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Design and optimization of 3D printing process parameters: A review

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Abstract: The Additive Manufacturing (AM) technology and more specifically the Fused Deposition Modelling (FDM), is well known for the possibility to produce complex components with high design freedom in order to obtain outputs with reduced material waste and at competitive costs. The process parameters, like build orientation, infill density, bed temperature, nozzle temperature, layer thickness and print speed, however, have a significant effect on the quality and performance of FDM-printed parts. So, it is very important to choose the best suited process parameters in order to enhance the mechanical properties, surface quality, dimensional accuracy and manufacturing efficiency. The present review article critically explores the new studies reported to date on optimization of the process parameters for FDM process, covering statistical method namely Taguchi method, Response Surface Methodology (RSM), Grey Relational Analysis (GRA) and Design of Experiments (DOE) among various Artificial Intelligence (AI) and Machine Learning (ML) techniques such as Artificial Neural Networks (ANNs) and Particle Swarm Optimization (PSO). This review provides a comparative analysis of statistical and AI-based optimization techniques for FDM process parameter optimization and identifies current research gaps and future directions. The review concludes that hybrid optimization methods combining statistical process with AI–based method are more accurate and more optimized, and could be the answer to next-generation additive manufacturing systems.

Keywords: 3D Printing, Additive Manufacturing, FDM, RSM, ANN, Surface Roughness

1. Introduction

1.1 Overview of 3D Printing Technology

AM, also known as 3D printing, is an advanced manufacturing technology that creates a 3D component by deposition of material from layer to layer directly from a digital model. Compared to traditional subtractive manufacturing approaches, whereby material is cut away from a solid stock block, AM enables the fabrication of complex geometries some of the most complicated geometries in a manner that generates significantly less material waste, reduces lead times and provides more design flexibility. The benefits have been making AM an emerging trend in manufacturing in a broad spectrum of industrial and research domains at an exceptionally rapid pace.

There are several AM technologies, the most commonly used is FDM due to its low cost, user-friendly, suitability to a wide range of thermoplastic materials and capability for fabricating functional parts and for rapid prototyping. FDM can be made up of several different types of materials, such as PLA plastic, ABS, PETG, nylon, or composite filaments. Apart from FDM,

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there are other commonly used AM methods, such as SLA, SLS, and DLP, all with different capabilities when it comes to material and application versatility.

The growing use of FDM in several sectors, including the aerospace, automotive, biomedical, consumer goods, and manufacturing sectors has greatly broadened the scope for research in the printing of high- quality components that are high in performance. Disadvantages of FDM parts, however, include that its mechanical properties, dimensional tolerances, surface quality and production efficiency strongly rely on the choice of process parameters. Therefore, the optimization and control of printing parameters have emerged as one of the most significant research interests for improving the quality of the products, manufacturing efficiency, and reliability of the process, which in turn, helps the overall adoption and implementation of AM technologies in the industries [1]. Since FDM is the most extensively investigated AM process for thermoplastic materials and offers significant opportunities for process parameter optimization, this review primarily focuses on FDM-based AM.

1.2 Importance of Process Parameter Optimization

Optimisation of process parameters is the most important step to achieve high quality, performance and manufacturing efficiency of components produced by FDM. The different process parameters for printing, such as layer thickness, print speed, nozzle temperature, bed temperature, infill density, raster angle and build orientation, directly affect various quality and overall characteristics such as mechanical strength, surface finish, dimensional accuracy, printing duration, and material consumption. The proper choice of these parameters is thus crucial for achieving high aspect ratios of components with optimum dimensional and shape accuracy and reliability. The improper choice of a manufacturing parameter can lead to several manufacturing problems such as poor interlayer bond quality, irregular surface morphology, dimension deviation, warpage, excessive material consumption and the reduction of mechanical strength of the structure. These defects have a significant impact on the functional performance and reliability of 3-D printed parts making the identification of the best combination of the process parameters a major goal of research.

One of the main drawbacks of the conventional manufacturing processes is optimization which is especially difficult within the FDM process since the process parameters are highly interdependent. For instance, the best nozzle temperature will vary based on the printing speed but also on the type of material printed; the best layer thickness will be governed by the diameter of the nozzle, the required surface finish and the printing duration. Likewise, the impact of infill density, raster angle, and build orientation are very much interdependent with the mechanical loading requirements of the end product. The combination of these factors renders optimization of its parameters as a multi variable problem which cannot be solved with the help of change of a single parameter. To address such issues many optimization techniques have been used by researchers, including the following statistical techniques: Taguchi method, RSM, GRA, and DOE. In recent years, various AI and ML models, such as ANN, PSO, and hybrid optimizations have been shown to have better modeling capability for nonlinear relationships and for prediction of process parameters for optimal operation. The advanced techniques will not only lessen the experimental trial and error process but will also be more accurate in prediction and help with multi-objective optimization, resulting in better product quality and manufacturing efficiency. Aerospace, automotive, biomedical, and industrial applications have become increasingly adopting the AM technique, and process parameter optimization has become the art of product reliability improvement to reduce production cost, minimise material waste, and intelligent manufacturing systems. Thus, it is one of the most critical research fronts to pursue in order to develop more effective optimization strategies in the context of AM by FDM [2].

