

Multi-Objective Optimization for Additive Manufacturing Process using Monarch Butterfly Optimization

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Abstract

This study investigates the influence of key Fused Deposition Modeling (FDM) process parameters i.e. nozzle temperature, part orientation, and layer thickness—on the mechanical properties and surface finish of 3D printed components using a Face-Centered Central Composite Design (FCCCD) approach. Experimental results showed that higher nozzle temperatures (250 °C), orientations at 0° or 90°, and thicker layers (0.35 mm) improved tensile and flexural strengths due to enhanced interlayer bonding. Conversely, a finer layer thickness (0.15 mm) yielded lower surface roughness but reduced mechanical strength. To address this trade-off, the Monarch Butterfly Optimization (MBO) algorithm was applied for multi-objective optimization, identifying 250 °C, 90°, and 0.15 mm as the optimal settings. This combination effectively balances strength and surface quality. While optimization results closely matched experimental data, the surface roughness model suggests potential for further refinement. The study demonstrates the effectiveness of integrating experimental design with nature-inspired optimization, offering a foundation for future work involving Pareto-based and non-linear modeling approaches.

Keywords: Additive Manufacturing, Fused Deposition Modeling (FDM), Process Parameter Optimization, Mechanical Properties, Surface Roughness, Monarch Butterfly Optimization (MBO)

1. Introduction

Additive Manufacturing (AM), or 3D printing, is a layer-by-layer fabrication approach that enables the production of lightweight, high-strength parts directly from digital models, offering greater design flexibility, reduced waste, and shorter development cycles compared to subtractive methods (Gibson et al., 2015). Major AM processes include material extrusion, vat photopolymerization, powder bed fusion, and directed energy deposition, each suited to specific applications. Industries such as aerospace, healthcare, automotive, and consumer goods leverage AM for lightweight components, customized implants, and rapid, low-volume production (Gautam, 2025; Frazier, 2014; Ventola, 2014). With ongoing advancements in materials and process control, AM is a key enabler in Industry 4.0, supporting sustainable, smart manufacturing (Mellor et al., 2014). Ensuring AM part performance requires evaluating both

mechanical properties—tensile strength, hardness, fatigue resistance—and surface characteristics roughness, microstructure, residual stress—since these directly affect structural integrity, wear, corrosion resistance, and fatigue life (Yadroitsev & Smurov, 2010; Levy et al., 2003; Ali et al., 2018; DebRoy et al., 2018). Poor parameter selection can lead to anisotropy, porosity, or rough surfaces, demanding post-processing to meet functional requirements. Current research focuses on optimizing parameters such as laser power, scan speed, layer thickness, hatch spacing, and build orientation to improve density, surface finish, and strength (Herzog et al., 2016). Statistical and computational tools—Design of Experiments (DOE), Response Surface Methodology (RSM), and machine learning—are increasingly applied. For example, RSM has been used to enhance density and surface quality (Mahmoudi et al., 2021), while ML models predict quality from process data and support adaptive control through digital twins (Scime & Beuth, 2018).

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Despite these advances, optimization remains challenging due to complex parameter interactions and material-geometry dependencies (Thompson et al., 2016). Machine Learning (ML) and Artificial Intelligence (AI) help by predicting defects and adjusting parameters in real time (Love et al., 2025; Karlekar, 2025; Zhang et al., 2020). Techniques like convolutional neural networks detect anomalies during builds (Scime & Beuth, 2018), decision trees and SVMs predict mechanical properties (Tapia & Elwany, 2014), and reinforcement learning dynamically tunes process settings to minimize residual stresses (Zhang et al., 2020). Nature-inspired algorithms offer another powerful route for AM optimization, efficiently navigating complex, non-linear search spaces (Deb et al., 2002). Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been applied to enhance surface finish, reduce defects, and optimize build orientation (Singh et al., 2018; Kumar et al., 2020; Zhou et al., 2021). However, these methods may suffer from premature convergence, high computational cost, and sensitivity to hyperparameters (Mirjalili, 2019; Jahangiri et al., 2021; Singh et al., 2020). The Monarch Butterfly Optimization (MBO) algorithm addresses many of these issues. Inspired by butterfly migration and interaction patterns, MBO combines strong global search capability with adaptive local refinement, reducing the risk of local optima and lowering experimental requirements (Wang et al., 2015). Its low parameter count, ease of implementation, and suitability for multi-objective, nonlinear problems make it attractive for AM. Studies have shown its effectiveness in

optimizing process parameters to improve part quality and reduce defects (Zhang et al., 2021).

