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Optimization of 3D Printing Process Parameters to Minimize Surface Roughness with Artificial Neural Network and Harris Hawks Optimization

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Abstract— ***Fused Deposition Modeling (FDM) is an additive manufacturing technique in which components are built layer-by-layer by extrusion of thermoplastic material. This technique offers the advantages of complex, customized geometries with lower material waste and production costs than conventional manufacturing. Despite these benefits, FDM often results in high surface roughness, characterized by the unevenness of a part's exterior surface. The surface roughness of the printed samples can be adversely affected by the selection of input parameters, such as infill density, printing speed, and layer thickness. This study aims to investigate the impact of these parameters on surface finish and optimize FDM printing parameters to minimize surface roughness by employing an Artificial Neural Network (ANN) integrated with Harris Hawks Optimization (HHO) method. The impact of five parameters, nozzle temperature, bed temperature, infill density, printing speed, and layer thickness, on the surface roughness of Polylactic Acid (PLA) printed parts were evaluated. The Taguchi Orthogonal Array (OA) was used to reduce the number of experiments and to optimize the process. The results of the study indicated the optimal settings for minimum surface roughness were a nozzle temperature of 219.98°C, bed temperature of 50.46°C, infill density of 37.94%, printing speed of 284.25 mm/s, and layer thickness of 0.20 mm, resulting in a surface roughness value of 2.7903 µm, upon printing the sample with the obtained optimal values, the surface roughness was measured as 4.4421 µm, which gives an error percentage of 37.18%.***

Index Terms— ***Artificial Neural Network, Fused Deposition Modeling, Harris Hawks Optimization, Surface Roughness***

I. INTRODUCTION

Fused Deposition Modeling (FDM) is one of the most widely used additive manufacturing technique due to its ability to fabricate complex and customized components with reduced material waste and production cost. In this process, thermoplastic material is extruded through a heated nozzle and deposited layer by layer to build three-dimensional parts. The simplicity of operation and availability of low-cost materials have made, FDM popular in prototyping, product development, and small-scale manufacturing applications.

Despite these advantages, the qualities of printed samples have high surface roughness. Surface roughness is a critical quality characteristic that influences the mechanical performance, dimensional accuracy, and aesthetic appearance of printed components. It is primarily affected by process parameters such as layer thickness, printing speed, nozzle temperature, and build orientation. Improper selection of these parameters can lead to uneven material deposition and surface defects.

Conventional approaches for improving surface quality rely on post-processing techniques, which are time consuming and increased manufacturing cost. In the recent years, optimization techniques have gained attention as effective alternatives for predicting and improving surface quality in additive manufacturing processes. Artificial Neural Network (ANN) are particularly effective in capturing the nonlinear relationship between process parameters and output response.