1.3 Objectives and Scope

The major aim of this review is to analyse critically recent advancements in process parameter optimization of FDM-based AM. The review is based on the identification of the effect of key parameters for the production of CAD models such as: layer thickness, print speed, nozzle temperature, bed temperature, infill density, raster angle, manufacturing build orientation in relation to the resulting mechanical properties, surface quality, dimensional accuracy, and manufacturing efficiency of printed items. The traditional statistical optimization methods such as the Taguchi method, RSM, GRA, and DOE are systematically discussed, along with new methods in the field of AI and ML, such as ANN, PSO and hybrid optimization methods. The techniques are critically juxtaposed with each other for their optimization capability, computational demand, benefits and drawbacks, and their ability to meet various manufacturing goals.

This paper revisits the available optimization techniques and highlights the interdependency of the process parameters, summarizes the latest research works conducted on optimisation of FDM processes, outlines the research gaps, and stresses the challenges of implementing the optimized FDM processes in the industry. It also spotlights a number of emerging trends, such as: intelligent manufacturing, the integration of Industry 4.0 and data-driven approaches to optimization. The author hopes that the results of this review will support the researchers, engineers and practitioners involved in the implementation of FDM based AMs, to gain the comprehensive understanding of the current optimization methods available and useful suggestions for the selection of suitable optimization method for monitoring the quality, reliability, and efficiency of FDM based AMs.

The entire workflow of optimisation of processing parameters for the AM process namely FDM is shown in Figure 1. The optimization process starts with choosing an appropriate 3D printing technology that matches application requirements, and the properties of the materials used. Afterwards, key process parameters, including infill density, print speed, infill angle, nozzle and bed temperatures, layer thickness, build orientation, and others, are determined since they have a direct effect on the quality and performance of printed parts. Finally, the printed components are assessed based on various factors such as mechanical properties, surface finishes, dimensional tolerances, printing speed, and material usage efficiency. Using such an evaluation result, the optimal combination of the process parameters is obtained with the use of the following optimization techniques: Taguchi method, RSM, GRA, DOE, ANN and PSO. The process is iterative in nature, allowing the capacity to produce high-quality (and high-strength) components with greater mechanical performance, dimensional accuracy, lower manufacturing costs and reduced material waste to be produced. The process is suitable not only for research but also for industrial applications.

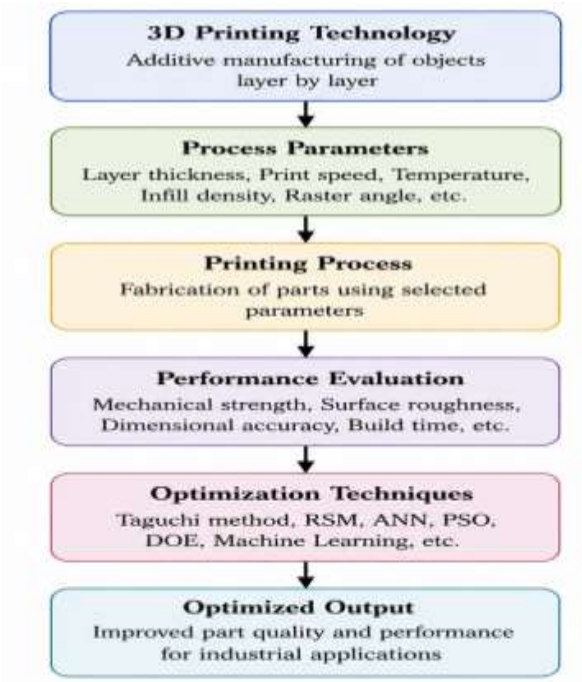

Figure 1: Flowchart of 3D Printing Process Parameter Optimization

Unlike previous review articles that primarily discuss individual optimization techniques, the present review provides a unified comparison of statistical and AI-based optimization approaches, emphasizes parameter interdependency, evaluates their industrial applicability, and highlights emerging trends such as hybrid optimization, Industry 4.0 integration, and intelligent manufacturing.

1.4 Literature Selection Strategy

In-depth literature search was completed to find the latest studies in the field of optimisation of process parameters in FDM additive manufacturing. Materials were identified and retrieved from the widely used scientific search databases, such as Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar, to provide a comprehensive representation of well-peer-reviewed studies in the fields of AM, Optimization methods, and AI. Further most of the reviewed studies date between 2020 and 2025, with a few earlier studies (2017–2019) being selected in reference to establishing fundamental concepts or optimization methods. Combinations of keywords were used in the literature search including 3D Printing, AM, FDM, Process Parameter Optimization, Layer Thickness, Print Speed, Nozzle Temperature, Taguchi Method, RSM, GRA, ANN, ML, PSO, and DOE. Search terms were combined using the Boolean operators (AND and OR) for better relevance of literature retrieved.

