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Research Article

Optimizing FFF Process Parameters to Enhance PLA Performance on Low-Cost 3D Printers

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Abstract: PLA (Polylactic Acid) is well known for its biodegradable properties and ease of use; however, a careful tuning of parameters such as infill density, layer height, feed rate, build orientation, and nozzle temperature is crucial to achieve the optimum strength and durability of the sample produced. While it has its own benefits, a low-cost FDM 3D printer often comes with limitations that affect the mechanical performance of printed parts, including calibration issues such as improper bed levelling, misaligned axes, and inconsistent extrusion, decreased temperature stability, and poorer build quality. To overcome these factors, a Design of Experiments (DoE) was applied using Response Surface Methodology (RSM). A total of 32 experiments were conducted to evaluate the influence of these parameters on tensile and flexural strength. In addition, a hybrid optimization technique combining Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) was applied. ANN determined strength predictions, whereas PSO was employed to yield the best parameter setups. The maximum tensile strength and flexural strength achieved 34.48 MPa and 71.07 MPa, respectively, indicating considerable enhancements in the mechanical traits of PLA prints. This study shows that with proper process parameter optimization, the performance of PLA can be increased even using low-cost printers.

Keywords: Fused Filament Fabrication process, Optimization, ANN, PSO, DOE

1.Introduction

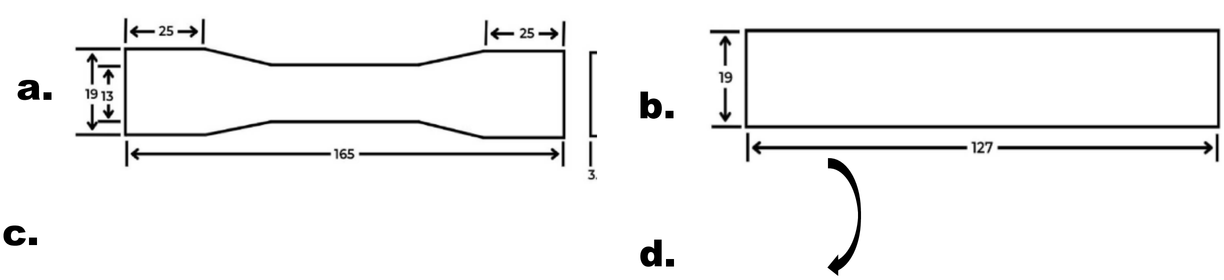
Additive Manufacturing (AM), commonly known as 3D printing has transformed manufacturing by using layer-by-layer fabrication of complex design while minimize waste output and reduced post-processing [1]. Among various AM techniques, Fused Filament Fabrication (FFF), is widely adopted method due to its affordability and ease of use [2]. This method involves extruding thermoplastic filaments, such as PLA, ABS, PETG, HIPS, TPU, PEEK, and nylon to create parts [3]. Among these, PLA stands out as a most popular material because it offers affordability alongside ease of use and it is biodegradable which makes it ideal for use in education, medical devices, consumer products, and industrial parts [4]. While FFF provides superior outcomes using expensive and industrial-grade machines but low-cost 3D printers struggle to deliver consistent mechanical performance and product quality. Industrial-grade FDM printers produce optimized prints with superior mechanical strength and finish yet low-cost printers suffer from calibration problems and inconsistent extrusion and temperature instability and insufficient layer adhesion [5]. Printed parts exhibit anisotropic behaviour due to process parameter dependencies which affect mechanical strengths including tensile and flexural strength [6-9]. Identifying and optimizing these parameters is essential to enhancing the quality of parts fabricated using low-cost 3D printer [10]. For example, Chacón et al. [11] highlighted that layer height, built orientation, and print speed significantly impact tensile and flexural strengths of PLA parts. It has been found that flat and on-edge orientations improve mechanical performance due to better inter-layer bonding compared to upright orientations. Nidagundi et al.[12] Used Taguchi's L9 orthogonal array and ANOVA to optimize FDM parameters which resulted in improved tensile strength and dimensional accuracy. Traditional methods like Taguchi and ANOVA work well for multi-objective problems yet struggle to handle the complex nonlinear interactions between process parameters [13]. The optimization of FDM process parameters has been studied through several experimental and statistical design approaches which include Full Factorial Design and Taguchi's method along with RSM [14-16]. Full Factorial Design executes numerous experimental tests to analyse all factor combinations at different levels while delivering complete analytical results [17]. Taguchi's method achieves simplified experimentation through orthogonal arrays that minimize experimental runs yet maintain parameter to output relationships [18]. RSM brings together experimental design with statistical modelling to study variable relationships and outcomes which provides a practical method for parameter optimization. [19]. To further improve process parameter optimization, advanced machine learning techniques such as ANN, Genetic Algorithms (GA), and PSO become popular [20-22]. These techniques are particularly useful for solving complex, multi-objective optimization challenges and identifying nonlinear relationships between variables. ANN is widely used for predictive modelling, while GA and PSO are recognized as effective metaheuristic optimization tools [23]. The combination of ANN-PSO approaches uses ANN predictive accuracy and PSO efficient search abilities to optimize mechanical properties in FFF processes effectively.

