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FDM Parameters Optimization for Improving Tensile Strength using Response Surface Methodology and Particle Swarm Optimization

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ABSTRACT

Fused deposition modelling (FDM) is a popular 3D printing technique that uses a thermoplastic filament as the build material. In FDM 3D printing, tensile strength can be an issue because the layers of the object are built on top of each other, and if the layers do not adhere properly, the object can be weak and prone to breaking. Typically, this problem is caused by incorrect parameter settings. Hence, this study was then carried out to analyse and improve the printing quality in term of tensile strength of the printed part using the response surface methodology (RSM) and the particle swarm optimization (PSO) method. The effect of four input parameters such as layer height, printing speed, infill density, and print temperature was examined on the tensile strength of polylactic acid (PLA) standard samples ASTM D638-IV. The experimental design was performed using face-centred central composite designs (FCCD). The experimental data were statistically analysed to form a regression model of the tensile strength. This model was used to approximate the actual process. The optimization was performed using desirability analysis from RSM and PSO to search for the optimal parameter for maximum tensile strength. Experimental results showed that PSO outperformed RSM with a 1.52 % reduction in tensile strength. The maximum tensile strength obtained from PSO was about 39.069 MPa with the optimal process parameters of layer height of 0.30 mm, printing speed of 30.17 m/s, infill density of 79.72 %, and print temperature of 205.92 °C.

1. Introduction

The need to reduce product development time has been a major concern for industries in maintaining their market competitiveness. Rapid fabrication techniques are being sought as an alternative to traditional product development methods. However, the majority of currently used techniques are time and labour-consuming. Additive manufacturing methods, including stereolithography (SL), laminated object manufacture (LOM), fused deposition modelling (FDM), and selective laser sintering (SLS), have been devised to enable the development of prototype parts

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quickly and with minimal human intervention, without the need for tooling, and at a reasonable cost. FDM is among the additive manufacturing techniques that builds components with different shapes by sequentially depositing semi-molten plastic in layers. The process utilizes semi-molten plastic that is extruded in a predetermined manner from the nozzle tip and subsequently solidifies at the filament print temperature. The component is manufactured through the *x-y* plane-contoured deposition of two-dimensional layers. Due to the stacking of distinct layers, the third dimension (*z*) is not a continuous *z*-coordinate. Fused deposition modelling (FDM) is becoming increasingly popular in various manufacturing sectors, including automotive, biomedical implants, aerospace, electronics, and telecommunications, due to its ability to produce high-quality prototypes or products. To guarantee the consistency and durability of fabricated parts in such circumstances, maintaining strict tolerances is crucial. The properties of parts produced via the FDM process, including their mechanical and physical characteristics, precision, and quality, are dependent on selected process parameters that may conflict with one another [1-3]. Furthermore, the complex nature of the FDM process and the conflicting parameters can make it difficult to determine these parameters. There are two common approaches to improving mechanical properties, such as developing new materials or adjusting the process parameters [4,5]. According to a comprehensive assessment from the literature, the qualities of printed components are reliant on many process input parameters and can be considerably enhanced with the appropriate adjustments. It is essential to evaluate the influence of these process factors on the mechanical characteristics in order to establish the optimal settings for manufacturing functioning components [6-9].

Studies have shown that enhancing the properties of parts manufactured using FDM, such as wear strength, tensile strength, compressive strength, and surface finish, can be achieved through two common approaches:

i. the utilization of advanced materials
ii. the optimization of FDM process parameters

The development of new materials seems to be good for the improvement of prototype models in terms of part quality and mechanical properties. However, it still depends on the process parameter settings. Improper setting could lead in poor mechanical qualities, low surface quality, longer production times, and material waste, which will ultimately increase manufacturing costs and resources [10-12]. The second approach has been quite successful as the quality of the printed model heavily relies on these settings. Optimizing process parameters can significantly enhance the mechanical characteristics and surface quality of a 3D printed model. To achieve optimal performance, it's imperative to analyse the influence of different process parameters on the output qualities, including dimensional accuracy, surface finish, and mechanical strength. The advancement of materials and technology has facilitated the evolution of 3D printing from a prototyping tool to a manufacturing process for final products. However, for additive manufacturing technology to be viable for mass production, the resulting products must meet strict requirements in terms of their essential mechanical properties, dimensional accuracy, surface quality, and other key characteristics. Therefore, it's critical to carefully select the optimal process parameters to ensure the consistency and reliability of the 3D printed parts for industrial-scale production.

Recent studies have focused on the optimization of FDM parameters on the effect of the output response expressed in terms of mechanical strength. It has been noted that mechanical strength is extremely anisotropic. Optimal selection of process parameters can enhance mechanical strength [13]. Researchers have used many advanced optimization methodologies to find the best process parameter combinations for improving the mechanical properties of printed parts. Numerous optimization techniques, including the classical approach and the modern approach, can be used to find the optimization process. FDM process optimization strategies have used a variety of conventional approaches, including the factorial design method, Taguchi method, and response surface methodology (RSM).