The review covers published articles in the English language which are subject to peer review, related to optimization of the process parameters of FDM, statistical optimization methods, as well as approaches based on AI and their applications to mechanical properties, dimensional accuracy, surface quality and manufacturing efficiency. The reviewed literature was limited to conference abstracts, duplicate publications, non-English publications and studies without optimization of the FDM process to help maintain the quality and relevance within the study of this literature. The selected studies were compared with regard to the printing material (substances) employed, the parameters tested, optimization methods used, the conditions the responses were measured, the main conclusions, reported performance enhancement and noted limitations. This made it possible to compare the various statistical approaches and new optimization methods based on AI, as the main analysis in the next part of this review.

2. 3D Printing Process Parameters

2.1 Major Process Parameters in FDM Printing

FDM is a common method of 3-D printing due to its cost-effectiveness, ease of use & compatibility with thermoplastic materials. A number of process parameters play a significant role in the quality & performance of the fabricated components from FDM processing. These parameters should be carefully selected to obtain good-quality as-printed parts having desired mechanical and dimensional properties. Thickness of the layers is one of the most significant parameters and specifies thickness of each layer that is deposited. Smaller the layer thickness, higher the surface quality and dimensional accuracy of the printed part while lengthening the printing time. On the other hand, thicker layers will yield faster printing time, but will lead to poorer results in terms of look and feel of the printed piece [3].

Some experimental works have been reported that 0.3 mm thickness layers caused lower surface finish & dimensional accuracy compared to the 0.1 mm thickness layers. Another important factor influencing production efficiency and bond in the layers is print speed. Higher the printing speed, the quicker the part is manufactured, but also the poorer the adhesion and the lower the mechanical properties of the part. Furthermore, nozzle temperature has an important effect on the material flow and the bonding of the layers created. Proper melting and extrusion of filament materials like PLA and ABS are achieved with the optimum nozzle temp setting. Bed temperature plays a critical role in first-layer adhesion and significantly influences warping, dimensional stability, and print quality. The strength, weight and material usage of the printed component are directly affected by infill density as this regulates internal structure. The factors of raster angle and build orientation are also important properties for tensile strength and surface quality since they decide the direction of material deposition in the printing process. When these parameters are properly adjusted, they can be able to enhance the mechanical properties, surface finish, dimensional accuracy and efficiency of printing 3D powder bed fusion products, which has been reported by researchers [4].

While each parameter has an independent impact on the printability, the interaction of such parameters results in the overall performance of FDM components. For instance, the nozzle temperature is a function of print speed, the optimum layer thickness is a function of nozzle diameter and desired surface finish. These interactions between the parameters should thus be taken into account when optimizing. These strong parameter interactions make trial-and-error optimization inefficient and justify the use of statistical and AI-based optimization techniques discussed in the following sections.

2.2 Influence of Parameters on Printed Part Quality

A lot of dependency between 3D printing process parameters affects the performance of the 3D printed components. These parameters influence a number of quality parameters such as surface roughness, tensile strength & hardness. The surface roughness and print resolution is directly affected by layer thickness. Thinner layers will achieve smoother surfaces and higher accuracy, while thicker layers can create a staircase-like appearance. Likewise, nozzle's temperature influences bonding between the layers and material flow characteristics. Too low of an abnormal temperature creates poor bonding and too high of abnormal temperature can result in material degradation and dimensional problems [5].

Print speed will affect both efficiency of manufacturing and quality of structure. Slower speeds will result in better layer adhesion and printing accuracy, but slower production speed. The quality of the finished print can be compromised by high printing speeds, including voids, bonding issues, and surface irregularities. Printed components have mechanical properties that are influenced by infill density. Increasing infill density generally improves mechanical strength; however, the optimum infill depends on the material type, loading conditions, and intended application. Excessively high infill may increase printing time and material consumption without proportional performance improvement. Anisotropic behavior of parts printed is also influenced by build orientation and raster angle, which reflect the direction of the layers in which the mechanical properties differ. Some researchers have highlighted the need for multiple parameter optimization simultaneously to obtain the desired quality-performance-manufacturing cost balance [6].

2.3 Materials Used in 3D Printing

Wide range of materials for 3D printing, due to the different needs of the application, and the printing technology. The thermoplastic polymers are the most widely used materials because they can be processed easily and are inexpensive enough. One of the most popular materials is called Polylactic Acid (PLA), as it can be printed easily, it has good surface finish, and is biodegradable. Acrylonitrile Butadiene Styrene (ABS) provides increased strength and resistance to heat but needs to be printed under carefully controlled conditions to eliminate warping. An application that has a requirement for flexibility, toughness, and wear resistance would be made from nylon materials [7]. Resin-based materials are also widely used in stereolithography and digital light processing (DLP). The materials also offer outstanding form and image quality for biomedical applications and precision tools.

