Asian Journal of Convergence in Technology
ISSN NO: 2350-1146 I.F-5.11

Investigation for Impact of Process Parameters on Mechanical Properties of Fused Filament Fabrication Components

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Abstract **: The purpose of this article is to look at a variety of tactics used in different industries to optimize the operating parameters of 3D printing systems. Fused Deposition Modeling (FDM), one of the most well-known methods, has drawn a lot of interest because of its broad range of applications in fields including die-making and prototype development. FDM creates three-dimensional objects by layering materials one after the other. Because of its great versatility, the technique makes it possible to produce complex geometries that would be challenging to accomplish with conventional manufacturing techniques. However, FDM still has drawbacks with regard to printing speed, production time, and the structural soundness of the printed parts. The quality of the finished product is directly impacted by a number of variables, including the distance between layers, orientation during printing, percentage of internal fill, deposition angle, path width, and layer depth. Determining and modifying the most important factors in accordance with the particular needs of the item being produced is therefore crucial. To tackle these challenges, numerous researchers have explored advanced optimization tools like experimental design approaches, surface response modeling, evolutionary algorithms, neural network models, and fuzzy logic systems. Many academics have investigated cutting-edge optimization tools such as fuzzy logic systems, evolutionary algorithms, surface response modeling, experimental design approaches, and neural network models in order to address these issues. Strength, accuracy, and dependability are some of the important product attributes that are improved by using these instruments. Objective of this work is to present a thorough analysis of the body of research on enhancing FDM results via efficient process parameter adjustment.**

Keywords: Additive manufacturing; 3D printing; fused filament fabrication; mechanical testing, process parameters optimization, Taguchi Method

I. INTRODUCTION

The continuous evolution of manufacturing technologies has led to innovative approaches that move beyond conventional subtractive methods. Among these, layer-wise fabrication techniques have gained prominence for their efficiency, design freedom, and material savings[1]. One such technology involves building parts directly from digital models by sequentially adding material, enabling the production of intricate components without the need for complex tooling or extensive machining[2].

Originally introduced as a tool for rapid prototyping to aid in design verification and concept visualization, this technique has now matured into a reliable solution for producing functional parts across diverse industries including aerospace, automotive, and biomedical sectors[3],[4],[5]. With advancements in process control and material compatibility, it is now possible to fabricate geometrically complex structures under simpler operating conditions. Several processes have emerged under this domain, such as stereo-lithography, powder bed fusion, binder jetting, and material extrusion[6],[7],[8]. Among them, the extrusion-based technique commonly referred to as Fused Deposition Modeling (FDM) has become particularly widespread[9],[10]. This process lets you make long-lasting and complicated shapes out of thermoplastic materials, and it is known for being easy to use and cost-effective[2],[11],[12].

In FDM, a solid filament is heated and pushed via a nozzle that is carefully controlled, that deposits the material along predefined paths[13]. The object is built layer by layer, providing both flexibility in design and efficiency in production[14]. While this method offers significant advantages over traditional manufacturing, It also makes it hard to get great dimensional accuracy, a good surface quality, and strong mechanics[2],[15]. Different processing variables, like layer height, infill density, deposition angle, and part orientation, have a big effect on these properties[6],[16],[17].

Given the sensitivity of final product performance to these parameters, researchers have explored numerous optimization techniques. Experimental frameworks and computational strategies—including Taguchi methods, genetic algorithms, neural networks, and fuzzy logic—have been applied to fine-tune these variables for improved results[14],[15],[19].

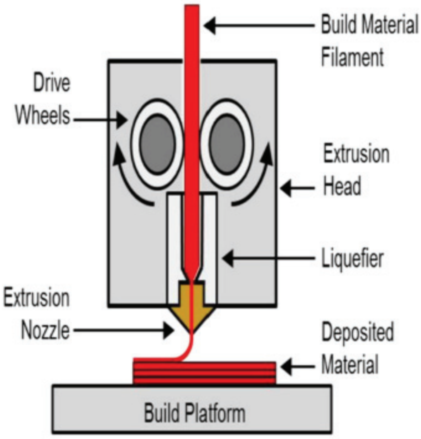

Fig. 1. FDM Block Diagram [18]

This paper provides a comprehensive review of current efforts in optimizing FDM process settings, with an emphasis on enhancing mechanical properties, minimizing build time, and improving overall part quality[20]. The following sections cover an overview of key process parameters, materials in use, optimization methodologies, and concluding insights with future research directions[18],[21].

