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OPTIMIZATION OF PROCESS PARAMETERS OF FUSED DEPOSITION MODELLING AND METHODS: A REVIEW

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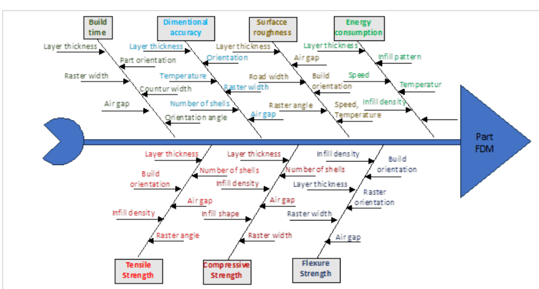
Graphical abstract



Abstract

Due to its various benefits, including changeable geometry, lower production costs, faster manufacturing cycles, and enhanced competitiveness, 3D printing technology has advanced rapidly in recent years. The Fused Deposition Modeling (FDM) technique is one that is frequently utilized in 3D printing technology. This is because compared to other techniques, this one is the most adaptable, affordable, and easy to apply. However, FDM components have poor dimensional and geometric accuracy, bonds between layers have low strength, and FDM accuracy is greatly affected by various process parameters that are often difficult to optimize**.** The primary process parameters are discussed in this paper, along with the factors that affect them and how they affect the features of goods made using FDM printing. Therefore, it will show the optimization of all process parameters and methods to all printing characteristics, namely manufacturing time, available in the current FDM study include dimensional accuracy, surface roughness, energy consumption, and mechanical strength. This review also presented some conclusions that answer this field's challenges and future research directions.

Keywords: 3D printing, FDM, Optimization, Process parameters, Printing characteristics, Method

1.0 INTRODUCTION

The method of layer-by-layer combining materials to create three-dimensional things is known as additive manufacturing (AM) [1]. Additive manufacturing (AM), sometimes referred to as 3D printing, has the power to transform industry through technology [2]. In 1986, Hull used 3D printing for the first time [3]. Due to its various benefits, such as configurable geometries, reduced production costs, faster production cycles, and enhanced competitiveness, Recent years have seen a rapid advancement in 3D printing technology. Binder jetting, inkjet printing, stereolithography (SLA), selective sintering printing (SLS), fused deposition modeling (FDM), and extrusion-based printing are some of the 3D printing techniques [3]. A frequently employed methodology in 3D printing technology is the Stratasys-patented Fused Deposition Modelling (FDM) process [1]. FDM can make complex components from various materials and difficult parts in a faster production cycle time [4]. In addition, it is also the easiest and cheapest technique to use and the most flexible than others [5]. Many researchers have researched parameter optimization engaged in developing 3D printing products. Standard parameters include fill properties, table temperature, nozzle temperature, print speed, and thin material thickness per layer [5]. The bed temperature, nozzle temperature, print speed, layer-by-layer material thickness, and filament characteristics are examples of standard parameters [6]. Another optimization problem is, as in research developed by Sood [7], Thus, there is a connection between the mechanical qualities of tensile strength, Ts (MPa), flexural strength, Fs (MPa), and impact strength, Is (MPa). Using the FDM technique, models are made by adjusting the air gap parameters, raster width, raster angle, orientation angle, and layer thickness [8]. Similar characteristics have also been utilized to evaluate the impact on the radial compression load, shrinkage percentage of the support thickness and breadth employing Response Surface Methodology (RSM) to measure stent flexibility, factors of the process, such as layer thickness, printing speed, and material composition were also used [9]. Studies that employ metal injection molded copper (MIM) as a raw material for 3D printing based on extrusion. Additionally, the relationship between green density and surface roughness and the parameters of the 3D printing process—namely, extrusion multiplier, temperature, layer thickness, and nozzle speed—has been explored. When the layer thickness was reduced from 0.25 to 0.05 mm and the nozzle speed was lowered from 100 mm/s to 20 mm/s, the green solids rose. In a similar vein, increasing the extrusion multiplier raises the surface roughness up to a specific degree [10].

The optimization criteria for the multipurpose optimization problem aimed at refining FDM procedures are shape correctness and printing time in terms of overall dimensional inaccuracy. Taking the dimensional deviation into account, the final criterion is developed of the created part from the predetermined nominal due to the displacement error of the 3D printer on the X, Y, and Z axes. The filler ratio (%), layer thickness (mm), and deposition angle (≦C) are the independent process parameters. This parameter is crucial for the successful operation of FDM because The mechanical qualities of the part being manufactured are impacted by its arrangement. Also, note that FDM parts' mechanical characteristics are structure-dependent. The nozzle's direction, which maintains the melted filament against the X or Y axis, is determined by the deposition angle. For every additional material addition, There is a correlation between layer height and layer thickness. The thickness and height of the layer largely dictate how long the 3D printing process takes; the lower the layer, the longer the printing time [8]. Currently, parameter optimization of multi-material 3D printing processes using multiple extruders is challenging for FDM methods. Choosing the right multi-material nozzle technology is still a difficult task. A detailed understanding of the control parameters, software capabilities, and electronic components of a 3D printer is necessary to manufacture a viable multi-material product. Various research methods are used to support the creation of good research academically. Statistical methods and optimization methods are used to acquire knowledge and its development and discoveries that can be tested for correctness. The primary process parameters are discussed in this paper, along with the factors that affect them and how they affect the features of goods made using FDM printing. Therefore, it will show the optimization of all process parameters and methods to all printing characteristics, namely manufacturing time, The highest level of surface roughness, dimensional accuracy, energy consumption, and mechanical strength yet discovered in FDM research. The results of this study will present conclusions that answer the challenges and the next direction of research that should be carried out in this field.

This article includes a review of single and multi-objective FDM optimization research published over the last twenty years, from 2003 to 2023. Various research articles use different keywords in titles, abstracts, and keyword sections from various searchable scientific databases and relevant published essays (journal and conference papers) selected from four major science publishers such as Taylor & Francis, Springer Link, Science Direct, and Inder Science indexed by Scopus. Obtained about 120 articles and reduced to 67 research articles finally selected for this survey. A summary of various optimization techniques applied in a published research article on FDM process parameter optimization will be given here.

2.0 FUSED DEPOSITION MODELING (FDM)

Fused deposition modeling (FDM) is a method of extruding liquid thermoplastic materials to create components layer by layer. One kind of additive manufacturing called FDM is thought to be the most widely utilized method. This is because it is much simpler and more cost-effective than other processes and can use many different raw materials [11]. FDM is a 3D printing technique that can produce better output response results in terms of mechanical attributes, surface roughness, dimensional accuracy, and microstructure features [12]. With reference to Figure 1, which illustrates the main components of an FDM printer, the process will be described here. The x, y, and z directions of FDM machines can be moved using the build platform (green arrow), the extrusion head (purple arrow), or a combination of the two. For instance, whereas build platform movement completes the Z direction, extrusion head movement completes the X and Y directions [13].

Although the main topics of the study have been thoroughly analyzed, there are some limitations that need to be noted. Adequate comparative studies on the cost aspects of various optimization methods used in FDM are not available. As a result, this study does not contain any conclusions regarding which optimization method is the most cost-efficient. The authors did not include cost analysis as part of the evaluation, and only concentrated on other aspects that were studied to achieve good print quality, such as mechanical performance, roughness level, dimensional accuracy, printing time, or energy efficiency.

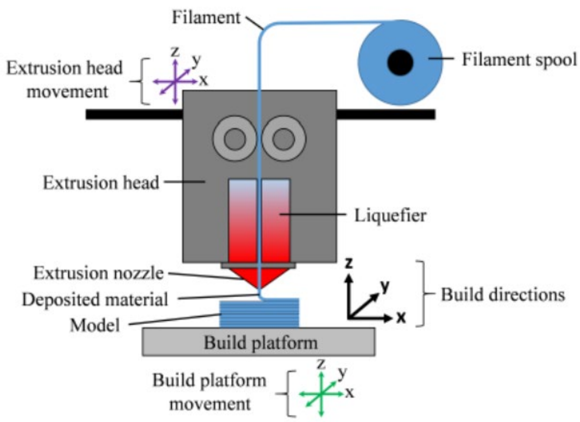


Figure 1 Main components of FDM machine [13]

2.1 Process Parameters

Process parameters in the FDM process affect the production efficiency and part characterization and can be changed to modify the properties of components that are made. Air gap, building orientation, extrusion temperature, filler density, filler pattern, layer thickness, shell number, print speed, raster orientation, raster width, and heat treatment temperature are the most often employed process parameters in study. The main process parameters are described below [14].

1. Air gap (AG): In the deposited layer, the space between two neighboring rasters. The overlap of two neighboring layers is referred to as a negative air gap. The air gap level most often used in various studies ranges from 0 to 0.02 mm.
2. Build orientation (BO): A method called wake orientation can be used to align the inside of a building platform with regard to the X, Y, and Z axes. Wake orientation is seen as a categorical variable in certain research but as a quantitative component in others (Figure 2).

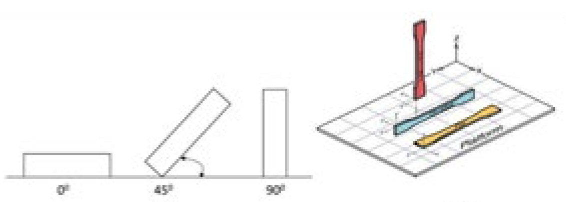


Figure 2 Build orientation parameters level: (a) numerical; (b) categorical [14]

3. During the FDM process, the material's filament is heated to the extrusion temperature. The kind of material and printing speed have an impact on the extrusion temperature. The printing temperature most commonly used in various studies and various types of materials ranges from 190 to 250^{0} C.
4. Infill density (ID): The exterior layer of an object printed in three dimensions (3D). On the other hand, the filler—also referred to as the internal structure—is an imperceptible interior component that is encased in an exterior layer that varies in size, shape, and pattern. The fraction of the filling volume made of filament material is known as the filler's density. The fill's thickness affects the FDM build parts' mass and strength. The infill density level most often used in various studies ranges from 50% to 100%.
5. Infill pattern (IP): To create a strong and durable interior structure, different filler patterns are applied in different areas. Hexagonal, diamond, and linear patterns are common filler designs (Figure 3).

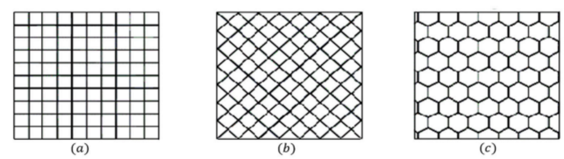


Figure 3 infill pattern parameters level: (a) linear, (b) diamond, (c) hexagonal [14]

6. Layer thickness (LT): The vertical axis of FDM machines, or the height of the layer deposited along the Z-axis, is known as this. It typically relies on the nozzles' diameter and is less than their diameter in extruder nozzles. The layer height becomes the level in this process parameter and usually the level frequently used ranges from 0.1 to 0.3 mm.
7. Print speed (PS): The length of time the extruder spends traveling in the XY plane during an extrusion. The print speed, expressed in mm/s, dictates the printing time. The speed levels most often used in various studies range from 75 to 100 mm/s.
8. Raster width (RW): The term refers to the settling bead's width. The diameter of the extrusion nozzles dictates this. The raster width level most often used in various studies ranges from 0.4 to 0.7 mm.
9. Raster orientation (RO): This is the direction in which the bed deposits material when using the FDM machine manufacturing X-axis platform (Figure 4).

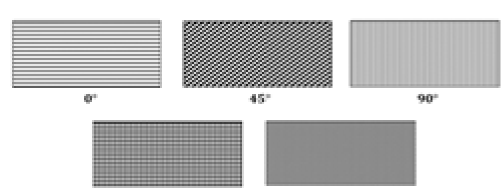


Figure 4 Raster orientation parameters level [14]

Furthermore, there are still a lot of process variables in FDM that have an impact on the manufactured component quality. Here are other FDM process parameters widely studied and used in FDM parameter optimization research [4].