II. LITERATURE REVIEW

FDM offers significant advantages such as design flexibility, material efficiency, and cost-effective production of complex and customized parts. However, the quality of FDM-printed components strongly depends on process parameters, and improper settings often result in poor interlayer bonding and `high surface roughness, limiting its use in precision applications [1]. A study on stereolithography (SLA) of dental models found that layer thickness and support structures significantly influence surface roughness, while model type and build position have minimal effect. Under optimized parameters, printed models can achieve better surface finishes compared to milled or conventionally fabricated models [2]. The research investigates the effect of infill density, material density, and extrusion temperature on the tensile strength of Acrylonitrile Butadiene Styrene (ABS), Polyethylene Terephthalate Glycol (PETG), and a combination of 50% of ABS and 50% of PETG and printed the samples using FDM 3D printing. Using a hybrid ANN- Genetic Algorithm (GA) approach, process parameters were optimized, achieving a 4.54% improvement in tensile strength, with experimental validation confirming the model accuracy [3]. A study investigated the optimization of FDM 3D printing parameters using Polylactic Acid (PLA) material on a Raise3D N2plus 3D printer and cylindrical sample of diameter 10mm, height of 15mm.The parameters taken for this study are layer thickness, printing time and materials consumption, without affecting the quality of the sample. Finally, layer thickness of 0.14 mm gives the lesser printing time and material consumption without affecting the quality of the printed sample [4]. A study optimization of FDM process parameters for PLA, focusing on layer thickness (0.15-0.35mm), nozzle temperature (210-220°C), and infill density (55-65%) using the Taguchi L9 orthogonal array to enhance surface roughness, tensile strength, and hardness of the specimen. The achieved optimal settings were 0.35 mm of layer thickness, 65% of infill density, and 220°C of nozzle temperature for tensile strength; 0.25 mm of layer thickness, 65% of infill density, and 215°C of nozzle temperature for hardness; and 0.15 mm of layer thickness, 55% of infill density, and 215°C of nozzle temperature for minimal surface roughness [5].This study aims to determine the optimal combination of input parameters to minimize the surface roughness using the ANN and particle swarm optimization (PSO) method. The 43 experiments are designed by using Central Composite Design (CCD) and the parameters considered for this study are nozzle temperature, layer thickness, printing speed, nozzle diameter and infill density. The optimal value are 192.20°C of nozzle temperature,100 µm of layer thickness, 97.06 mm/s of printing speed,0.3 mm of nozzle diameter and 24.88% of infill density lead to the surface roughness of 11.319 µm.The hybrid algorithm predicted the surface roughness with an error of 4.88% [6].The purpose of this research is to optimize the surface roughness in FDM 3D printing by comparing Response Surface Methodology (RSM), Particle Swarm Optimization (PSO), and Symbiotic Organism Search (SOS) algorithms. Layer height, printing speed, print temperature, and outer shell speed are the key parameters considered for this study. The predicted value of surface roughness using RSM is 2.295 µm with an error of 6.10%. Similarly, for PSO and SOS is 2.176 µm and 2.18 µm with an error of 2.68% and 2.21% respectively. This study shows that metaheuristic algorithms can be used for enhancing 3D printing components surface quality [7]. This paper focuses on minimizing circularity error and surface roughness in FDM-based biomedical implant fabrication. The selected significant parameters are printing temperature, printing speed and layer thickness. Using the Taguchi method, the influence of selected parameters was analyzed, and optimal settings were identified to minimize circularity error are 210°C of printing temperature, layer thickness of 0.2 mm, and 50mm/min of printing speed. Similarly for achieving minimal surface roughness, the optimal values are 190°C of printing temperature, same values of layer thickness and printing speed. This study also reveals that printing speed and printing temperature are the influencing parameters for circularity error and surface roughness respectively [8]. This study aims on single and multi-objective optimization to FDM process parameters. The input variables chosen for this study are layer height, infill, printing temperature, and print speed. The output parameters are weight, printing time, and tensile strength. For single objective optimization, the Taguchi L16 orthogonal array was used for Design of Experiments (DOE). Infill, and printing temperature influences the weight. While, layer height and print speed influences the printing time. Layer thickness, and infill the tensile strength of the printed components. For multi-objective optimization, the RSM and Non-Dominated Sorting Genetic Algorithm (NSGA-II) was used to find the best combination of the three output variables [9]. The purpose of this research is to optimize the PLA samples manufactured by using FDM process. The input factors for this process are layer thickness, print speed, print temperature, retraction distance, and infill percentage. The output response is to minimize the dimensional error. Since, there is large error between the theoretical and experimental value. This optimal value are taken from the third experimental run(X_3) and the values are layer thickness of 0.05 mm, printing speed of 50mm/s, print temperature of 210°C, retraction distance of 1.5 mm, and infill percentage of 25% [10].

