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Process parameter modelling and optimization techniques applied to fused deposition modelling: A review

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Abstract. Manufacturing is the foundation of any industrialized country and involves making products from raw materials using various processes. Additive manufacturing (AM) was originally created as a method for swift prototyping, allowing the visualization, testing, and validation of a design prior to final production for end-users. FDM is the most commonly used additive manufacturing process for constructing products and prototypes. It encompasses numerous process parameters that impact the quality of manufactured products. Properly selecting these process parameters is crucial for producing products at a lower cost while enhancing mechanical properties, build time, and part quality, among other factors. Therefore, in the past, researchers have optimized the process parameters to achieve the desired product outcomes. In the present study, we provide an overview of FDM process parameters and review various design optimization methods. We present several experimental designs, such as the Taguchi method, response surface methodology, and design of experiments, as well as computational approaches like artificial intelligence, and machine learning.

1. Introduction

In any industry, manufacturing is a challenging sector due to its extraordinarily complex components. Among the recent advances in the manufacturing sector, additive manufacturing (AM) is the most recent method for fabricating complex components from 3D Computer-Aided Design (CAD) geometry, using the process illustrated in Figure 1 [1]. The AM process builds 3D objects or products layer by layer from a Computer-Aided Design (CAD) model, and this capability has experienced unprecedented growth as a manufacturing tool in some corporations. Combined with the advances in topology optimization, AM process aims to reduce mass or utilize materials where needed and has been successfully adopted in many engineering applications [2]. The main advantage with use of AM process is its ability to directly transform a computerized 3D model data into a finished product with no need for auxiliary tools. This facilitates the fabrication of parts having complex geometry that are difficult tfor conventional manufacturing methods [3].

Figure 1. General additive manufacturing process flow (Adapted from [4])

Among the first forefront industries that utilized the amazing capabilities of additive manufacturing to transform their production are aerospace[5], medical[6], electronics[7], transportation, automotive[8], construction[9], healthcare monitoring[10] and sustainable energy generation [11]. There are different types of additive manufacturing techniques that have been developed recently. According to the American Society for Testing Materials (ASTM), AM has been classified into seven processes technologies as illustrated in Figure 2(a) [12,13].

From the various AM techniques, fused deposition modelling (FDM) process is one of the most popular and commonly used [14,15] in the industry. The main reason for its wider application are that FDM is cost-effective in manufacturing of thermoplastic parts and prototypes. Moreover, the wider availability of thermoplastic materials has made the lead times minimal and the process to be cheaper than other AM processes [12]. FDM was made commercially available in early1990s following the patent by the co-founder of Stratasys, Scott Crump in 1989 [16]. In the process, a continuous supply of thermoplastic filament is utilized for printing layers of materials to build the part. As illustrated in Figure 2(b), the material filament is heated to a semi-liquid phase upon heating the element inside the liquefying head, and this semi-liquid material is extruded through the nozzle on the printing platform.

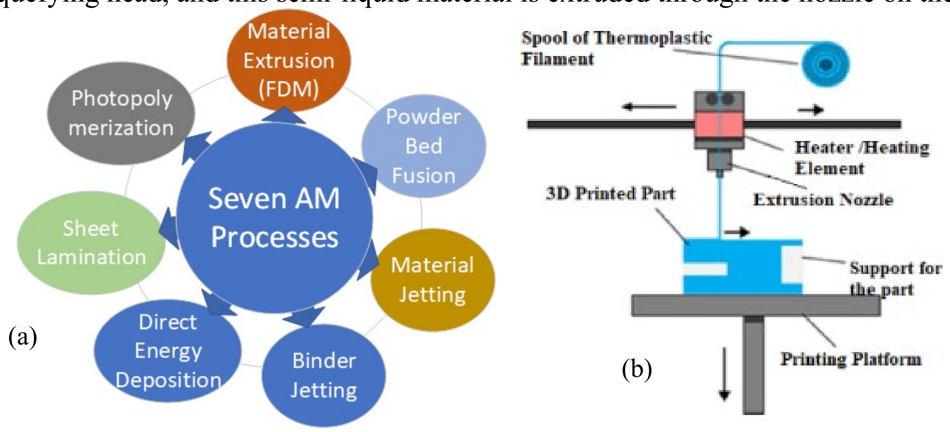

Figure 2. (a) Categorization of AM technologies (Adapted from[12]) and (b) Setup of FDM process [15,17]