The employment of conventional approaches for enhancing process parameters of fused deposition modelling (FDM), such as layer thickness, printing speed, infill density, infill pattern, printing temperature, platform temperature, and part orientation, has garnered significant interest in the research community. These factors have significantly affect the mechanical properties of the 3D printed components, requiring proper parameters adjustment to achieve optimal results. As a result, a comprehensive analysis of the effects of these process parameters on the mechanical characteristics of the printed parts is essential to establish the optimal settings for FDM. Recently, Yilan *et al.*, [14] conducted an experimental investigation using fused deposition modelling (FDM) to evaluate the impact of three variables, namely infill patterns, infill densities, and printing time, on the tensile strength of PLA+ materials. The experiments involved the 3D printing of test specimens with various infill patterns and densities using FDM technology. The tensile testing machine's settings were optimized through a signal-to-noise ratio analysis to ensure the most precise and reliable test results. The results showed that triangle infill pattern had the highest tensile strength at 100% infill density and 40 mm/sec printing speed, while the lowest production time was seen with the gyroid infill pattern. John *et al.*, [15] employed a Taguchi experimental design with grey relational analysis (GRA) to study the influence of input factors on the tensile strength of polylactic acid samples. The investigation found that the square pattern produced the highest quality, and the diamond angle pattern exhibited the lowest strength (5 MPa) when using a nozzle diameter of 0.8 mm and 0.4 mm, respectively. Furthermore, the mechanical properties of the printed samples were primarily affected by the geometric patterns and strain rates, whereas nozzle diameter had a less significant effect. Three input factors, namely layer thickness, printing speed, and infill %, were studied by Bhosale *et al.*, [16] to determine their effect on the surface quality, printing time, and tensile strength of PLA-printed objects. Box-Behnken designs were used as part of the study's experimental technique. Both layer thickness and infill % were shown to have a significant impact on the strength and surface quality of the printed items. It was noticed that lowering the layer thickness improved the strength and surface quality of FDM-fabricated items. Torres *et al.*, [17] employed the Taguchi method to study the influence of FDM parameters and implemented the optimization PLA part using analysis of variance. The parameters set by the printer include layer thickness, infill density, printing speed, extrusion temperature, infill direction, and part orientation. Results showed that infill density and layer thickness affect the tensile strength. Lower layer thickness and slower printing speed, on the other hand, will improve surface finish. However, lowering the layer thickness may decrease the strength. Furthermore, Altan *et al.*, [18] conducted an analysis of the influence of production process variables on the final quality of products manufactured using fused deposition modelling (FDM), specifically focusing on surface roughness and tensile strength. The study utilized polylactic acid (PLA) as the printing material, and controlled the layer height, deposition head velocity, and nozzle temperature independently. It was conducted using a Taguchi L16 orthogonal array. According to the findings, the two most important factors in determining the output responses were the layer thickness and the velocity of the deposition head. The best tensile strength and surface quality were achieved at the lowest layer thickness values.

The utilization of metaheuristic algorithms for optimizing complex combinations of parameters has proven to be a reliable method, capable of providing exceptional results in comparison to conventional optimization techniques. These algorithms can be seamlessly integrated with various experimental design methodologies, such as the Taguchi method, factorial design, response surface method, and others. The outcome is highly encouraging and demonstrates the efficacy of this approach in solving optimization problems. Some of the commonly used meta-heuristic methods include genetic algorithms (GA), particle swarm optimization (PSO), differential evolution (DE), grey wolf algorithm (GWO), whale optimization algorithm (WOA), and bacterial foraging optimization (BFO). Kumar *et al.*, [19] employed the Taguchi methods and genetic algorithm (GA) to improve the dimensional accuracy of FDM components made from polymeric bio-composites. The four response factors are combined into a single variable, with the width of the FDM components being the most important factor for both medical and aeronautical applications. The study revealed that layer thickness and orientation angle were critical factors impacting dimensional accuracy, with a highest fitness value of 0.377. The use of advanced optimization and manufacturing approaches produced positive outcomes, which were confirmed by advanced algorithms. Mohanty *et al.*, [20] evaluated the effect of five major processing restrictions on the dimensional accuracy of 3D printed components made using FDM technology. Taguchi's technique and different optimization methods such as genetic algorithm, simulated annealing, particle swarm, grey-wolf, moth flame, whale, Jaya, sunflower, Lichtenberg, and forensic based inquiry were used in 27 tests. The findings revealed that part orientation was the most important factor influencing dimensional accuracy. Fountas *et al.*, [21] utilized the grey wolf algorithm (GWO) to study the most optimal FDM process parameters for improving the functionality and strength of 3D printed parts. The experiments were structured using the response surface method and involved testing 27 standard samples made from polyethylene terephthalate glycol (PET-G) material, as per ASTM D790 standards. The study took into consideration 5 important factors, namely printing speed, angle, infill density, layer height, and temperature, and found that the GWO effectively determined the best parameters for maximum flexural strength. This resulted in a remarkable 15% increase compared to the highest value obtained from the experimental data. Deshwal *et al.*, [22] proposed an investigation into the performance of hybrid modelling and optimization techniques that combine genetic algorithms with conventional and artificial intelligent modelling, namely genetic algorithm-response surface methodology (GA-RSM), genetic algorithm-artificial neural network (GA-ANN), and genetic algorithm-adaptive neuro fuzzy interface system (GA-ANFIS) to find the best FDM parameter settings for maximum tensile strength. Among the proposed methods, GA-ANN had the highest prediction accuracy as well as good tensile properties. GA-ANN outperformed the other offered methods in terms of prediction accuracy and tensile strength. Sai *et al.*, [23] employed artificial intelligent modelling with an adaptive neuro-fuzzy inference system [23] and optimize using whale optimization algorithm (WOA) to demonstrate artificial intelligence modelling and optimization on the compressive strength, surface roughness, and build time for implant component in biomedical applications. A model of the adaptive neuro-fuzzy inference system (ANFIS) was developed using data obtained through face-centred central composite design (FCCD) experiments. The input parameters for the model were layer thickness, infill density, raster angle, and internal structure. The results showed that the ANFIS-WOA approach yielded an optimal and precise set of fused deposition modelling (FDM) process parameters that can lead to good compressive strength, surface roughness, and minimized build time.