10. Bed temperature (BT): This is the 3D printer's base's surface temperature. The temperature affects how well the first molding layer adheres to the printing bed. According to reports, when the bed temperature is just a little bit higher than the printed material's glass transition temperature adequate adhesive qualities are achieved. A suitable adhesive is needed to avoid warping parts and improve the dimensional accuracy of details. The bed temperature most commonly used in various studies and various types of materials ranges from 60 to 105^0 C.
11. Contour width (CW): The outer solid shell of the FDM part is printed as a set of contours of the liquid material. The contour width (Figure 5) is the width of a contour.
12. Contour air gap (CIG): The distance between two adjacent contours is the contour air gap when a part's filling force is selected as many contours.
13. The perimeter to raster air gap is the length of time that separates the innermost contours from the raster fill's boundary.
14. Number of contours (NoC): Indicates how many contours there are on a part's shell. The number of contours that become levels in each study that is most often used ranges from 1 to 6.

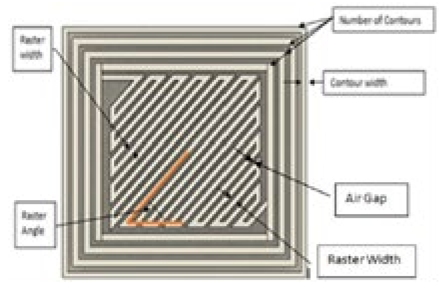


Figure 5 FDM tool path parameters [4]

The most optimum FDM process parameters are listed below, based on the studies listed in Table 1.

Table 1 Research related to FDM process optimization based on parameters

Parameters	Authors
Layer Thickness	[7], [8], [12], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58].
Air Gap	[7], [15], [16], [17], [18], [19], [20], [21], [23], [27], [28], [30], [35], [38], [40], [49], [59].
Build Orientation	[17], [18], [19], [20], [22], [26], [27], [28], [29]), [30], [32], [35], [38], [40], [41], [42], [43], [47], [49], [60], [61], [62], [63], [64], [65].
Raster Width	[7], [15], [16], [17], [18], [19], [20], [22], [23], [27], [28], [30], [34], [35], [38], [40], [48], [49], [53], [61].
Print Speed	[25], [26], [27], [29], [31], [37], [38], [39], [41], [42], [43], [44], [45], [50], [51], [52], [53], [54], [55], [56], [57], [66], [67], [68] [69], [70], [71].
Raster Orientation	[8], [15], [16], [18], [19], [20], [21], [22], [23], [24], [27], [28], [30], [35], [38], [40], [46], [49], [55], [59], [60], [61], [62], [63], [64], [72], [73], [74].
Nozzle Temperature	[12], [26], [27], [29], [33], [37], [38], [39], [43], [46], [48], [50], [55], [56], [57], [59], [70], [71], [73], [74].
Shell Width	[22], [35], [38], [44], [66].
Number of Shell	[26], [28], [38], [49], [58].
Infill Density	[8], [12], [26], [29], [33], [38], [44], [46], [47], [48], [50], [51], [52], [54], [55], [57], [58], [59], [63], [69],[73], [75].
Infill Pattern	[11], [29], [38], [41], [42], [44], [51], [52], [65], [66], [69], [75].
Others	[32], [36], [45], [48], [50], [55], [57], [64].

Most process parameter optimization research looks at how process parameters impact mechanical characteristics, dimensional accuracy, manufacturing time, and surface roughness. Similar to searches based on filament materials, various keywords are utilized to look up publications in scientific web databases in order to examine these investigations. Fused Deposition Modeling, Fused Deposition Model Optimization, Process Parameters, and Part Characteristics of Fused Deposition Model Manufacturing are these keywords. Because a single process parameter can have an impact on several response characteristics, there are instances where some process parameters and the response characteristics of optimization solutions overlap. For example, research conducted by Panda [18], Sood [20], Liu [30], and Fountas [40], use the same five process parameters—layer thickness, air gap, build orientation, raster width, and raster orientation—to determine the impact of mechanical forces, such as compressive, flexural, and tensile strength. While Mohamed [28], add the Number of Shell parameters to determine the effect of its mechanical strength so that it becomes six process parameters.

These five process parameters are often chosen for parameter optimization in the FDM process. The five process characteristics are commonly employed in addition to testing mechanical strength and optimized to see the impact of printing time, such as research conducted by Srivastava [35] and Giri [49]. Another part of the FDM process that the five process parameters can determine is dimensional accuracy, as performed by Sood [19] and Kaveh [27]. In research conducted by Kaveh [27], Alafaghani [29], and Enemuoh [44]. Dimensional accuracy may be affected by process variables such as density, infill pattern, speed, and temperature. Research that calculate the impact of other elements of the FDM process, like surface roughness, is carried out using the five parameters above, plus speed, temperature, and number of shells by Kaveh [27] and Giri [49], While on research by Shirmohammadi [50], and Patil [52] utilizing additional variables, particularly the density and infill pattern. The final step of the FDM process, energy consumption, is frequently utilized as a study target for process parameter improvement. Energy consumption itself is new research that has begun to be developed and began to be researched since 2018 until now. The process parameters that are often used to see energy usage by Enemuoh [44], Zgodavova [48], Warke [54], Vidakis [55], Poonia [57] and Rinanto [73] on a 3D machine are layer parameters of thickness, speed, temperature, and infill density.

Figure 6 provides fishbone diagrams as a visual aid to show how different process parameters affect distinct FDM product characteristics. Fishbone diagrams are developed based on the results of a review of multiple studies that have been collected. Each process parameter's impact on FDM parts is ranked from most significantly impacting to least significantly affecting, starting from the topmost spot on the left side of the side and moving down to the bottom position. Tensile strength, for instance, is primarily influenced by process parameters such as layer thickness, build orientation, infill density, number of shells, air gap, and raster angle. Similarly, how to determine which process parameter level affects other FDM components the most.

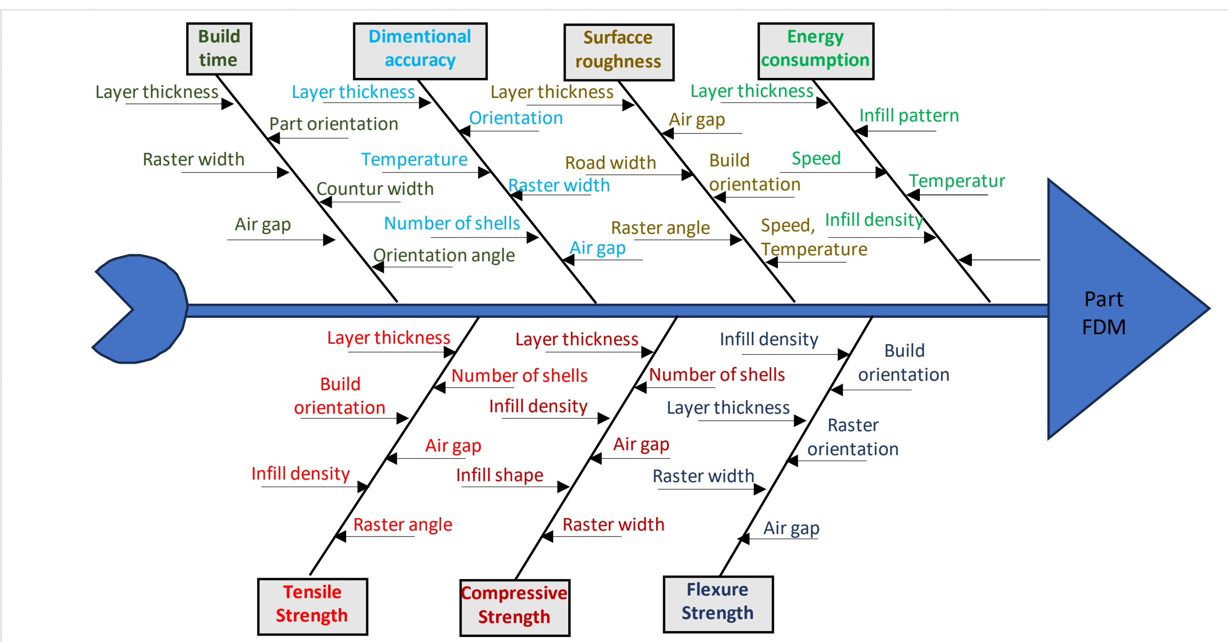


Figure 6 Fishbone diagram: the effect of process parameters on FDM parts

2.2 FDM Material

Hot filaments that go through nozzles create pieces in the FDM process. Filaments made of various thermoplastics can be employed. Most published research on FDM technology-based 3D printing concentrates on materials that are often used in industry, including PLA and ABS [13]. These materials have properties that are useful for 3D printing, as shown in Table 2. These materials are commonly used in FDM.

1. Acrylonitrile butadiene styrene (ABS)
   An amorphous thermoplastic polymer called ABS is frequently utilized in the FDM technique to create 3D printed items. Styrene, butadiene, and acrylonitrile are the constituents of the copolymer ABS. ABS must have both toughness and compressive strength as fundamental

mechanical properties. ABS, the industry standard for printing, has a higher melting point of 230°. ABS is not biodegradable, unlike PLA is, however it has a decreased chance of nozzle obstruction.

2. Poly Lactic Acid (PLA)
One of the thermoplastics that is frequently used in FDM is PLA. Because PLA is a biodegradable polymer, its use is growing [14]. Furthermore, processing high-quality functional components and prototypes requires less heat and energy. PLA is a popular filament for 3D printers since it doesn't need a heated bed, but while printing, it sometimes gets stuck in the nozzles of the printer. Compared to ABS, PLA is more tensile strong, has a lower curvature, and is less ductile. For post-processing, components made by PLA require extra care compared to ABS.

Table 2 General properties of various thermoplastics [4]

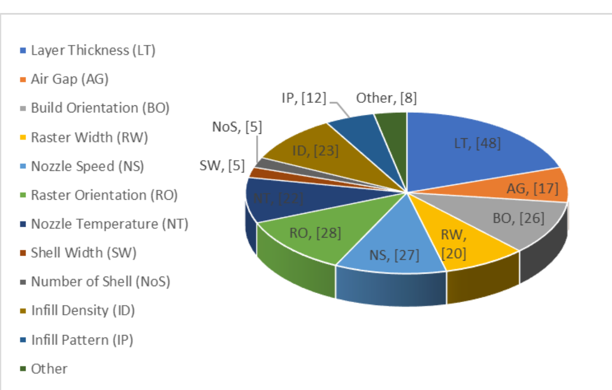
Material / Properties	PLA	ABS	HIPS	PET	Nylon	PC
Nozzle Temperature ⁰C	180-220	210-240	220-230	230-255	235-270	270-315
Bed Temperature ⁰C	20-55	80-110	50-60	55-77	60-80	90-120
Tg ⁰C	60-65	105-110	100	70-78	47-60	145-150

Material, often called filament in 3D printing, is essential in determining the object you want to produce. Table 3 shows the classification of research articles related to FDM process parameter optimization based on filament materials used to make components.

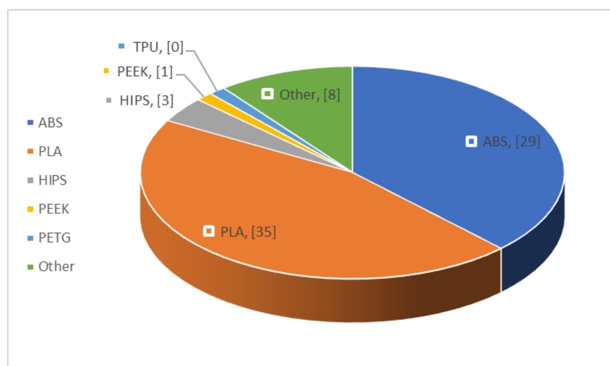
Table 3 Research related to the optimization of FDM process parameters based on filament materials

Material	Author(s)
ABS	[7], [8], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [28], [32], [35], [40], [41], [42], [54], [55], [58], [60], [61], [62], [65], [66], [69], [72], [76].
PLA	[11], [12], [24], [26], [29], [30], [31], [34], [36], [37], [38], [39], [41], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [56], [57], [59], [63], [64], [69], [70], [71], [73], [75], [76].
HIPS	[27], [41], [76]
PEEK	[33]
PETG	[48]
Other	[28], [36], [45], [48], [62], [68], [74], [77].