A. Process Parameters

FDM has a lot of process settings that can change the quality of the parts it makes. Following are the most widely studied FDM process parameters:

1) ***Layer Thickness*** **-** Layer Thickness is an important part of Fused Deposition Modelling (FDM) that tells you how thick each layer of material is when it is printed[16],[22]. It has a direct effect on the printed part's surface polish, dimensional accuracy, mechanical qualities, and construction time[23]. Thinner layers usually make surfaces smoother and features sharper, but they also make the printing take longer. On the other hand, thicker layers make the print time shorter, but they could make the finish rougher and the resolution poorer[24]. The selection of optimal layer thickness depends on the application requirements whether high precision or faster production is prioritized[23].

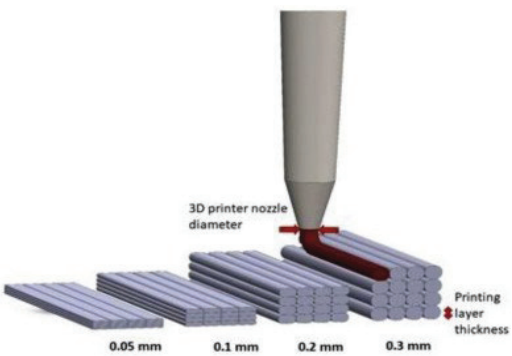

Fig. 2. Layer Thickness [23]

2) ***Build Orientation*** **-** Build orientation is the angle or location of a part on the build platform during the 3D printing process. It is very important for figuring out the ultimate quality, strength, surface finish, and print time of the part[25]. A good orientation can cut down on the requirement for support structures, use less material, and improve mechanical qualities in the right ways. Conversely, poor orientation may lead to ***increased*** warping, reduced dimensional accuracy, and weaker inter-layer bonding[26],[27]. Therefore, selecting an optimal build orientation is essential for improving the overall efficiency and performance of the printed part[25].

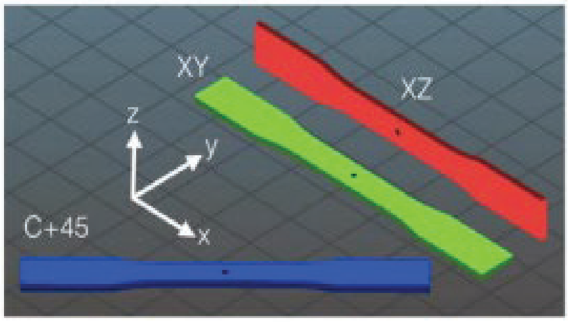

Fig. 3. Build Orientation [25]

3) ***Raster Angle*** **-** Raster angle refers to the orientation of the infill lines (or toolpath) inside each layer of a 3D printed part, typically measured in degrees relative to the X-axis[28]. It determines the direction in which the material is deposited within each layer during the Fused Deposition Modeling (FDM) process. Common raster angles include 0°, 45°, 90°, or alternating patterns (e.g., ±45°)[29]. The selection of raster angle significantly affects the part's mechanical properties, such as tensile strength, stiffness, and surface finish[18]. For example, parts printed with alternating raster angles often exhibit improved strength due to better inter-layer bonding and more uniform stress distribution[24].