III. METHODOLOGY

A. Test Configuration

The experimental work begins with designing the National Advisory Committee for Aeronautics (NACA) 2412 airfoil model by using the Computer Aided Design (CAD) software, SolidWorks 2024.The NACA 2412 airfoil is a well-regarded profile from the NACA 4-digit series, frequently analyzed within aerodynamic research. This particular model was selected due to its advantage in both aerodynamic efficiency and structural integrity [11]. It features a camber of 2%, with its maximum camber located at 40% of the chord length from the leading edge, alongside a maximum thickness accounting for 12% of the chord length [12]. The coordinates for the NACA 2412 airfoil were collected and modeled accordingly. The airfoil is chosen for the study, because of the approach to optimize the curved top surface of the airfoil, instead of the flat surface. Since, the bottom of the airfoil is also curved, to provide a stable reference during roughness measurement, a flat bottom is added. The study utilized a Mingda MD-400D, a FDM 3D printer and the overall specifications of this FDM 3D printer are detailed in Table 1. Mingda MD-400D FDM 3D printer machine shown in figure 1. The Computer Aided Drawing (CAD) of the sample was converted into STL format and processed in MINGDA slicer software to generate G-Code that is readable by the FDM 3D printer. Figure 2 shows the sample dimensions and the dimensions are in millimeters (mm). The isometric view of airfoil is shown in figure 3.The five input parameters influencing the surface roughness (the output parameter) of the 3D printed samples are, nozzle

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temperature (*A*), bed temperature (*B*), infill density (*C*), layer thickness (*D*), and printing speed (*E*).The printing material utilized for the model was Polylactic Acid plus (PLA+), a biodegradable thermoplastic similar to PLA but with enhanced properties through the addition of various kind of additives. The main reason for choosing PLA+ is due to durability and flexibility [13]. The properties of PLA+ are shown in Table 2. To assess the surface roughness of the specimens, measurements were conducted using a Mitutoyo Surftest SJ-410 series device. The Mitutoyo Surftest SJ-410 series surface roughness tester is shown in figure 4.

Table I. Specification of FDM 3D Printer

Parameters	Units	Values
Printing speed	mm/s	300
Nozzle diameter	mm	0.4
Print volume	mm^3	400 x 400 x 400
Extruder temperature	°C	Recommended below <320 Maximum = 350
Material types	Subject	PLA, TPU, PETG
Machine dimension	mm^3	690 x 790 x 910
Maximum flow	mm^3/s	40

Table.II Properties of PLA+ material

Properties	Units	Values
Density	g/cm^3	1.23
Tensile Strength	MPa	60
Flexural Strength	MPa	74
Flexural Modulus	MPa	1973
Elongation at break	%	20
Extruder Temperature	°C	210-230
Bed Temperature	°C	45-60
Printing Speed	mm/s	40-100

Fig.1 FDM 3D Printer

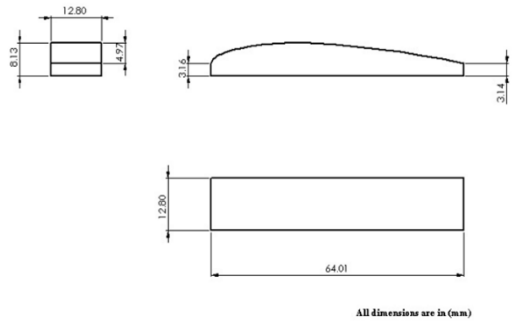

Fig.2 Sample Dimensions

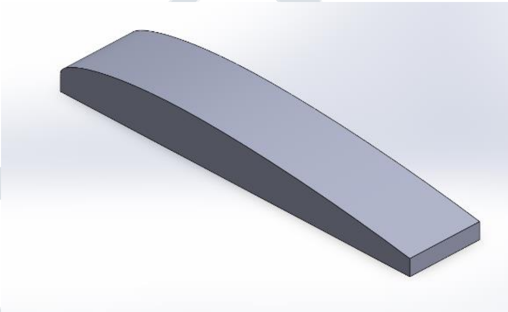

Fig.3 Isometric view of NACA 2412 airfoil

Fig.4 Mitutoyo Surf test SJ-410 series surface roughness tester

B. Design of Experiment

The Taguchi is the one of the most widely used DOE in the field of additive manufacturing. It able to work well for single optimization problem and this method helps to reduce the number of experiments and gives the similar results like other DOE[9].Taguchi is simple to apply and easy to understand and it has three specific situations, they are nominal-the-better, larger-the-better, and smaller-the –better[14].Since, there are five input parameters and three levels, the appropriate Orthogonal Array(OA) for this criteria is Taguchi L27 Orthogonal Array (OA).It has 27 different runs of experiment. For full factorial design, the 243 experiments has to be done which is time consuming and increase the cost of production for each sample. So, L27 OA is used to study the impact of input variables instead of doing 243 experiments while maintaining robust data for analysis. This reduces an experiment percentage to 88.9%. Here, the aim is to minimize the surface roughness by optimizing the process parameters.

