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Review Article

A review on optimization of process parameters of fused deposition modeling

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Abstract

The purpose of this review is to explore various techniques used in the optimization of process parameters of 3D printing machines for different applications. Fused Deposition Modeling (FDM) is an emerging technology that has been widely used in diverse areas including new product development, mould manufacturing, etc. FDM is the process of depositing the material in a layer-by-layer manner to manufacture the part. FDM provides a lot of flexibility in fabricating a part. Many complex parts can be manufactured by FDM easily which are very difficult to manufacture through conventional manufacturing methods. However, build-in time, manufacturing speed, and mechanical strength of FDM fabricated parts are still challenging and critical. The quality of FDM fabricated parts is affected by various machining parameters, such as air gap, build orientation, infill percentage, raster angle, raster width, layer thickness, etc. The selection of significant process parameters needs to be identified and optimized as per the usage of apart. Many researchers have used different techniques, such as the design of experiment (DOE) technique, response surface method(RSM), genetic algorithm(GA), artificial neural network(ANN), and fuzzy, to optimize the FDM process parameters to improve the desired part quality, such as mechanical properties, and dimensional accuracy. This survey paper attempts to critically review various research articles published on the optimization of process parameters to improve the performance parameters of FDM.

1.Introduction

Additive Manufacturing (AM) is a process to fabricate components by incrementally adding materials layer-by-layer using details available in a CAD model. Contrary to the traditional subtractive machining processes to generate a shape by removing materials, additive manufacturing builds a component by adding the material to the desired places. This additive process reduces material wastage and manufacturing time.AM was developed initially as a technique for rapid prototyping to visualize, test, and authenticate a design, before end-user production of the design. However, with recent developments, now AM can rapidly fabricate components with complex shapes without much geometric restriction under more comfortable work conditions. It is currently used in various fields, from industrial products to medical appliances, as a production technology [57]. Over the years, many additive manufacturing processes, such as photo-polymerization, fused deposition modeling, material jetting, and powder bed fusion, have been developed. However, fused deposition modeling (FDM), also called the extrusion method, is one of the most popular additive manufacturing techniques due to its ability to create complex components from a wide range of materials.
FDM utilizes a long thermoplastic fiber that passes through a CNC-controlled and temperature-controlled moving extrusion head to deposit material at the desired locations. FDM

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incrementally builds components by laying a thin layer over the top of the previous layer [84]. Fig. 1 shows a block diagram of FDM. Due to its capacity to generate complicated parts in a faster production cycle time than traditional machining procedures, FDM is now regarded as a quick manufacturing approach. Due to its use of the net shape manufacturing principle and lack of additional tooling requirements, FDM also has the advantage of being the least expensive production system. Despite these benefits, creating components for end use with FDM is still a difficult task since FDM has a number of process parameters that affect the quality, mechanical characteristics, manufacturing process, and dimensional accuracy of the part.

Air gap, build orientation, infill proportion, raster angle, layer height, and other characteristics of the FDM process are some of them. These process parameters need to be carefully chosen according to the application for which a part is made using FDM. Some process parameters are more important than others for a given output need.
In order to achieve the best results, it is necessary to identify and optimize these important process characteristics. The various experimental or statistical design of experiment (DOE) methodologies have been studied and used by several researchers over the years to optimize the FDM process parameters for the mechanical characteristics and component quality.The Taguchi approach, genetic algorithms (GA), grey relational, fractional factorial, artificial neural networks (ANN), fuzzy logic, ANOVA, , and other DOE techniques are frequently employed.

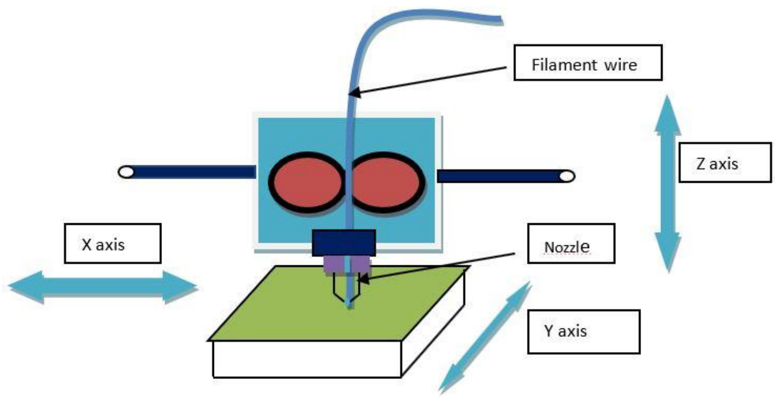


Fig. 1 Block diagram of FDM

This article aims to present a state-of-the-art review of the current research on FDM process parameter optimization focusing on enhancing mechanical properties, reducing build time, and improving part quality. The remaining part of the paper is organized as follows: section 2 briefly explains various FDM process parameters. Section 3 discusses commonly used materials. Section 4 reviews the optimization of various process parameters and section 5 concludes the paper and gives future research directions.

2. Process Parameters of FDM

FDM has many process parameters which affect the quality of fabricated parts. Following are the most widely studied FDM process parameters:

1. Build orientation: FDM 3D printed parts have inherently anisotropic mechanical properties, i.e., the parts are much stronger in the XY direction than in the Z direction. Build orientation is the orientation of the part on the print table. In FDM, a part can be printed at any orientation. However, build orientation affects the strength of the part in different

directions, the requirement of supports during printing, and the surface finish of different surfaces of the part [53]. As shown in fig 2, the same part requires a different amount of support structure during printing based on its build orientation.

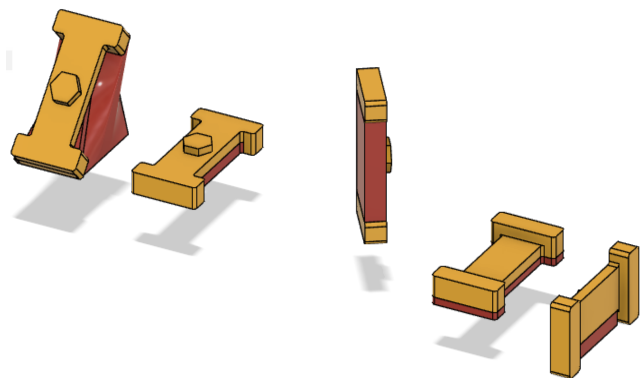
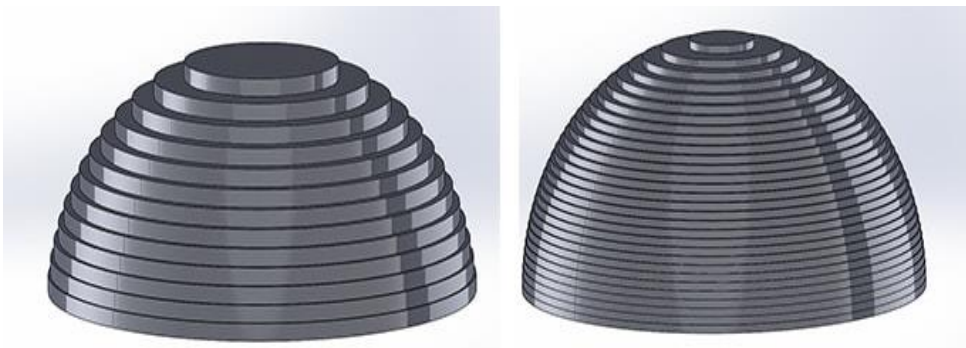


Fig. 2 Various build orientations of a part. The golden shade shows the part and the red shade shows the support structure

2. Layer thickness: Layer thickness, also called layer height, is the thickness of the material of a layer deposited by the FDM process. The layer thickness parameter affects the surface finish and build-time of a part. Layer thickness depends on the tip size, printing speed, and material [42]. Fig 3 shows the effect of different layer thicknesses on the surface finish of an FMD printed part.