The semi-liquid thermoplastic filament materials do not solidify immediately after extrusion from the nozzle onto the printing plate; instead, the material remains partially liquid and mergse during the construction of a specific layer, and then they solidify into a part that is built layer by layer at the prevailing ambient temperature [18]. As observed in Figure 2(b), support structures are essential in FDM process to ensure the stability of intricate designs. FDM offers versatile support options, including soluble support for complex geometries and break-away support for simpler ones. The requirement for support structures depends on the maximum overhang angle, which is influenced by material, layer height, and printer capabilities. Typically, most materials have a maximum overhang angle of around 45°, but advanced printers can exceed this without the need for support [19]. Among the main benefots of FDM, process simplicity, high-speed printing, and low cost can be mentioned. On the other hand, the disadvantages of the process include anisotropic properties, poor surface quality, layer-wise or stair case appearance, and limitation to access thermoplastic polymers because thermoplasticity is the essential property for a material to be 3D printed through FDM technique [15][20]. Since the mechanical characteristics and product quality of FDM-printed parts depend on the proper (or optimal) selection of process parameters, making the process suitable for mass production and more acceptable in the industries, finding the optimal process parameter combinations to improve the part quality and mechanical properties is very important [21]. The effect of the process parameters has a significant impact on the mechanical characteristics of the parts fabricated by FDM under static and dynamic loads [22]. The various common FDM process parameters, along with their descriptions are presented in Table 1.

Table 1 Process parameter of FDM and its description

Process parameter	Description	Reference
Layer thickness	Height of layers deposited after extrusion, determined by nozzle tip diameter and material	[14,15]
Build Orientation	Positioning of the part within the build platform in relation to X, Y, and Z directions.	[14,21].
Raster Angle/ Orientation	Angle of material deposition with respect to the X-direction on the build platform.	[14,15,21]
Air Gap	Distance between adjacent FDM-printed tool paths on a single layer.	[14,15,21]
Extrusion temperature	Temperature of thermoplastic filament materials inside the nozzle before extrusion.	[15,21]
Print Speed:	Speed of the nozzle tip in the XY plane during material deposition.	[15,21]
Infill pattern	Pattern used to form the internal structure of the FDM printed part (e.g., diamond, honeycomb).	[15,21]
Infill density/Interior infill	Solidity of the internal structure of FDM printed parts.	[15,21]
Nozzle diameter	Diameter of the extruder nozzle tip.	[15]
Raster width	Width of deposited beads along the extruder tool path.	[14,15,21]
Number of contours	Number of solid outer layers surrounding the internal infill pattern.	[14,15].
Contour width	Thickness of the outer contour layers.	[14,15]
Contour to contour Air gap	Distance between solid outer layers (contours).	[15]

The list in this table (Table 1) indicates that fabrication of components using FDM printing methods involve different processing parameters that play crucial roles in quality and performance of the printed parts. Accordingly, effects of these parameters on the quality of AM manufactured components have been investigated in several research works [14,15,21,23] Finding an optimum process parameter that improves the surface quality and mechanical properties (i.e., tensile strength, fracture toughness, plasticity, hardness, brittleness, and fatigue strength) of manufactured components is one of the research areas studied by researchers. To find an optimum amount of each parameters different optimization techniques were used. Thus, the goal of this survey is to summarize the optimization techniques that are applied in FDM AM methods. This review covers the period from 2000 to September 2023, and it offers well-organized information on objectives, process parameters studied, constraints, and optimization techniques for FDM process. This information can be valuable for researchers seeking to identify trends, challenges, and future directions in research gaps that exist in FDM process parameter optimization.