Materials and Methods

Sample fabrication using material extrusion based AM process

The specimens were produced using fused deposition modeling (FDM) on a Stratasys F170 3D printer. This printer is equipped with a heated build chamber and a touchscreen interface, facilitating straightforward operation. Printing with Stratasys ASA™ is conducted in a controlled laboratory environment to maintain uniformity across all production batches. Material properties The specifications of the machine are provided in Table 1. Table 2 shows key mechanical and thermal characteristics are summarized in Stratasys ASA™. Specimen fabrication is planned using Design of Experiments (DoE) based on the Response Surface Methodology (RSM), specifically applying the Face-Centered Central Composite Design (FCCCD) technique. The Face-Centered Central Composite Design (FCCCD) was selected for its ability to efficiently model quadratic response surfaces while minimizing the number of experimental runs. Unlike other central composite designs, FCCCD places axial points at the midpoints of each cube face, ensuring all design points lie within practical process bounds. This makes it especially suitable for FDM studies where factors have fixed limits, while still allowing the detection of curvature and interaction effects with fewer trials.

Table 1. Specifications of Stratasys F170 Machine

Technology	Fused Deposition Modeling (FDM)
Build Size (X×Y×Z)	254 × 254 × 254 mm
Layer Thickness	0.127 mm / 0.178 mm / 0.254 mm
Supported Materials	PLA, ABS-M30, ASA, ABS-P400
Nozzle Diameter	0.4 mm
Software Compatibility	GrabCAD Print
Heated Build Chamber	Yes
Build Accuracy	±0.2 mm or ±0.002 mm/mm, whichever is greater

This approach was selected because it effectively models quadratic response surfaces while minimizing the number of experiments needed, and it also accounts for interactions between

variables. The FCCCD is especially advantageous when the factors have fixed boundaries, as it places axial points at the midpoint of each face of the factorial cube, making it well-suited for practical implementation in FDM processes.

Table 2. Material properties of ASA

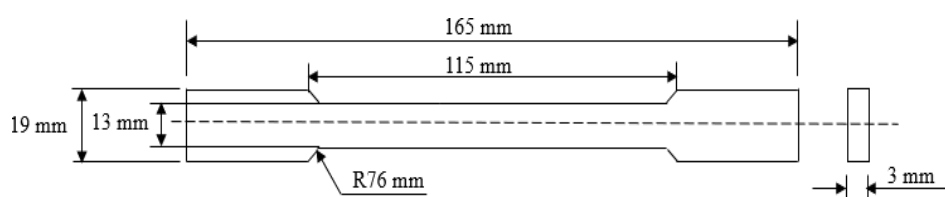
Tensile Strength	30 MPa – 40 MPa
Flexural Strength	50 MPa – 70 MPa
Young's Modulus	~2.0 GPa
Elongation at Break	3% – 6%
Glass Transition Temperature	~105°C
Density	~1.04 g/cm ³
Impact Strength (Notched Izod)	~100 J/m

Table 3. FDM process parameters setting ranges and their levels

FDM Process	Parameters	Levels
	Layer Thickness	
	Part Orientation	
	Nozzle Temperature	
	Units	

Table 3 presents the chosen FDM process parameters along with their respective levels. The parameters i.e. layer thickness, infill density, printing speed, and nozzle temperature were systematically varied to examine their impact on the mechanical behavior of the printed samples. Table 4 presents the Design of Experiments (DoE) schema formulated using a Face-Centered Central Composite Design (FCCCD) approach. The three selected input parameters are nozzle temperature (230–300 °C), part orientation (0°–90°), and layer thickness (0.1–0.35 mm). A total of 30 experimental runs were executed to study the interaction and quadratic effects of these parameters. The

design includes repeated center points to ensure model adequacy and to evaluate experimental variability. This structured approach aids in optimizing process parameters for enhanced additive manufacturing performance. The design ensures a balanced representation of all factor levels, enabling accurate prediction and modeling of process responses. Repetition of central points also facilitates the assessment of experimental error and curvature. This systematic schema is essential for generating statistically reliable insights into the additive manufacturing process.