The novelty of the current work addresses challenges associated with low-cost FFF 3D printers because these machines have problems in delivering consistent mechanical performance and surface quality. By employing a hybrid ANN-PSO approach, this study aims to optimize the tensile and flexural strengths of FFF process parameters such as infill density, print speed, built orientation, layer height and nozzle temperature to overcome the inherent limitations of low-cost printers.

2.Research Methodology

2.1 Experimentation

This study focused on optimizing the tensile and flexural strengths of PLA components manufactured using FFF technology. The 3D models for tensile and flexural specimens were designed using Autodesk Fusion 360 and exported as STL files, as shown in figure 1c and 1d. The slicing was performed using Ultimaker Cura software to adjust process parameters and generate G-code for the fabrication process. The test specimens followed ASTM standards while tensile specimens used ASTM D638 Type 1 (figure 1a) and flexural specimens used ASTM D790 standards (figure 1b) [24, 25].



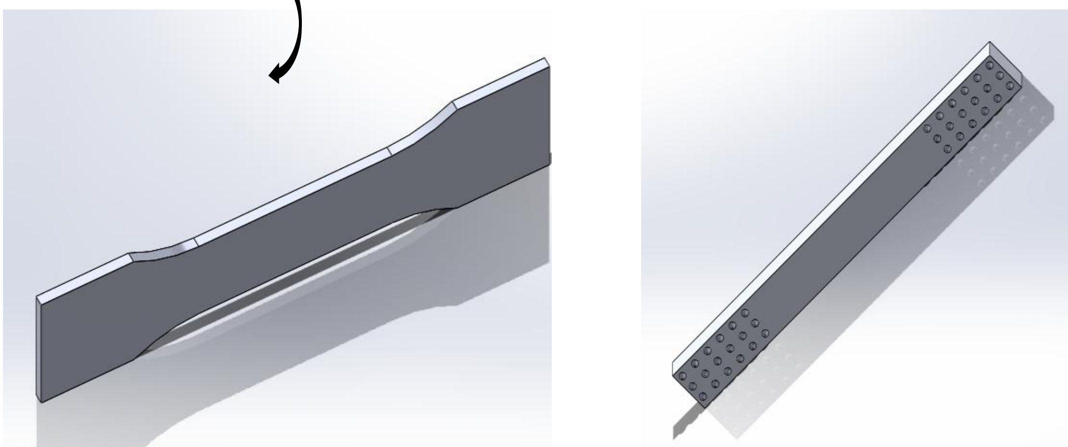


Figure 1: Tensile and Flexural Specimens: **(a)** ASTM D638 tensile dimensions, **(b)** ASTM D790 flexural dimensions, **(c)** 3D tensile model, **(d)** 3D flexural model.