There has been recent progress in AM, which has also added composite materials and fiber-reinforced polymers (FRP) and multi-material printing technology. These materials add better mechanical, thermal and functional performance properties to the printed component. Choosing appropriate material as well as their optimal process parameters is one of the most important factors for the final quality and performance of 3D printed products [8]. Different printing materials require different process parameter optimization strategies because their thermal, rheological, and mechanical properties vary considerably. For example, PLA can be printed successfully at relatively low nozzle and bed temperatures due to its low thermal shrinkage, making it suitable for rapid prototyping and educational applications. In contrast, ABS requires higher nozzle and bed temperatures to minimize warping and improve interlayer adhesion, while nylon requires careful control of printing temperature and environmental conditions because of its high moisture absorption and tendency to deform during cooling. Similarly, composite filaments reinforced with carbon or glass fibres often require lower printing speeds and hardened nozzles to ensure uniform material extrusion and reduce nozzle wear. Consequently, the optimum process parameters are material-dependent, and optimization strategies should be selected according to the specific material properties and intended engineering application rather than applying a single parameter combination to all FDM materials.

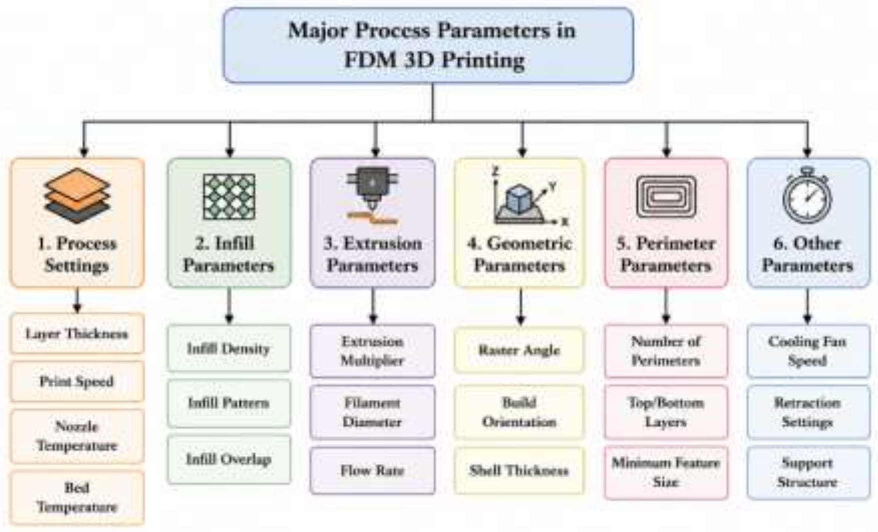

Figure 2: Classification of Major Process Parameters in FDM 3D Printing

The major process parameters that affect the quality and performance of the FDM fabricated parts are classified in Figure 2. The parameters are categorized into a total of six groups, which are process settings, infill parameters, extrusion parameters, geometric parameters, perimeter parameters and other auxiliary parameters. Each category has an impact on the quality attributes of the print. The mechanical strength, surface quality and dimensional accuracy are the areas most affected by process parameters like layer thickness, printing speed, nozzle and bed temperature, etc. Parameters that affect the internal structure and stiffness of the component are infill parameters, while extrusion and geometric parameters influence in the area of material flow, bonding and load distribution. Additional parameters, such as perimeter, auxiliary parameters, further contribute to the appearance of the surface, the stability of printing and manufacturing efficiency. It is also worth highlighting here that the figure demonstrates that, since multiple process parameters are interdependent, optimizing one parameter alone is insufficient to achieve high-quality printing of the FDM. This classification serves as a basis for determining possible optimizations discussed in later sections.

2.4 Interaction Among Process Parameters

FDM refers to the technology of fabricating components based on fused deposition techniques, whose performance is affected by the interactions among the many process variables. The testing results obtained by FDM are quite interesting, as the multiple number of parameters involved in the process presents several interdependent aspects that are different from traditional manufacturing processes and have a significant impact on the mechanical properties, dimensional accuracy, surface finish of printed components, the time it takes to produce them and their overall manufacturing efficiency. Therefore, changes in one parameter within a specific process can only improve performance if it is done in consideration of interactions with other parameters in that process.

The temperature of the nozzle and the speed at which the fan prints are one of the ever-important interactions. The general rule is that the higher the print speed, the higher the nozzle temperature must be for the job, making sure to have all the filament melted and the interlayer bonds are robust. At a relatively low nozzle temperature, when printing speed is raised, the effect of insufficient materials fusion may be shown, which will lead to the poor mechanical properties and surface quality. On the other hand, for low printing speeds, conditions with too high of a nozzle temperature can lead to degradation, stringing, and a loss of dimensional accuracy of the material.