(a) Larger layer thickness (b) Smaller layer thickness

Fig. 3Effect of the layer thickness of the surface finish of a part

3. Extrusion temperature: Extrusion temperature is the temperature at which the filament material is heated inside the nozzle during the FDM process. It depends on the printing material and printing speed.
4. Print Speed: Print speed is the speed, normally specified in mm/sec, of the printing head in the XY plane of the 3D printer. Print speed affects the build time [13]. After a certain level, it also affects the strength of printed parts [38].
5. Bed temperature: It is the temperature of the top surface of the 3D printer bed. The adhesion between the first printed layer and the printing bed is dependent on the bed

temperature. It is reported that a bed temperature slightly above the glass transition temperature of the printing material provides good adhesive property. Good adhesion is required to avoid the part warping and improve the dimensional accuracy of the part. [41]

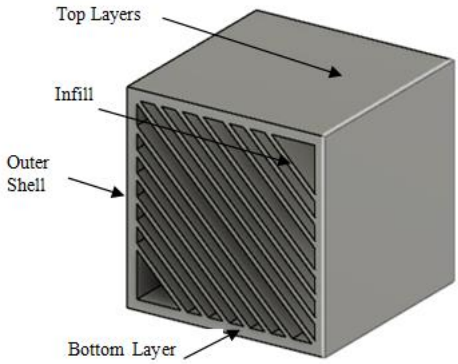


Fig. 4 Structure of a 3D printed part

6. Raster Angle: A layer in a 3D FDM printed part consists of a number of linear segments of the molten metal, called raster, extruded from the nozzle. Raster angle is the angle from the x-axis of the build table at which the printing head deposits a raster of a layer (see fig 5). The typical values of the raster angle are in the range of 0°to 90° in a step of 15° [13, 42]. Typically, raster angles of two adjacent layers differ by 90°. Raster angle affects the directional mechanical property of printed parts.

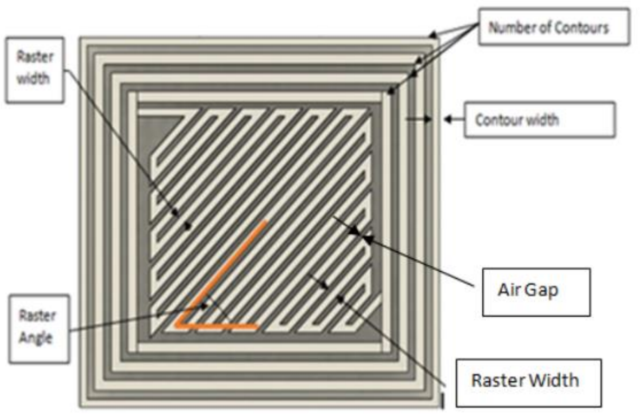


Fig. 5 FDM tool path parameters

7. Raster width: Raster width, also called road width, refers to the width of a raster. The value of raster width varies based on the diameter of the nozzle [13, 42].A larger value will increase the strength of the interior of the part [42].
8. Air gap: Air gap is the distance between two adjacent rasters of a layer (Fig 5). If two adjacent rasters overlap with each other, then Air gap is negative.
9. Infill Density: The outer surface of a 3D printed part is normally solid but the internal structure of the part is filled with various styles of infills. Infill density is the percentage of

the volume of infill filament material with the total volume of the part covered with the infills. Typically 20% infill density is used for parts used only for visualization and higher infill density is used for end-use parts to achieve the required mechanical properties(strength and mass). Infill density plays a major role in the mechanical strength of an FDM printed part [13]

10. Infill pattern: Infill pattern is the structure and shape of the infill to fill the internal space of a part. Commonly used infill patterns are shown in fig 6. Infill patterns influence the mechanical properties and printing time of parts.
11. Contour width: Outer solid shells of an FDM part are printed as a set of contours of molten material. Contour width (fig 5) is the width of a contour [13].
12. Contour air gap: Contour air gap is the distance between two adjacent contours when the part fill style is selected as multiple contours [13].

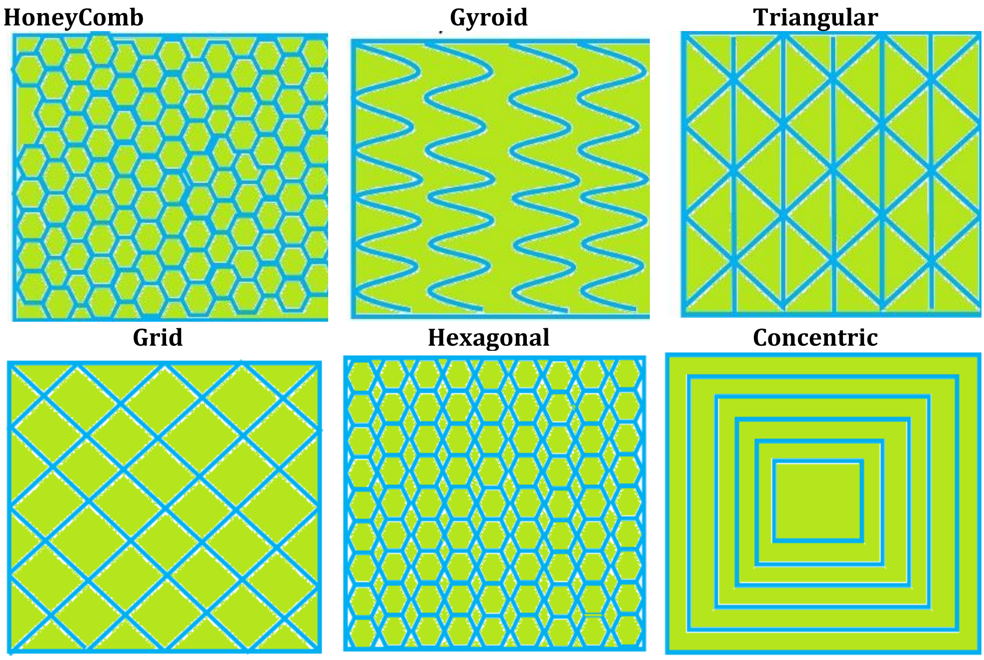


Fig. 6 Commonly used infill patterns

13. Perimeter to raster air gap: It is the distance between the edge of the raster fill and the innermost contour [13].
14. The number of contours: It is the number of contours in the shell of a part [13].

3. FDM 3D printing Materials

With the growing popularity and capability of FDM 3D printing, researchers are experimenting with various thermoplastics and their composites to fabricate parts using FDM. In this section, commonly used thermoplastics in FDM were discussed in brief. Table 1 summarizes the properties useful for 3D printing of these materials. Following are the commonly used materials in FDM:

3.1. Acrylonitrile Butadiene Styrene (ABS)

ABS is a thermoplastic, amorphous polymer that is widely used in FDM. ABS is styrene, butadiene, and acrylonitrile copolymer. ABS has two critical mechanical properties: impact resistance and toughness. The melting point of ABS is 230°C [13].

3.2. Polylactic Acid (PLA)

In FDM, PLA is one of the most commonly utilized thermoplastics. PLA is produced from corn, sugarcane starch roots, and so forth. Since PLA is a biodegradable and renewable thermoplastic, PLA is becoming increasingly more popular. Additionally, it offers manufacturing prototypes and functioning parts with good quality and precision and uses less energy and temperature. Further, it does not require a heated bed. However, it is prone to jamming the printer nozzle during printing. When compared to ABS, PLA has a stronger tensile strength, a lower warp, and a lower ductility [13]. PLA is currently used in various applications, such as packaging of food, and medical implants. The melting point of PLA ranges between 170 and 180 °C depending on the amount of residual monomer.

3.3. Nylon

Nylon is a family of petroleum-based synthetic polymers composed of polyamides. From the FDM point of view, Nylon's characteristics are comparable to those of ABS. If more flexible and durable parts are needed, nylon can be used. It has a high level of toughness and impact resistance, but it is extremely vulnerable to moisture as nylon is hygroscopic. Moisture absorption degrades filament properties leading to poor quality parts. The melting point of nylon ranges between 190 and 350 °C.

3.4. Polyethylene Terephthalate (PET)

PET is a strong, stiff synthetic fiber of the polyester family of polymers and is a popular material for FDM. PET is commercially available in a variety of forms, such as PETP, PETG, GPET, and PETT. It is employed in the production of water bottles and food packaging. The melting point of PET is 260 °C.

3.5. Polyether Ether Ketone (PEEK)

PEEK is an organic thermoplastic polymer of the polyaryletherketone family. It is a heat-resistant material with better mechanical and chemical characteristics than PLA and ABS. PEEK is used in human prostheses due to its potential bone healing property. The melting point of PEEK is 343 °C.