Specimens were printed using a CADX Arya Pro 3D printer with Black PLA filament. Samples were produced with different process parameters determined by the design of experiments. Mechanical testing was carried out using a Universal Testing Machine (UTM) with a 50 KN capacity. The UTM adheres to ISO 9001-2015 standards, ensuring precise and reliable measurements of tensile and flexural strength.

2.2 Response surface Methodology

RSM is a statistical approach designed to minimize the number of experiments needed to analyse multiple variables and their interactions, making it particularly suited for optimizing complex processes like 3D printing [26]. In the current work, RSM employing a Central Composite Design (CCD) was applied to study the effects of five input parameters on the tensile and flexural strengths of PLA parts (Table 1). The tensile and flexural specimens are shown in Figures 2a and 2b, and the experimental results are summarized in Table 2. The CCD design consisted 32 experiments with 16 cube points, 10 axial points, and 6 centre points, using an alpha (α) value of ±2. This method significantly reduced the number of experiment while providing robust data for predictive modelling, enabling the optimization of FDM process parameters to enhance mechanical performance.

Table 1: highlights the low and high values for the input process parameter

S. No.	Input process parameter	Low	High
1	Build orientation (degree)	0	90
2	Print Speed (mm/sec)	40	50
3	Infill density (%)	40	80
4	Temperature (^{0}C)	210	230
5	Layer thickness (mm)	0.2	0.25

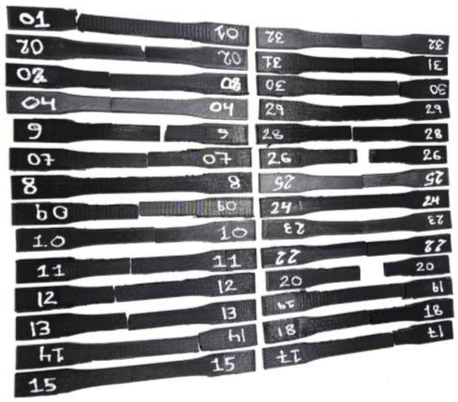
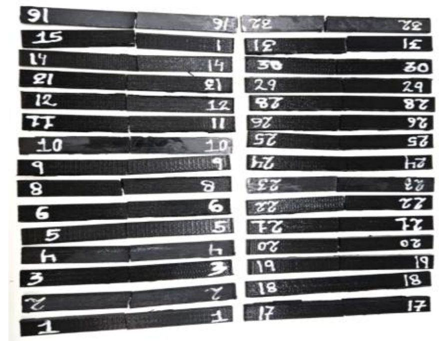
	

Figure 2(a): Tensile Test specimens	**Figure 2(b)** Flexural Test specimens

2.3 Hybrid ANN and PSO

A hybrid ANN and PSO approach optimizes 3D printing process parameters to achieve maximum tensile and flexural strengths. The input process parameters considered as infill density, build orientation, nozzle temperature, layer height, and print speed, which are known to significantly influence the mechanical properties of printed parts as suggested from literature review. The output parameters are tensile and flexural strengths, which represent the critical objectives of the optimization process. Experimental observations organized in a matrix structure showed individual samples as rows and input and output variables as columns. Data normalization to a [0, 1] range before training improved both the ANN's efficiency and accuracy. The ANN model included one hidden layer with 10 neurons which trained through the Levenberg-Marquardt backpropagation algorithm. To prevent overfitting and maintain model robustness, the data was split into three subsets: 70% for training, 15% for validation, and 15% for testing

Table 2: Experimental Matrix of Input process Parameters and Output Strengths

S NO	**Build orientation (Degree)**	**Print Speed (mm/s)**	**Infill density (%)**	**Temperature (^{0}C)**	**Layer height (mm)**	**Tensile strength (Mpa)**	**Flexural strength (Mpa)**
1	90	50	40	210	0.20	20.98	56.48
2	0	60	40	230	0.26	22.06	54.75
3	135	55	60	220	0.23	24.86	58.75
4	0	50	80	210	0.20	29.88	63.90