Literature demonstrates that metaheuristic algorithms have been used in a considerable number of FDM optimization studies. Several studies have discovered the use of PSO for FDM optimization. Raju *et al.*, [24] conducted a study on the optimization of parameter settings for achieving optimal mechanical and surface quality during additive manufacturing. Hybrid particle swarm and bacterial foraging optimization (PSO-BFO) evolutionary algorithm and Taguchi method experimental design have been utilized to identify the best parameter settings for ABS material. The results showed that the optimal mechanical properties could be achieved with a layer thickness of 0.007 mm, part orientation of 60◦, sparse type support material, and high infill density. This study provides valuable insights for improving part performance and optimizing parameter settings in additive manufacturing. Shirke *et al.*, [25] investigated the use of 3D printing to generate prototypes and enhance their mechanical qualities, particularly the tensile strength of ABS prototypes manufactured using the fused deposition modelling (FDM) technique. Taguchi's design of experiments was used to investigate the mechanical qualities with various process parameters such as layer thickness, nozzle diameter, and part bed temperature. The ideal values of these parameters were determined using the particle swarm optimization (PSO) technique to attain the highest tensile strength, according to the research. Saad *et al.*, [26] also studied the issue of insufficient techniques to select the best parameter setting to increase the flexural strength of 3D-printed components. Response surface methodology (RSM) was used to collect data using a central composite design and performed analysis of variance to obtain a regression model. The input parameters comprised layer thickness, printing speed, printing temperature, and outer shell speed, with flexural strength being the output response. PSO optimization have obtained the flexural strength of 96.62 MPa with the optimal parameters setting. This work provides valuable insights for enhancing the mechanical characteristics of 3D-printed part via the use of RSM and PSO.

Although metaheuristic algorithms have gained substantial attention in several research areas of FDM, the PSO approach for optimizing FDM process parameters for the tensile strength of printed parts has received comparatively less attention. Consequently, the RSM and PSO optimization approaches were combined in this work to model and optimize the tensile strength of the printed sample in FDM process. The experimental design employed face-centred central composite designs (FCCD) with four input parameters (layer height, infill %, printing temperature, and printing speed) and a single response (tensile strength). Analysis of variance (ANOVA) was utilized to analyse the effect of input factors on the tensile strength of printed parts. In addition, the model accuracy between the predicted output and the experimental data was evaluated. Finally, an experimental confirmation test was performed to confirm the simulation findings.

2. Methodology

2.1 Experimental Details

In this study, the samples were printed using the FDM 3D printed model Ender-3 V2 Pro. The material used was polylactic acid (PLA). The CAD drawing for the test sample was prepared according to ASTM D638 standard and modelled using Catia software. Figure 1 depicts the standard sample and its dimensions. The CAD drawing is converted into STL format. Then, the STL file is uploaded into CURA slicing software to be transformed into G-code that can be read by the FDM machine.