3.6. High Impact Polystyrene (HIPS)

HIPS, also known as PS (Polystyrene), is an amorphous thermoplastic material. HIPS has comparable mechanical properties to ABS but it is cheaper than ABS. However, it has low flexibility but it can be bonded, punched, and sawn successfully. It's widely utilized in the toy industry and on building signage. The melting point of HIPS ranges between 150 to 180°C.

Table 1: Common properties of various thermoplastics

Material/Property	PLA	ABS	HIPS	PET	Nylon	PC
Extrude temp. ^{o}C	180-220	210-240	220-230	230-255	235-270	270-315
Bed temp. ^{o}C	20-55	80-11-	50-60	55-70	60-80	90-120
T_g (^{o}C)	60-65	105-110	100	70-78	47-60	145-150

4. Modeling and Optimization Techniques Used in The Investigation of The FDM Process

For easy comprehension of this review paper, this section briefly discusses various optimization techniques used to investigate the effect of various process parameters on the quality and desired properties of FDM printed parts.

4.1. Genetic Algorithm:

Darvin proposed the genetic algorithm (GA) with the Theory of Evolution and the Survival of the Fittest as its guiding principle. The algorithm generates a set of random initial population, called chromosomes and then optimizes the population using a number of operations. Cromosomes are normally represented as integer strings. In order to generate a new population and to found best optimum solution, several procedures including reproduction, cross-over and mutation are utilized, as well as the solution from the prior population. The best chromosomes (around 20%) are saved during reproduction for the next population on the basis of fitness function. The crossover of two parent strings generates offspring (new solutions) by switching around the genes or portions of the chromosomes. Mutation is a technique to raise in population variety caused by the random modification of parts of one solution. The belief that the incoming population would be better than the outgoing one serves as motivation. Based on the fitness function, solutions are chosen to create new solutions (Off springs). This process is repeated until the end condition is satisfied. For more details, researchers could refer to [89].

4.2. Grey Analysis:

Various researchers implemented Grey relational analysis to determine the best combination of the process parameters to achieve the desired performance parameters on the basis of grey relational grade [32]. In Grey Analysis, firstly experimental data is preprocessed using normalization. Normalized data of each experimental run is used to determine the Grey Relational coefficient for the same. Grey relation grade is calculated by averaging the grey relational coefficient for each sequence. High grey relational grade provides the optimum process parameters setting for the desired performance parameters. Researchers might consult [31] for further information.

4.3. Particle Swarm Optimization (PSO):

In a study published in 1995, Kennedy and Ebehart introduced the PSO global heuristic search method. PSO has seen significant revisions since 1995. Particles in PSO follow the best moving particles at any given time to move through the problem space. Every particle in the problem space keeps track of its coordinate position, which aids in identifying the current optimal solution. Particles are assessed using a fitness function following each repetition. Compared to other optimization techniques, PSO can achieve a point of convergence more quickly. Only a few parameters can be used to calculate the optimal value. Reducing the number of particles can boost the PSOs performance [83].

4.4. Factorial Design Method:

Researchers can examine the effects of multiple independent variables and the extent of their interaction simultaneously using the factorial design method. In statistics, a full factorial design is made up of two or more variables in the experiment design, each of which has discrete possible values or levels, and whose experimental units take on any possible combination of these levels across all variables. This method can be used to study the effects of each component on the response variables as well as the effects of the interactions among the factors on the response variable [65].

4.5. Taguchi Methodology:

The Taguchi method integrates the statistical and mathematical techniques to optimize performance traits through the selection of design parameters. With fewer experiments, Taguchi technique discovers some effects resulting from statistical fluctuation. Additionally, the Taguchi approach identifies the ideal experimental setting with the least amount of variability. The noise factor which is difficult to regulate, is the primary contributor to unpredictability. In contrast, the signal or control factor is simple to manage. The Taguchi method is a statistical quality control technique where the level of controllable factors, input process parameters, or independent variables are chosen in a way to minimize the variation in responses caused by uncontrollable or noise factors like humidity, vibration, and environmental temperature [65].

4.6. Response Surface Method (RSM):

RSM combines mathematical and statistical techniques for modelling and optimization. The fundamental goal of this approach is to optimize the responses that are affected by numerous input parameters or factors. RSM uses the design of experiments to gather enough data. The relationship between the controllable input parameters and the results can be established using RSM [65].

4.7. Teaching Learning Based Optimization (TLBO):

The teaching-learning procedure in a classroom is replicated by the TLBO algorithm. The top solution from the most recent iteration is regarded as a teacher, and all other solutions are regarded as students. The majority of students complies with teacher's instructions and benefit from peer teaching. An academic field corresponds to an independent variable or candidate solution feature in the TLBO algorithm. The Teacher Phase and Learners Phase are two crucial phases in the TLBO algorithm [66]. Students interact with one another to enhance their knowledge in the learner phase while teachers refine the knowledge of all students in the teacher phase.

4.8. Artificial Neural Network (ANN):

Artificial neural networks (ANNs) are effective data modelling and analysis tools that can construct the complicated input-output relationship. ANNs are inspired by the human brains learning from experience paradigm. A neural network is made up of numerous simple computing units, known as neuron, that are arranged in the shape of a massively connected network. Each input link has a weight, and each neuron computes a weighted total of all the links it receives. Using a training dataset made up of input and output, a network is trained by methodically altering the weights of the networks. An artificial neural network can successfully depict the nonlinear and interaction effects using experimental data sets [66].

5. Research on FDM Process Parameters Optimization

Many researchers optimized the process parameters of Fused Deposition Modeling. This section provides a comprehensive and critical literature review to analyze the effect of various process parameters of FDM on dimensional accuracy, surface roughness, tensile strength, compressive strength, build cost, etc. This section includes research papers published during the last two decades, i.e., from 2001 to 2022.

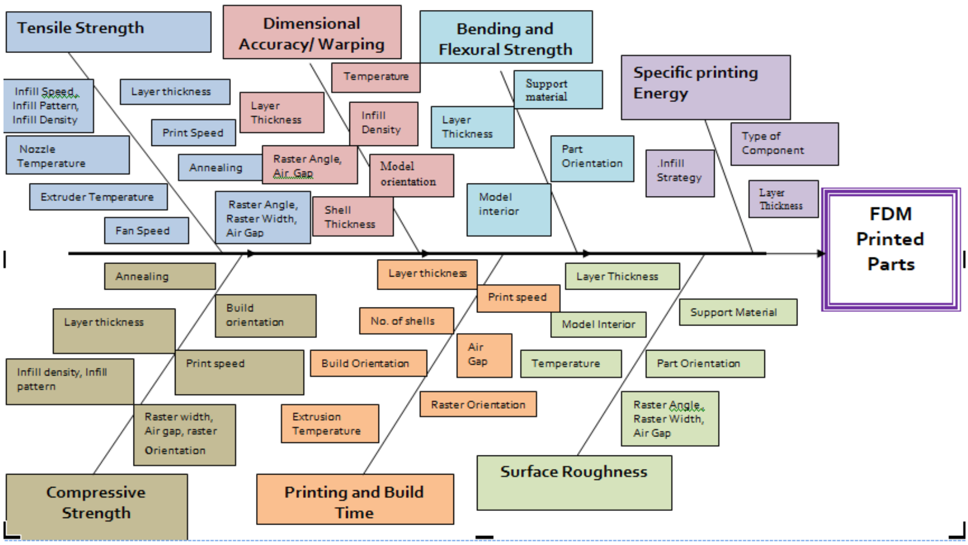


Fig. 7Cause and effect diagram for FDM parts

Table 2. Research articles related to optimization of process parameters of FDM based on filament materials

Material	Researchers
ABS	Anitha et al.[4] ,Nazan et. al.[52] , Asadollahi-Yazdi et al. [5], Lunetto et al.[39], Dong et al.[15], Vishwas et al. [84], Yadav et al. [88], Raju et al. [63], Gurrala et al. [25], Haque et al. [28], Eswaran et al. [18], Sood et al. [74], Khan et al. [33], Rao et al. [66], Mahmood et al. [43], Sajan et al. [72], Wankhede et al. [87], Chaudhari et al. [9], Dev et al. [12], Srinivasan et al. [76], Fountas et al. [21].
PLA	Sharma et al. [73], Tontowi et al. [80], Pazhamannil et al. [57], Qattawi et al. [60], Rajpurohit et al. [61], Beniak et al. [6], Fountas et al. [21], Deshwal et al. [11], Rao et al. [67], Beniak et al. [7]

Various research papers using different keywords in titles, abstracts, and keyword sections of various scientific databases were searched and the relevant published articles (journal and conference papers) were selected from four major science publishers: Taylor and Francis, Springer Link, Science Direct, and Inderscience. Around 80 papers were finally selected for this survey. A cause and effect diagram (Fig. 7) was developed based on factors identified in these research articles that affect various responses. Process parameters of FDM were optimized based on the response requirement. Table 2 provides the summary of various optimization techniques implemented in the research articles published on the optimization of process parameters of FDM. The following subsections describe the research in this domain. Table 2 shows the classification of research articles related to the optimization of process parameters of FDM based on filament material used to fabricate the parts.