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The input variables and levels are chosen from the previous literature and the specifications of FDM 3D printer. The input variables for this study are nozzle temperature, bed temperature, infill density, layer thickness, and printing speed. The three levels are selected for the study. The input parameters and its levels are shown in Table 3.A total of 27 experimental run were designed and tabulated in Table 4. Fig.5 shows the FDM printed samples from 27 different runs.

Table III. FDM Parameters units and Levels

Parameter	Units	Level 1	Level 2	Level 3
Nozzle temperature(*A*)	(°C)	215	220	225
Bed temperature(*B*)	(°C)	49	53	56
Infill density(*C*)	(%)	20	50	80
Layer thickness(*D*)	(mm)	0.1	0.2	0.25
Printing speed(*E*)	(mm/s)	200	250	300

C. Hybrid Approach

This study provides clear information about Artificial Neural Networks (ANN), inspired by how the human brain works. It learns from examples, adapt to data easily. The ANN has the input, hidden, output neurons [15]. But the limitation in ANN is slow learning. So, the metaheuristic algorithm is adopted to overcome this limitation and to find the optimal 3D printing process parameters [6]. The combination of ANN with HHO method referred as hybrid approach. The meta-heuristic algorithm chosen for the study is Harris Hawks Optimization (HHO) algorithm. The algorithm models the cooperative hunting behaviour and surprise pounce strategy of Harris hawks in nature. This algorithm mathematically mimics the dynamic chasing patterns and behaviours of these predatory birds to develop an effective optimization technique [16]. First, the ANN is model is developed with 10 hidden neurons, which gives the objective function for the HHO algorithm. Based on these objective function the HHO algorithm starts to find the optimal values of the selected 3D printing process variables. The ANN-HHO convergence curve is shown in figure 6 and the curve starts to converge from the 70th iterations. The maximum iteration used for study is 100 and at, the 100th iteration the value of surface roughness is 2.7903 µm.

Table IV. Experimental Data for Surface Roughness

Number of Samples	*A*(°C)	*B*(°C)	*C* (%)	*D*(mm)	*E*(mm/s)	Surface Roughness (µm)
1	215	49	20	0.1	200	3.811
2	215	49	20	0.1	250	3.883
3	215	49	20	0.1	300	6.017
4	215	53	50	0.2	200	5.02
5	215	53	50	0.2	250	4.723
6	215	53	50	0.2	300	5.04
7	215	56	80	0.25	200	5.542
8	215	56	80	0.25	250	5.474
9	215	56	80	0.25	300	6.311
10	220	49	50	0.25	200	5.5
11	220	49	50	0.25	250	5.849
12	220	49	50	0.25	300	5.294
13	220	53	80	0.1	200	5.372
14	220	53	80	0.1	250	4.525
15	220	53	80	0.1	300	5.102
16	220	56	20	0.2	200	4.54
17	220	56	20	0.2	250	5.14
18	220	56	20	0.2	300	4.474
19	225	49	80	0.2	200	5.721
20	225	49	80	0.2	250	6.434
21	225	49	80	0.2	300	5.833
22	225	53	20	0.25	200	5.456
23	225	53	20	0.25	250	5.246
24	225	53	20	0.25	300	4.795
25	225	56	50	0.1	200	5.418
26	225	56	50	0.1	250	6.696
27	225	56	50	0.1	300	3.743