The results of the article collection found that PLA and ABS materials were the most often utilized materials in 3D printing studies utilizing the FDM Technique. The data also shows that the use of ABS has been more commonly used in the last 20 years, from 2003 until now, while PLA began to be widely used and replaced the use of ABS, which started in 2014. According to the observation result HIPS was also used several times in 2015 and 2020 as a material combined with PLA and ABS materials. An outline of how process and material parameters were used based on review findings is presented in Figure 7 below.



(a)



(b)

Figure 7 (a) Uses of process parameters (b) Uses of material

2.3 FDM Part

Process parameter optimization to extend printing times and enhance printing quality. The majority of research on FDM process parameters focuses on improving mechanical properties, dimensional accuracy, and surface roughness. Additionally, studies on process parameter optimization to examine FDM machine energy usage have advanced. Numerous experts suggest using statistical design and appropriate optimization techniques to look into how process factors affect parts that have been FDM-processed. The subsequent subsections provide a detailed review of the research on each quality attribute.

2.3.1 Mechanical Characteristic

Mechanical properties are an essential part of testing 3D printing products. Testing a part's mechanical characteristics is one way to find new uses for it or estimate how long it will last. There are numerous ways to investigate how process variables affect mechanical attributes. The three mechanical properties that are most frequently examined in FDM parts are their tensile, compressive, and flexural strengths [78]. A Universal Testing Machine is a type of machine used to test these three mechanical properties, namely tensile, compressive and bending strength of materials. Table 4 provides a comprehensive review of recent research on tensile strength, compressive strength, and flexural strength is given in this section.

1. Tensile Strength

   One of the mechanical requirements that is most often examined is tensile strength. The majority of studies discuss how to create parts according to the American Standard for Testing and Materials (ASTM) D638 standard for tensile testing (Figure 8 a). In this method, the test object is clamped in a testing machine with a load that continues to increase until a certain load reaches its peak so that the test object breaks. The units for this test result are still in Newton form and are then converted to MPa. The tensile characteristics of thermoplastics are tested using this standard. Rodriguez [60], introduce and develop mathematical models based on approximate minimization algorithms to determine the ideal parameter values for improved stiffness and tensile strength by Panda [18], investigated the impact of raster angle, air gap, layer thickness, orientation, and width on the tensile strength of ABS P400 components. In order to get more strength, bacterial foraging (BFO) approaches are used to calculate the theoretically ideal value of process parameters. Other research by Torres [26], looks at how different build orientations affect the tensile properties of PLA materials in terms of temperature, speed, raster orientation, infill density, layer thickness, and number of shells. The findings indicate that one of the most important tensile strength criteria is construction orientation. Alafaghani [29], Identify the parameters that affect tensile strength: build orientation is the first, Layer thickness, temperature, speed, and infill pattern and density come next. Tensile properties such as yield strength, tensile strength, and Young modulus are significantly influenced by construct orientation, layer thickness, infill density, temperature, and other six parameters. Liu [30], determine the most practical combination of process parameters for tensile characteristics, examine layer thickness, build orientation, raster width, raster orientation, and air gap. The parts for the tensile test and experiment were designed by the author using Taguchi orthogonal arrangement and GB/T 1040.2-2006 (Chinese Standard), respectively. Out of the five parameters, build orientation and layer thickness (height) (60), and the strength at break is significantly influenced by the raster orientation (¬45/45). The degree of parameter optimization differs greatly from the majority of previous research. Research conducted by Raju [32] also demonstrates that, out of the four tensile characteristics parameters, layer thickness and construction orientation are the two most important parameters [36], created and suggested a multi-nozzle FDM system for carbon fiber composite 3D printing that is sustainable. Various volume sizes of carbon fiber composite materials are achieved by incorporating carbon fiber layers into models made using PLA. Parts made with a volume of 60% PLA and 40% carbon fiber have a tensile strength that is 287.9% higher than parts made with pure PLA. Fountas [40], conduct research to maximize tensile strength, bending strength, and compressive strength. The experimental studies and associated empirical models created by Sood [20], The relationship between the mechanical qualities of tensile, bending, and impact strength forms the basis of this optimization problem. By modifying the layer thickness, orientation angle, raster angle, width, and air gap, the model was produced via FDM technology. The goals, dimensions, and constraints of the procedure taken into consideration in this matter are the same as those taken into consideration by Sood [20].

2. Compressive Strength

   Like the characteristics of other sections, compressive strength is one of the most significant mechanical properties and is affected by process conditions. Since there is no standard for evaluating the mechanical characteristics of components made using additive manufacturing, nearly all papers that conduct compressive tests adhere to the ASTM D695 standard for rigid thermoplastic compression tests (Figure 8 b). Compressive testing is carried out by measuring the dimensions of the specimen and then applying a load (F) in the middle with two supports according to the three-point bending standard. Maximum force in Newton units and maximum stress in MPa obtained from the results of several tests. Chin Ang [17], using FDM processes to generate ABS support structures for network engineering and evaluate the effects of various process variables (build layer, build profile, and build orientation). The recommended levels for both air gap and raster width are the lower and upper levels for each of these parameters, which are two important criteria for compressive strength. [7] create formulas to ascertain the ideal conditions for utilizing Quantum Particle Swarm Optimization (QPSO) to attain the required compressive strength.

3. Flexure Strength
Bending strength is a mechanical property as crucial as tensile and flexure strength. An international standard for evaluating the flexural characteristics of thermoplastics is ASTM D790 (Figure 8 c). This bending strength testing method uses a load perpendicular to the sample. Three points of bending and anchoring are used as distances. The center of the sample is the loading point. In this test, there is a bend at the midpoint of the sample. This amount of bending is called deflection. After that, the maximum load in Newtons and the strain of the specimen in MPa at fracture were recorded. Three-point loading systems are often used for flexure strength. When a weight is placed on the specimen, it solely acts as a supported beam. The body of current research on how FDM process parameters affect bending properties is compiled in this section [14]. In addition to tensile strength, Panda [18], examined how flexure strength was affected by layer thickness, build orientation, raster width, raster orientation, and air gap. Their statistical analysis and experimental research have shown that all parameters, individually and in combination, have a considerable impact on flexure strength. Sood [20], The link between the process parameters and the forces achieved was demonstrated by a response surface equation for bending strength, taking the same parameters into account. To further highlight the significance of the two-parameter interaction for bending strength, response surface plots are used. It is believed that utilizing low values for other parameters and high values for layer thickness and raster width will boost bending strength. For flexural strength, the ideal raster orientation is established by Fatimatuzahraa [79], using ABS material that was manufactured using four distinct orientation rasters on an SST 768 FDM dimension machine. They came to the conclusion that $45^0/-45^0$ is the maximum flexure strength at raster orientation.

Table 4 Research summary of FDM process parameter optimization for mechanical properties

Material	Method	Parameter Proses	Optimum Value	Mechanical Properties	Author(s)
PLA	DOE	Infill pattern	The Honeycomb and the Gyroid pattern	Stronger mechanical resistance	[11]
ABS	ANOVA	Raster width, raster angle, build orientation, air gap, and layer thickness	Layer thickness= 0.1318 mm, Orientation= 9.610^0, Raster angle= 59.9937^0, Raster width= 0.4196mm, Air gap= 0.0074mm	Tensile strength= 174.3177 MPa	[18]
			Layer thickness= 0.1278 mm, Orientation= 4.9504^0, Raster angle= 54.7311^0, Raster width= 0.4960mm, Air gap= 0.4960mm	Flexure strength = 126.4818 MPa	
			Layer thickness= 0.2531 mm, Orientation= 29.9963^0, Raster angle= 59.9951^0, Raster width= 0.5063mm	Impact strength = 1.6056 kJ/m^2	
ABS	ANOVA	Raster width, raster angle, build orientation, air gap, and layer thickness	Layer thickness = 0.2540mm, Orientation = 0^0, raster angle = 60^0, Raster width = 0.4064mm, Air Gap = 0.0080mm	Tensile strength = 18.0913 MPa, flexure strength= 39.2423 MPa, impact strength= 0.482292 kJ/m^2	[20]
PLA	Taguchi, ANOVA	Temperature, layer thickness, and infill density	Layer Thicness = 0,1 mm, Infill density = 100%	Ultimate shear strength= 42.15 MPa	[26]
ABS, PC	ANOVA, Factorial design (FD)	Air gap, build orientation, layer thickness, raster width, raster angle, and shell count	layer thickness of 0.3302 mm, air gap of 0.00 mm, raster angle of 0.0^0, build orientation of 0.0^0, road width of 0.4572 mm, and 10 contours.	The storage modulus = 1468.33 MPa, loss modulus = 166.98 MPa	[28]
PLA	Taguchi, ANOVA, GR	Raster width, Deposition style, deposition orientation, air gap, and layer thickness	Deposition orientation= 0^0, Layer thickness= 0,3mm, Deposition style=0	Tensile strength = 50.34MPa	[30]
			Deposition orientation= 0^0, Layer thickness= 0,1mm, Deposition style=0	Flexure strength = 83.51MPa	

Material	Method	Parameter Proses	Optimum Value	Mechanical Properties	Author(s)
			Deposition orientation= 0^0, Layer thickness= 0,3mm	Impact strength = 23.07kJ/m^2	
ABS	Taguchi, PSO-BFO	Layer thickness, model interior, build orientation, and support material	Layer thickness (LT)= 0.07mm, support material (SM)= sparse, part orientation (PO)= 45^0, material interior (MI)= high density.	Tensile strength = (22.21 + 2.52LT + 0.718PO + 0.657SM + 1.777MI) MPa	[32]
PEEK	Taguchi method	Layer thickness, filling ratio, speed, and temperature	Printing speed= 60 mm/s, layer thickness= 0.2 mm, temperature= 370^0 C, filling ratio=40%	Tensile strength = 40 MPa, flexure strength= 68,2 MPa, impact strength= 101,2 kJ/m^2	[33]
ABS	RSM, PSO, Multy Objektive Dragonfly (MODA)	Raster width, raster angle, build orientation, air gap, and layer thickness	Layer thickness = 0.2540mm, Orientation = 0^0, raster angle = 60^0, Raster width = 0.4064mm, Air Gap = 0.0080mm	Tensile strength = 17,838 MPa, flexure strength= 38,200 MPa, impact strength= 0,448 MJ/m^2	[40]
PLA, HA composit e	ANOVA	Layer content, HA content, infill density, and speed	HA content= 10%, layer thickness= 0.1 mm, printing speed= 30 mm/s, filament feeding speed= 0.8 mm/s	Bending strength = 103.1 ± 5.24 MPa,	[45]
PLA	RSM, open pyramid sample	retraction speed, deposition angle, and number of walls	retraction speed = 75 mm/s	Tensile strength increases 10-15 percent with higher retraction speeds	[53]
PLA	ANOVA	Temperature, raster angle, layer thickness, and infill density	Infill Density= 60%, Extrusion Temperature= 220°C, Raster Angle= 0°/90°, Layer Thickness= 0.1 mm.	Ultimate Tensile Strength= 40,65 *MPa/g*, the Yield Tensile Strength = 11,40 *MPa/g*, Modulus of Elasticity= 0,74 *GPa/g*	[59]
PLA	Taguchi, ANOVA	Filling structures, Occupancy rates, table orientation	Filling structures= rectilinier, occupancy rates = 50%, table orientation = 0^0	Tensile strength 33.99 MPa	[64]
ABS	FD	Build orientation, infill pattern	Build orientation = 0°	Higher mechanical properties	[65]
PLA, coconut wood composit e	DOE	Infill density, infill pattern	Infill pattern= concentric, Infill density= 75%	Tensile Strength PLA= 37,55 MPa, PLA/Coconut wood = 19,35 MPa	[75]

According to research conducted Dey and Yodo [14], There aren't many studies that compare the mechanical properties of components made of various materials at this time. This represents a gap in the literature that needs to be filled in this area. Furthermore, color plays a crucial role in tensile strength, with natural color filaments having the highest tensile qualities. Concurrent examination of additional factors as one of the next study directions to determine the overall effect of mold components on flexure strength would be beneficial for public knowledge.