5	90	60	40	210	0.26	20.17	55.17
6	45	55	100	220	0.23	32.45	65.86
7	90	60	80	230	0.26	26.85	60.55
8	45	55	60	200	0.23	22.75	57.85
9	90	50	40	230	0.26	20.28	55.17
10	0	50	40	230	0.20	24.98	57.74
11	45	55	60	220	0.23	25.86	59.75
12	45	65	60	220	0.23	25.86	59.76
13	45	55	60	220	0.23	26.94	59.86
14	90	50	80	210	0.26	26.75	61.73
15	45	55	60	220	0.23	23.86	57.65
16	0	50	40	210	0.26	21.23	55.90
17	45	45	60	220	0.23	25.86	59.75
18	45	55	20	220	0.23	17.45	51.73
19	90	60	40	230	0.20	20.56	56.74
20	90	60	80	210	0.20	27.98	62.84
21	90	50	80	230	0.20	27.07	60.76
22	-45	55	60	220	0.23	25.75	58.77
23	0	50	80	230	0.26	28.85	62.90
24	45	55	60	220	0.23	23.76	57.76
25	0	60	80	230	0.20	30.21	63.98
26	45	55	60	220	0.23	22.86	56.86
27	0	60	80	210	0.26	28.54	61.89
28	45	55	60	240	0.23	23.86	58.86
29	45	55	60	220	0.23	24.86	58.87
30	45	55	60	220	0.29	22.01	57.65
31	45	55	60	220	0.17	28.85	60.65
32	0	60	40	210	0.20	23.45	58.74

The trained ANN underwent validation through experimental output comparison which resulted in performance evaluation using mean squared error (MSE). The trained ANN functioned as a surrogate model to predict tensile and flexural strengths from specified input parameters.

PSO is an evolutionary algorithm that mimics bird and fish group social behaviours to discover optimal solutions through multidimensional particle movement simulation [27]. Each particle represents a potential solution, and its movement is influenced by two key factors the particles own best position and the global best position discovered by the swarm. The velocity and position of particles are updated iteratively using equation 1 and 2, which balance exploration and exploitation. The velocity update process combines particle inertia with cognitive (c1) personal best knowledge and social (c2) global best knowledge through random numbers (r1 and r2) to introduce stochasticity. There are two main variations of the PSO algorithm: standard PSO and improved PSO. Standard PSO maintains a static inertia weight that constrains its dynamic adaptation throughout the search process. Improved PSO introduces linear inertia weight reduction, which starts with a higher inertia to allow broader exploration and gradually decreases it to focus on exploitation. This adjustment improves convergence and ensures efficient optimization [28].

The PSO algorithm during optimization identified optimal parameter combinations which maximized tensile strength and flexural strength simultaneously. The PSO algorithm started with 30 particles distributed across defined parameter ranges where cognitive and social coefficients (c1 and c2) were set to 2. The optimization framework included a multi-objective definition where the fitness function used ANN-predicted tensile and flexural strengths in negative form to achieve maximization [29]. The algorithm performed an iterative process of position and velocity updates through the combination of inertia weight reduction with cognitive and social components to achieve exploration-exploitation balance. The optimization ran for 30 iterations while checking convergence through fitness history plots. The final stage of the process revealed the best particle which provided the optimal input parameters alongside their corresponding tensile and flexural strengths [30]. The hybrid ANN-PSO methodology combines predictive modelling techniques with optimization features to drive data-based process parameter adjustments which result in better mechanical performance outcomes in 3D printing. The detailed methodology of the current work is shown in figure 3.