As well, there's a more direct relationship between nozzle diameter and layer thickness. More thick layer depositions can be achieved with larger nozzle diameters, typically to speed print times with a slight loss in surface finish and dimensional accuracy. Thinner layers, however, with smaller nozzle diameters, yield high surface quality and high dimensional accuracy but result in longer printing times. Thus, choosing a suitable nozzle diameter and desired layer thickness is crucial for achieving a balance between production speed and product quality.

The second interaction of interest are the interactions between the bed temperature and the printing material. Artificial variables such as the choice of thermoplastic to be used will depend upon the required bed temperature for good first-layer bond and to prevent warping on cooling. For instance, in the case of PLA, generally less heat will be needed in the bed temperature than in ABS. In the case of engineering polymers like Nylon, a higher bed temperature may be needed to minimize the thermal stresses and afford more dimensional stability.

The proportion of infill density, thickness of the material and the angle of the raster can also have a significant impact on the mechanical properties of the components produced by FDM. The higher infill density generally leads to high tensile and compressive strength; it also means higher material usage and longer printing time. Likewise, the influence of raster angle on the transfer of load in the printed structure depends on the different build orientations and loading directions. Hence it is crucial for such parameters to be optimized together instead of individually, so as to obtain the required mechanical properties and still keep up the cost-effective manufacturing.

With all of these relationships, the optimization of the process parameters pertaining to the FDM in turn is a multi-variable optimization. Traditional trial and error techniques are frequently not capable of determining the most flexible set of parameters. To model parameter interactions and find the optimal printing conditions, statistical optimization methods, such as the Taguchi method, RSM, GRA, and DOE, have also been applied and are given increasing attention, along with AI-based methods like ANN, PSO, or hybrid optimization methods. These optimisation methods allow the process parameters to be assessed simultaneously and generate a better product quality, higher process certainty and higher manufacturing efficiency.

3. Optimization Techniques Used in 3D Printing

3.1 Statistical Optimization Methods

Optimization of 3D printed components quality and/or performances is among the most widely used techniques, which is in the focus of statistical optimization. These techniques are used to identify the best process conditions and to save experimental resources (laboratory/high expense time). Some methods that are widely used in process optimization for AM processes are the Taguchi method, GRA & RSM. The Taguchi method is very popular due to its ability to design efficient experiments (using orthogonal arrays) for determining the interaction of several parameters & their influence on output responses. The Taguchi method has been employed in several studies to optimize layer thickness, & nozzle temperature for enhancing tensile strength, and reducing the surface roughness [9].

Another significant important statistical technique used to model & analyse the relations between the input variables and the performance characteristics is RSM. Mathematical models and contour maps are used to assist in predicting responses and optimal parameter settings for the various functions as shown by RSM [10]. GRA can be widely used in the multi-objectives' optimization problem, which involves multiple quality characteristics that need to be optimized simultaneously. This approach allows the multi-responses to be unified as a single grey relational grade for ease in decision making. These statistical techniques are useful because they facilitate understanding of the process, limit the number of experiments to run, and lead to reliable optimization responses [11]. Taguchi is preferred for screening experiments because of its low experimental cost. RSM is more suitable when parameter interactions and mathematical modelling are required, whereas GRA is advantageous when multiple quality characteristics must be optimized simultaneously.

3.2 AI & ML Approaches

AI and ML has proven to be an effective tool for optimizing parameters in FDM process as it is able to model the complex non-linear relationship between the output responses and FDM process parameters. AI-based models are different from traditional statistical modelling in that they do not need to assume mathematical relations, they learn from experimental data, and continually improve their accuracy of prediction. These methods are especially beneficial when more than one process parameter affects mechanical, dimensional, surface quality, printing, and material usage. ANNs are the most popular of the AI techniques for predicting the effect of process parameters on the quality of printed parts. The ann model is trained with experimental data collected from different variables like layer thickness, print speed, nozzle temp, bed temp, infill density, etc., the raster angle and build orientation. The network trained for output characteristics and then, for various parameter combinations, it can foretell properties like tensile strength, surface roughness, dimensional accuracy, printing time, etc. It had been reported in several studies that ANN models can outperform the conventional regression-based models particularly for the complex nonlinear manufacturing processes, especially after fitting with measuring techniques like the back-propagation method.

Another popular optimization technique that is based on the collective behaviour of bird flocks and the fishes in a schooling is PSO. In the optimization of the FDM process, each particle refers to one combination of process variables to print. Particles, in successive runs, adjust their positions based on their own best solution, along with that of the best solution found by the swarm to search the space of solutions effectively for the global optimum. PSO has been proven to be effective in decreasing surface roughness, increasing dimensional accuracy, decreasing printing time and increasing mechanical strength. Recently, ANOVA optimization techniques that integrate ANN with other evolutionary methods such as PSO are gaining interest. In these techniques, ANN is used as predictive model and PSO is used for searching optimum set of process parameters on the basis of the ANN prediction. This hybridizing approach will help to save the number of experiments to be conducted physically, enhance the accuracy of optimization, and solve multi-objective optimization problems with multiple conflicting performance criteria in an efficient manner.