2. Highlights of studies on FDM process

In 2021, Dezaki, et al. [24] provided an overview of the research, development, and process optimization of FDM throughout history. They also presented an overview of the popular materials investigated to find out their features and mechanical properties in the FDM process. Similar work was also reported in [25], where a review was made to know the insights of one such AM process, i.e., FDM. Dey and Yodo

[21] conducted a comprehensive review of the current literature regarding the influence of parameters on part quality and process parameter optimization. In 2015, Mohamed et al. [14] conducted a comprehensive review of the research conducted up to that point to identify and enhance the process parameters in the FDM process. Future directions for FDM research in this domain are outlined focusing on the research on each quality characteristics (static and dynamic properties, material behavior, surface quality and build time). Quite recently, Rajan et al. [19] reported a review that explains the various 3D printing techniques used in FDM process as well as the polymer materials and polymer composites. The study also discussed the conducted investigations on different materials, parameters, properties, and the potential applications of FDM parameters. Kohad et al. [26] reviewed the identification of various FDM process parameters that affect the quality of the fabricated parts. They were also evaluated on two factors that influence fabricated parameters.

Even though there have been research achievements on FDM based AM process parameter optimization, the research directions for future development needs improvement. Some reviews about process parameter optimization in AM have been published, but mainly aiming at analyzing and discussing the general process parameter optimization work in[14,15,19] but gaps are observed on study of the modelling and optimization methods of process parameter in FDM as main study. The review also does not identify the objectives, design variables, and constraints that were used by the researchers. There is no doubt that the methods of modelling selecting or predicting an optimum process parameter for manufacturing high-quality components are a common problem for obtaining high quality product. Therefore, it is necessary to present a review of the process parameter modelling and optimization methods to summarize the existing achievements and give some future directions for further exploration in the finding of optimum process parameter for FDM based AM process. Besides, as far as the authors knowledge, similar review papers for process parameter optimization methods for FDM are neither under consideration nor have already been published elsewhere.

3. FDM process parameter modelling and optimization methods

Different optimization techniques have been used to obtain an optimal combination of all control variables to either minimize or maximize one or more desired outputs. These techniques are also used to identify the most influential parameters, the interactions between various parameters, and the extent to which an AM process parameter individually affects the output variables. Thus, this section presents experimental design approach and computational approach used for process parameter optimization of FDM based AM.

3.1. Experimental design approach

3.1.1. Taguchi method. The Taguchi method, a statistical approach also known as robust design, is often used in experimental design to enhance the quality of manufactured goods across various industries [27]. It minimizes the number of experiments needed, providing a systematic means to optimize designs in terms of quality and cost using orthogonal arrays of factors. Taguchi's primary goal is to reduce variability around target product properties through statistical experimental design, known as robust design. This method is extensively employed in AM research too to explore the impact of process parameters on additively manufactured components using this method. It integrates statistical and mathematical techniques to optimize performance traits, revealing effects with fewer experiments and focusing on controlling signal factors while mitigating noise factors that contribute to unpredictability [28].

Many studies used the Taguchi method along with analysis of variance (ANOVA) procedures to optimize the process parameters of FDM. These parameters include layer thickness [29–34], infill density [29,34] road width [31,32,35], speed of deposition [31,34], raster angle [30,32,33,36], air gap [30,32,33,36], raster width [30,36], slice height [36], deposition style [35], support style [35], print speed [29], direction of rotation [36], build orientation angle [36] and deposition orientation [35]. Most of the studies were conducted for ABS (acrylonitrile butadiene styrene) material with the goal of improving surface roughness [31,34,35] surface quality [32], dimensional accuracy [32,35], tensile strength [35], elastic performance [30,36], impact strength [34,36] build time [29,34] and production time [33]. Using the ANOVA, the researchers found significant parameters such as layer thickness[31,33] raster angle [36], raster width [36], and build orientation.

The Taguchi method was also employed for the optimization of FDM process parameters, namely extrusion and filling velocity, wire-width compensation and layer thickness of ABS material, to improve dimensional accuracy and reduce warpage deformation in printed parts [37]. Additionally, fuzzy logic was employed to optimize process parameters, including air gap, raster angle, layer thickness, raster width and orientation, aiming to enhance dimensional accuracy [38]. Gray Taguchi method was also utilized to optimize FDM process parameters, including wire-width compensation, extrusion and filling velocities, and layer thickness of ABS material to address dimensional errors and reduce warpage deformation in printed parts [39].