$$\text{“}v_i^{k+1} = wv_i^k + c_1 r_1 \left(P_{best(i)}^k - x_i^k\right) + c_2 r_2 \left(G_{best(i)}^k - x_i^k\right) \tag{1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}\text{”} \tag{2}$$

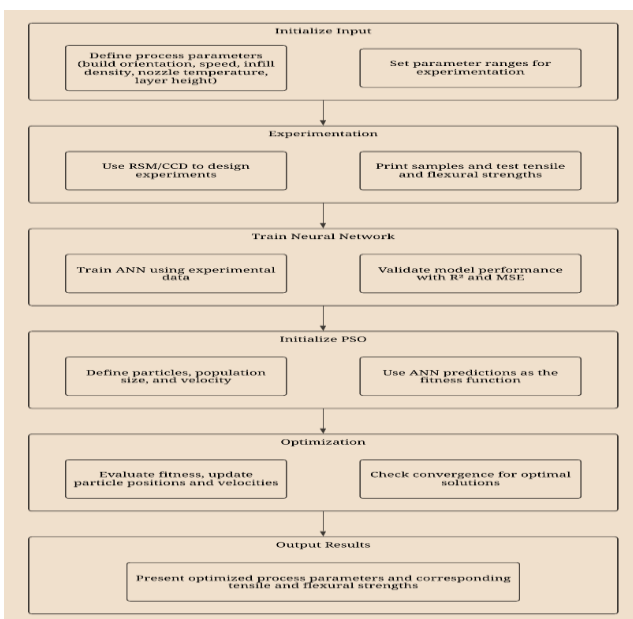


Figure 3: Methodology

3.Results

3.1 Trained neural network and validation

The development of an ANN algorithm through MATLAB 2023a allowed the prediction of tensile and flexural strengths from five input variables. The best performing ANN configuration was determined to have one hidden layer with 10 neurons shown in figure 4. The Levenberg–Marquardt (trainlm) algorithm served as the selection because of its efficient nature while employing Tan-sigmoid and Purelin activation functions for the hidden and output layers. The dataset consisted of 32 experimental runs, which were split into 70% for training, 15% for validation, and 15% for testing. The training process achieved a minimum mean squared error (MSE) of 0.00125 within five epochs. The experimental and predicted values matched strongly as shown by the high coefficient of determination (R^2 = 0.97407) in the regression plots. The ANN's generalization capabilities were validated through results showing a maximum relative error of 0.115 according to table 3. The combined results from table 3 and the regression plots from Figure 5 highlight the accuracy of the ANN in predicting tensile and flexural strengths. Also the comparison of actual and predicted tensile and flexural strength is shown in figure 6.