Besides ANN and PSO, various ML methods such as Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF) as well as Deep Learning (DL), and

Reinforcement Learning (RL) have been recently investigated for process monitoring, defect prediction, and optimization in real time. These systems will constantly monitor the printing process, identify any issues and adjust production parameters as needed, ensuring the product remains consistent and of high quality.

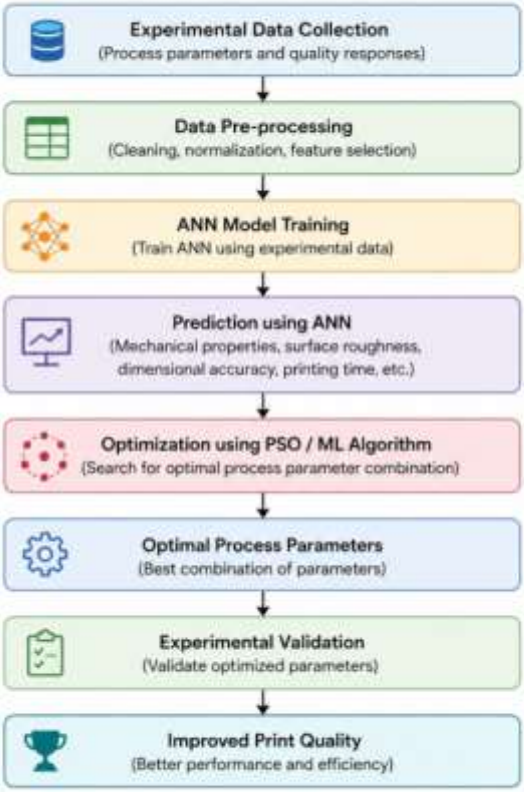

Figure 3: AI-Based Workflow for FDM Process Parameter Optimization

AI and ML techniques have many advantages over traditional optimization approaches, as they are able to analyze a number of simultaneously influencing parameters of the processes, predict exact product performance, and provide a support for intelligent decisions on optimization. The possibility of their integration with Industry 4.0, Internet of Things (IoT) monitoring, digital twins and cloud manufacturing is anticipated to enable future autonomous, adaptive and highly efficient AM Systems [12]. Figure 3 illustrates the general AI-based optimization workflow for FDM process parameter optimization. Experimental data are first collected and pre-processed before training predictive models such as ANNs. The trained model estimates important quality characteristics, including tensile strength, surface roughness, dimensional accuracy, and printing time. Optimization algorithms such as PSO then identify the optimal combination of process parameters. Finally, the optimized parameters are experimentally validated to ensure improved product quality, manufacturing efficiency, and process reliability.

3.3 DOE Approaches

DOE is a methodology for designing, conducting and analyzing experiments in an efficient manner. DOE techniques can be used to determine influence of process factors & their interactions on outputs. DOE methods are extensively employed to study the effect of key 3D printing parameters, such as layer thickness, infill density, the angle of the raster and printing speed in 3D printing research. In order to investigate interaction of parameters and to optimize the printing process, a full factorial or fractional factorial design is often used [13].

One other special application of DOE in AM is multi-objective optimization. Often researchers want to optimize several characteristics at the same time, such as both the tensile strength and the printing time and surface roughness. Recent work has been focused on incorporating DOE methods with ML algorithms that have enhanced the predictive and optimization power. These approaches are known as hybrid, which allow for a better understanding of process behavior and help in making data-driven manufacturing decisions. The most significant advantages of DOE based optimization method are reduction in experimental efforts, better statistical analysis and better reliability of the optimization results. DOE continues to play an important role by generating statistically reliable datasets that are frequently used to train AI models such as ANN and other ML algorithms. Table 1 presents a comparative analysis of the major optimization techniques used in FDM-based 3D printing, highlighting their applications, advantages, and limitations.

Table 1: Comparative Analysis of Optimization Techniques Used in FDM-Based 3D Printing

Method	Best Application	Advantages	Limitations
Taguchi	Small experiments	Low cost	Limited nonlinear modelling
RSM	Continuous optimization	Models' interactions	Requires regression assumptions
GRA	Multi-response optimization	Simple	Limited prediction capability
ANN	Nonlinear optimization	High accuracy	Large datasets required
PSO	Global optimization	Excellent search ability	High computational cost
DOE	Experimental planning	Studies interactions	More experimental runs

4. Review of Research Findings

4.1 Optimization for Mechanical Performance

Engineering application suitability and reliability are two essential quality factors of FDM parts which can be directly assessed through mechanical performance. The process parameters such as layer thickness, infill density, raster angle, build orientation, nozzle temperature, and printing speed all have a significant effect on mechanical properties like tensile strength, flexural strength, compressive strength, impact strength and stiffness. These parameters can interact with each other so that optimizing one parameter without optimizing the others may not give the desired mechanical performance. Thus, series of optimization approaches should be carried out to obtain the optimal process parameters taking into account strength, its production efficiency, and material usage.