Other areas of application of the Taguchi method includes enhancing the quality of printed materials made from Polylactic Acid (PLA). For example, Maguluri et al [40] studied the influence of infill density, nozzle temperature, and printing speed on tensile properties using a Taguchi L8 array and obtained optimum values for each PLA specimens. Lokesh et al [41] examined the influence of various printing parameters on the mechanical properties of PLA specimens processed and tested as per ASTM standards through the Design of an Experiment (DOE), where the Taguchi approach by L9 orthogonal array was employed. To assess whether process variables have any significant effects, an ANOVA was performed. It was observed that layer thickness has more influence than build orientation and raster angle. Liu et al. [42] established a new theoretical model to reveal the distortion mechanism of PLA thin-plate parts in the FDM process, a theoretical model based on the theory of elastic thin plates in thermoelectricity. An experimental research methodology, utilizing the Taguchi method, was employed to design unique test specimens. Moreover, 81 test specimens were designed and prepared through the FDM process and measured by a portable 3D laser scanner. Two statistical analysis methods, the ANOVA and signal-to-noise ratio (S/N) were utilized to optimize process parameters and mitigate thin-plate part distortion. The experimental results indicated that the optimal process parameters can be obtained and that the proposed theoretical model was efficient.

In several studies, the Taguchi method was employed to optimize various process parameters in FDM. Santhakumar et al. [43] investigated the improvement of impact strength by optimizing FDM process parameters for polycarbonate material. They studied four key process parameters (1) layer thickness, (2) build orientation, (3) raster angle, and (4) raster width, and concluded using ANOVA analysis, that the most influential factor for impact strength in polycarbonate material is layer thickness. In their study, Anitha et al. [44] investigated the effects of parameters like layer thickness, road width, and deposition speed on FDM parts. They utilized an L18 orthogonal array for their experimental design. They found that layer thickness significantly affects the minimum surface roughness of FDM parts. Similarly, Alhubail et al. [45] investigated the effects of FDM variables, including layer thickness, air gap, raster width, contour width, and raster orientation, on surface roughness and tensile strength using Taguchi design (L32). Jiang et al. [46] explored the optimization of process parameters for FDM of Polyetheretherketone (PEEK) for biomedical implants, employing the Taguchi method to enhance tensile strength, print speed, layer thickness, temperature, and extrusion width. Finally, in [47], Gray Taguchi design of experiments was used to optimize FDM parameters leading to improvements in tensile strength, flexural strength, impact strength, and compression strength. Filippidis et al. [48] used a combined Taguchi with I optimality and grey analysis to determine the optimal combination: priming/retraction speed (8 mm/s), layer thickness (0.4 mm), temperature (190 °C) and nozzle speed (40 mm/s). The major influential factors for FDM process parameter optimization were layer thickness followed by printing speed and temperature.

3.1.2. Response Surface Method. Response surface methodology (RSM) integrates mathematical and statistical techniques to model and optimize processes. Its primary objective is to enhance responses influenced by various input parameters or factors. RSM employs the Design of Experiments (DoE) approach to collect sufficient data, enabling the establishment of a connection between controllable input parameters and the resulting outcomes[49]. This method is also used for the modelling and optimization of process parameter of FDM to improve the quality of printed parts.

In the research conducted by Wang et al. [50], RSM was used to optimize a multi-temperature parameter system for FDM by examining the effects of temperature conditions (nozzle, platform and environment temperature) on the tensile strength of carbon fiber/polylactic acid composite specimens using the constructed RSM model. The results showed that the RSM optimization method significantly improved tensile strength with a 3.2% gap compared to FDM results. Similarly, Mandge et al.'s research [51] utilized RSM to study the effect of process parameters on ABS specimen using RSM and validating the significance using ANOVA. The work aimed to overcome the shortcoming of the process while optimizing mechanical and thermal properties.

In the research conducted by Mohamed, et al. [52], they examined crucial FDM parameters using Q-optimal response surface methodology to investigate these parameters and how these parameters affect performance variables. To gauge the reliability of these models, ANOVA was employed to assess their adequacy and significance. This analysis led to the identification of optimal process parameter settings. To validate both the models and these optimized settings, a confirmation test was carried out. The results affirmed that the Q-optimal design approach shows promise as a method for optimizing FDM process parameters and validated the dependability of the developed models.