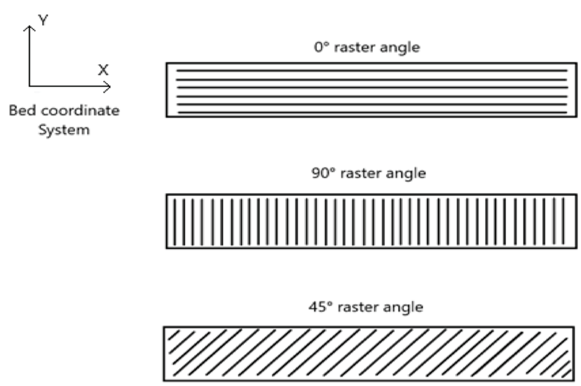

Fig. 4. Raster Angle [24]

4) ***Infill Pattern*** - The infill pattern in Fused Deposition Modeling (FDM) refers to the internal structure or layout used to fill the inside of a 3D printed object[30],[31]. It is very important for figuring out how strong, heavy, and long the item will take to print. Grid, honeycomb, triangle, gyroid, and line are all common infill patterns[32]. Each one has its own set of ***mechanical*** qualities and print speeds[33]. For instance, honeycomb and gyroid designs are strong and light, while line or grid patterns are faster to print but may not be as strong. Selecting an appropriate infill pattern depends on the specific application requirements, such as load-bearing capacity or flexibility[32].

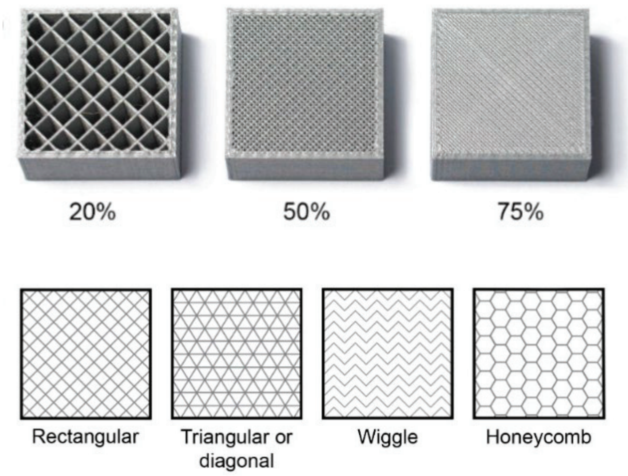

Fig. 5. Infill Pattern [32]

II. LITERATURE REVIEW

Jatti et.al investigates the influence of FDM process parameters on the tensile strength of PLA parts and employs six meta-heuristic optimization algorithms: PSO, TLBO, GA, SA, CI, and JAYA[1]. The input factors that were looked at are infill density, layer height, print speed, and temperature during extrusion. Tensile strength testing was done per ASTM D638 standards. Among all optimization techniques, the Jaya algorithm yielded the best performance with a maximum tensile strength of 55.475 N/mm²[12]**.** The consistency of multiple algorithms runs indicated their reliability. Validation experiments confirmed that the optimized parameters closely matched predicted outcomes with low error margins[1]. This work also presents a comprehensive literature review of past studies that investigated similar mechanical properties of 3D-printed materials using statistical and experimental approaches[13]. It emphasizes the importance of operational range, material choice, and interaction between variables in determining final mechanical properties[34],[35].

This study explores the recycling of waste PLA from 3D printing into usable filament using a self-developed extrusion system. The work applies a Design of Experiments (DOE) methodology, particularly the Taguchi method (L9 orthogonal array)**,** to identify optimal process parameters affecting filament diameter and strength[36]. Barrel temperature, extrusion speed, cooling distance, and the ratio of recycled material are all factors. The aim was to achieve a filament diameter of 1.7 mm with good mechanical strength. The study indicated that the most important component was the temperature of the barrel, followed by the amount of recycled material, the speed, and the distance from the cooling. Filaments produced from 40% recycled PLA exhibited a tensile strength 1.1 times that of commercial filament. Cost analysis revealed that recycled filament was 40% cheaper to produce[2].

This study investigates the shear behavior of PLA components fabricated via FDM, with a focus on optimizing mechanical properties through key process parameters: layer thickness**,** infill density**,** and heat treatment duration**.** A Taguchi L9 orthogonal array was used to design 27 experiments with three levels for each parameter. Specimens were tested in torsion using an electromechanical torsion tester to evaluate ultimate shear strength (Sus), 0.2% yield strength (sy), proportional limit (spl), shear modulus (G), and fracture strain (cf)[6]**.**