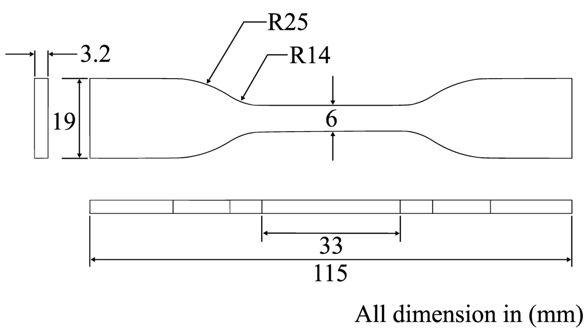

Fig. 1. Sample design according to ASTM D638-IV

The tensile strength of the samples was measured using a universal testing machine (Shimadzu AG-X 250kN) as shown in Figure 2. Finally, all the printed samples were analysed using analysis of variance (ANOVA) via Design Expert software. The regression model obtained will be used as the objective function for the PSO algorithm to performed the optimization process.

Fig. 2. Universal testing machine

2.2 Experimental Design

Design of experiments (DOE) have been widely used in the optimization process because it is considered to have a simple and reliable experimental outcome. In addition, the DOE methodology is described as the branch of applied statistics concerned with designing, conducting, and analysing controlled experiments to ascertain what factors affect the significance of a given parameter or set of parameters. The printing process parameters considered in this present work were described as follows:

i. Layer height: is the measured height of each layer as it extrudes from the 3D printer's nozzle.
ii. Infill percentage: is the amount of filament printed within the part, and it has a direct impact to the material consumption, strength and printing time. With a higher infill density, it is possible to print a sturdy part; but it will use more materials and take longer time to print.
iii. Printing temperature: describes the nozzle's temperature during printing, along with the modified extrusion rate. A slightly varied printing temperature is used in each printing profile to provide optimal printing quality.
iv. Printing speed: It is the speed for the motors in *x*-axis, *y*-axis and *z*-axis of the 3D printer. Improper setting may cause print deformation due to the nozzle sitting on the plastic for too long.

The experiment design was held using response surface methodology (RSM) based on face-centred central composite design (FCCD). There were four input parameters such as layer height (*A*), printing speed (*B*), infill percentage (*C*) and printing temperature (*D*). Table 1 shows the levels for all the input parameters.

Table 1
Levels of input parameters

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

The experimental data for the tensile strength is shown in Table 2.

Table 2
Experimental data for tensile strength

Number of samples	Parameter setting				Tensile strength (MPa)
	A (mm)	*B* (mm/s)	*C* (%)	*D* (°C)	
1	0.30	30.00	20.00	195.00	32.294
2	0.10	60.00	80.00	195.00	26.872
3	0.20	45.00	50.00	205.00	29.109
4	0.30	60.00	20.00	215.00	33.418
5	0.30	60.00	80.00	215.00	36.481
6	0.10	60.00	20.00	215.00	22.056
7	0.30	30.00	80.00	215.00	35.527
8	0.20	45.00	50.00	195.00	29.778
9	0.10	30.00	20.00	195.00	21.673
10	0.20	45.00	50.00	205.00	28.674
11	0.30	45.00	50.00	205.00	32.886
12	0.20	45.00	50.00	205.00	28.840
13	0.30	30.00	20.00	215.00	32.292
14	0.30	30.00	20.00	215.00	33.482
15	0.10	30.00	80.00	195.00	25.417
16	0.10	30.00	20.00	195.00	20.084
17	0.10	30.00	80.00	195.00	25.241
18	0.10	30.00	80.00	215.00	24.537
19	0.10	30.00	80.00	215.00	23.233
20	0.30	30.00	20.00	195.00	30.901
21	0.30	60.00	80.00	215.00	35.881
22	0.30	60.00	20.00	215.00	31.849
23	0.10	30.00	20.00	215.00	14.876
24	0.20	45.00	80.00	205.00	31.057
25	0.20	30.00	50.00	205.00	27.549
26	0.30	60.00	20.00	195.00	32.156
27	0.20	45.00	50.00	205.00	28.232
28	0.20	45.00	20.00	205.00	27.269
29	0.20	45.00	50.00	205.00	30.202
30	0.10	45.00	50.00	205.00	22.250
31	0.20	45.00	50.00	205.00	28.935
32	0.10	30.00	20.00	215.00	16.569
33	0.10	60.00	20.00	215.00	20.764
34	0.30	60.00	20.00	195.00	30.984
35	0.10	60.00	80.00	195.00	25.920
36	0.20	45.00	50.00	215.00	27.335
37	0.20	60.00	50.00	205.00	28.459

38	0.30	60.00	80.00	195.00	33.261
39	0.30	30.00	80.00	195.00	35.955
40	0.30	30.00	80.00	195.00	36.597
41	0.10	60.00	80.00	215.00	26.056
42	0.10	60.00	80.00	215.00	25.425
43	0.30	60.00	80.00	195.00	36.065
44	0.30	30.00	80.00	215.00	37.042
45	0.10	60.00	20.00	195.00	21.793
46	0.10	60.00	20.00	195.00	21.555

The 46 runs of the printed samples are shown in Figure 3.