*Fig. 1. Tensile Specimen detail drawing as per ASTM D638 type-I*

2.2 Measurement of Mechanical Properties

The mechanical behavior of ASA (Acrylonitrile Styrene Acrylate) specimens was evaluated through tensile and flexural tests. All samples were conditioned at room temperature for 24 hours prior to testing. Tensile testing followed ASTM D638 using Type I specimens and was conducted on a universal testing machine (UTM) with a 10 kN load cell at a crosshead speed of 5 mm/min. Parameters such as ultimate tensile strength, tensile modulus, and elongation at break were recorded. Fig. 1 illustrates the specimen geometry in accordance with

ASTM D638. Flexural testing was performed in accordance with ASTM D790 using a three-point bending setup. Rectangular specimens were tested at a crosshead speed of 2 mm/min to determine flexural strength and flexural modulus. These tests were essential to assess the material's strength, stiffness, and deformation behavior under both tensile and bending loads. The results were used to analyze the influence of print orientation and process parameters on the mechanical performance of ASA parts.

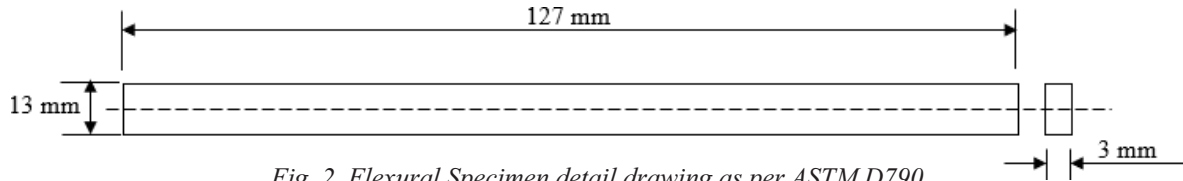


Fig. 2. Flexural Specimen detail drawing as per ASTM D790

In the present work, the surface roughness of the fabricated samples was measured using a contact stylus profilometer, calibrated according to standard guidelines to ensure accuracy. Before measurement, all samples were cleaned thoroughly to remove any contaminants that might affect the results. The profilometer stylus, applying a controlled force, traversed multiple

locations on each sample surface to capture representative roughness profiles. Key parameters such as average roughness (R_a), root mean square roughness (R_q), and peak-to-valley height (R_z) were recorded over a standard evaluation length. Each measurement was repeated three times to ensure reliability, and the results were averaged to minimize variability. The collected data were then analyzed statistically to assess surface quality and compare the effects of different processing conditions on the surface finish.

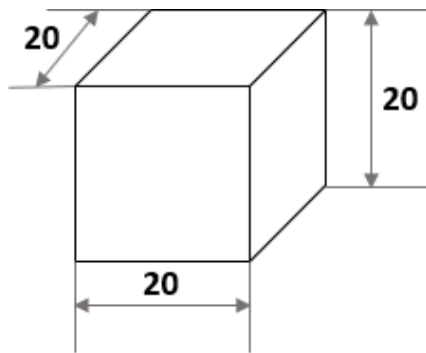


Fig. 3. Detail drawing of cuboid for surface roughness measurement

$$X_i = [x_{i1}, x_{i2}, \dots, x_{id}]; i = 1, 2, \dots, N$$

Where,

$$x_i = i^{th} \text{ butterfly}$$

$d = \text{decision variables}$

$N = \text{population size}$

The population is split into two subpopulations:

- Land 1 (Migratory subpopulation): size $N_1 = \rho \cdot N$
- Land 2 (Stationary subpopulation): size $N_2 = (1 - \rho) \cdot N$

Where, $\rho \in (0,1)$ is the migration ratio.

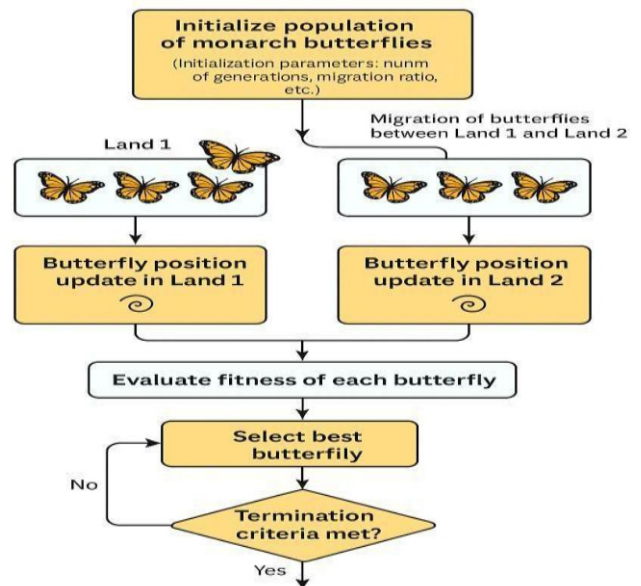


Fig. 4. Monarch Butterfly Optimization

Monarch Butterfly Optimization

Monarch Butterfly Optimization (MBO) is a population-based metaheuristic algorithm inspired by the seasonal migration behavior of monarch butterflies. Introduced by Wang et al. in 2019, the algorithm emulates the butterflies' two distinct behavioural patterns migration and adjustment to perform global and local search operations in an optimization space. Following stepwise approached considered in MBO:

Step 1: Population Initialization

The algorithm begins with a randomly initialized population of candidate solutions (butterflies), each representing a potential set of input parameters as per equation (1),

Step 2: Migration Operator (Global Search)

For each individual in Land 1, the migration behavior is simulated as per equation (2),

$$X^t, \quad \text{if } r < S$$

$$X^{t+1} = \begin{cases} X^t, & \text{otherwise} \end{cases}$$

Where,

r = is a random number uniformly distributed in $[0,1]$,

S = is the migration probability, typically set between 0.1 and 0.3,

X_j^t = is a randomly selected butterfly from Land 1 (within – group influence),

X_k^t = is a butterfly from Land 2 (cross – group migration).

Step 3: Adjustment Operator (Local Search)

For butterflies in Land 2, the adjustment behavior is used as per equation (3),

$$X_i^{t+1} = X_i^t + \text{Stepsize} \cdot (2r - 1)$$

Where,

r = is a random number uniformly distributed in [0,1],

Step 4: Butterfly Adjustment Factor

To improve diversity and control convergence, a butterfly adjustment factor (BAF) is often introduced to modify the local search dynamically using equation (4),

$$\text{Stepsize}_i = \text{BAF} \cdot \left(1 - \frac{t}{T_{\max}}\right) \longrightarrow \quad (4)$$

Where,

t = current iteration, and $T_{\max}$ = maximum number of iterations

Step 5: Boundary Check and Constraint Handling

After each update, the position of each butterfly is checked and corrected if it exceeds the search space bounds as per equation (5),

$$x_{ij} = \min(\max(x_{ij}, x_j^{\min}), x_j^{\max})$$

Step 6: Fitness Evaluation

The objective function (e.g., flexural strength, surface roughness, tensile strength,) is evaluated for each butterfly as per equation (6),

$$\text{Fitness}(X_i) = f(x_{i1}, x_{i2}, \dots, x_{id})$$

Step 7: Elitism and Replacement

The best individuals are retained across generations to ensure solution quality does not degrade a technique known as elitism. The updated population for the next iteration is formed by combining the best solutions and newly generated ones.

Step 8: Termination Criterion

The process is repeated until a predefined maximum number of iterations, or a convergence threshold is reached.

RESULTS AND DISCUSSIONS

The mechanical properties of the 3D printed specimens, including tensile strength, flexural strength, and surface roughness, were evaluated based on the FCCCD design of experiments (Table 4). The results indicate significant

influence of nozzle temperature, part orientation, and layer thickness on the measured outcomes. The highest tensile strength was recorded in Run 1 (53.62 MPa) and Run 16 (53.5 MPa), both having a nozzle temperature of 250 °C, part orientation of 0°, and a larger layer thickness of 0.35 mm. This suggests that higher nozzle temperature combined with horizontal orientation and thicker layers promotes stronger interlayer bonding, leading to improved tensile strength. In contrast, the lowest tensile strength was observed in Run 20 (35.8 MPa), where a lower nozzle temperature (210 °C), vertical orientation (90°), and minimal layer thickness (0.15 mm) were used. This reflects the adverse effect of vertical orientation and low deposition temperature on layer adhesion. Similar trends were noted for flexural strength. Runs 1 and 16 also exhibited high flexural values of 58.5 MPa and 58.3 MPa, respectively. The optimal combination of 250 °C nozzle temperature, 0° orientation, and 0.35 mm layer thickness again proved favourable. The lowest flexural strength

(41.7 MPa) was observed in Run 20, consistent with its poor tensile performance, emphasizing the compounded negative influence of low temperature and unfavorable orientation. Surface roughness exhibited a different pattern. The lowest surface roughness (1.2 µm) was observed in Runs 4, 12, and 20. Notably, Run 4 and 12 had high or moderate nozzle temperatures with 0° and 90° orientations respectively, indicating that surface finish benefits from either increased temperature or specific build orientations. Interestingly, Run 20, despite having the lowest mechanical strengths, showed one of the smoothest surfaces, possibly due to fine layer thickness (0.15 mm) and better control over material deposition. Conversely, Run 7 presented the highest surface roughness (2.8 µm), highlighting that 0° orientation with low nozzle temperature (180 °C) and medium layer thickness (0.25 mm) can lead to poor surface finish due to insufficient melting and rough layer stacking.