Equbal et al. [53] examined the performance of ABS P400 parts manufactured using FDM under compressive loading. They studied the effects of varying levels of three FDM process parameters: (1) raster angle, (2) air gap, and (3) raster width on three responses, including compressive stress, percentage deformation, and breaking stress of the fabricated parts. Experimental results were analyzed using ANOVA, response graphs, and 3D surface plots, revealing the anisotropic nature of ABS P400 parts and the significant impact of chosen process parameters on compressive properties. The relationships between process parameters and responses were complex, and predictive models for these responses were developed and validated through additivity tests. Multi-objective optimization using the desirability function approach was employed to discover the best combination of FDM process parameters, and the results were validated with a confirmatory test. The study provided valuable insights into the effects of critical FDM parameters on compressive properties beyond CS, including % D and BS of ABS P400 fabricated parts.

Comparison of Taguchi method with RSM was also reported in [54] using four parameters, namely (1) layer thickness, (2) extrusion temperature, (3) print speed and (4) raster width. In addition, their interaction terms are identified as control variables having three levels, where tensile strength and compressive strength are selected responses. L27 orthogonal array and face-centered central composite design (FCCCD) were used in the experiment using Taguchi and RSM, respectively. The S/N ratio and ANOVA were used to get the optimal FDM parameter combination as well as the main factors that influence the performance of the PLA samples. The results of the experimental results revealed that both Taguchi method and RSM succeeded in predicting better results compared with the original groups. In addition, the optimum combinations for tensile strength and compressive strength obtained from the RSM were 2.11% and 8.15% higher than the Taguchi method, respectively. Furthermore, in a study conducted by Panda et al. [55], they explored the influence of five crucial parameters: air gap, layer thickness, orientation, raster angle and raster width. Their investigation aimed to reveal the impact of these parameters on three specific outcomes of the test specimens:

(1) tensile strength,
(2) flexural strength, and
(3) impact strength.

The experiments were carried out using a central composite design (CCD), and they developed empirical models that established the relationships between each response and the process parameters. To verify the reliability of these models, ANOVA was employed for validation. In the end, a bacterial foraging technique was employed to recommend a theoretical combination of parameter settings that would yield strong performance across all the responses simultaneously

3.1.3. Factorial design. Full Factorial Design (FFD) is a classical optimization approach that employs statistical methods to demonstrate the relationship between variable parameters influencing the response through a linear regression model [56]. Information necessary for constructing the response model is gathered through experimental or simulation work, and the FFD method can be used to simultaneously investigate the effect of multiple independent variables and their interactions. Statistically, a FFD incorporates two or more variables within the experimental design, where each variable has distinct possible values or levels. The experimental units are displayed to all conceivable combinations of the levels over all variables. This approach facilitates the investigation of how each component influences the variables and the interactions among the factors affecting them [28].

Various factorial designs were utilized for modeling and optimizing process parameters in FDM printed parts, such as 2^3 [57], 3^2 [57], 2^5 [58], and 2^4 [59] full factorial designs. These designs encompassed parameters such as model temperature [57,60], layer thickness [57,58], part fill style [57], orientation [58], contour width [58], raster angle [58,59], part raster width [58], air gap [59–61], raster orientation [60], bead width [60], color [60], build orientation [61], raster width [59–61], build layer [61], part orientation [59], and build laydown pattern [61]. The primary objectives of these studies were to enhance tensile strength [59,60], surface roughness [57], reduce porosity [61], improve compressive yield strength [61], compressive modulus [61], compressive strength [60], support material volume [58], and build time [58] for FDM printed parts. Also for the 3D printed bottom housing part made from PLA, Haidiezul et al. [62] employed FFD to optimize shrinkage on the printed parts. The results of the optimization work demonstrated that the FFD significantly improved dimensional accuracyof the printed part. Gebisa and Lemu [63,64]conducted a FFD experiment on the high-performance ULTEM 9085 polymeric material. They analyzed the influence of five process parameters: air gap, contour number, raster width, raster angle and contour width. Their research findings indicated that only the raster angle had a substantial impact on the material's tensile properties [64], while both raster width and raster angle had the most effect on the flexural strength [63].