This study analyzed how FDM 3D printing parameters—temperature, speed, and layer height—affect the mechanical strength, surface roughness, dimensional accuracy, and print time of ULTRA PLA parts. Using a factorial design of experiments, 30 tests were conducted. Results showed that higher temperatures (up to 300°C) and smaller layer heights (0.1 mm) significantly improve tensile strength and surface quality**.** Printing speed had minimal effect. Mathematical models and Pareto charts identified temperature and layer height as key factors. Optimal settings for strong, precise parts were 300°C, 60 mm/s, and 0.1 mm[15]**.**

This study examined the effects of raster orientation and printing speed on the mechanical properties of PLA parts made via FDM. Tensile tests on 60 specimens revealed that raster orientation had the most significant impact—0° orientation gave the highest strength, while 90° showed the lowest. Tensile strength dropped by up to 46% with increased raster angle. Higher printing speeds (80 mm/s) slightly reduced strength and elongation. The study also analyzed fracture modes and used two theoretical models to predict strength, both matching well with experimental data. The findings emphasize optimizing raster direction for better mechanical performance in 3D-printed PLA parts[18].

III. OPTIMIZATION TECHNIQUES

A. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are computer programs that are modeled after the composition and operations of the human brain. Unlike traditional computers that follow strict programming, ANNs learn from experience by recognizing patterns and adapting over time[37]. They are made up of linked processing units that collaborate to solve challenging issues, much like artificial neurons such as image recognition, speech processing, and adaptive control. Instead of exact instructions, ANNs improve through training, adjusting internal connections similar to how the brain forms memories[19]. This brain-like approach to computing is energy-efficient, adaptable, and represents a major shift in the development of intelligent machines[37].

B. Teaching Learning Based Optimization (TLBO)

Teaching-Learning-Based Optimization (TLBO) algorithm, inspired by the learning dynamics between teachers and students. Since its introduction in 2011, TLBO has shown success across multiple domains due to its simplicity, fast convergence, and no need for algorithm-specific parameters[38]. Researchers have since proposed various improvements and hybrid versions of TLBO to enhance performance and tackle issues like premature convergence. Examples include integrating chaotic functions, local search mechanisms, weighted averages, and hybrid models with neural networks or other optimizers[38]. A recent advancement is RLTLBO, which integrates reinforcement learning into the learner phase and uses Random Opposition-Based Learning (ROBL) to avoid getting stuck in local optima. This improved method was tested against standard benchmark functions and engineering design problems[1].

C. Response Surface Method (RSM)

Response Surface Methodology (RSM) is a commonly used statistical tool for optimizing processes and product development. It combines mathematical and statistical methods to design experiments, build predictive models, and find the best conditions for input variables to achieve desired outcomes. RSM is especially useful when multiple factors influence a process, allowing analysis of both individual and interactive effects[36]. Using polynomial regression, RSM models the relationship between inputs and outputs, helping to fine-tune parameters and forecast responses accurately. Its predictive strength and ability to analyze multiple variables make it valuable for process enhancement across industries. Design of Experiments (DoE) complements RSM by identifying key variables affecting outcomes. Common designs include 2^k factorial, simplex, and Plackett-Burman for first-order, and central composite, 3^k factorial, and Box-Behnken for second-order studies[36].

D. 4. Particle Swarm Optimization (PSO)

The algorithm known as Particle Swarm Optimization (PSO) draws inspiration from nature and designed to solve complex, non-linear, and multidimensional problems efficiently with minimal tuning. Introduced by Kennedy and Eberhard in 1995, PSO is based on the collective behavior seen in nature, such as bird flocking or fish schooling, and is part of the broader field of Swarm Intelligence[39].

In PSO, a group of candidate solutions, called particles, explores the solution space guided by a fitness function. Each particle evaluates its position and learns from both its own experience and that of others[12]. Randomness in movement helps the particles explore new areas, increasing the likelihood of finding optimal solutions effectively[1].

E. Genetic Algorithm (GA)

Genetic Algorithms (GAs), inspired by natural evolution and introduced by J. Holland in the 1970s, are optimization methods that simulate the process of natural selection. In GA, potential solutions are treated as individuals in a population, and better solutions evolve over successive generations. Each individual, or chromosome, is evaluated using a fitness function[1]. Through repeated cycles of selection (choosing the fittest), crossover (combining parents), and mutation (random changes), new generations are formed. This process continues until a stopping condition is met[12]. GAs is effective for exploring complex, multi-modal, and discrete solution spaces, making them powerful and flexible tools for optimization[38].

