confirmation results from the Mitutoyo SV-C4500 Formtracer, shown in Figures 12 and 13, further validate the effectiveness of PSO and its ability to significantly reduce the surface roughness of printed parts by searching for the optimal parameter settings.

Fig. 12 Graph for RSM validation

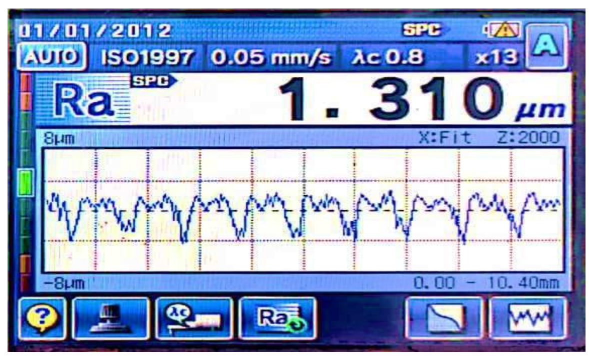

Fig. 13 Graph for PSO validation

The findings clearly demonstrate that the PSO algorithm outperforms the traditional method in terms of optimization. This can be attributed to the nature of how the PSO works, utilizing a population-based searching method with randomization. In contrast, RSM optimizes based on the gradient descent approach. The population-based searching method in PSO allows for a more comprehensive exploration of the parameter space, leading to better convergence and more accurate optimization results. On the other hand, the gradient descent approach of RSM may sometimes get stuck in local minima, limiting its ability to find the global optimum. Therefore, the PSO algorithm proves to be a more effective and robust optimization technique in this study. Moreover, the findings underscore the potential of metaheuristic optimization algorithms in advancing the field of 3D printing and optimizing various performance parameters in future research.

Table 7. Experimental confirmation test for RSM and PSO.

	Input Parameter				Predicted	Experiment
	A (mm)	*B* (mm/s)	*C* (%)	*D* (°C)		
RSM	0.10	30.00	79.41	196.73	1.08	1.48
PSO	0.10	30.36	77.10	195.12	1.05	1.31
Percent Improvement					2.26 %	13.5 %

4. Conclusion

In conclusion, the study demonstrated that utilizing the PSO method to optimize FDM process parameters effectively improves the surface quality of printed parts. The results of the ANOVA analysis showed that layer height and printing speed were the most significant factors affecting surface roughness.

The experimental confirmation test using the optimized parameters confirmed that the PSO algorithm significantly improved surface roughness compared to traditional RSM optimization methods, with a reduction of about 2.26 % for predicted tests and 13.5 % for experimental tests.

The findings clearly demonstrate that the PSO algorithm outperforms the traditional method in terms of optimization.

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