Fig. 3. Printed samples

2.3 Statistical Analysis and Regression Modelling

Analysis of variance (ANOVA) is a statistical analysis method that evaluate the impact of independent factors on the dependent variable. In this study, ANOVA will be used to examine the effect of input factors on tensile strength. The significant of the fitted cubic models is calculated by the contribution percentage, *p*-values for ANOVA. For *p*-values, the parameter is assumed to be substantially efficient if the value is less than 0.05. The real relationship between the input factor and the output response is unknown. Therefore the step in the RSM is to obtained an approximation of the true functional real relationship between the output response and the input factor [27]. The regression model from ANOVA was developed to demonstrate how the response reacts as a function of the input parameter. In most cases, a quadratic model of the second order is utilized because of its superior performance in curvature modelling near promising regions [28]. The relationship between the various input components and the final response is expressed by Eq. (1).

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i<j} \sum_{j=1}^{k} \beta_{ij} x_i x_j + e \tag{1}$$

where *y* is the predicted output response while β_0 is a constant. The terms β_j, β_{jj} and β_{ij} are referred as the coefficients for the first order, second order and the interaction of input parameters respectively. The input process parameter value is represented by the terms x_j, and the experimental measurement error is represented by the terms *e*.

2.4 PSO Algorithm

Particle swarm optimization (PSO) is a nature-inspired optimization algorithm that effectively searches for the optimal solution within the search space. It is a population-based optimization method inspired by the behaviour of schooling fish and flocking birds. PSO operates using a methodology that is practically identical to that of evolutionary computation techniques. The initialization process is based on random populations, and the optimal solution is located via updating generations. Unlike typical optimization techniques, this technique just requires the objective function and does not rely on the gradient or differential form of the objective function [29].

Particle swarm optimization and a regression model for tensile strength were used to find the best process parameters. The PSO flowchart that represents the 3D printer optimization approach is shown in Figure 4. Several variables must be set during the PSO initialization phase, including the number of iterations, the number of populations, the dimension of particle velocity, the dimension of particle position, and the size of the process input parameters such as layer height (*A*), printing speed (*B*), infill density (*C*), and print temperature (*D*). The particle's position consists of the process input parameters of the FDM 3D printer, whereas the fitness function is represented by the regression model of the tensile strength. The fitness function for each particle position will be evaluated to complete the initialization process. Once the initialization process is completed, the main program will run to search for the optimal input parameter for the maximum tensile strength. The main program consists of three sections which is updating particle velocity and its position, evaluation particle position, and updating local best and global best. The particle velocity and particle position are updated based on Eq. (2) and Eq. (3), respectively.

$$v_i(k+1) = v_i(k) + c_1.rand_1(x_{pbest} - x_i) + c_2.rand_2(x_{gbest} - x_i) \tag{2}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{3}$$

where *i* is the particle number, *k* is the iteration counter, v_i is the *i*-th particle velocity, x_i is the *i*-th particle position, $rand_1$ and $rand_2$ are the random variables, c_1 is the cognitive parameter, and c_2 is the social parameter.

The main program begins with updating the particle velocity and particle position. Then, the fitness function is evaluated based on the current particle position. If the new fitness function (i.e., tensile strength value) is better than the old one, then the new fitness function value will replace the old fitness value and become the local best fitness (*pbest*). The new particle position will also replace its previous position and become the new local best position (*pbest*). Then, at the next level, the same fitness function value is compared with the global best fitness (*gbest*). If the new fitness value of tensile strength is more than the previous global best fitness (*gbest*), the new fitness value will replace the previous global best fitness (*gbest*). The process described will be repeated iteratively until a pre-determined maximum number of iterations has been reached. At this point, the algorithm will terminate, and the solution that was found at the end of the last iteration will be returned as the final result. The maximum number of iterations is typically set in advance to ensure that the algorithm terminates within a reasonable amount of time and does not continue searching indefinitely. The choice of the maximum number of iterations can be influenced by various factors such as the complexity of the problem, the number of variables, and the computational resources available. It is important to choose a suitable value for the maximum number of iterations to balance the need for a thorough search of the solution space with the need for efficient computation.