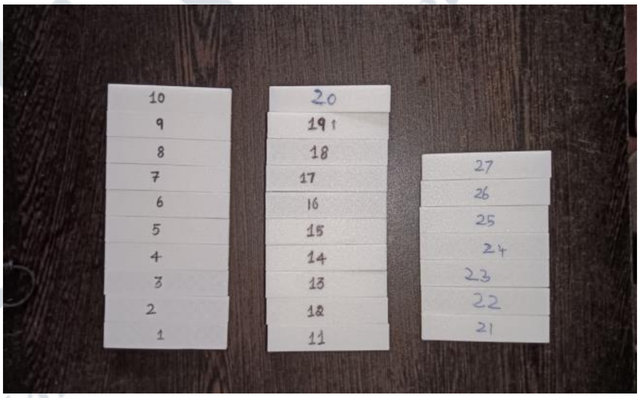

Fig.5 FDM Printed Samples

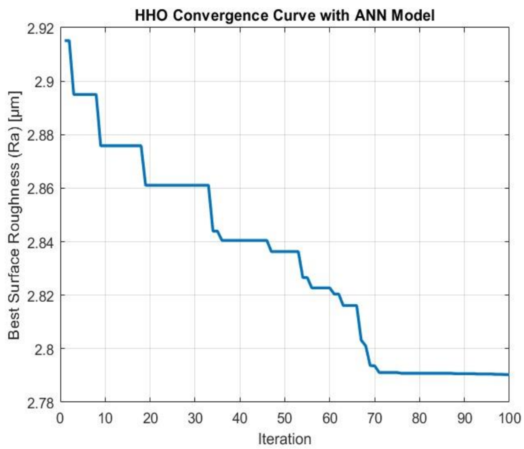

Fig.6 ANN-HHO convergence curve

IV. RESULTS AND DISCUSSION

The predicted optimal values of the ANN-HHO algorithm are shown in Table 5. The predicted value of surface roughness from the model is 2.7903 µm.But while performing the experiment using the optimal values, the surface roughness is 4.4421 µm. This shows a high error percentage whose value is 37.18%. This high error is mainly due to two reasons, limited number of data and lack of model fit. The model has an R^2 value of 0.683. The parameter sensitivity analysis is also done to identify how the input parameters affects the output parameters.Fig.7 show the ANN-HHO performance in actual and predicted surface roughness values. The parameter sensitivity analysis revealed that the most influencing parameter is layer thickness, next to that nozzle temperature and finally bed temperature. The infill density and printing speed had negligible effect on surface roughness.Fig.8 shows the parameter sensitivity analysis.

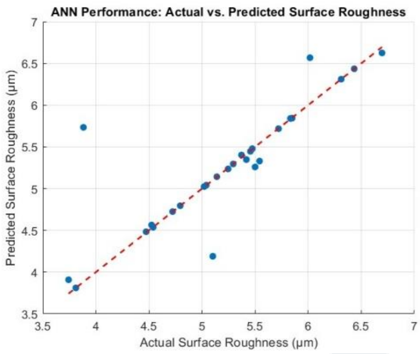

Fig.7 Actual Vs. predicted surface roughness

Table V. Optimal parameters values from ANN-HHO Optimization

Process Parameters	Units	Values
Nozzle Temperature(*A*)	(°C)	219.98
Bed Temperature(*B*)	(°C)	50.46
Infill Density(*C*)	(%)	37.94
Layer Thickness(*D*)	(mm)	0.20
Printing Speed(*E*)	(mm/s)	284.25
Predicted Surface Roughness (R_a)	(µm)	2.7903

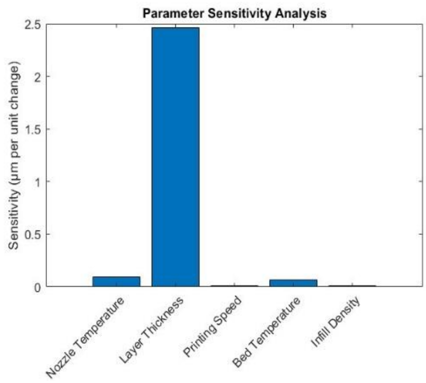

Fig.8 Sensitivity analysis

V. CONCLUSION

This study successfully investigated the influence of key FDM process parameters on the surface roughness of PLA components and proposed an integrated optimization approach using ANN-HHO method. The Taguchi L27 orthogonal array is used to design the experiments. The hybrid model identified an optimal combination of printing parameters that minimized surface roughness. But, the high error is due to the lack of data required for the model. Future work may focus on adding additional parameters, such as cooling rate and raster orientation, and enhancing model accuracy through larger datasets to further improve prediction value of the model and optimize the process**.**

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