Tensile strength of a part is largely affected by layer thickness and construction orientation, according to current studies. The maximum tensile strength is observed in part orientation 0. Tensile strength increases with decreasing layer thickness. In addition to these two factors, tensile strength is also strongly impacted by infill density, number of shells, air gap, and raster angle. Numerous research investigations looked at how different process variables affected the FDM mold components' compressive strength. They concluded that the number, form, and density of the infill have the greatest influence on compressive strength. There are very few published studies that address the flexure strength of FDM molded items. At low layer thickness and 100% infill density, flexure strength reaches its maximum. Future research can examine the effects of process variables, such as temperature, infill pattern, raster width, and their combination, based on the evaluated publications, to create components with high flexure strength. Tensile strength is not greatly impacted by annealing the FDM portion; instead, it

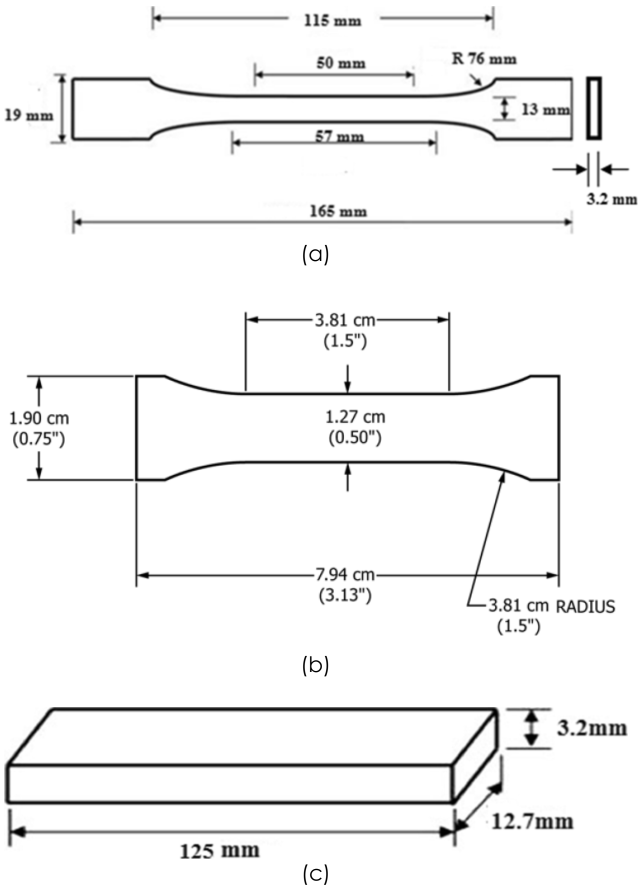


Figure 8 (a) ASTM D639 type -I for tensile strength [80] (b) ASTM D695 for compressive strength [81] (c) ASTM D790 for flexure strength [80]

2.3.2 Build Time

Because parts take a long time to manufacture, using additive manufacturing for mass production in industry is currently difficult. Fusion deposition modeling creates the parts layer by layer. It takes much time to make even minor parts. Component printing failure due to clogged nozzles also increases component manufacturing time. Similarly, the characteristics of other parts and machining parameters also affect the manufacturing time. Build time is simply measured using a stop watch. Time calculation starts when the 3D printing machine starts printing the specimen and ends when the machine finishes printing, then the time required is recorded. Build time units should be in seconds. Manufacturing time can be optimized by selecting optimal settings of various process parameters [4]. Reducing lead and production times to match conventional manufacturing processes is one of the primary issues facing industrial settings' utilization of additive manufacturing technologies. Therefore, producing functional parts with characteristics like surface roughness, dimensional correctness, and mechanical quality requires reducing production time. It's also critical to manage "failures" for manufacturing time. For instance, clogged nozzles might cause construction to take much longer. Comparable to the characteristics of

Table 5 Summary of significant research in FDM process parameter optimization for build time

Material	Method	Process Parameters	Optimum Value	Build Time	Author
ABS	AHP, ANOVA	Raster angle, air gap, and layer thickness	Layer thickness= 0,330mm, air gap= 0,020mm, raster angle= 45^0	Minimum processing time	[21]
ABS	full factorial, ANOVA	Build orientation, layer thickness, raster angle, shell width, and raster width	layer thickness= 0,01mm, raster angle= 90^0, Build orientation= 5^0, countur width=0,028in, raster width= 0,028in	Build Time= 78 min	[22]
ABS	Fuzzy logic, RSM	Layer thickness, width, raster angle, raster angle, air gap and countur width	Layer thickness= 0.254mm, contour width= 0.48mm, air gap= 0.4mm, raster width= 0.48mm, raster angle= 0°	Build Time= 0,4500 Hours	[35]
PLA	Taguchi, ANOVA	Shell width, layer thickness, infill density, speed, and pattern	Layer thickness of 0.3 mm, print speed= 80 mm/s. infill density =20%, infill pattern= triangle, shell thickness= 0.4 mm,	Minimum production time	[44]
PLA	ANN	Layer thickness, air gap, raster width, raster angle, and number of contours	layer thickness = 0.25mm, air gap= -0.002mm, raster width = 0.4048 mm, build orientation = 0^0, raster angle = 90^0 , number of contours = 6	Build Time= 5.5618 min.	[49]
PLA	Taguchi, GR	Layer thickness, infill density, speed, and pattern	Layer thickness= 0.2 mm, pattern= Triangles, infill density= 70%, printing speed= 100 mm/h	Printing time= 88 min	[51]

By choosing the best possible combination of process parameters, manufacturing time can be reduced for the FDM part as well as other parts [14]. Nancharaiah [21], discovered that the raster angle and air gap significantly affected the building time. The production time can be shortened by choosing a thicker layer and a positive air gap. Gurrala [22], created a model utilizing full factorial design trials to examine the effects of section orientation, layer thickness, raster angle, and section raster width on construction time and support structure volume. It was determined that the following factors significantly impact construction time: raster width, contour width, section orientation, and layer thickness. Based on studies by Srivastava [35], it was found that important process variables included the orientation angle, slice height, and air gap that affected the construction time variation It was found that the construction time variation was significantly influenced by the air gap, slice height, and orientation angle, among other process parameters.

However, The build time was less affected by other process parameters such as contour width, raster width, and raster orientation. Based on research conducted by Giri [49], air gaps, raster angles, raster width, and layer thickness greatly minimize build time, but build time increases in constructing orientation angles from zero degrees to ninety as the number of contours increases. Using the following assumptions, this analysis forecasts a minimum build time of 5.5618 minutes: air gap: 0.4588 mm, raster width: 0.5032 mm, raster angle: 0, layer thickness: 0.33 mm, and build orientation: 0. the same order as that of energy usage, the average impact of controllable process factors on build time is rated. The layer thickness and print speed are the most important process factors, followed by filler density, filler pattern, and shell thickness [44]. Patil [51], Find the optimal FDM parameters using the gray rational technique for multi-purpose optimization in order to reduce filament usage, expedite manufacturing, and monitor the effects of surface roughness. This study concluded that the triangular filling pattern, 70% filling density, 100 mm/h printing speed, and 0.2 mm layer thickness are optimal values of the parameters used as optimization process parameters. Table 5 illustrates a brief description of a research article investigating how process factors affect built time. Choosing a positive air gap, a larger raster width, and a thicker layer can all reduce the build time, according to a survey of several journals. Additionally, several academics have looked into how part orientation affects build time. Different directions for printing a part require other volumes of support structures. Thus, the time to print supporting materils and parts varies according to part orientation. The final product's reaction to process variables including temperature, raster angle, and shell width is still unclear. Layer thickness also affects surface roughness and dimensional accuracy. Multi-objective optimization is one area of future research that can be used to examine how different process parameters affect construction time, dimensional accuracy, and surface roughness [4]. Examining how temperature and infill patterns affect build time is another line of inquiry.

2.3.3 Dimentional Accuracy

Dimensional accuracy using a digital caliper by measuring product dimensions consisting of length, width and height/thickness. Next, the measurement results are compared with the product dimensions that have been determined. Dimensional accuracy units are in percentage (%). Sood [19], Analyze the impact of several process parameters on the dimensional accuracy of the FDM-created ABSP400, including component orientation, layer thickness, raster angle, raster width, air gap, and their combinations. Along the ‘x’ and ‘y’ axes of the printing bed, shrinkage is seen, and the printed part's thickness along the ‘z’ axis is consistently more than the design size. The Taguchi 'L27' orthogonal array determines the significance of parameters and their interactions before they are recommended to be the optimal parameter level. Gray Taguchi's methodology has been used to minimize the combination of all objective functions, i.e., minimize the percentage change in dimensions along the axis. Peng [25], Implemented a fuzzy interface system to convert three outputs into one comprehensive response: warp deformation, dimensional accuracy, and build time. A model that linked the full response and four input Second-order RSM was used to construct the variables—line width compensation, extrusion velocity, filling velocity, and layer thickness—and ANN was used for additional validation. Mohamed [28], The findings demonstrate that the best conditions for minimizing the dimensional deviation of length, width, and thickness are low layer thickness and a restricted number of shells. Furthermore, there are numerous optimal combinations for dimensional accuracy in various directions for the other four parameters (air gap, raster width, construct orientation, and raster orientation). Therefore, the best set of parameters for 3D deviation can be found using the chosen approximation function. In the study that was done [14], Likewise, additional research on the temperature and shell count is necessary to validate findings. It has been noted that the building platform's X and Y directions experience shrinkage, whereas the development platform's Z direction experiences expansion. Thus, it follows that a crucial component of dimensional accuracy is also building orientation. At the moment, it's unclear how many process variables—like raster width and infill pattern—will be, temperature, and number of shells, affect dimensional accuracy. Understanding how these factors affect the part's dimensional accuracy is crucial for producing high-precision parts. Most current research only considers two or three levels of parameters as listed in Table 6 below.

Table 6 FDM process-specific research summary for dimensional accuracy

Material	Method	Process Parameters	Optimum Value	Dimensional Accuracy	Author
ABS	Taguchi, ANOVA	Air gap, raster width, raster angle, and layer thickness	Air gap= Solid fine, raster width= 0,729, raster angle= 30/60, and layer thickness= 0,305	Not reported	[16]
ABS	Taguchi, ANOVA	Raster width, raster angle, build orientation, air gap, and layer thickness	Raster width= 0.4564mm, raster angle= 0^0, layer thickness= 0.178 mm, air gap= 0.008 mm, part orientation= 0^0	Improve the quality of overall dimensional accuracy	[19]
HIPS	Cross-sectional photography	Layer thickness, air gap, build orientation, raster width, speed, raster orientation, temperature	Temperature= 210 ^{0}C, layer thickness= 0.25mm, raster width= 0.605 mm	thickness 0.0646 ,mm part dimensions= 0.0514 mm, hole dimension= 0.129mm	[27]
Gelatin, alginate	DOE	Nozzle speed, rotation speed, presure	Nozzle speed= 0,75mm/s, rotation speed= 4,25r/s, pressure=0,224MPa	Higher forming accuracy	[67]
Lemon juice gel	ANOVA	Diameter nozzle, extrusion rate, nozzle speed	the 1 mm Nozzle diameter= 1mm extrusion rate= , 24 mm3/s, nozzle speed= 30 mm/s	Smooth geometry	[68]

In order to improve decision accuracy and understand how the least understood parameters—such as temperature, infill patterns, or diameter nozzles—affect dimensional accuracy, it is necessary to investigate more than three tiers of parameters [14]. The findings of the literature review indicate that temperature, shell count, and layer thickness all significantly affect dimensional accuracy [4]. A low layer thickness is recommended to improve dimensional accuracy. Shrinkage and expansion are observed along the X, Y, and Z directions, respectively. Thus, orientation is also an essential factor affecting dimensional accuracy. To find out how other factors, such the number of shells, their width, raster angle, and raster angle, impact dimensional accuracy, more investigation is needed. Many researchers have considered two or three levels of factors to reduce dimensional aberrations. The Taguchi and RSM methods are widely used for their experimental modeling and optimization. For subsequent research, optimization of process parameters considering more than three levels using modern optimization techniques, such as genetic algorithm (GA), the teaching-learning-based optimization (TLBO), and quantum behaved particle swarm optimization (QPSO), can be used.