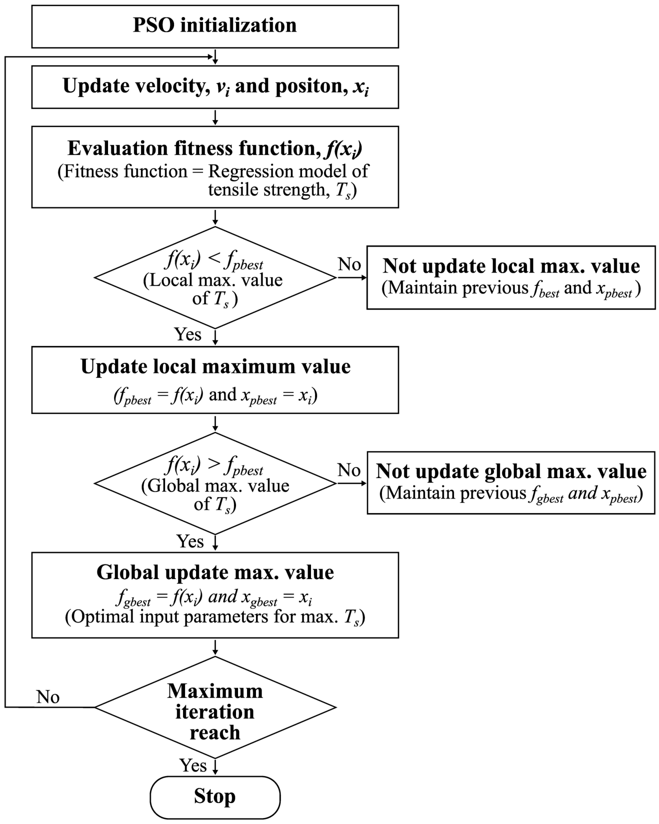

Fig. 4. PSO algorithm for optimization of tensile strength

3. Results

3.1 Analysis of Variance

An analysis of variance (ANOVA) is applied to examine the effect of input parameters on the output response, i.e., tensile strength. The effect of process factors such as layer height (*A*), printing speed (*B*), infill density (*C*), and print temperature (*D*) on the output response (tensile strength) has been evaluated using analysis of variance (ANOVA). The ANOVA results are shown in Table 3.

Based on the 95 % confidence level, *p*-values of less than 0.05 indicate that the parameter has a significant impact on tensile strength. According to Table 3, the most significant parameter for tensile strength is layer height and infill density, which has a *p*-value of < 0.0001, followed by print speed, and print temperature. layer height and print speed (*AB*), layer height and infill density (*AC*), layer height and print temperature (*AD*), print speed and infill density (*BC*), and print speed and print temperature (*BD*) are significant model terms for the tensile strength interaction between parameters.

Table 3
ANOVA results for tensile strength

Source	Sum of squares	*df*	Mean square	*p*-value	Comment
Model	1322.82	9	146.98	< 0.0001	Significant
A	1092.71	1	1092.71	< 0.0001	-
B	7.27	1	7.27	0.0095	-
C	172.35	1	172.35	< 0.0001	-
D	2.78	1	2.78	0.0988	-
AB	16.26	1	16.26	0.0002	-
AC	6.04	1	6.04	0.0172	-
AD	16.24	1	16.24	0.0002	-
BC	3.12	1	3.12	0.0810	-
BD	6.06	1	6.06	0.0170	-
Residual	34.84	36	0.97		-
Lack of Fit	18.52	15	1.23	0.1611	Not Significant
Pure Error	16.32	21	0.78		-
Cor Total	1357.66	45			-
				0.9743	Adequate
				0.9679	Adequate

Figure 5 shows the comparison between experimental and predicted values of the RSM model for tensile strength. In order to assess the quality of the fit, it is important to examine the distribution of the data points around the fitted line. A good fit is indicated by data points that are closely clustered around the line. However, data points that are far from the mean, located on either the left or right of the plot, can have a significant effect on the fitted line by exerting a greater influence on its slope or intercept. Such data points are known as leverage points and can effectively pull the fitted line towards them.

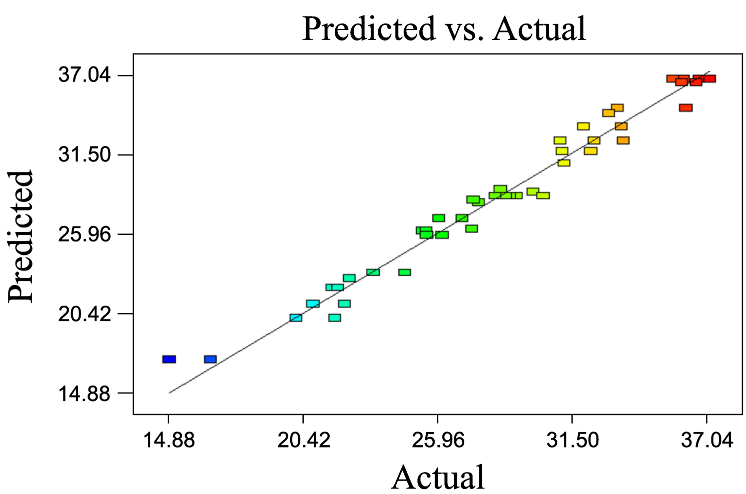

Fig. 5. Comparison of experimental and predicted tensile strength values

As a result, the developed regression model fits the experimental tensile strength value quite well. The regression model for the tensile strength is shown in Eq. (4).

$$\begin{aligned} \textit{Tensile strength},\ Ts \ = \ & 66.4798 - 60.71685A - 0.4343B + 0.13523C - 0.30163D - 0.47515AB - \ldots \\ & -0.14478AC + 0.71233AD - 6.93896\times10^{-4}BC + 2.90173\times10^{-3}BD \end{aligned} \tag{4}$$

3.2 RSM Optimization Results

The optimization was employed using Response Surface Methodology (RSM) to find the best parameter settings for the maximum tensile strength. This optimization process was carried out via Design Expert software. The input parameters and output response must be set before performing the optimization process. All the limits for the input parameters were set based on the minimum and maximum level factors (i.e., level 1 and level 3). The goal for tensile strength is set to ‘maximize' to achieve maximum tensile strength.