5.2. Surface Roughness

The quality of parts manufactured by FDM depends on several parameters. Surface finish is an important quality parameter useful in many real-life engineering problems. Many attempts have been made in the last few decades to improve the surface finish of FDM printed parts. This literature review attempts to study the effect of various process parameters on the surface roughness of printed parts.

Anitha et al. [4] analyzed the effect of various process parameters, for instance, layer thickness, raster width, and speed of deposition on surface roughness. Optimal settings of these process parameters to minimize surface roughness were found with the help of the Taguchi L18 orthogonal array. It was found that layer thickness is the most significant factor among all the considered parameters that affect the surface roughness [4]. Byun et al. [92] introduced a method to determine optimal part orientation using the genetic algorithm to improve the average weighted surface roughness (AWSR) generated due to the staircase effect [90]. Kumar et al. [68] proposed a robust process optimization to improve the surface roughness from feature and dimensional accuracy. The raster angle and air gap, were reported as significant factors for surface roughness [92]. Nancharaiah et al. [50] investigated the effect of layer thickness, road width, air gap, and raster angle on surface roughness. It was found that road width is another factor other than layer thickness that affects the surface roughness and dimensional accuracy of parts manufactured by FDM [50]. Raju et al. [63] investigated the effect of layer thickness, support material, model interior, and part orientation on surface roughness, tensile strength, flexural modulus, and hardness. It was reported in the research that surface roughness increases with the value of support structure from high density to low density and decreases with infill style or model interior from low to high density [63]. Taguchi's 'L18' orthogonal array was used as the design of the experiment. In this research, multi-responsive optimization has been implemented by Particle Swarm Optimization (PSO), Bacterial Foraging Optimization (BFO), and hybrid PSO-BFO to improve the surface roughness, hardness, tensile strength, flexural modulus.

Sharma et. al [73] have reported the optimization and process capability analysis for surface properties of 3D printed functional prototypes of polyvinyl chloride (PVC) reinforced with polypropylene (PP) and hydroxyapatite (HAP) for possible bio-sensing applications. Various experiments according to Taguchi's L9 orthogonal array were conducted to investigate the surface properties of FDM filament comprising PVC, PP, and HAP. This research considered infill density, layer thickness, and deposition speed as process parameters to minimize the surface roughness. It was found that infill density is the most influential factor affecting the surface roughness. It has been observed in this research that with the increase in infill density from low level to medium level, the surface finish of the parts has been improved [73].

The surface roughness of parts fabricated by FDM can be improved by treating them chemically. Galantucci et al. [22] have investigated the effect of process parameters and post-processing on the surface roughness of a part. The study was conducted in two phases. In the first phase, the effect of various process parameters on surface roughness was analyzed. It was found that layer thickness and raster angle affect surface roughness of ABS printed part. In the second phase, the prototype was treated with a solution of 90% dimethyl ketone and 10% water for 300 seconds. Significant improvement in surface roughness of part was observed [22]. Tiwary et al. [78] further studied the effect of layer thickness, extrusion width, and emersion time in the solutions having different compositions (1) 100% 1,2- Dichloroetahne, (2) 90% Acetone + 10% distilled water and (3) 50% 1,2-Dichloroetane + 50% Acetone. It was concluded that layer thickness, extrusion width, and immersion time significantly influence the surface roughness of ABS printed parts [78].

Apart from controlling the various machining parameters, Khan et al. [33] analyzed the effect of chemical post-processing on the surface roughness of an ABS specimen containing flat, inclined, and curved surfaces. Specimens were treated with vaporized acetone and significant improvement in surface roughness was observed. It was also observed that surface roughness was largely affected by the air gap [33].

Li et al. [36] investigated the effect of post-processing parameters such as immersion time, temperature, and concentration of chloroform solution on the surface roughness of PLA-printed parts. PLA printed test specimens were exposed to hot vapors of chloroform solution in a special heating thermostatic system. PLA is soluble in chloroform at room temperature. It was observed that surface roughness after treating with chemical first decreases and then increases. It was observed that 5 minutes is the optimal time for optimum surface roughness. It was also reported that temperature affects surface roughness significantly. Table 3 illustrates the major research works that studied the impact of process parameters on surface roughness [36].

Nagendra et al. [48] investigated the effect of infill density, infill style, layer thickness, print temperature, and raster angle on the surface quality of the printed part of nylon and aramid. Taguchi DOE was utilized to determine the optimum values of factors. As a result, the improved surface finish was found at the optimal condition of 0.2 mm layer thickness, tetrahedral infill style, 90 % infill density, 90-degree raster angle, and 280 C print temperatures [48]. Patil et al. [56] developed an optimization model to analyze the effect of various process parameters such as infill style, infill density, printing speed, and layer thickness on surface roughness. It was concluded that layer thickness is the most influencing factor for surface roughness. Infill pattern also affects the surface roughness. Gyroid infill style provides better results for surface roughness [56].

Table 3. Optimization techniques used to identify the impact of process parameters on surface roughness

Authors	**Material**	**Optimization Technique**	**Process Parameters**	**Performance Parameters**
Sharma et al. [73]	PLA	Taguchi Philosophy	1.Layer thickness 2. Infill density 3. Deposition speed	1. Surface roughness
Anitha et al. [4]	ABS	Taguchi Philosophy	1. Layer thickness, 2. speed of deposition 3. road width	1. Surface finish
Asadollahi-Yazdi et al. [5]	ABS	NSGA -II	1. Layer thickness 2. Part orientation	1. Build time 2. Tensile Strength 3. Surface Roughness 4. Material
Raju et al. [63]	ABS	Hybrid PSO-BFO	1. Layer thickness, 2. Support material, 3. Model interior 4. Part orientation	1.Surface roughness 2.Hardness 3. Tensile Strength 4. Flexural Modulus
Khan et al. [33]	ABS	Taguchi Philosophy	1. Raster Angle (degree) 2. Raster Width (mm) 3. Air gap (mm)	1. Surface Roughness

			4. Temperature (C)	
			5. Time (s)	
Haque et al. [28]	ABS	DOE with face cantered composite design(FCCCD)	1. Layer thickness,	Surface Roughness
			2. Part orientation,	
			3. Raster width,	
			4. Overlap distance	
Sajan et al. [72]	ABS	Taguchi L'27'	1. Bed Temperature	1. Circularity error
			2. Nozzle Temperature	2. Surface Roughness
			3. Print Speed	
			4. Infill	
			5. Layer thickness	
			6. Number of loops	
Wankhede et al. [87]	ABS	Taguchi 'L8'	1. Layer thickness	1. Surface roughness
			2. Infill density	
			3. Support style	

5.3. Discussion and Future Aspects

From the above research works, it can be concluded that surface finish is affected by layer thickness, road width, raster angle, and air gap, significantly. Low layer thickness reduces the staircase effect and improves the surface finish. Print orientation also affects the surface finish. It was observed that the top surface is better finished than the side surfaces. Therefore, it is recommended to build the shortest side surface in the z-direction. ABS and PLA parts can be further treated with acetone and chloroform to improve surface finish.