2.3.4 Surface Roughness

The quality of items produced using FDM depends on a number of parameters. Surface polish is an important quality parameter in many real-world engineering difficulties. The surface roughness of FDM molded components has been greatly improved in the last few years with a lot of work. Surface roughness is measured with a surface roughness tester. Two sides are tested: one at the side of the specimen curve and the other at the top of the specimen. Ra and μm are units for surface roughness. The purpose of this literature review is to investigate how different process variables affect the surface roughness of components that are produced (Table 7). Nancharaiah [21], Analyze how surface roughness is affected by raster angle, road width, air gap, and layer thickness. It was discovered that road width influences layer thickness as well as the surface roughness and dimensional accuracy of FDM components. Raju [32], It also shows that build orientation and layer thickness are two critical components of surface quality. Patil [52], Create optimization models to examine how different process parameters, such as layer thickness, printing speed, infill style, and density, affect surface roughness. It was determined that the primary factor influencing surface roughness is layer thickness. Infill style also affects surface roughness. Gyroid-type infill style gives better results for surface roughness.

Research results by Dey and Yodo [14], state that by using a low layer thickness, which helps to lessen the influence of steps on the printed item, good surface finishing can be accomplished. To obtain improved print precision, low nozzle temperature and speed are preferred in addition to layer thickness. Elevated temperatures at the nozzle enhance the filament material's fluidity, leading to increased dimensional deviation and surface roughness. For all process parameter settings, Most data suggest that the surface finish of the upper mold surface is superior to that of the side surface. For the FDM process, it is therefore advised to print a section's shortest side in the Z direction in order to minimize surface roughness. For the orientation of inclined parts, neither the horizontal nor vertical orientation increases the roughness of the surface. Therefore, it is advisable to refrain from printing in an oblique manner. Studies have been conducted [4]. It was also discovered that road width, air gap, raster angle, and layer thickness had a major impact on surface finish. A thin layer improves surface finish and lessens the impact of the ladder. Build orientation also affects surface finish. ABS and PLA parts can be further treated with acetone and chloroform to improve the surface finish.

Table 7 FDM process-specific research summary for surface roughness

Material	Method	Process Parameters	Optimum Value	Surface Roughness	Author
PLA	RSM, PSO, SOS	Layer thickness, speed, temperature	Layer thickness= 0,1mm, speed= 37,84mm/s, temperature= 192,7^{0}C	Surfacce roughness Improved about 8.5% and 8.8% = 2.229 µm.	[37]
PLA	ANN, RSM, PSO	Layer thickness, speed, temperature, infill density, nozzle diameter	Layers' thickness = 100 µm, Temperature of 192.20 °C, speed= 97.06 mm/s, nozzle diameter= 0.3 mm, infill density= 24.88%	Surface roughness= 11.319 µm.	[50]
PLA	ANOVA, RSM	Layer thickness, speed, infill density, infill pattern	Infill density= 70 to 90 %, layer thickness of 0.2-0.22 mm, speed of 70-90 mm/s	Gyroid= 18.6726µm, Zigzag= 19.6155 µm, Triangles= 19.5894 µm.	[52]
ABS	DOE	Speed	Low speed, choosing azimuth angle, make a rampart, make toolpath planner	Better surface roughness	[66]

2.3.5 Energy Consumption

The claim that 3D printers consume less energy than other production methods is one that is frequently stated [82]. The production process's time and energy needs both simple and complicated mechanical components utilizing rapid prototyping and traditional manufacturing techniques are presented in this study. The subject of when 3D printing may be utilized effectively is addressed in this article, in addition to suggestions for the optimal technology to employ based on requirements for materials, complexity, batch size, and element size. Energy consumption is simply measured using a watt meter. The measurement starts when the 3D printing machine starts printing the specimen and ends when the machine finishes printing, then the electrical energy required is recorded in the form of KWh. Jiang [83], Enhancing processing speed, lowering energy usage, and elucidating additive manufacturing technology that rivals traditional manufacturing technology have long been popular study areas. However, compared to traditional technology, additive technology's production is still slower and its energy consumption is still one to two times higher. Utilize physical and mathematical principles to provide quantitative print speed performance indicators and identify potential obstacles and limitations for next developments. [84] examines the various ways that AM additive manufacturing subsystems, such as high energy beam generators, control systems, cooling systems, etc., can operate and how much energy they need. A summary of a recent study on the energy consumption of machinery and processes is also included. The mechanical characteristics and microstructure of components that are produced, as well as the process's sustainability, can be impacted by AM metal's energy consumption. The percentage of energy consumption that is indirectly realized as a result of material use is highlighted in the life cycle assessment of energy consumption. Increasing capacity utilization in AM can help lower energy consumption. Energy consumption can also be reduced by designing parts as optimally as possible and optimizing AM pre-process plans. The ideal temperature, infill density, and raster orientation must be established for tensile strength, energy consumption, and build time. Rinanto [73], Using order performance by resemblance to the optimum solution (PCR-TOPSIS) utilizing the process capability ratio technique. This paper discusses multi-objective optimization techniques that can provide a single optimal solution. The impact of the five FDM process parameters—infill density, infill pattern, layer thickness, print speed, and shell thickness—on energy usage, production time, part weight, dimensional accuracy, hardness, and tensile strength was assessed through additional research [44]. By optimizing mechanical and physical attributes while decreasing resource consumption and production time, this research can assist FDM processes better match design specifications for goods created by Fused Deposition Modeling (FDM). Using energy is what a machine or system does when it consumes energy [54]. This study examined the effects of various process variables on the energy consumption and manufacturing time of fused deposition modeling (FDM) components printed from polylactic acid (PLA) and acrylonitrile butadiene styrene (ABS).

The outcomes demonstrated that PLA prints faster and uses less energy per unit volume than ABS. Another study sought to determine the ideal scale, extruder temperature, printing speed, layer height, and infill value to simultaneously maximize specific energy, scrap, and surface roughness. This work presents a realistic method for multi-objective optimization of surface roughness, scrap weight, and specific energy performance responses in 3D printing. This leads to the conclusion that specific energy and residual weight increase with increasing surface polish [57].

The most significant factors that affect a print's energy usage, according to recent study, are layer thickness, infill density, print speed, shell thickness, and infill pattern as shown in Table 8. The energy consumption was optimal at 0.3 mm layer thickness, 20% infill density, triangle infill pattern, 80 mm/s print speed, and 0.4 mm shell thickness [44]. Research comparing the use of ABS and PLA materials to energy consumption shows that the energy required to print ABS materials is higher than printing PLA materials. The results of the investigation showed that for each experiment, printing with ABS material used 1.5–2 times more energy than printing with PLA material [54]. There aren't many published studies on multi-objective optimization of FDM process parameters to take energy consumption into account. Therefore, there is still much room for further research in this direction.

Table 8 Research summary of FDM process parameter optimization for energy consumption

Material	Method	Process Parameters	Optimum Value	Energy Consumption	Author
PLA	Taguchi, ANOVA	Layer thickness, speed, shell width, infill density, infill pattern	Layer thickness of 0.3 mm, print speed= 80 mm/s. infill density =20%, infill pattern= triangle, shell thickness= 0.4 mm	Minimum energy consumption	[44]
PLA, PETG, PHA	Taguchi, ANOVA	Type of material, Layer thickness, raster width, temperature, infill density, number of perimeters	PLA: Layer thickness=0,3mm, raster width=0,4mm, temperature=207,8^{0}C, infill density=15%, number of perimeters= 4	PHA Bio WOOD Rosa 3D is most suitable material	[48]
			PETG: Layer thickness=0,3mm, raster width=0,51mm, temperature=248^{0}C, infill density=15%, number of perimeters= 4		
			PHA: Layer thickness=0,3mm, raster width=0,4mm, temperature=248^{0}C, infill density=31,1%, number of perimeters= 1		
PLA	RSM	Layer thickness, speed, infill density	Layer thickness= 0,3mm, speed= 75mm/s, infill density= 100%	ABS= 0,2KWh, PLA=0,1KWh ABS is higher than PLA for energy consumption	[54]
PLA	Taguchi, AHP-TOPSIS, ANN-GA	Layer thickness, speed, temperature, infill density, scale	Layer thickness= 0,2mm, speed=230mm/s, temperature=194,8^{0}C, infill density=18,2%, scale=96,8%	Specific Energy Consumption= 9,02 E^{-3}	[57]
PLA	Taguchi, PCR-TOPSIS	Temperature, raster orientation, and infill density	Infill density=40%, temperature=210°C, raster orientation= 45°	Energy consumption= 0.0154KWh	[73]

2.4 Optimization Methods Used and Their Comparison

According to the literature review, a number of optimization techniques, including as the Taguchi method, response surface method (RSM), artificial neural network (ANN), particle swarm optimization (PSO), and genetic algorithm (GA), have been used to optimize the parameters of the FDM process, gray relational (GR), fuzzy logic, factorial design, and others like group method data handling (GMDH).

2.4.1 Taguchi Method

The most popular technique for peer-reviewed research is Taguchi. By choosing levels of controllable factors, input process parameters, or independent variables in a way that minimizes response variations brought on by uncontrollable factors or disturbances like humidity, vibration, and ambient temperature, the Taguchi Method is a statistical quality control technique. The Taguchi method integrates statistical and mathematical techniques to optimize performance properties by selecting design parameters. With fewer experiments, Taguchi's technique discovered some effects of statistical fluctuations. In addition, Taguchi's approach identifies an ideal experimental environment with the least amount of variability [4]. In the research conducted by Omar [56], Taguchi's L9 orthogonal array design served as the basis for the planning of the experimental trials. This design was used to lower the number of attempts, or 81 tests, while utilizing a full factorial design. Taguchi's approach helped reduce experiment time and resource use.

2.4.2 Response Surface Method (RSM)

RSM is an optimization and modeling methodology that combines statistical and mathematical techniques. This method's main goal is to maximize responses that are influenced by different input factor characteristics. RSM connects controllable input parameters in an experimental design to gather enough data to calculate outcomes [4]. Regular regression methods, like RSM, use an experiment design that covers the range of all relevant variables with a minimum number of repetitions, making it very dependable. Relationship structure methodology (RSM) is a methodical and systematic way to determining the connections between the variables influencing a process and its results. RSM uses the program Design-Expert V8 to statistically analyze experimental data [58].

2.4.3 Artificial Neural Network (ANN)

An artificial neural network, or ANN, is a sophisticated model that is inspired by the way the biological nervous system, particularly in human brain cells, processes information, and can forecast how ecosystems will react to changes in environmental variables. Neural networks are better at illustrating nonlinear functions than RSM, which makes ANN a more accurate and superior modeling technique [85]. In studies carried out by Poonia [57], ANN was used to create the predictive model, and mean square error and regression value metrics were used to assess it. In the next stage, the developed ANN model is coupled with the genetic algorithm (GA) technique to obtain a Pareto solution. With printing parameter limitations, the integrated ANN-GA yields predictive models with Pareto solutions.

2.4.4 Particle Swarm Optimization (PSO)

In a study published in 1995, Kennedy and R. Eberhart [86], introduced the heuristic search method of global particle swarm optimization (PSO). The PSO has undergone significant revisions since 1995The PSO's particles travel in the issue region by trailing the most efficient particles that are moving at a certain moment. The coordinate position of every particle in the problem region is tracked, directly contributing to the identification of the best solution. Particles are assessed using the suitability function after repetition. Compared to other optimization techniques, PSOs can reach convergence points faster. Only a few parameters can be used to calculate the optimal value. Reducing the number of particles can improve PSO performance [4]. Combining them is one of the benefits of using metaheuristic algorithms. Neural networks have several limits, such lengthy operations, even if they can track intricate and nonlinear interactions between independent and dependent variables. Consequently, ANN performance can be greatly increased by utilizing optimization methods like PSO. In order to solve engineering challenges, some researchers have used hybrid ANN and PSO models with success [87].