3.2. Computational approaches

3.2.1. Genetic Algorithm (GA). The GA is a computational method employed for optimizing process parameters within both conventional manufacturing industries [65] and in the realm of FDM. Specifically, it played a pivotal role in optimizing a myriad of process parameters. These encompassed layer thickness [66–69], orientation angle [66,67,69], raster angle [66,67,69], raster width [66,67,69], printing temperature [68], infill pattern [68], slice thickness [70], road width [70], liquefier temperature [70], and air gap [67,69,70]. The overarching aim was to minimize dimensional variability [67], reduce build time [71] , enhance accuracy [71], refine surface roughness [70], and meticulously control porosity [70] in FDM parts. Furthermore, this adaptable algorithm tailored its optimization strategies for various materials, including polymeric biocomposites [67], ABS [66], and copper-reinforced ABS [68]. Diverse GA types were harnessed, exemplified by the hybrid genetic algorithm [66] and the innovative three-step genetic algorithm-based approach [71]. Moreover, the GA was seamlessly integrated with different experimental design methodologies to optimize FDM process parameters. Notably, it harmonized with the Taguchi L9 technique [68] and was paired with RSMs [66,70] to achieve unprecedented precision.

3.2.2. Artificial Neural Network. The optimization of FDM process parameters for part quality improvement by using traditional methodologies will be costly and time consuming for the required level of precision. Thus, researchers give attention to an artificial neural network (ANN) method for process parameter modelling and optimization.

In their study, Giri et al. [72], employed critical process parameters as input variables for an ANN and utilized the number of contours to optimize and enhance the properties of 3D printed parts using FDM. The 3D printing material in this case was PLA. They trained the data sets and optimized them by utilizing ANN's function approximation. The ANN effectively forecasted the experimental data, achieving notably high correlation coefficients of $R = 0.9981$ for tensile strength, $R = 0.9984$ for build time, and R = 0.99837 for surface roughness, demonstrating the accuracy of the predictions. The root mean square error obtained for the three ouputs was 0.5543, 0.578 and 0.241. Furthermore, their research identified that the build orientation is the most crucial parameter for achieving optimal results in their study. Research from Lyu and Manoochehri[73] presented the study on the predictive model of FDM to optimize the dimensional accuracy of the process. Three process parameters, (1) extruder temperature, (2) layer thickness, and (3) infill density were considered. To achieve better prediction accuracy, three models were studied, (1) multivariate linear regression, (2) ANN and (3) SVR. These models were employed to characterize the complex relationship among the input variables and dimensions of fabricated parts. Based on the experimental dataset, it was observed that the ANN model performs better than the other two models. Correspondingly, the paper presented by Selvam et al. [74] characterized the influence of five manufacturing parameters on a part's ultimate tensile strength (UTS) and modulus of elasticity (E) experimentally, which was used to train an ANN. This ANN forms the basis of a capability profile that was shown to be able to represent the mechanical properties with RMSEP of 1.95 MPa for UTS and 0.82 GPa for E. They validated the capability profile and incorporated into a generative design methodology enabling its application to the design and manufacture of functional parts.

In addition to the above-discussed methods, there are also other methods used for optimizing process parameters of FDM. For instance, enabled teaching learning based algorithms [75] and particle swarm optimization [76–78] were employed to optimize the process parameters of FDM in order to enhance the quality of the manufactured parts.

4. Discussions

4.1. Observation of the trends and challenges in FDM parameter optimization

In today's competitive market, the quality of manufactured parts like dimensional accuracy, surface finish, manufacturing cost, mechanical strength, etc. is highly crucial to satisfy and attract customers. But as discussed earlier in this paper, the quality of parts produced by FDM based AM process highly depends on various process parameters. As a result, the ongoing research needs to focus on the continuous optimization of process parameters in the FDM process. Different process parameter modelling and optimization methods were applied by researchers during the development history of FDM based AM. In the present work, a review of methods used for AM process parameter optimization is presented.

To provide a review of optimization procedures for AM parameters, the applications of different optimization methods, such as the Taguchi method, genetic algorithms, artificial neural networks, response surface methodology, and factorial design, in the optimization process of FDM parameters are investigated. From this review, it is clearly observed that Taguchi method is mostly used and suggested for optimizing the process parameter of FDM process parameters. Taguchi helps to determine optimal sequence and ANOVA technique helps to determine which parameters are most significant and their percentage contribution. Taguchi methodology is widely used for the single and multi-optimization.