The different process parameters directly affect interlayer bonding (thickness of layers, temperature of the nozzle, etc.) or load distribution, print speed, infill density and structural integrity (raster angle, build orientation, etc.). Thinner layers typically will enhance the bonding of the subsequent layer and minimise voids within – which means better tensile and flexural components. In his turn, a higher infill density provides greater stiffness and load-bearing capacity and optimized raster angles means better stress distribution when the machine is under mechanical force. The improvement, however, is often accompanied by higher printing time or material consumption, so a multi-objective optimization is required to obtain an appropriate balance of the part quality and the material consumption and printing time.

Multibank optimization techniques have been applied to optimize the mechanical properties of components made by FDM, all of which have proven successful. To achieve this, systematic optimization of the printing parameters is carried out, which helps to identify the most influential ones in order to improve the overall performance of printed parts, as done by Mushtaq et al. [1]. Pereira et al. [3] used a multi-objective optimization approach (DOE) to examine how several process parameters interact each other and thus to establish the optimal operating conditions. Marković et al. [7] also showed that the mechanical properties of AM metal components can be improved by optimising different production factors such as layer thickness, nozzle temperature, and build orientation, to increase the level of bonding between layers and to minimise product defect rates. A similar study was conducted by Bayas and Kumar [14] where they also verified that statistical optimization is an effective tool for optimizing the structural properties of the FDM components by adopting a proper approach to parameter selection. Likewise, it was found that the Taguchi method could be used to gain insight into the significant printing parameters during optimization with considerable number of experimental trials, which is especially suitable for preliminary optimization study [6, 15, 16].

While statistical methods work well in optimizing experiments, they are not suitable for handling more intricate nonlinear relations. To this backdrop, the introduction of AI based optimization has drawn a significant focus due to its ability to use experimental data to accurately model mechanical behaviour, while minimizing on significant number of physical tests. Panico et al. [9] incorporated the ML algorithms into DOE to enhance the accuracy of the prediction and to support efficient multi-objective optimization process parameters for FDM. Similarly, an ANN was shown by Yadav et al. [13] to predict the mechanical properties of multi-material FDM parts for various processing conditions. When multiple interacting variables simultaneously affect multiple performance characteristics, these approaches are especially beneficial.

The comparison of the studies reviewed implies that there is no universal best optimization technique which is applicable for every manufacturing situation. Although these methods have existed, statistical tools, such as the Taguchi method, RSM and DOE still have wide application in experimental design, factor screening and identification of process parameters of significance due to their low number of experimental trials and computational efficiency. For solving complex nonlinear optimization problems with multiple interacting variables and conflicting optimization objectives, however, AI-based techniques, like ANN and hybrid ML models are more appropriate. Taking this into account, a hybrid optimization system combining statistical experimental design and AI has been developed, offering a more comprehensive and stable optimization system for mechanical properties of FDM components.

In summary, the literature reviewed indicates that optimizing the printing process parameters systematically could be very beneficial as it leads to the enhancement in the mechanical reliability and structural integrity of the printed components. The synergistic use of statistical methods and new AI-based techniques allows for better predictive power, process efficiency and versatility with more complex production environments which opens up wide new application areas of FDM technology in the aerospace, automotive, biomedical and advanced engineering industries. Table 2 summarizes the primary process parameters in FDM-based 3D printing, highlighting their effects on part quality and the associated trade-offs.

Table 2: Influence of Process Parameters on Mechanical Performance

Parameter	Primary Effect	Typical Trade-off
Layer Thickness	Tensile strength, interlayer bonding	Increased printing time
Infill Density	Strength and stiffness	Higher material consumption
Raster Angle	Load distribution	Depends on loading direction
Nozzle Temperature	Layer adhesion	Stringing if too high
Print Speed	Productivity	Reduced bonding at high speed

4.2 Optimization for Surface Quality and Accuracy

The FDM components represent a special category of Additively Manufactured Parts (AMPs) whose surface quality and dimensional accuracy are specifically important for the functionality of the part, to integration into the intended systems, as well as in the special aesthetic aspects. There are some parameters influencing the process that control these characteristics, such as the bed temperature, infill density, raster angle, layer thickness, print speed, build orientation and nozzle temperature at various positions in the process. It should be noted that these parameters have interactions; optimizing one of them alone may not result in the surface roughness and dimensional accuracy needed for optimum performance. It is therefore necessary to use multi-parameter optimization techniques to reduce the defects in the prints during manufacture without comprising the rate of production.