5.4. Mechanical properties

Many researchers studied the effect of various process parameters on the mechanical properties of FDM printed parts. Montero et al. [45] investigated the effect of raster orientation, air gap, bead width, colour, and model temperature on the tensile strength of the parts fabricated by FDM. Raster orientation and air gap were found two significant factors that affect the tensile strength [45]. Ahn et al. [91] observed that the tensile strength and compressive strength of parts fabricated with a negative air gap were observed to be 65-72% and 85 -90% as compared to the corresponding injection-molded ABS parts, respectively [91]. Bellini and Güçeri [70] investigated the effect of deposition angle and part orientation on tensile strength and flexural strength using experimental and analytical techniques. Rodriguez et al. (2003) introduced and developed a mathematical model based on an approximate minimization algorithm to find the optimal settings of parameters for better tensile strength and stiffness [70]. Weinmann et al. [93] recommended a small air gap and low layer thickness to achieve better yield strength and ultimate strength [93]. Lee et al. [34] optimized the process parameters values to maximize the elastic performance. It was found that air gap, raster angle and layer thickness was the most influential factors [34].

Lee et al. [35] fabricated a cylindrical specimen to analyse the effect of build orientation on the compressive strength of printed parts. The compressive strength of the axial FDM specimen was

41.26 MPa, which was 11.6% greater than the transverse FDM specimen. It is important to study the influence of various parameters on compressive strength for improving the service life of parts due to the anisotropic and brittle nature of parts fabricated by FDM [35]. Panda et al. [55] examined the influence of layer thickness, orientation, raster angle, raster width, and air gap on the tensile strength of parts fabricated by ABS P400. The Bacterial Foraging technique (BFO) was implemented to determine the theoretical optimal value of process parameters to achieve better strength [55]. Sood et al. [75] developed an equation to determine the optimal setting to achieve desired compressive strength through quantum-behaved particle swarm optimization (QPSO)[75]. Rao et al. [66] formulated the single objective and multi-objective problems based on fused deposition modelling and solved these problems with the help of the Teaching Learning Based Optimization (TLBO) algorithm [66]. This research used two case studies to formulate these problems based on the empirical model developed by Sood et. al (2009). Qattawi et al. [60] used ASTM D638 type IV specimen of PLA to investigate the effect of building direction, infill percent, print speed, extrusion temperature, layer height, and infill pattern on tensile strength, dimensional accuracy, and ductility. In this research, various parameters were considered at 4 levels and optimized the process parameters using the response surface method. It is observed in this research that the dimensional accuracy is affected by building direction, extrusion temperature, and layer height more than infill percentage, infill pattern, and printing speed [60]. Higher extrusion temperature and larger layer height were suggested to improve the mechanical properties of the printed part. Mishra et al. [44] attempted to identify the effect of layer thickness, raster width, contour chamber part orientation, and air gap on compressive strength. It was concluded that part orientation, contour number, and gaps between raster have a significant effect on compressive strength. An equation was developed to compute compressive strength from process parameters using RSM [44].

Vishwas et al. [84] experimentally identified the impact of the independent variables (layer thickness, shell thickness, and part orientation) on the dependent variable (ultimate tensile strength, dimensional accuracy, and manufacturing time of printed parts). ASTM standard D638-10specimenof ABS and Nylon were printed. Using Taguchi L9 orthogonal array, it was concluded that raster angle and shell thickness are the most significant process parameters for the ultimate tensile strength and dimensional accuracy for ABS and Nylon printed parts [84]. Dong et al. [15] studied the effect of the extruder temperature, print speed, fan speed, and layer height on the tensile strength. Lattice structure was used as a specimen to identify the effect of all independent variables mentioned above on the dependent variable. The lattice structure was deconstructed into horizontal and inclined struts. Taguchi's 'L16' orthogonal array was implemented to investigate which factor is most influential. In this research, it was found that fan speed is the most significant factor for inclined strut but for horizontal strut it is layer thickness [15]. Rajpurohit et al. [61] concluded that the highest tensile strength was obtained at the 0° raster angle and a lower value of layer height. The tensile strength of the parts fabricated using PLA improves as raster width increases but after a certain value of raster width, the tensile strength decreases [61].

Nagaraj et al. [47] found the optimal values of infill density, print speed, and layer thickness to achieve desired tensile strength for FDM printed ABS parts. The maximum tensile strength, 24.66 N/mm^2, was achieved with 80% infill density, 100 mm/min speed, and 0.2 mm layer thickness [47]. Luo et al. [40] developed and proposed dual nozzle FDM technology for continuous carbon fiber composite 3D printing. Various volume fractions of carbon fiber composite materials were achieved by inserting layers of carbon fiber into the model fabricated using PLA. The tensile strength of the fabricated part with a volume fraction of 40% Carbon fiber and 60 % of PLA was 287.9% better than parts fabricated with pure PLA [40]. Gebisa et al. [24] developed a regression model to predict the tensile strength of ULTEM 9085 thermoplastic material based on an experimental study to identify the effect of the air gap, raster angle, raster width, contour width, and contour number. It was concluded that the raster angle was the most influential factor among all considered factors [24]. Rao et al. [67] implemented a full factorial ANOVA analysis to study the effect of layer thickness, print temperature, and infill style on the tensile strength of parts fabricated by carbon fiber PLA. The maximum tensile strength (26.59 MPa) was obtained for a 0.1 mm layer thickness, cubic infill style, and 220 ^{0}C extrusion temperature [67].

Beniak et al. [6] fabricated a cylindrical specimen to investigate the effect of annealing on tensile strength and compressive strength of FDM printed volcano PLA parts. Tensile strength and compressive strength were found to be maximum when parts were heated after fabrication for 20 minutes in a heating chamber [6]. Deshwal et al. [7] fabricated the ASTM D 638 V standard specimen using PLA by varying process parameters of FDM. The RSM-based center composite design was developed to determine parameter combinations. A hybrid technique like GA-ANN, GA-RSM, and GA-ANFIS was deployed to determine the optimized value of process parameters to achieve maximum tensile strength. The maximum tensile strength, 47.0212 MPa, was achieved with infill density of 100%, temperature of 210 ^{0}C, and speed of 124.778 mm/s by GA-ANN, with an accuracy of 99.89% [7]. Kumar et al. [92] obtained desired tensile strength of carbon-reinforced PLA thermoplastic by optimizing process parameters according to Taguchi L9 experimental design. The optimum tensile strength, 21.961 MPa, of the fabricated part,was achieved at 80 % infill density, 80mm/sec print speed, and 100 microns layer thickness [92]. Kain et al. [30] identified the effect of infill orientation on the mechanical performance of parts fabricated by FDM. Parts were fabricated using wood filament of PLA. In the wood filament of PLA, wood dust, cork, and other powdered wood derivatives are mixed with PLA. It was reported that parts fabricated with 25% wood fiber achieved better tensile strength [30]. Pazhamannil et al. [57] investigated the influences of nozzle temperature, layer thickness, and infill density on the tensile strength of the ASTM D638 specimen of PLA. It was found that the tensile strength of the specimen decreased with higher layer thickness. The main cause behind the above observation is the poor inter-layer bonding with large micro-voids at higher layer thickness and hence lower tensile strength. As the nozzle temperature increases, the tensile strength increases significantly. At high nozzle temperature, the intermolecular diffusion occurs across the interface for a longer period which increases the rate of neck growth gradually. The interface disappears which causes a decrease in the void density of the specimen [57]. Yadav et al. [88] discussed the effects of infill density, material density, and extrusion temperature on the tensile strength of ABS, PETG, and multi-material test pieces. Multi-material by merging ABS and PETG was fabricated in a ratio of 50:50 and 30 test pieces of ASTM D638 type-IV specimen with different inputs were printed to optimize the process parameters for multi-material using GA-ANN. It was found that extrusion temperature was the most influential factor that affects tensile strength. Higher extrusion temperature favors the high tensile strength of the test pieces up to a certain limit. The tensile strength of PETG is 44 N/mm^{2}at the extrusion temperature of 225 ^{0}C at 40% infill density was reported. The hybrid GA-ANN tool maximized the tensile strength of PETG to 46 N/mm^2 [88]. Fountas et al. [20] optimized the compressive strength using various evolutionary algorithms such as dragonfly (DA), ant lion algorithm (ALO), grey wolf algorithm (GWO), and wale optimization algorithm (WOA) by considering the equation developed by Sood et al. [75] and found better result in less number of iteration as compared to QPSO [20].