Even if different process parameter optimization methods were employed to determine optimal process parameters to improve aesthetics, build time, mechanical properties, surface finish and model material consumption, it's important to note that there are no universally ideal conditions that apply to all types of parts and materials [14]. It depends on the materials and indicates that for some materials, layer thickness is the critical parameter, and for others, another critical parameter do exist. So, future researchers must focus on finding the optimal condition for each material. With the same concept, there is no optimal condition for different mechanical properties. For instance, layer thickness is critical for flexural, tensile, and compressive strength. But for surface roughness and other properties, layer thickness is not the first critical parameter. Thus, identifying the optimal condition for each parameter for each property based on the applications area is expected. Also, it has been observed that there is no any method which considered all process parameters of FDM in optimization. So, for the future, it is expected that all parameters will be considered.

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In comparison to components produced using traditional manufacturing processes like injection molding, FDM-manufactured parts typically exhibit lower mechanical properties and surface finish [14,79]. To enhance the quality and mechanical characteristics of parts produced through FDM, it is imperative to gain a comprehensive understanding of the interplay between material properties and process parameters.

Regarding material properties, the majority of studies have primarily concentrated on optimizing process parameters, utilizing the previously mentioned methods, to enhance the mechanical properties of ABS parts. However, there is a notable absence of published research articles that address the optimization of FDM process variables for the chemical, thermal and dynamic properties of FDM-fabricated parts using different materials. Consequently, there is a considerable need for extensive research in this domain in the future.

The majority of researchers have considered air gap, layer thickness, raster angle, raster width, and build orientations as input parameters or variables in their studies. While studying the effects of process parameters on the required response, air gap, layer thickness, and raster angle are important parameters to be considered. In this method, the majority of the researchers have done their work by considering the FDM parameters like air gap, layer thickness, and raster angle. In the end, they concluded that layer thickness is the most significant factor for build time, increasing impact strength, and minimizing surface roughness in FDM.

In the context of optimization, it's important to consider the physical constraints that impact the selection of optimal process settings in FDM. These constraints include limited choices for layer thickness, often confined to four specific values like 0.1270, 0.1778, 0.2540, and 0.3302 mm, which are determined by the nozzle diameter, leaving operators with no flexibility to choose other values. Additionally, each nozzle diameter is associated with its own range of raster widths. Furthermore, there is a restriction on the number of contours an operator can use when needed, and they must operate within predefined limits. These constraints have significant implications for FDM process optimization and should be taken into account in future research [14,15]. As a result, it becomes challenging to optimize the FDM process parameters in the presence of several such constraints. As a result, traditional Design of Experiments (DOEs) may face challenges in effectively addressing this type of problem. Therefore, new optimization techniques and mathematical modeling must be created in order to get around these restrictions and make the ideal parameters realistic and practicable in real-world applications.

FDM processes involve a multitude of interconnected parameters, often leading to complex, nonlinear relationships. Adjusting one parameter can have unexpected consequences on others, making it challenging to predict the overall impact on the final product's quality. This complexity is further exacerbated in high-dimensional parameter spaces, where optimization becomes resource-intensive and time-consuming. Engineers and researchers often grapple with finding the right balance between various parameters to achieve the desired results.

The use of computational methods for FDM parameter optimization can place significant demands on resources. Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), and machine learning algorithms require substantial computational power and time, limiting their applicability in environments with resource constraints. The iterative nature of optimization can also lead to extended production times, potentially affecting project schedules. Moreover, collecting and processing large datasets for machine learning-based optimization approaches can be daunting, requiring careful data management and analysis.

FDM encompasses a wide range of materials, each with its unique properties and behavior. This material variability poses a considerable challenge in optimization efforts. Different materials may demand distinct optimization approaches due to variations in melting points, viscosities, and thermal conductivities. Material properties can change over time due to factors such as humidity and storage conditions, necessitating adjustments to optimization parameters. Additionally, maintaining consistent material extrusion throughout the printing process is crucial, and any deviations can lead to variations in printed parts, making it harder to maintain optimized settings.

4.2. Future directions

As FDM technology continues to evolve, several promising avenues and innovations are shaping the future of FDM parameter optimization. These future directions aim to further enhance the efficiency, quality, and adaptability of FDM processes.