2.4.5 Genetic Algorithm (GA)

Darwin's theory of evolution states that natural selection and the survival of the more fit individuals are the foundations for genetic adaptation. Natural selection aims to produce offspring that have a greater resemblance to the traits of their forebears. With the advancement of molecular biology, several theories of evolution other than Darwinian natural selection have been established. New evolutionary theories are therefore helpful to computer science in understanding its basic ideas and creating clever heuristics to help with engineering problem-solving from a critical optimization perspective [8]. Similar to the preceding approach, GA can be used with another approach, specifically ANN. The primary goal of the study conducted by Rojek [38] is to optimize the computational 3D printing process in terms of features and material selection using ANN paired with GA in order to enhance the tensile force of exoskeleton samples. Material strength can be increased by the novel strategy of combining the ANN and GA approaches for material selection. The strategy also solves the issue of optimizing parameters associated with the 3D printing technical process.

2.4.6 Factorial Design (FD)

Although it can also be used to understand and optimize processes, the major use of the factorial experiment design is the estimation of critical elements and their interactions. There are two types of factorial design: complete factorial design and fractional factorial design. The major benefit of full factorial design is that it allows you to assess all significant effects of variables and their interactions; however, it requires more experiments as the number of components goes up. Fractional factorial design results in fewer trials being conducted. Compared to full factorial design, fractional factorial design limits the influence of interactions while enabling exact main effect assessment with fewer procedures. Fractional factorial design is the most often used approach for process development and quality improvement since it saves time and money [28].

2.4.7 Gray Relational (GR)

Some researchers utilize GR analysis to determine the best set of process parameters based on GR levels in order to achieve targeted performance metrics [4]. In research by Patil [51], FDM performance is seen from several responses: surface roughness, printing duration, and filament consumption length. GA analysis is effective at optimizing the FDM process's parameters when multiple responses are used. The process parameters that have been chosen for examination include layer thickness, printing speed, infill pattern, and infill %. The study concluded that GR analysis is suitable for optimizing FDM parameters. In another study conducted by Liu [30], FDM parts have to withstand many mechanical properties at once and are subjected to various loading scenarios. To tackle this problem, many responses are simultaneously optimized through the use of GR analysis. GR analysis is a quantitative analysis that explores similarities and differences between factors. It uses GR levels to find the degree of factor correlation.

2.4.8 Fuzzy Logic (FL)

Using FL to achieve multi-objective optimization is a very attractive approach. In the study done by Srivastava [35], FL was used to accomplish multi-objective optimization while RSM was used to plan and assess experiments. Consequently, With the combination of FL and RSM analysis, this work presents a novel way to simultaneously optimize the build time and volume of supporting material. According to the study's findings, FL was effectively used for the FDM process' multi-objective optimization.

2.4.9 Group Method Data Handling (GMDH)

Research published by Rayegani [88], derived the required link between each process parameter and tensile strength using the GMDH modeling approach. The created model can be used as a predictive model to determine the optimal theoretical parameter settings that will produce the optimum response characteristics. In order to find non-linear correlations between input and output variables, Ivakhnenko's GMDH modeling framework served as the foundation for the modeling framework used in this investigation. GMDH is a form of multi-layered iteration (MIA) networks.

2.4.10 Other Methods

Research that uses other methods uses more design of experimental (DOE) methods that are not mentioned. Some other studies also use methods such as experimental method, cross-sectional photography by Kaveh [27], dynamic mechanical analysis (DMA) by Arivazhagan and Masood [61], bacterial foraging optimization (BFO) by Raju [32], process capability ratio (PCR) by Rinanto [73], and NSGA-II algorithm by Kafshgar [46].

Here is an overview of DOE used in FDM process parameter optimization based on the number of users of the optimization method shown in Figure 9.

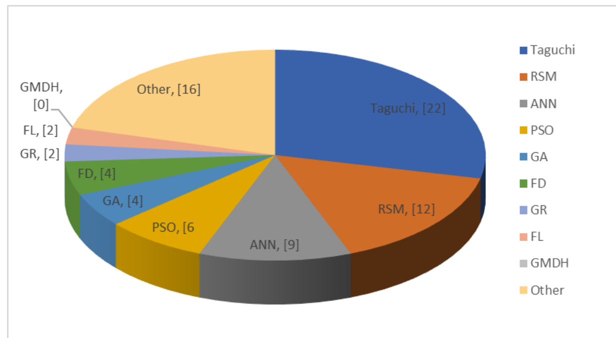


Figure 9 Number of users of optimization methods in the research reviewed

The following is a comparative summary of some DOEs often used in FDM process parameter optimization, as shown in Table 9.

Table 9 Comparison between standard experiment designs and optimization techniques

No	Capability	Techniques								
		Taguchi	**RSM**	**ANN**	**PSO**	**GA**	**FD**	**GR**	**FL**	**GMDH**
1	Understanding	Normal	Moderate	Moderate	Mudah	Difficult	Mudah	Normal	Difficult	Moderate
2	Multi-response optimization	No	Yes	Yes	Yes	Yes	Tidak	Yes	Yes	Yes
3	Usefulness	Widely	Widely	Widely	Widely	Rarely	Rarely	Widely	Rarely	Rarely
4	Shape of the experimental region	Regular or irregular	Regular only	Regular or irregular	Regular or irregular	Regular or irregular	Regular only	Regular or irregular	Regular or irregular	Regular or irregular
5	Computational time	Short	Short	Long	Short	Very long	Short	Short	Very long	Medium
6	Prediction accuracy	Low	Very high	Very high	Very high	High	Normal	Normal	High	High
7	Model linear dynamics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	Model non-linear	No	Yes	Yes	No	Yes	No	No	Yes	Yes

No	Capability	Techniques								
		Taguchi	RSM	ANN	PSO	GA	FD	GR	FL	GMDH
	dynamics									
9	Developing of mathematical model	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes
10	Data requirement for a given output	Mid	Low	High	High	High	Mid	Mid	High	High
11	Optimal solution	Straight	Through model	Through model	Through model	Straight	Straight	Straight	Throug h model	Through model
12	Ability to study interaction effects between variables	Yes	Yes	No	Yes	No	Yes	Yes	No	No
13	Availability in simulation software	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3.0 CONCLUSION

This literature review critically examined the influence of Fused Deposition Modeling (FDM) process parameters on the quality and performance of printed components. The discussion synthesized findings from previous studies that investigated how variations in process parameters, materials, and optimization techniques affect key output characteristics, including mechanical properties, surface roughness, dimensional accuracy, printing time, and energy consumption. Particular attention was given to commonly evaluated mechanical responses such as tensile, compressive, and bending strength, which remain central indicators of part quality in FDM applications.

The review shows that layer thickness, raster width, raster angle, build speed, and build orientation are the most frequently investigated parameters in FDM optimization studies. Across different research contexts, optimum parameter ranges are often reported within relatively consistent intervals, with layer thickness typically between 0.2 and 0.3 mm, raster width between 0.4 and 0.5 mm, raster angles commonly set between 45° and 90°, printing speeds ranging from 75 to 90 mm/s, and a build orientation of 0°. Among these parameters, layer thickness consistently emerges as the most influential factor affecting multiple quality attributes, indicating its critical role in determining overall printing performance.

From a material perspective, PLA and ABS remain the dominant materials in FDM research due to their availability and stable processing characteristics. However, recent studies increasingly explore the potential of combining these primary materials with alternative polymers such as HIPS, either to enhance specific performance attributes or to address application-specific requirements. This trend suggests a growing research interest in multi-material and hybrid material systems within FDM.

In terms of optimization approaches, the Taguchi method is the most widely adopted technique, followed by response surface methodology, artificial neural networks, particle swarm optimization, and other computational or hybrid methods. The popularity of the Taguchi approach is largely attributed to its ability to reduce experimental effort and resource consumption while still providing meaningful insights into parameter effects. Nevertheless, many studies have demonstrated the benefit of integrating multiple optimization techniques to improve prediction accuracy and decision-making robustness.

Despite the breadth of existing studies, this review also identifies limitations in the current body of literature. In particular, there is a lack of in-depth quantitative analysis regarding the strength of correlations between process parameters and output responses. As a result, direct and systematic comparisons between different optimization approaches remain limited. Future research is therefore encouraged to focus on multi-objective optimization frameworks that simultaneously consider a wider range of process parameters, material combinations, and performance metrics, including printing time and energy consumption.

Further research directions may also include more detailed investigations into the mechanical and non-mechanical behavior of different component types, as well as the influence of machine-related factors such as drive mechanisms, stepper motors, extruder configurations, and printer architectures. In addition, comprehensive cost-oriented analyses covering manufacturing, operation, and maintenance aspects are recommended to support the transition of FDM technology from prototyping toward large-scale and economically viable production. Such studies would provide valuable insights for investment planning, technology selection, and industrial implementation of FDM systems.

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Conflict of Interest

The authors affirm that they have no conflicts of interest with respect to this paper's publication.

References

[1] Tlegenov, Y., G. S. Hong, and W. F. Lu. 2018. Nozzle Condition Monitoring in 3D Printing. *Robotics and Computer-Integrated Manufacturing.* 54: 45–55. https://doi.org/10.1016/j.rcim.2018.05.010.

[2] Sharma, V., H. Roozbahani, M. Alizadeh, and H. Handroos. 2021. 3D Printing of Plant-Derived Compounds and a Proposed Nozzle Design for the More Effective 3D FDM Printing. *IEEE Access.* 9: 57107–57119. https://doi.org/10.1109/ACCESS.2021.3071459.

[3] Feng, C., M. Zhang, and B. Bhandari. 2019. Materials Properties of Printable Edible Inks and Printing Parameters Optimization during 3D Printing: A Review. *Critical Reviews in Food Science and Nutrition.* 59(19): 3074–3081. https://doi.org/10.1080/10408398.2018.1481823.

[4] Suniya, N. K., and A. K. Verma. 2023. A Review on Optimization of Process Parameters of Fused Deposition Modeling. *Research in Engineering and Structural Materials*. https://doi.org/10.17515/resm2022.520ma0909.

[5] Herianto, M. R. Setyawan, and H. Mastrisiswadi. 2022. 3D Print Continuation Process Parameter Setting to Optimize the Tensile Strength. *International Journal on Advanced Science, Engineering and Information Technology*. 12(1): 61. https://doi.org/10.18517/ijaseit.12.1.13973.

[6] Pamasaria, H. A., T. H. Saputra, A. S. Hutama, and C. Budiyantoro. 2020. Optimasi Keakuratan Dimensi Produk Cetak 3D Printing Berbahan Plastik PP Daur Ulang dengan Menggunakan Metode Taguchi. *JMPM* 4(1). https://doi.org/10.18196/jmpm.4148.

[7] Sood, A. K., R. K. Ohdar, and S. S. Mahapatra. 2012. Experimental Investigation and Empirical Modelling of FDM Process for Compressive Strength Improvement. *Journal of Advanced Research.* 3(1): 81–90. https://doi.org/10.1016/j.jare.2011.05.001.

[8] Fountas, N. A., and N. M. Vaxevanidis. 2021. Optimization of Fused Deposition Modeling Process Using a Virus-Evolutionary Genetic Algorithm. *Computers in Industry.* 125: 103371. https://doi.org/10.1016/j.compind.2020.103371.

[9] Singh, J., G. Singh, and P. M. Pandey. 2021. Multi-Objective Optimization of Solvent Cast 3D Printing Process Parameters for Fabrication of Biodegradable Composite Stents. *International Journal of Advanced Manufacturing Technology.* 115(11–12): 3945–3964. https://doi.org/10.1007/s00170-021-07423-6.

[10] Singh, G., J.-M. Missiaen, D. Bouvard, and J.-M. Chaix. 2021. Copper Extrusion 3D Printing Using Metal Injection Moulding Feedstock: Analysis of Process Parameters for Green Density and Surface Roughness Optimization. *Additive Manufacturing.* 38: 101778. https://doi.org/10.1016/j.addma.2020.101778

[11] Birosz, M. T., D. Ledenyák, and M. Andó. 2022. Effect of FDM Infill Patterns on Mechanical Properties. *Polymer Testing.* 113: 107654. https://doi.org/10.1016/j.polymertesting.2022.107654.