From Table 4, the maximum tensile strength of 36.149 MPa has been predicted with the optimum setting of the input parameters: layer height, printing speed, print temperature, and infill density at 0.30 mm, 30.00 mm/s, 209.85 °C and 75.72 % respectively. It shows that tensile strength could be improved with the minimum setting of layer height and printing speed, and the higher setting for infill density and printing temperature. According to the ANOVA analysis, layer height and infill density have the most influence on tensile strength. Lower layer thickness and higher infill density with higher printing temperature will give a good bonding within the molten material. From this results, proper tuning of input parameters may improve the tensile strength of the printed part.

Table 4
RSM optimization result for tensile strength

Process parameter	Unit	Values
Layer Height (*A*)	mm	0.30
Printing Speed (*B*)	mm/s	30.00
Infill Density (*C*)	%	75.72
Printing Temperature (*D*)	°C	209.85
Optimum Tensile Strength (T_s)	MPa	36.149

3.3 PSO Optimization Results

The aim of PSO optimization is to search for the optimal parameter settings that lead to the maximum tensile strength. The optimal parameters setting of the objective function (tensile strength) is searched within the range of process input parameters. The tensile strength regression model in Eq. (4) is set for the objective function in the PSO optimization process. In this optimization process, the input process parameters are represented by the particle position and velocity, while the fitness or objective function is represented by the regression model. Therefore, the accuracy and reliability of the tensile strength regression model are crucial for the success of the PSO optimization process. It is worth noting that selecting the optimal values for these parameters is crucial for achieving the best possible performance of the PSO algorithm. Table 5 depicts these parameters, which have a significant impact on the speed and accuracy of the PSO algorithm.

Table 5
Optimal solution of PSO setting

Parameter	Setting value
Population number (No of particles)	300
Iteration number (Particles steps)	500
Dimension (No. of process parameter)	4
C1 (cognitive acceleration constant)	1.5
C2 (social acceleration constant)	1.5
W (PSO momentum)	0.4

Figure 6 illustrates the convergence profile for determining the maximum tensile strength using PSO. After 150 iterations, the fitness value quickly converges to the optimal solution.

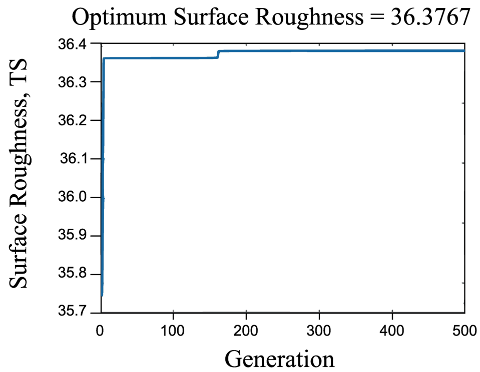

Fig. 6. Convergence of PSO algorithm for tensile strength

The optimal solution is presented in Table 6. It demonstrates that the maximum tensile strength could be achieved with a layer height of 0.30 mm, a print speed of 30.17 mm/s, an infill density of 79.72 %, and a print temperature of 205.92 °C. These results indicate that increasing the layer height and infill density may enhance the tensile strength of the printed part.

Table 6
Tensile strength optimal result from PSO

Process parameter	Unit	Values
Layer Height (*A*)	mm	0.30
Printing Speed (*B*)	mm/s	30.17
Infill Density (*C*)	%	79.72
Printing Temperature (*D*)	°C	205.92
Optimum Tensile Strength (T_s)	MPa	36.377

3.4 Experimental Tests

To confirm the effectiveness of the proposed optimization method in determining the optimal FDM process parameters for achieving maximum tensile strength, a confirmation experiment was carried out. The results of the experiment are presented in Table 7, which indicates that the PSO optimization method has generated superior results for tensile strength when compared to the RSM method. Specifically, the PSO method has yielded an improvement of about 0.63% and 1.52% for the predicted and actual experimental tests, respectively, when compared to the RSM method. These findings serve as evidence of the efficacy of the PSO optimization method in enhancing the tensile strength of FDM products.