Run	Nozzle Temperature (°C)	Part Orientation (°)	Layer Thickness (mm)	Tensile Strength (MPa)	Flexural Strength (MPa)	Surface Roughness (µm)
1	250	0	0.35	53.62	58.5	1.5
2	250	0	0.15	51.2	56.3	1.8
3	180	45	0.25	47.7	52.4	1.7
4	210	0	0.35	51.3	56.9	1.2
5	210	90	0.15	37.6	43.2	2.2
6	180	45	0.25	44.7	50.1	2.1
7	180	0	0.25	48.2	53.3	2.8
8	180	45	0.25	47.6	52.5	2.76
9	180	45	0.25	47.3	52.2	1.78
10	210	0	0.15	47.2	46.9	1.8
11	210	90	0.35	42.2	47.1	2.3
12	250	90	0.35	53.1	57.8	1.2
13	180	90	0.25	41.8	46.7	1.3
14	180	45	0.25	43.2	51.7	1.9
15	250	90	0.15	52.3	47.3	2.1
16	250	0	0.35	53.5	58.3	1.5
17	210	0	0.15	51.8	53.9	2.3
18	250	0	0.15	53.3	55.1	1.8
19	210	90	0.35	39.7	45.5	1.7
20	210	90	0.15	35.8	41.7	1.2

The Monarch Butterfly Optimization (MBO) algorithm was employed to identify optimal process parameters for maximizing tensile and flexural strengths while minimizing surface roughness in FDM-printed parts. The objective functions were modelled as linear equations derived from experimental data, correlating mechanical properties with three key process parameters: nozzle temperature (A), part orientation (B), and layer thickness (C). Through a weighted-sum multi-objective optimization approach (weights: 0.4 for tensile strength, 0.4 for flexural strength, and 0.2 for surface roughness), the optimal solution was determined at a nozzle temperature of 250 °C, part orientation of 90°, and a layer thickness of 0.15 mm. This observation suggests that while the optimization algorithm efficiently explores the solution space, the linear surface roughness model may require refinement or regularization to better reflect realistic physical constraints. Comparison with the experimental dataset reveals that the optimal parameter set aligns with the upper bounds of nozzle temperature and orientation values used in the experiments, indicating that higher energy input and vertical orientation positively influence mechanical performance. Additionally, thinner layer thickness contributes to improved detail resolution and interlayer bonding, hence enhancing strength.

However, this may come at the cost of longer print times and potentially increased energy consumption.

The results validate the effectiveness of using MBO for process optimization in additive manufacturing, offering a robust metaheuristic framework capable of navigating complex design spaces. Future work may involve integrating Pareto-based multi-objective optimization to visualize trade-offs among objectives and incorporating non-linear models for improved accuracy.

CONCLUSION

This study successfully investigated the influence of key FDM process parameters—nozzle temperature, part orientation, and layer thickness—on mechanical performance and surface finish using an FCCCD experimental approach. The analysis revealed that higher nozzle temperatures (250 °C), horizontal or vertical part orientations (0° and 90°), and thicker layers (0.35 mm) generally resulted in improved tensile and flexural strengths due to enhanced interlayer bonding. In contrast, fine layer thickness (0.15 mm) was beneficial for minimizing surface roughness, though often at the cost of mechanical strength. The application of the Monarch

Butterfly Optimization (MBO) algorithm enabled effective multi-objective optimization, yielding an optimal parameter set of 250 °C nozzle temperature, 90° orientation, and 0.15 mm layer thickness. This solution balances high mechanical strength with improved surface quality, confirming the algorithm's ability to navigate complex trade-offs. While the optimization outcome

closely matched high-performing experimental runs, the surface roughness model's simplicity indicates scope for refinement. Overall, the integration of experimental data with MBO-based optimization demonstrates a promising pathway for enhancing the performance of 3D printed components, with potential extensions toward Pareto-based methods and non-linear modeling in future work.

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