IV. CASE STUDY ON TAGUCHI METHOD

The Taguchi Method is a statistical approach used to optimize process parameters with minimal experiments. In a case study with three factors—temperature, pressure, and time—each at three levels, an L9 orthogonal array was used to reduce the number of trials from 27 to 9[40]. After conducting the experiments and analyzing the results using the "smaller-the-better" signal-to-noise (S/N) ratio, the optimal setting was found to be 70°C, 20 bar pressure, and 10 minutes[41]. This minimized defects, improved quality, and saved time and resources, showing the efficiency of the Taguchi Method in process optimization[42].

Step 1: Define the Problem – Clearly identify the objective of the study, such as minimizing defects, improving product quality, or enhancing performance[43]. Select the key process parameters (factors) that may influence the output and decide how many levels each factor will have[16].This forms the basis of the experimental design.

Factors	Parameters	Levels		
		1	2	3
A	Layer thickness(mm)	0.1	0.15	0.2
B	Feed rate (mm/s)	20	40	60
C	Raster angle	0°	45°	90°
infill pattern	Infill density	Nozzle temperature	Bed temperature	
Lines	80%	210 °C	60 °C	

Fig. 6. Parameters [44]

Step 2: Select Orthogonal Array – Choose an appropriate Taguchi orthogonal array, such as L9, L18, or L27, depending on the number of factors and levels[6],[21],[19]. This reduces the total number of experiments needed while still covering all possible interactions in a balanced way[45].

Step 3: Conduct Experiments and Measure Output – Perform the experiments as per the combinations given in the selected orthogonal array[19]. Carefully measure the output or response for each trial, such as surface roughness, number of defects, or processing time[46],[47],[22].

Step 4: Analyze Results Using S/N Ratio (Smaller is Better) – Convert the measured outputs into Signal-to-Noise (S/N) ratios to identify which factor levels provide the best performance[42]. If the goal is to minimize the output (like defects), the "smaller-the-better" formula is used[41]. This analysis helps to evaluate both the mean and variability of results[39].

Step 5: Identify Optimal Factor Levels – Based on the S/N ratio analysis, determine the optimal level of each factor that contributes to the best performance. These levels represent the ideal settings for the process[48].

Result of case study: To investigate the interactions among different factors, the Taguchi L16 orthogonal array was selected. The primary objectives of the experiment were to identify the optimal results while minimizing the number of experimental runs**.** The study focused on analyzing three key parameters**:** layer height**,** feed rate**,** and raster angle**,** to understand their influence on the material's behavior[28],[29].

V. CONCLUSION

This review investigated how the settings of the Fused Deposition Modeling (FDM) method affected the properties of 3D printed components and examined various optimization techniques commonly applied in this field. Techniques such as Genetic Algorithms (GA), Response Surface Methodology (RSM), and the Taguchi Method were highlighted for their effectiveness in identifying key parameters that affect properties like mechanical strength, surface quality, and accuracy. The review discussed a wide array of studies where these methods have been used to refine FDM processes, though it noted that most research has focused on enhancing part properties and process performance. Areas like improving 3D printer design, investigating new materials, and developing preventive maintenance strategies have received less attention.

Several opportunities for future research were identified in the review. For example, while ABS and PLA are the most widely used materials, other thermoplastics such as Nylon, PETG, and HIPS could offer valuable alternatives for 3D printing. Additionally, process parameters such as infill pattern, shell width, air gap, and annealing have not been studied as extensively as other parameters like layer thickness and build orientation, presenting an opportunity for further optimization. There is also limited research on multi-objective optimization, where several factors are balanced simultaneously, which could be an important area for future work. Other potential avenues for research include developing methods for 3D printing in multiple planes to minimize the need for support structures, as well as exploring 3D printing on uneven surfaces or for repairing broken parts, both of which could lead to significant advancements in the field of additive manufacturing

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