Dev et al. [12] have conducted a multi-objective optimization study to investigate the effect of layer thickness, build orientation, and infill patterns on material consumption and compressive strength. The Taguchi L9 orthogonal array was used for experimental design. Non- sorting genetic algorithm (NSGA-II) was used to optimize the objective function. It was concluded that the sample fabricated with 80% infill with gyroid pattern, 0.2 mm layer thickness, and 90^0 build orientations provide almost equal compressive strength with a lesser amount of material as compared to solid ABS part [12].

Srinivasan et al. [76] conducted an RSM-CCD-based experimental study to investigate the factors affecting the hardness and tensile strength of parts fabricated using ABS. Infill density and layer thickness were the two most significant factors that affect both responses. Maximum tensile strength was obtained when the infill style was triangular and trailed by grid and cubic [76]. Ramesh et al. [64] found that infill density has a higher contribution to improve tensile strength, to be maximum at 100% infill density and 0.1 mm layer thickness. Table 4 shows the summary of research works conducted to optimize the process parameters of FDM to achieve desired mechanical strength [64].

Dev et al. [12] combined Response Surface Methodology (RSM) and Genetic Algorithm to determine the optimal values of layer thickness, nozzle temperature, and print head speed to achieve desired flexural strength of the ABS printed part. As a result, the Flexural strength (58.3862 MPa) was predicted at a layer thickness of 0.120 mm, 224.958^0 C nozzle temperature, and 30.356 mm/s using the above-developed GA- RSM model is validated through experiments and only 0.69% deviation from predicted flexural strength was found [12]. Kam et al. [29] investigated the effect of infill style and infill density on the printed parts' tensile strength and Izod impact values. It was concluded that the tensile strength and Izod impact values improve with infill density [29]. Feng et al. [19] developed a machine-learning model to reduce the residual stress and warpage effect based on FEM simulation [19].

Mubeen et al. [46] identified the influence of layer thickness, print temperature, infill density, and infill pattern on the impact strength of PLA. It is observed that layer thickness is the most significant factor for impact strength compared to other factors. Lower the layer thickness, the higher the impact strength [46]. Tosto et al. [82] improved the mechanical properties and the density of the sintered part manufactured by metal polymer filament by optimization of various process parameters of FDM. Flow rate is the most significant factor in enhancing mechanical properties and sample density. As a result, better mechanical properties were observed with layer thickness from 90 to 140 micrometres [82]. Lim et al. [37] investigated the effect of nozzle diameter, layer thickness, and infill percentage on the strength of prosthetic socket, Fabrication time, and weight of the prosthetic socket. It was observed that the optimum performance parameters could be achieved at the combination of 1.0 mm nozzle diameter, 0.48 mm layer thickness, and 30% infill density. PCR-TOPSIS was used to find the optimal process parameters condition [37]. Muhamedagic et al. [95] investigated the effect of layer height, print speed, raster angle, and wall thickness on the tensile strength of the specimen built using short carbon fiber reinforced polymide composite. The reduced cubic model was established using RSM and the correlation between selected process parameters and performance parameter was anlyzed by ANOVA. The layer thickness and raster angle were found most influential factors for tensile strength [95]. Ahmed et al. [2] identified the influence of layer thickness, build orientation, infill density, and print speed on tensile strength, Young's modulus, and flexural strength. Build orientation was the most significant factor which affects tensile strength, Young's modulus, and flexural strength. The optimal setting of various process parameters for FDM using oil palm fiber composite was flat (0 degree) build orientation, 10 mm/s printing speed, 0,4 mm layer thickness, and 50% infill density [2].

Table 4. Summary of major research in optimization of process parameters optimization of fused deposition modeling for mechanical properties

Authors	**Material**	**Optimization Technique**	**Process Parameters**	**Performance Parameters**
Tontowi et al. [80]	PLA	RSM, Taguchi	1. layer thickness	1. Tensile strength
			2. Temperature	2. Dimensional accuracy.
			3. Raster angle	
Asadollahi-Yazdi et al. [5]	ABS	NSGA-II	1. layer thickness	1.Build time
			2.Part orientation	2. Tensile strength

				3. Surface Roughness
				4.Material
Pazhamannil et al. [57]	PLA	ANN	1. Nozzle temperature(C)	1.Tensile strength
			2. Layer thickness	
			3. Infill speed	
			4. Tensile strength	
Beniak et al. [6]	Volcano PLA thermoplastic	NSGA-II	Annealing time	1. Tensile strength
				2. Compressive Strength
Dong et al. [15]	ABS	Taguchi Philosophy	1. Extruder Temperature	1. Tensile Strength
			2. Print Speed	
			3. Fan Speed	
			4. Layer Height	
Vishwas et al. [84]	ABS, Nylon	Taguchi Philosophy	1. Shell thickness	1. ultimate tensile Strength
			2. Model Orientation	2. Dimensional accuracy.
			3. Layer Thickness	
Yadav et al. [88]	ABS	GA-ANN	1. Infill density	1. Tensile strength
			2. Material Density	
			3. Extrusion temperature	
Qattawi et al. [60]	PLA	Taguchi Philosophy	1. Building Direction	1. Young's Modulus
			2. Infill Percent	2. Tensile Strength
			3. Print Speed	3. Ductility
			4. Extrusion Temperature	
			5. Layer height	
			6. Infill pattern	
Rajpurohit et al. [62]	PLA	Taguchi Philosophy	1. Raster Angle	1. Tensile strength
			2. Raster Width	
			3. Layer Height	
Raju et al. [63]	ABS	Hybrid PSO-BFO	1. Layer thickness	1. Surface Roughness
			2. Support Material	2. Hardness
			3. Model Interior	3. Tensile Strength
			4. Part Orientation	4. Flexural Modulus
Garg et al. [23]	ABS	Factorial Design	1. layer thickness	1. Compressive Strength
			2. Raster angle	
			3. Orientation	
			4. Raster width	
			5. Air gap	
Rao et al. [66]	ABS P400	TLBO	1. layer thickness	1. Compressive Strength
			2. Orientation	
			3. Raster angle	
			4. Raster Width	
			5. Air Gap	

Mishra et al. [44]	Rigid Plastic	RSM-FCCD	1. Cotour Number 2. Layer thickness (mm) 3. Raster width 4. Part Orientation 5. Raster Angle 6. Air Gap	1. Compressive Strength
Fountas et al. [21]	PLA	RSM	1. layer thickness 2. Shell thickness 3. Infill density 4. Part Orientation 5. Printing Speed	1. Tensile strength
Dev et al. [12]	ABS	Taguchi Philosophy, NSGA-II	1. layer thickness 2. orientation angle 3. Infill density with pattern	1. Compressive Strength 2. Material usage
Deshwal et al. [11]	PLA	GA-ANN GA-ANFIS GA-RSM	1. Infill density 2. Temperature 3. Speed	1. Tensile strength
Srinivasan et al. [77]	ABS	RSM-CCD	1. Infill density 2. Infill pattern 3. Layer thickness	1. Tensile strength
Ramesh et al. [65]	Nylon	Taguchi Philosophy, NSGA-II	1. Print speed 2. Layer Height 3. Infill density	1. Tensile strength 2. Impact Strength 3. Shore D-hardness 4. Flexural Strength
Gebisa et al. [25]	ULTEM 9085 thermoplastic	Full Factorial Design	1. Air gap 2. Raster Angle 3. Raste width 4. Contour Number 5. Contour width	1. Tensile strength
Fountas et al. [20]	ABS	DA ALO GWO MFO WOA	1. Layer thickness 2. Orientation 3. Raster angle 4. Raster width 5. Air gap	1. Compressive strength 2. Sliding wear
Rao et al. [68]	PLA	Full Factorial design	1. layer thickness 2. Infill pattern 3. Temperature	1. Tensile strength

5.5. Effect of Post-Processing on Mechanical Properties of Parts Printed Using FDM Technology:

Torres et al. [82] investigated the effect of process parameters including the layer thickness, infill density, and post-processing heat-treatment time at 100^{0}C on the shear properties of FDM printed PLA parts. Infill density and layer thickness were the most influential factors for the strength, whereas infill density, and post-processing for ductility. Wach et al. [86] fabricated PLA specimen parts at different temperatures and processed them at 215^{0}C to increase the degree of crystallinity. The flexural strength of the samples improved with the increase in the degree of crystallinity of FDM-PLA by 11–17%. Pagano et al. [55] investigated the effect of annealing on the mechanical properties of PLA parts. It was concluded that annealing has no effect on tensile strength but significantly affected the Young modulus (stiffness).