The integration of real-time monitoring and control systems is a crucial step in the evolution of FDM parameter optimization. By incorporating sensors and feedback mechanisms into 3D printers, manufacturers can dynamically adjust parameters during the printing process. This capability enables rapid response to variations in environmental conditions, material properties, or part geometry. Real-time monitoring can also detect anomalies or defects as they occur, allowing for immediate corrective actions. The adoption of Industry 4.0 principles, including the Internet of Things (IoT) and data analytics, will play a pivotal role in realizing this vision of adaptive and self-optimizing FDM systems.

The development of new materials specifically tailored for FDM applications is an exciting frontier. Innovations in materials chemistry and engineering are expected to yield materials with improved properties, such as enhanced strength, thermal resistance, or biocompatibility. These advanced materials will expand the range of applications for FDM, from aerospace components to medical implants. Moreover, material development will address the challenges of material variability in parameter optimization, as optimized settings may need to adapt to the unique characteristics of each material.

The integration of FDM into smart factories and Industry 4.0 environments is a transformative trend. Smart manufacturing systems will seamlessly connect FDM printers with other production equipment and databases, facilitating data-driven decision-making and process optimization. This integration will enable real-time tracking of production progress, quality control, and inventory management. Furthermore, it will allow for the exchange of optimization insights across the entire manufacturing ecosystem, fostering collaboration and knowledge sharing among manufacturers and researchers.

Research suggests that when it comes to mass production, FDM technology faces significant challenges that arise from both production times and costs, as well as the environmental impact associated with FDM when compared to other selective technologies like SLS and MJF [80]. Consequently, there may be a need to conduct a break-even point analysis for all materials, similar to what has been done for Direct Metal Laser Sintering [81], and compare it with traditional high-pressure die-casting and FDM with injection molding [82]. This analysis can help determine the maximum number of parts that should be manufactured using FDM, ensuring that production covers costs and assisting businesses in making informed decisions regarding pricing, investments, and profitability.

Future FDM parameter optimization approaches will likely incorporate multi-objective optimization techniques. Rather than focusing solely on a single optimization criterion (e.g., cost or quality), these methods will consider multiple objectives simultaneously. This will enable manufacturers to strike a balance between conflicting goals, such as minimizing production time while maximizing part quality. Multi-objective optimization algorithms will provide decision-makers with a range of Pareto-optimal solutions, allowing them to choose the one that best aligns with their priorities.

Future research in FDM should focus on the integration of Design for Manufacturing and Assembly (DFMA) principles into the context of Design for Additive Manufacturing (DFAM) and the concurrent optimization of process parameters. Researchers are encouraged to explore how the design freedom and reduced assembly constraints inherent in DFAM-informed designs can inform and enhance the selection and optimization of process parameters in FDM. Interdisciplinary collaboration between design and manufacturing teams, the incorporation of advanced computational tools and machine learning techniques, the development of materials tailored for DFAM-centric designs, and a focus on sustainability and environmental considerations are all promising avenues for further investigation. These directions hold the potential to revolutionize additive manufacturing by improving design flexibility, cost efficiency, and environmental sustainability [83].

Artificial intelligence (AI) and machine learning (ML) will continue to advance in the context of FDM parameter optimization. These technologies will become more sophisticated in predicting optimal parameters and identifying patterns in data, making them invaluable tools for manufacturers. As datasets grow and computational power increases, AI and ML models will provide more accurate and efficient optimization solutions.

5. Conclusions

Optimizing additive manufacturing process parameters is crucial for achieving cost-effective production while enhancing mechanical properties, build time, part quality, and more. In this paper, we examine several Design of Experiments (DOE)-based parameter optimization techniques applied to optimize process parameters in FDM. The methods considered encompass both experimental design and computational approaches for FDM process parameter optimization. Common methods include the Taguchi method, RSM, ANN, full factorial design method, among others, which are widely used in optimizing process parameters for FDM technique. This review work identified key FDM process parameters, including air gap, layer thickness, nozzle temperature, bed temperature, build orientation, raster width, and raster angle, that have been subjects of previous studies and possibly to be further investigated.

As AI techniques continue to mature, they are expected to remain attractive and powerful tools for optimizing process parameters in FDM. Thus, future works in this direction will focus on use of ML techniques in AI.

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