[12] Mani, M., A. G. Karthikeyan, K. Kalaiselvan, P. Muthusamy, and P. Muruganandhan. 2022. Optimization of FDM 3-D Printer Process Parameters for Surface Roughness and Mechanical Properties Using PLA Material. *Materials Today: Proceedings.* 66: 1926–1931. https://doi.org/10.1016/j.matpr.2022.05.422.

[13] Gordelier, T. J., P. R. Thies, L. Turner, and L. Johanning. 2019 Optimising the FDM Additive Manufacturing Process to Achieve Maximum Tensile Strength: A State-of-the-Art Review. *RPJ,* 25(6): 953–971. https://doi.org/10.1108/RPJ-07-2018-0183.

[14] Dey, A., and N. Yodo. 2019. A Systematic Survey of FDM Process Parameter Optimization and Their Influence on Part Characteristics. *JMMP.* 3(3): 64. https://doi.org/10.3390/jmmp3030064.

[15] Lee, B. H., J. Abdullah, and Z. A. Khan. 2005. Optimization of Rapid Prototyping Parameters for Production of Flexible ABS Object. *Journal of Materials Processing Technology.* 169(1): 54–61. https://doi.org/10.1016/j.jmatprotec.2005.02.259.

[16] Laeng, *et al.* 2006. Optimizing Flexible Behaviour of Bow Prototype Using Taguchi Approach. *Journal of Applied Sciences.* 6(3): 622–630.

[17] Chin Ang, K., K. Fai Leong, C. Kai Chua, and M. Chandrasekaran. 2006. Investigation of the Mechanical Properties and Porosity Relationships in Fused Deposition Modelling-Fabricated Porous Structures. *Rapid Prototyping Journal.* 12(2): 100–105. https://doi.org/10.1108/13552540610652447.

[18] Panda, S. K., S. Padhee, A. K. Sood, and S. S. Mahapatra. 2009. Optimization of Fused Deposition Modelling (FDM) Process Parameters Using Bacterial Foraging Technique. *IIM.* 1(2): 89–97. https://doi.org/10.4236/iim.2009.12014.

[19] Sood, A. K., R. K. Ohdar, and S. S. Mahapatra. 2009. Improving Dimensional Accuracy of Fused Deposition Modelling Processed Part Using Grey Taguchi Method. *Materials & Design.* 30(10): 4243–4252. https://doi.org/10.1016/j.matdes.2009.04.030.

[20] Sood, A. K., R. K. Ohdar, and S. S. Mahapatra. 2010. Parametric Appraisal of Mechanical Property of Fused Deposition Modelling Processed Parts. *Materials & Design.* 31(1): 287–295. https://doi.org/10.1016/j.matdes.2009.06.016.

[21] Nancharaiah, T. 2011. Optimization of Process Parameters in FDM Process Using Design of Experiments. *International Journal on Emerging Technologies.* 2(1): 100–102.

[22] Gurrala, P. K., and S. P. Regalla. 2011. Optimization of Support Material and Build Time in Fused Deposition Modeling (FDM). *Advanced Materials Research.* 110–116: 2245–2251. https://doi.org/10.4028/www.scientific.net/AMM.110-116.2245.

[23] Panda, B. N., M. V. A. R. Bahubalendruni, and B. B. Biswal. 2014. Comparative Evaluation of Optimization Algorithms at Training of Genetic Programming for Tensile Strength Prediction of FDM Processed Part. *Procedia Materials Science.* 5: 2250–2257. https://doi.org/10.1016/j.mspro.2014.07.441

[24] Tymrak, B. M., M. Kreiger, and J. M. Pearce. 2014. Mechanical Properties of Components Fabricated with Open-Source 3-D Printers under Realistic Environmental Conditions. *Materials & Design.* 58: 242–246. https://doi.org/10.1016/j.matdes.2014.02.038.

[25] Peng, A., X. Xiao, and R. Yue. 2014. Process Parameter Optimization for Fused Deposition Modeling Using Response Surface Methodology Combined with Fuzzy Inference System. *International Journal of Advanced Manufacturing Technology.* 73(1–4): 87–100. https://doi.org/10.1007/s00170-014-5796-5.

[26] Torres, J., M. Cole, A. Owji, Z. DeMastry, and A. P. Gordon. 2016. An Approach for Mechanical Property Optimization of Fused Deposition Modeling with Polylactic Acid via

Design of Experiments. *RPJ*. 22(2): 387–404. https://doi.org/10.1108/RPJ-07-2014-0083.

[27] Kaveh, M., M. Badrossamay, E. Foroozmehr, and A. Hemasian Etefagh. 2015. Optimization of the Printing Parameters Affecting Dimensional Accuracy and Internal Cavity for HIPS Material Used in Fused Deposition Modeling Processes. *Journal of Materials Processing Technology* 226: 280–286. https://doi.org/10.1016/j.jmatprotec.2015.07.012.

[28] Mohamed, O. A., S. H. Masood, J. L. Bhowmik, M. Nikzad, and J. Azadmanjiri. 2016. Effect of Process Parameters on Dynamic Mechanical Performance of FDM PC/ABS Printed Parts Through Design of Experiment. *Journal of Materials Engineering and Performance*. 25(7): 2922–2935. https://doi.org/10.1007/s11665-016-2157-6.

[29] Alafaghani, A., A. Qattawi, B. Alrawi, and A. Guzman. 2017. Experimental Optimization of Fused Deposition Modelling Processing Parameters: A Design-for-Manufacturing Approach. *Procedia Manufacturing*. 10: 791–803. https://doi.org/10.1016/j.promfg.2017.07.079.

[30] Liu, X., M. Zhang, S. Li, L. Si, J. Peng, and Y. Hu. 2017. Mechanical Property Parametric Appraisal of Fused Deposition Modeling Parts Based on the Gray Taguchi Method. *International Journal of Advanced Manufacturing Technology*. 89(5–8): 2387–2397. https://doi.org/10.1007/s00170-016-9263-3.

[31] Andriyansyah, Deni, Herianto, and Purfaji. 2018. Optimasi Parameter Proses 3D Printing Terhadap Kuat Tarik Filamen Polylactic Acid Menggunakan Metode Taguchi. In *Prosiding Seminar Nasional Pendidikan Teknik Otomotif*. 61–68

[32] Raju, M., M. K. Gupta, N. Bhanot, and V. S. Sharma. 2019. A Hybrid PSO–BFO Evolutionary Algorithm for Optimization of Fused Deposition Modelling Process Parameters. *Journal of Intelligent Manufacturing*. 30(7): 2743–2758. https://doi.org/10.1007/s10845-018-1420-0.

[33] Deng, X., Z. Zeng, B. Peng, S. Yan, and W. Ke. 2018. Mechanical Properties Optimization of Poly-Ether-Ether-Ketone via Fused Deposition Modeling. *Materials*. 11(2): 216. https://doi.org/10.3390/ma11020216.

[34] Elkholy, A., and R. Kempers. 2018. Investigation into the Influence of Fused Deposition Modeling (FDM) Process Parameters on the Thermal Properties of 3D-Printed Parts. In *Progress in Canadian Mechanical Engineering*. York University Libraries. https://doi.org/10.250

[35] Srivastava, M., S. Rathee, S. Maheshwari, and T. K. Kundra. 2018. Multi-Objective Optimisation of Fused Deposition Modelling Process Parameters Using RSM and Fuzzy Logic for Build Time and Support Material. *International Journal of Rapid Manufacturing*. 7(1): 25.

[36] Luo, H., Y. Tan, F. Zhang, J. Zhang, Y. Tu, and K. Cui. 2019. Selectively Enhanced 3D Printing Process and Performance Analysis of Continuous Carbon Fiber Composite Material. *Materials*. 12(21): 3529. https://doi.org/10.3390/ma12213529.

[37] Saad, M. S., A. M. Nor, M. E. Baharudin, M. Z. Zakaria, and A. F. Aiman. 2019. Optimization of Surface Roughness in FDM 3D Printer Using Response Surface Methodology, Particle Swarm Optimization, and Symbiotic Organism Search Algorithms. *International Journal of Advanced Manufacturing Technology*. 105(12): 5121–5137. https://doi.org/10.1007/s00170-019-04568-3.

[38] Rojek, I., D. Mikołajewski, E. Dostatni, and M. Macko. 2020. AI-Optimized Technological Aspects of the Material Used in 3D Printing Processes for Selected Medical Applications. *Materials*. 13(23): 5437.

[39] Godec, D., S. Cano, C. Holzer, and J. Gonzalez-Gutierrez. 2020. Optimization of the 3D Printing Parameters for Tensile Properties of Specimens Produced by Fused Filament Fabrication of 17-4PH Stainless Steel. *Materials*. 13(3): 774.

[40] Fountas, N. A., J. D. Kechagias, D. E. Manolakos, and N. M. Vaxevanidis. 2020. Single and Multi-Objective Optimization of FDM-Based Additive Manufacturing Using Metaheuristic Algorithms. *Procedia Manufacturing*. 51: 740–747.

[41] Baca, D., and R. Ahmad. 2020. The Impact on the Mechanical Properties of Multi-Material Polymers Fabricated with a Single Mixing Nozzle and Multi-Nozzle Systems via Fused Deposition Modeling. *International Journal of Advanced Manufacturing Technology*. 106(9–10): 4509–4520. https://doi.org/10.1007/s00170-020-04937-3.

[42] Dev, S., and R. Srivastava. 2020. Experimental Investigation and Optimization of FDM Process Parameters for Material and Mechanical Strength. *Materials Today: Proceedings*. 26: 1995–1999. https://doi.org/10.1016/j.matpr.2020.02.435.

[43] Pratama, W. H., H. -, and H. -. 2021 Optimasi Parameter Proses 3D Printing Terhadap Kuat Tarik Material Filamen PLA Menggunakan Metode Taguchi. *SJoME*. 3(1): 39–45. https://doi.org/10.36655/sprocket.v3i1.568.

[44] Enemuoh, E. U., S. Duginski, C. Feyen, and V. G. Menta. 2021. Effect of Process Parameters on Energy Consumption, Physical, and Mechanical Properties of Fused Deposition Modeling. *Polymers*. 13(15): 2406. https://doi.org/10.3390/polym13152406.

[45] Aihemaiti, P., H. Jiang, W. Aiyiti, and A. Kasimu. 2021. Optimization of 3D Printing Parameters of Biodegradable Polylactic Acid/Hydroxyapatite Composite Bone Plates. *International Journal of Bioprinting*. 8(1): 490. https://doi.org/10.18063/ijb.v8i1.490.

[46] Kafshgar, A. R., S. Rostami, M. Aliha, and F. Berto. 2021. Optimization of Properties for 3D Printed PLA Material Using Taguchi, ANOVA and Multi-Objective Methodologies. *Procedia Structural Integrity*. 34: 71–77. https://doi.org/10.1016/j.prostr.2021.

[47] Pawar, S., S. A. Quadri, and D. Dolas. 2021. Optimization of Fused Deposition Modeling Process Parameters for Material Consumption and Manufacturing Time. *Journal of Engineering Research* (JER). https://doi.org/10.36909/jer.ICIPPSD.15539.

[48] Zgodavová, K., K. Lengyelová, P. Bober, J. A. Eguren, and A. Moreno. 2021. 3D Printing Optimization for Environmental Sustainability: Experimenting with Materials of Protective Face Shield Frames. *Materials*. 14(21): 6595. https://doi.org/10.3390/ma14216595.

[49] Giri, J., P. Shahane, S. Jachak, R. Chadge, and P. Giri. 2021. Optimization of FDM Process Parameters for Dual Extruder 3D Printer Using Artificial Neural Network. *Materials Today: Proceedings*. 43: 3242–3249. https://doi.org/10.1016/j.matpr.2021.01.899.

[50] Shirmohammadi, Mohammad, Saeid Jafarzadeh Goushchi, and Peyman Mashhadi Keshtiban. 2021. Optimization of 3D Printing Process Parameters to Minimize Surface Roughness with Hybrid Artificial Neural Network Model and Particle Swarm Algorithm. *Progress in Additive Manufacturing*. 6(2): 199–215. https://doi.org/10.1007/s40964-021-00166-6

[51] Patil, P., D. Singh, S. J. Raykar, and J. Bhamu. 2021. Multi-Objective Optimization of Process Parameters of Fused Deposition Modeling (FDM) for Printing Polylactic Acid (PLA) Polymer Components. *Materials Today: Proceedings*. 45: 4880–4885. https://doi.org/10.1016/j.matpr.2021.01.353.