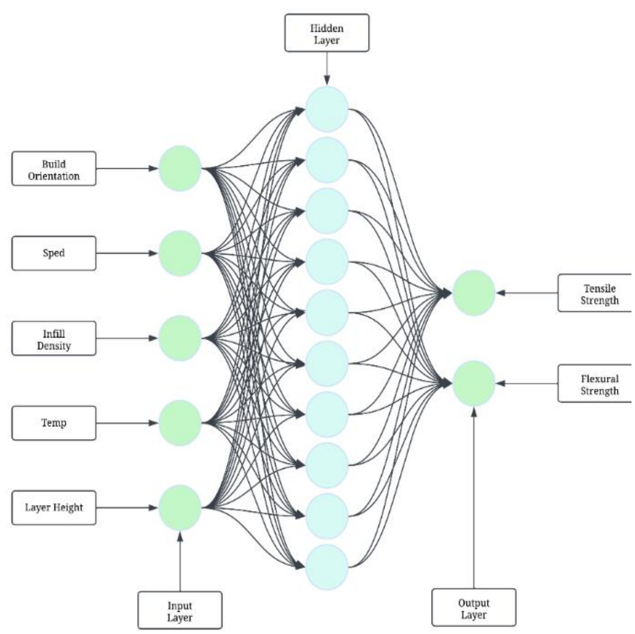


Figure 4: Architecture of Neural Network

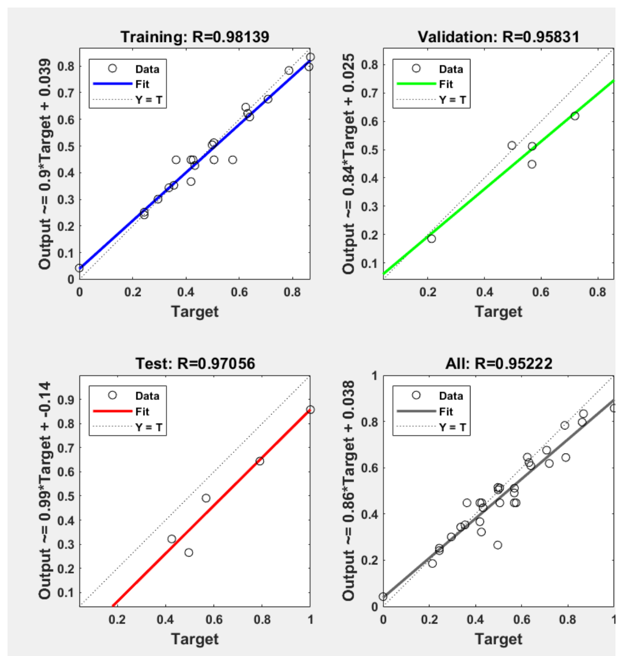


Figure 5: Regression Plots for Training, Validation, Testing, and Overall Performance of ANN

3.2 Optimization

PSO-based optimization of FFF process parameters produced significant enhancements in mechanical properties. The best set of parameters consists of 0° build orientation with 65 mm/s printing speed and 100% infill density at 220°C temperature and 0.17 mm layer height. With these optimized conditions the tensile strength reached 34.48 MPa and the flexural strength achieved 71.07 MPa. The combined best fitness value showing the sum of tensile and flexural strengths, was calculated as 105.55, as shown in Figure 7. These findings highlight the effectiveness of process parameter optimization in enhancing the mechanical performance of parts produced using low-cost FFF 3D printers, achieving results comparable to those of industrial-grade machines.

Table 3: Predicted and Actual Mechanical Strengths with Relative Errors

S NO	Tensile strength (Mpa)	Predicted Tensile strength (Mpa)	Relative error for Tensile strength	Flexural strength (Mpa)	Predicted Flexural strength (Mpa)	Relative Error for flexural strength
1	20.98	21.005	0.001	56.48	56.582	0.002
2	22.06	22.004	0.003	54.75	54.354	0.007
3	24.86	24.749	0.004	58.75	59.003	0.004
4	29.88	29.927	0.002	63.90	62.992	0.014
5	20.17	19.985	0.009	55.17	55.29	0.002
6	32.45	34.183	0.053	65.86	63.848	0.031
7	26.85	26.972	0.005	60.55	60.852	0.005
8	22.75	22.6512	0.004	57.85	57.763	0.002
9	20.28	20.261	0.001	55.17	55.144	0.000
10	24.98	24.964	0.001	57.74	56.28	0.025
11	25.86	25.493	0.014	59.75	58.063	0.028
12	25.86	25.834	0.001	59.76	58.958	0.013
13	26.94	25.493	0.054	59.86	58.063	0.03
14	26.75	26.865	0.004	61.73	61.28	0.007
15	23.86	25.493	0.068	57.65	58.063	0.007
16	21.23	21.146	0.004	55.90	55.978	0.001
17	25.86	26.258	0.015	59.75	58.666	0.018
18	17.45	17.439	0.001	51.73	52.329	0.012
19	20.56	20.574	0.001	56.74	56.712	0.000
20	27.98	29.395	0.051	62.84	62.796	0.001
21	27.07	17.149	0.003	60.76	60.333	0.007
22	25.75	25.641	0.004	58.77	58.857	0.001
23	28.85	28.6172	0.008	62.90	60.833	0.033
24	23.76	25.493	0.073	57.76	58.063	0.005
25	30.21	30.197	0.000	63.98	63.51	0.007
26	22.86	25.4932	0.115	56.86	58.063	0.021
27	28.54	28.297	0.009	61.89	60.469	0.023
28	23.86	23.907	0.002	58.86	58.968	0.002
29	24.86	25.493	0.025	58.87	58.063	0.014
30	22.01	21.86	0.007	57.65	56.91	0.013