5.6. Discussion and Future Aspects

Tensile strength is one of the most analyzed mechanical properties of FDM printed parts. It can be concluded from existing research works that layer thickness and build orientation are the most significant factors that affect the tensile strength of parts. Tensile strength was found to be maximum at 0^0 -part orientation. The smaller layer thickness leads to better tensile strength. Apart from these two factors, infill density and number of shells, air gap, and raster angle also play an important role in tensile strength. Many researchers studied the effect of various process parameters on the compressive strength of FDM printed parts and concluded that infill density, infill shape, and the number of shells are the most significant factors impacting compressive strength. Very few works are reported that studied the flexural strength of FDM printed parts. Flexural strength was found to be maximum at 100% infill density and low layer thickness. Based on reviewed articles, the impact of process parameters including extrusion temperature, infill pattern, raster width, infill pattern, and their combinations can be analyzed in the future to build a part with good flexural strength. Annealing of the FDM parts improves the stiffness but does not affect tensile strength, significantly. Only a few articles have been published on multi-objective optimization of process parameters of FDM to improve the mechanical properties of parts. Hence, there is a scope for further research in this direction.

5.7. Dimensional Accuracy

The dimensional accuracy of an FDM printed part is influenced by many factors including material characteristics, part geometry, and FDM process parameters. Wang et al. [86] observed that thermoplastic fiber shrinks when it cools down from melting temperature to glass transition temperature, which causes dimensional inaccuracy in parts [86]. Nazan et al. [52] investigated the effect of layer temperature, infill density, first layer thickness, and other layer thickness on the dimensional accuracy of parts. Cuboids of size 30mm x 100mm x 5mm were printed and RSM-central composite design was implemented to optimize different process parameters to reduce the warping of the parts [52]. Sood et. al [74] presented an experimental investigation on the effect of various process parameters, such as part orientation, layer thickness, raster angle, raster width, and air gap along with their combinations on the dimensional accuracy of FDM printed ABSP400 parts. Shrinkage was observed along the x and y-axis of the build platform and the thickness of the printed part along the z-axis was always found to be more than the design value. Taguchi's 'L27' orthogonal array was used to determine the significance of parameters and their interactions before recommending the optimum level of parameters. Grey Taguchi methodology has been adopted to minimize the combination of all objectives, i.e., minimizing the percentage change in the dimension along all the axes [74]. Dani et al. [10] implemented multi-objective optimization of process parameters, including build material, the number of layers, support structure, build time, and part orientation to reduce dimensional inaccuracy [10]. Sahu et al. [71] conducted an experimental study and integrated fuzzy logic with the Taguchi method for decision-making in selecting the optimal set of parameters to improve dimensional accuracy. The results of the multi-response predicted model was validated by conducting a confirmation test [71]. Peng et al. [59] implemented a fuzzy interface system to convert three outputs including build time, dimensional accuracy, and warp deformation into one comprehensive response. A model was developed relating the comprehensive response and the four input variables namely, line width compensation, extrusion velocity, filling velocity, and layer thickness using second-order response surface methodology and further validated by the artificial neural network [59]. Gurrala et al. [25] developed a functional relationship between the independent variable and response variable. In this study, the model interior, the horizontal direction along the xy plane, and the vertical direction along the xz plane were considered the independent variable. This paper concluded that the effect of the depositing direction along the horizontal direction was found predominant through ANOVA. The width and shrinkage were varying as the length of the part increased [25]. Dimensional accuracy is an important factor for the fit and finish requirement of assembly. The dimensional accuracy of the printed part deviates from the CAD model due to the heating and cooling cycle of the FDM process. Equbal et al. [16] incorporated the parametric optimization of FDM to enhance the dimension accuracy of parts fabricated by ABS and concluded that raster angle and raster width affect the dimensional accuracy significantly [16]. Narang et al. [51] recommended lower layer thickness to achieve better dimensional accuracy and surface roughness [51]. Tontowi et al. [80] optimized the process parameter of the 3D printer to improve the quality of poly-lactic acid printed parts. Layer thickness, temperature, and raster angle were selected as process parameters. This study investigated the effect of process parameters on tensile strength and dimensional accuracy.RSM and Taguchi methods were used to develop equations between dependent variables, i.e. tensile strength and dimensional accuracy, and independent variables, i.e., layer thickness, temperature, and raster angle. It was found that tensile strength was prominently affected by layer thickness rather than raster angle or temperature. This study also compared two different methodologies of design of experiments: RSM Taguchi methods and concluded that RSM could significantly reduce the dimensional error and improve the tensile strength as compared to the Taguchi method [80]. Cekic et al. [8] compared the dimensional accuracy of parts fabricated using PLA and PLA-wood composite and concluded that PLA wood composite parts' dimensional accuracy was found better than PLA parts [8]. Sajan et al. [72] conducted an experimental investigation to identify the effect of six parameters including bed temperature, nozzle temperature, print speed, infill percentage, layer thickness, and the number of loops on circularity and surface finish. Bed temperature, number of loops, nozzle temperature, print speed, layer thickness, and infill affect the circularity and surface roughness in descending order [72]. Mahmood et al. [43] investigated the effect of 13 parameters on dimensional accuracy and geometric characteristics of benchmarked components fabricated using ABS material. It was found that deviation increased with more features. The number of shells was found to be the most significant factor affecting dimensional accuracy. Layer thickness, infill speed, infill shell spacing multiplier, number of shells, and extruder temperature were the most influencing factors for geometric characteristics [43]. Eswaran et. al [18] used Taguchi's ‘ L9’ orthogonal array to optimize the process parameter such as infill density, horizontal orientation, and vertical orientation to minimize the circularity error of the printed part. In this study, It was observed that 50% infill density, 0 degrees horizontal, and vertical orientation minimizes the circularity error of the considered printed part [18]. Beniak et al. [7] investigated the effect of layer thickness and extrusion temperature on dimensional accuracy through ANOVA. This research concluded that printing temperature has a significant effect on the shape and dimensional tolerance. Agarwal et al. [1] analyzed the impact of wall thickness, infill density, print bed temperature, print speed, layer thickness, and extrusion temperature on dimensional accuracy. This research concluded that layer thickness and print speed significantly impact the dimensional accuracy of the printed parts. Therefore, low layer thickness and high print speed were suggested to achieve better dimensional accuracy [1].

Table 5. presents the summary of research articles published to investigate the effect of various process parameters on dimensional accuracy.