[52] Patil, P. 2022. Modeling and Analysis of Surface Roughness in Fused Deposition Modeling Based on Infill Patterns. *International Journal of Engineering and Management Sciences*. 29(1). https://doi.org/10.56042

[53] Jackson, B., K. Fouladi, and B. Eslami. 2022. Multi-Parameter Optimization of 3D Printing Condition for Enhanced Quality and Strength. *Polymers*. 14(8): 1586. https://doi.org/10.3390/polym14081586.

[54] Warke, S., and V. S. Puranik. 2022. Comparison of Energy Consumption of ABS and PLA While 3D Printing with Fused Deposition Modeling Process. *Materials Today: Proceedings*. 66: 2098–2103. https://doi.org/10.1016/j.matpr.2022.05.509.

[55] Vidakis, N., J. D. Kechagias, M. Petousis, F. Vakouftsi, and N. Mountakis. 2023. The Effects of FFF 3D Printing Parameters on Energy Consumption. *Materials and Manufacturing Processes.* 38(8): 915–932. https://doi.org/10.1080/10426914.2022.2105882.

[56] Omar, N. W. Y., N. A. Shuaib, A. I. Azmi, and M. H. J. A. Hadi. 2022. Effect of Build Parameters on Process Energy Consumption and Material Usage in Fused Deposition Modelling Method. *Journal of Physics: Conference Series* 2312(1): 012015.

[57] Poonia, V., R. Kumar, R. Kulshrestha, and K. S. Sangwan. 2023. Optimization of Specific Energy, Scrap, and Surface Roughness in 3D Printing Using Integrated ANN-GA Approach. *Procedia CIRP*. 116: 324–329. https://doi.org/10.1016/j.procir.2023.02.055.

[58] Moradi, M., R. Beygi, N. Mohd. Yusof, A. Amiri, L. F. M. Da Silva, and S. Sharif. 2023. 3D Printing of Acrylonitrile Butadiene Styrene by Fused Deposition Modeling: Artificial Neural Network and Response Surface Method Analyses. *Journal of Materials Engineering and Performance*. 32(4): 2016–2028. https://doi.org/10.1007/s11665-022-07250-0.

[59] Fernandes, João, Augusto M. Deus, Luis Reis, Maria Fátima Vaz, and Marco Leite. 2018. Study of the Influence of 3D Printing Parameters on the Mechanical Properties of PLA. In *Proceedings of the 3rd International Conference on Progress in Additive Manufacturing (Pro-AM 2018)*. 547–552. https://doi.org/10.25341/D4988C.

[60] Rodriguez, J., *et al.* 2003. Design of Fused-Deposition ABS Components for Stiffness and Strength. *Journal of Mechanical Design.* 125(3): 545–551. https://doi.org/10.1115/1.1582499.

[61] Arivazhagan, Adhiyamaan, and S. H. Masood. 2012. Dynamic Mechanical Properties of ABS Material Processed by Fused Deposition Modelling. *International Journal of Engineering Research and Applications.* 2(3): 2009–2014.

[62] Cantrell, J. T., *et a*l. 2017. Experimental Characterization of the Mechanical Properties of 3D-Printed ABS and Polycarbonate Parts. *Rapid Prototyping Journal.* 23(4): 811–824. https://doi.org/10.1108/RPJ-03-2016-0042.

[63] Hanon, Muammel M., Róbert Marczis, and László Zsidai. 2021. Influence of the 3D Printing Process Settings on Tensile Strength of PLA and HT-PLA. *Periodica Polytechnica Mechanical Engineering.* 65(1): 38–46. https://doi.org/10.3311/PPme.13683.

[64] Kam, Menderes, Ahmet İpekci, and Ömer Şengül. 2022. Taguchi Optimization of Fused Deposition Modeling Process Parameters on Mechanical Characteristics of PLA+ Filament Material. *Scientia Iranica*. 29(1B): 79–89. https://doi.org/10.24200/sci.2021.57012.5020

[65] Bernardez, L. D., G. Campana, M. Mele, J. Sanguineti, C. Sandre, and S. M. Mur. 2022. Effects of Infill Patterns on Part Performances and Energy Consumption in Acrylonitrile Butadiene Styrene Fused Filament Fabrication via Industrial-Grade Machine. *Progress in Additive Manufacturing.* 8: 117–129. https://doi.org/10.1007/s40964-022-00316-4

[66] Hergel, J., and S. Lefebvre. 2014. Clean Color: Improving Multi-Filament 3D Prints. *Computer Graphics Forum.* 33(2) : 469–478. https://doi.org/10.1111/cgf.12318.

[67] Liu, H., H. Zhou, H. Lan, T. Liu, X. Liu, and H. Yu. 2017. 3D Printing of Artificial Blood Vessel: Study on Multi-Parameter Optimization Design for Vascular Molding Effect in Alginate and Gelatin. *Micromachines.* 8(8): 237. https://doi.org/10.3390/mi8080237.

[68] Yang, F., M. Zhang, B. Bhandari, and Y. Liu. 2018. Investigation on Lemon Juice Gel as Food Material for 3D Printing and Optimization of Printing Parameters. *LWT – Food Science and Technology.* 87: 67–76. https://doi.org/10.1016/j.lwt.2017.08.054.

[69] Abeykoon, C., P. Sri-Amphorn, and A. Fernando. 2020. Optimization of Fused Deposition Modeling Parameters for Improved PLA and ABS 3D Printed Structures. *International Journal of Lightweight Materials and Manufacture*. 3(3): 284–297. https://doi.org/10.1016/j.ijlmm.2020.03.003.

[70] Oehlmann, P., P. Osswald, J. C. Blanco, M. Friedrich, D. Rietzel, and G. Witt. 2021. Modeling Fused Filament Fabrication Using Artificial Neural Networks. *Production Engineering Research and Development.* 15(3–4): 467–478. https://doi.org/10.1007/s11740-021-01020-y.

[71] Napolitano, F., E. Cozzolino, I. Papa, A. Astarita, and A. Squillace. 2022. Experimental Integrated Approach for Mechanical Characteristic Optimization of FDM-Printed PLA in an Energy-Saving Perspective. *International Journal of Advanced Manufacturing Technology.* 121(5–6): 3551–3565. https://doi.org/10.1007/s00170-022-09535-z.

[72] Ziemian, S., M. Okwara, and C. W. Ziemian. 2015. Tensile and Fatigue Behavior of Layered Acrylonitrile Butadiene Styrene. *Rapid Prototyping Journal.* 21(3): 270–278. https://doi.org/10.1108/RPJ-09-2013-0086.

[73] Rinanto, Andhy, Adi Nugroho, Hoedi Prasetyo, and Eko Pujiyanto. 2018. Simultaneous Optimization of Tensile Strength, Energy Consumption and Processing Time on FDM Process Using Taguchi and PCR-TOPSIS. In *Proceedings of the 2018 4th International Conference on Science and Technology (ICST)*, 1–5. Yogyakarta, Indonesia: IEEE, August 7-8, 2018. https://doi.org/10.1109/ICSTC.2018.8528667

[74] Vidakis, N., M. Petousis, N. Mountakis, E. Maravelakis, S. Zaoutsos, and J. D. Kechagias. 2022. Mechanical Response Assessment of Antibacterial PA12/TiO2 3D Printed Parts: Parameters Optimization through Artificial Neural Networks Modeling. *International Journal of Advanced Manufacturing Technology.* 121(1–2): 785–803. https://doi.org/10.1007/s00170-022-09376-w

[75] Kananathan, J., K. Rajan, M. Samykano, K. Kadirgama, K. Moorthy, and M. M. Rahman. 2023. Preliminary Tensile Investigation of FDM Printed PLA/Coconut Wood Composite. In *Technological Advancement in Instrumentation & Human Engineering*, edited by M. H. A. Hassan, M. H. Zohari, K. Kadirgama, N. A. N. Mohamed, and A. Aziz, 339–350. Lecture Notes in Electrical Engineering, vol. 882. Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-19-1577-2_26.

[76] Baca Lopez, David Moises, and Rafiq Ahmad. 2020. Tensile Mechanical Behaviour of Multi-Polymer Sandwich Structures via Fused Deposition Modelling. *Polymers.* 12(3): 651. https://doi.org/10.3390/polym12030651

[77] Liu, H., H. Zhou, H. Lan, F. Liu, and X. Wang. 2018. Multinozzle Multichannel Temperature Deposition System for Construction of a Blood Vessel. *SLAS Technology.* 23(1): 64–69. https://doi.org/10.1177/2472630317712221.

[78] Popescu, D., A. Zapciu, C. Amza, F. Baciu, and R. Marinescu. 2018. FDM Process Parameters Influence over the Mechanical Properties of Polymer Specimens: A Review. *Polymer Testing.* 69: 157–166. https://doi.org/10.1016/j.polymertesting.2018.05.020.

[79] Fatimatuzahraa, A. W., B. Farahaina, and W. A. Y. Yusoff. 2011. The Effect of Employing Different Raster Orientations on the Mechanical Properties and Microstructure of Fused Deposition Modeling Parts. In *Proceedings of the 2011 IEEE Symposium on Business, Engineering and Industrial Applications (ISBEIA)*, 22–27. Langkawi, Malaysia: IEEE, September 2011. https://doi.org/10.1109/ISBEIA.2011.6088811.

[80] Prabhu, P., B. Karthikeyan, R. R. R. M. Vannan, and A. Balaji. 2022. Mechanical, Thermal and Morphological Analysis of Hybrid Natural and Glass Fiber-Reinforced Hybrid Resin Nanocomposites. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-022-02632-9.

[81] ASTM D20 Committee. 2015. Test Method for Compressive Properties of Rigid Plastics. ASTM D695-15. West Conshohocken, PA: ASTM International. https://doi.org/10.1520/D0695-15.

[82] Dudek, P., and K. Zagórski. 2017. Cost, Resources, and Energy Efficiency of Additive Manufacturing. *E3S Web of*

Conferences 14: 01040. https://doi.org/10.1051/e3sconf/20171401040.

[83] Jiang, Rui. 2017. *Processing Rate and Energy Consumption Analysis for Additive Manufacturing Processes: Material Extrusion and Powder Bed Fusion*. PhD diss., Massachusetts Institute of Technology.

[84] Liu, Z. Y., C. Li, X. Y. Fang, and Y. B. Guo. 2018. Energy Consumption in Additive Manufacturing of Metal Parts. *Procedia Manufacturing* 26: 834–845. https://doi.org/10.1016/j.promfg.2018.07.104.

[85] Desai, K. M., S. A. Survase, P. S. Saudagar, S. S. Lele, and R. S. Singhal. 2008. Comparison of Artificial Neural Network (ANN) and Response Surface Methodology (RSM) in Fermentation Media Optimization: Case Study of Fermentative Production of Scleroglucan. *Biochemical Engineering Journal*. 41(3): 266–273. https://doi.org/10.1016/j.bej.2008.05.009.

[86] Kennedy, J., and R. Eberhart. 1995. Particle Swarm Optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1942–1948. Perth, WA, Australia: IEEE. https://doi.org/10.1109/ICNN.1995.488968.

[87] Momeni, E., D. Jahed Armaghani, M. Hajihassani, and M. F. Mohd Amin. 2015. Prediction of Uniaxial Compressive Strength of Rock Samples Using Hybrid Particle Swarm Optimization-Based Artificial Neural Networks. *Measurement*. 60: 50–63. https://doi.org/10.1016/j.measurement.2014.09.075.

[88] Rayegani, F., and G. C. Onwubolu. 2014. Fused Deposition Modelling (FDM) Process Parameter Prediction and Optimization Using Group Method for Data Handling (GMDH) and Differential Evolution (DE). *International Journal of Advanced Manufacturing Technology*. 73(1–4): 509–519. https://doi.org/10.1007/s00170-014-5835-2.