31	28.85	28.843	0.000	60.65	60.521	0.002
32	23.45	24.084	0.027	58.74	55.483	0.055

Table 3: Optimized Process Parameters and Corresponding Mechanical Strengths

Build orientation (Degree)	Print Speed (mm/s)	Infill density (%)	Temperature (^{0}C)	Layer height (mm)	Tensile strength (Mpa)	Flexural strength (Mpa)
0	65	100	220	0.17	34.48	71.07

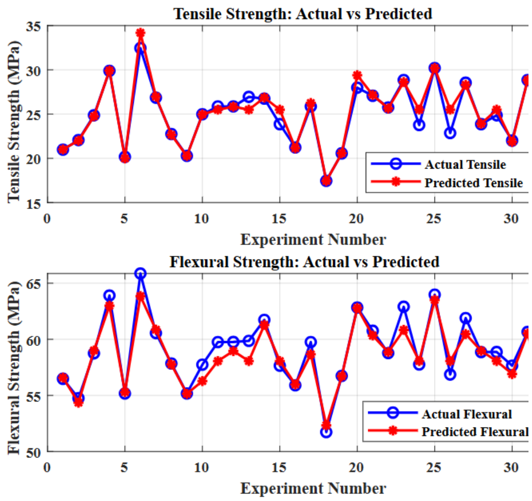


Figure 6 Comparison of Actual vs Predicted Tensile and Flexural Strengths

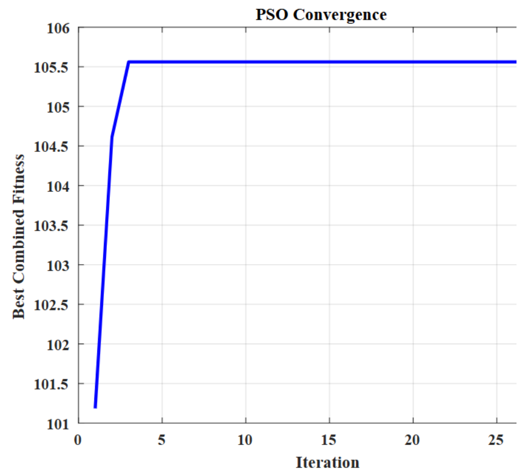


Figure 7 PSO Convergence Plot for Best Combined Fitness

4.Conclusion

- This study investigated the influence of key FFF process parameters like infill density, layer height, nozzle temperature, print speed and build orientation on the tensile and flexural strengths of PLA parts. A hybrid ANN-PSO method was used for optimization methods.
- The optimized process parameters identified through PSO were infill density (100%), nozzle temperature (220 °C), build orientation (0°), speed (65 mm/s) and layer height (0.17 mm). These parameters resulted in maximum tensile strength of 34.48 MPa and flexural strength of 71.07 MPa.
- The ANN model demonstrated excellent predictive capabilities by achieving an R^2 value of 0.952 which validated its ability to identify nonlinear relationships between process parameters and mechanical properties.
- A comparison between predicted and experimental values showed minimal errors, demonstrating the effectiveness of the hybrid ANN-PSO approach for FFF optimization.
- The hybrid ANN-PSO optimization technique enhanced process parameter which resulted in substantial mechanical performance improvements of PLA parts. This study explores

the potential of integrating machine learning and optimization algorithms to enhance 3D printing quality and reliability.

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