Table 7
Tensile strength optimal result from PSO

	Input Parameter				Predicted, T_s (MPa)	Exp., T_s (MPa)
	A (mm)	*B* (mm/s)	*C* (%)	*D* (°C)		
RSM	0.30	30.00	75.72	209.85	36.149	38.484
PSO	0.30	30.17	79.72	205.92	36.377	39.069
Percent Improvement					0.63 %	1.52 %

Figure 7 shows the experimental confirmation results for tensile strength taken from the universal testing machine. It may be inferred that the application of metaheuristic approaches, such as PSO, can reduce the tensile strength of printed parts due to their ability to search for the ideal parameter settings.

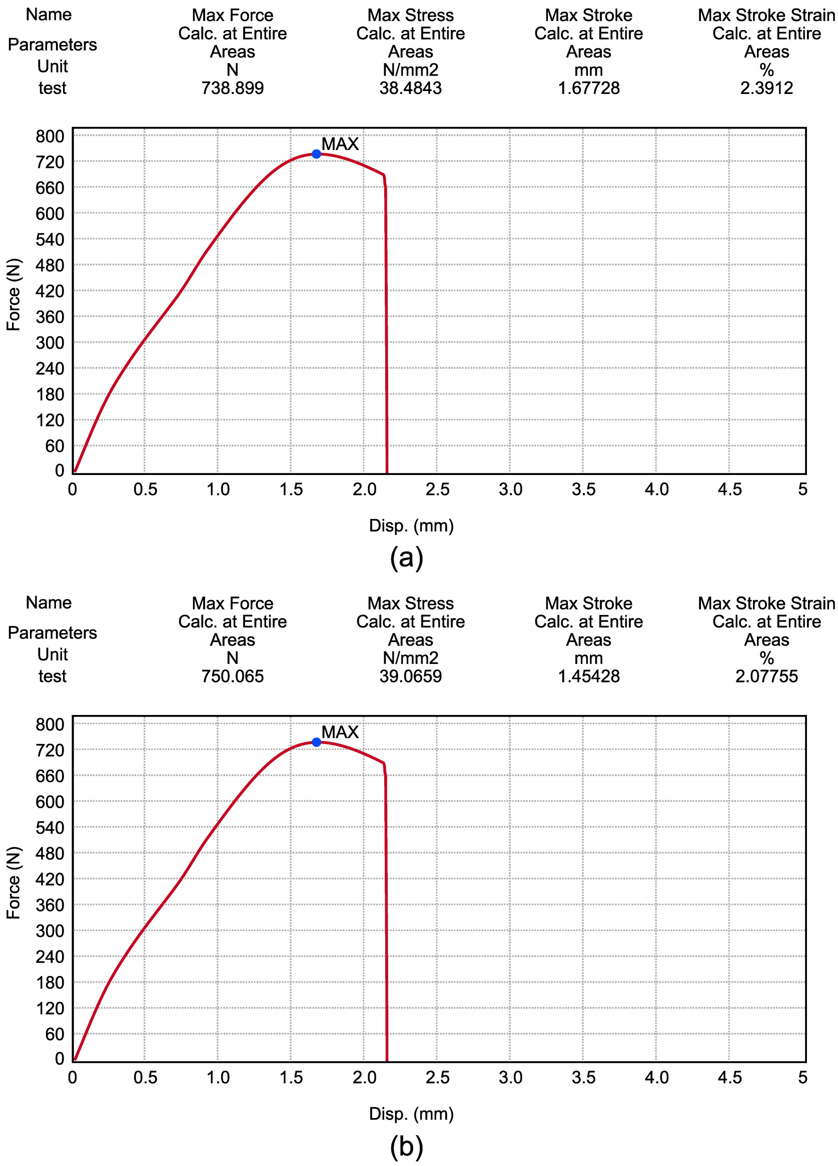

Fig. 7. (a) Graph from Universal Tensile Machine for RSM validation.
(b) Graph from Universal Tensile Machine for PSO validation

4. Conclusions

In this study, the optimization of the process parameters of the FDM machine with respect to maximizing the tensile strength has been implemented using the PSO algorithm and RSM. Furthermore, regression and ANOVA analysis were used to develop the functional relationship between process parameters and tensile strength. The process parameters considered are layer height, print speed, infill density, and print temperature. A comparison study showed that the performance of the PSO algorithm has improved the tensile strength on the sample part by about 0.63 % and 1.52 % for the predicted and actual experimental tests, respectively. On the basis of the statistical analysis, the layer thickness and infill density were considered to be the two most significant parameters. This can be attributed to the fact that increasing the layer height and infill density may enhance the tensile strength of the printed part. The optimum parameters for setting the maximum tensile strength were found to be a layer height of 0.3 mm, a print speed of 30.17 mm/s, and infill density of 79.72 %, respectively. This research can be expanded to encompass other output characteristics of the printed model, such as surface roughness, dimensional accuracy, material consumption, and build time, by utilizing the same optimization method. By exploring the impact of FDM process parameters on these outputs, it is possible to achieve even greater improvements in the overall quality and efficiency of the manufacturing process.

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