Authors	Material	Optimization Technique	Process Parameters	Performance Parameters
Tontowi et al. [81]	PLA	RSM, Taguchi	1. Layer thickness	1. Tensile strength
			2. Temperature	2. Dimensional accuracy.
			3. Raster angle	

Nazan et al. [53]	ABS	Response Surface Method	1. layer temperature	1. Warping
			2. infill density	
			3. first layer thickness	
			4. other layer thickness	
Beniak et al. [6]	Volcano PLA thermoplastic	NSGA-II	1. Annealing time	1. Tensile strength
				2. Compressive Strength
Sood et al. [75]	ABS	Taguchi 'L27' and Grey Rational Method	1. Layer thickness,	Dimensional Accuracy
			2. Raster angle,	
			3. Raster width,	
			4. Air gap,	
			5. Build Orientation	
Eswaran et al. [18]	ABS	Taguchi 'L9'	1. Infill density,	1.Circularity Error Internal
			2. Horizontal orientation,	2.Circularity error External
			3. vertical orientation	
Mahmood et al. [44]	ABS	Taguchi L'27'	1. Chamber Temp.	Dimensional Accuracy
			2. Layer Thickness	
			3. Extruder Temp.	
			4. Platform Temp.	
			5. No. of shells	
			6. Infill shell spacing multiplier	
			7. Inset distance multiplier	
			8. Floor/roof thickness	
			9. Infill density	
			10. Infill speed	
			11. Outline speed(mm/s)	
			12. Inset speed(mm/s)	
Sajan et al. [73]	ABS	Taguchi L'27'	1. Bed Temperature	1. Circularity error
			2. Nozzle Temperature	2. Surface Roughness
			3. Print Speed	
			4. Infill	

			5. Layer thickness	
			6. Number of loops	

5.8. A short discussion and future aspects:

The critical literature review concludes that dimensional accuracy is significantly affected by layer thickness, extrusion temperature, and the number of shells. The low layer thickness was recommended to improve dimensional accuracy. Shrinkage and expansion were observed along the X and Y directions and the Z direction, respectively. Thus, orientation is also an important factor that affects dimensional accuracy. It is required to further investigate the effect of other factors, such as the number of contours, contour width, raster angle, and raster width on dimensional accuracy. Many researchers have considered the two-level or three-level factors to reduce the deviation in dimension. Taguchi method and response surface methodology were used for experimental modeling and optimization. In the future, optimization of process parameters considering more than three-level using modern optimization techniques, such as GA, TLBO, QPSO, can be investigated.

5.9. Build Time

The adoption of additive manufacturing for mass production in industries is still challenging due to the large build time of parts. Fused deposition modeling fabricates the parts in the layer-by-layer manner. It consumes a lot of time to fabricate even a small part. Failure of part printing due to blocked nozzle also increased the build time of parts. Similarly, other part characteristics and machining parameters also affect the build time. Build time can be optimized by selecting the optimum setting of various process parameters. Thrimurthulu et al. [79] presented a multi-criteria genetic algorithm to determine optimal settings of part orientation to enhance surface finish and reduce printing time [79]. Nancharaiah [50] observed that raster angle and air gap influence the build time greatly. Build time can be reduced by selecting a higher layer thickness and positive air gap [50]. Gurrala et al. [25] developed a model to investigate the effect of layer thickness, raster angle, part orientation, contour width, and part raster width on build time and support structure volume using a full factorial design of experiments. It was concluded that layer thickness, part orientation, contour width, and raster width affect the build time significantly [25]. Ali et al. [3] reduced the build time by selecting high layer thickness, positive air gap, and larger raster width. High layer thickness, positive air gap, and larger raster width fulfill the aggregate model in less number of slices. This results in reduced build time [3]. Espalin et al. [17] explored build process deviation to improve surface roughness and build time by integrating two legacy FDM machines. Build time was reduced by 53% more than the standard FDM process [17]. Rathee et al. [69] conducted an experimental case study using a cylindrical specimen to investigate the effect of layer thickness, shell width, air gap, raster width, raster orientation, and build orientation to reduce the build time. Quadratic response surface equations relating build time and the considered factors for each spatial orientation (rotation around different axes) were developed using a central composite design (CCD) approach.

Table 6. Summary of major research in optimization of process parameters optimization of fused deposition modeling for build time

Authors	Material	Optimization Technique	Process Parameters	Performance Parameters
Hallmann et al. [28]				1. Build Time

	Water Soluble filament	Simulation in MATLAB	The angle of the 3RRR mechanism	2. Support Structure
Asadollahi-Yazdi et al. [5]	ABS	NSGA-II	1.Layer thickness	1.Build time
				2. Tensile strength
			2.Part orientation	3. Surface Roughness
				4.Material
Chaudhari et al. [9]	ABS	Taguchi 'L9'	1. layer thickness,	1. Production Time
			2. infill,	
			3. orientation	2. Production cost
			4. post-processing	

The outcome of the study showed that layer thickness and air gap were the most significant parameters for all the spatial orientations [69]. Srivastava et al. [77] implemented multi-objective optimization using RSM embedded fuzzy logic to determine the optimal setting of process parameters to improve build time and reduce support structure volume simultaneously. The intermediate value of layer height and air gap were found optimal for a multi-objective function [77]. Patil et al. [58] conducted multi-objective optimization using the grey rational method to find out the optimal settings of FDM parameters to enhance surface finish, reduce build time, and consumption of filament. This study concluded that a triangular infill pattern, 70% infill density, 100 mm/h printing speed, and 0.2 mm layer thickness are the optimum value of the considered parameters to improve the objective. Table 6 illustrates a brief description of research articles that investigated the impact of process parameters on build time [58].

5.10. A Short Discussion and Future Aspects

It was found from the critical literature review that the build time was reduced by selecting high layer thickness, larger raster width, and positive air gap. Some of the researchers also investigated the effect of part orientation on build time. Various orientations to print a part required different volumes of the support structure. Thus, the time to print support structure and part vary with part orientation. The effect of some process parameters, such as extrusion temperature, raster angle, and shell thickness, is still unexplored. Layer thickness also affects surface roughness and dimensional accuracy adversely. One further research direction could be multi-objective optimization to study the effect of various process parameters on surface roughness, dimensional accuracy, and build time.

5.11. Other Responses

The effect of various process parameters of FDM on support structure minimization, energy consumption, build cost, etc. are still least explored. Few experimental investigations to identify the effect of various process parameters on these responses have been conducted. Lunetto et al. [39] investigated the effect of types of components, material, infill styles, and layer thickness on specific printing energy, specific energy consumption, and process time using the regression method. The results of the study reported that the contribution due to the non-printing phases, i.e., switch-on, idling, heating, and calibration, on the total process time and energy consumption can be modeled as a constant. A linear correlation was highlighted between build time and energy demand for printing during the printing phase [39]. Dani et al. [10] recommended 0°build orientation to reduce support structure, build time, and build cost [10]. Raut et al. [94] fabricated the ABS parts in various orientations and identified the effect of build orientation on the required number of layers, time to fabricate the part, support structure volume, and total cost. Build orientation 0°about the y-axis was found optimal for tensile strength and build cost [94].

Table 7. optimization techniques used to identify the impact of process parameters on other performance parameters such as specific printing energy, specific energy consumption, production cost, etc.

Authors	Material	Optimization Technique	Process Parameters	Performance Parameters
Lunetto et al. [40]	ABS PC ABS	Linear Correlation method	1. Type of Component	1.Specific Printing Energy (SPE)
			2. Infill Strategy	2.The Specific Energy Consumption (SEC)
			3. layer thickness	
Fountas et al. [21]	PLA	RSM	1. layer thickness	1. Tensile strength
			2. Shell thickness	
			3. Infill density	
			4. Part Orientation	
			5. Printing Speed	
Chaudhari et al. [9]	ABS	Taguchi 'L9'	1. layer thickness,	1. Production Time
			2. infill,	
			3. orientation	2. Production cost
			4. post-processing	

6. Conclusion:

This literature review attempted to critically analyze and discuss FDM process parameters and their impact on various properties of FDM printed parts. Various optimization tools such as GA, RSM, Taguchi etc., are also summarized which are commonly used in these research. This work explored the existing research that has been carried out on the optimization of process parameters of FDM using various tools such as genetic algorithm, grey analysis, factorial design method, Taguchi methodology, response surface method, teaching learning based optimization, artificial neural network. In these optimization methods, attempts are made to identify the significant parameters responsible for a desired property. Many works have been reviewed that focuses on the mechanical properties, quality of parts, and efficiency of the FDM process but very few research were conducted to improve the 3D printer design, identification of newer printing material and preventive maintenance of 3D printer. The following could be the potential future research directions:

- ABS and PLA are the two most commonly used materials to print the parts. Other materials such as Nylon, PETG, and HIPS, can be used as thermoplastic filament for future research.

- Some process parameters, such as infill pattern, shell width, air gap, annealing, contour width, number of contours are less analyzed compared to layer thickness, build orientation, raster width, etc. The least known parameter such as annealing, support structures may be considered as a variable for future research direction.
- There is limited research on multi-objective optimization of process parameters of fused deposition modeling, which can be another direction for future work.
- 3D printing in different planes to reduce or eliminate the support structure can also be a research direction for future work, which is very challenging.
- Future research may be possible on "3D printing on the uneven surface" and "3d printing for repairing the broken parts".

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