In layer-by-layer manufacturing, out of all the process parameters surface finish is most affected by the thickness of the layers, which already creates the staircase effect. Thinner layers result in a smoother surface, and more accurate dimensions but more time in print. In the same way, print speed and nozzle temperature affect the deposition of the material and the bonding between layers, and bed temperature helps in the bonding of the first layer and reduces thermal distortion. The level of dimensional stability also depends on the build orientation and raster angle, as they relate to the distribution of residual stress in prints and deformation during printing. Therefore, it is required to know how to apply an optimum combination of process parameters with respect to the surface quality, dimensional accuracy, production time, and amount of material.

The surface and dimensional accuracy of FDM fabricated components have been enhanced using several statistical optimization techniques successfully. The research conducted by Mushtaq et al. [1] established that the process variability can be reduced and the overall print quality can be improved in the system by optimising the layer thickness, the print speed and the nozzle temperature. Tontowi et al. [4] optimized the processing conditions for obtaining PLA components in which they reported that choosing the appropriate parameter offers an improvement in the accuracy and surface properties of the components. Sumalatha et al. [10] and Sharma et al. [16] showed Taguchi's optimization and GRA are effective reduction methods for the experimental number and finding the optimum combination of the parameters to optimize more than one quality characteristic. Raju et al. [12] reported that Taguchi's optimization, along with GRA, can be used to find optimum combination of the parameters to optimize more than one quality characteristics and reduce the number of experimental trials at the same time. These statistical methods offer reliable and efficient ways to optimize experiments and control the process.

The prediction and optimization of surface quality have been improved even more by the use of AI-based optimisation techniques by using effectively the feature of modelling the complex non-linear relationship between the various process parameters. In the past, Shirmohammadi et al. [5] showed that a hybrid ANN–PSO model is capable of delivering highly accurate prediction of the surface roughness and search of optimal printing conditions with a lower number of experiments. In the same way, Panico et al. [9] combined ML algorithms and a DOE method to enhance the improvement of the prediction capability and multi-objective optimization of FDM process parameters. With the use of these AI techniques, a large number of experimental studies could be avoided and the accuracy of optimization problem resolution for complicated production processes with multiple variables interacting with each other could be enhanced.

Comparative analysis of the identified studies showed that the conventional statistical methods, such as the Taguchi method, RSM, DOE, and GRA, are still suitable for determining meaningful process parameters as well as optimum process conditions for rigorous and systematic experimentation. But, in most cases, these methods are not applicable for highly nonlinear relationships or more than one conflicting objective being optimized at a time. On the contrary, AI/ML techniques have the superior prediction capability since they have the ability to learn complicated interactions between the process parameters, and also access the surface quality and dimensional accuracy at different printing parameters with reasonable accuracy. Thus, hybrid optimisation methods, integrating a statistical experimental design with an AI-driven predictive model, provide a more integrated solution up to production of good FDM components and enhanced manufacturing efficiency.

In conclusion, the literature reviewed support that optimization of the process parameters significantly can improve surface finish, dimensional accuracy and manufacturing consistency, and manufacturing defects like warping, poor layer bonding and dimensional deviation. This combination between statistical DOE with new AI techniques gives more flexibility, better accuracy in predictions and increased reliability of processes, thus allowing the use of FDM technology in precision engineering and wider industrial manufacturing.

4.3 Comparative Analysis of Previous Studies

While traditional statistical methods have been employed for optimizing the parameters of FDM processes, recent developments have shifted towards more advanced AI-based techniques, each with its own set of advantages based on the optimization goal, complexity of the process, and the experimental data that is available. However, it is not possible to fix one optimum solution for all problems; care must be taken to choose the right optimization method according to the nature of the problem. The Taguchi method is well known and popular among the conventional statistical methods because it is used for reduction in the number of experimental trials and helps in identification of the influence of the process parameters. It is especially adapted to the preliminary-optimizing study of a small number of variables and the number of experimental resources. Nevertheless, the Taguchi method takes up only the main effects; as a result, any nonlinear interactions of parameters and the presence of higher-order effects is limited in its ability to accurately model [5, 9].

The RSM has much more flexibility as it can be presented with mathematical models that describe the relationship between process parameters and responses. RSM is not similar to

Taguchi method, because it is effective in estimating the maximum performance in the design space and the interactions between the parameters. However, standardizing to precision prediction relies on the correct choice of regression models and can become inadequate where the relationships between variables are very nonlinear. A GRA has attracted many attentions due to the ability to simultaneously optimize the multiple quality characteristics, such as tensile strength, surface roughness, dimensional accuracy, and printing time. GRA is simple and useful in decision making if there are multiple responses, but it is not very accurate, because it is mostly based on experimental observations and has limited ability to learn; predict.

AI-based methods, especially ANNs, have shown better results in modeling a complex nonlinear relationship between process parameters in the FDM technique and product quality. ANN models learn from experimental data to accurately predict many performance characteristics without resorting to a mathematical equation. But training decently sized and quality ann models is hard and they are considered as black boxes, i.e., the processes inside the model are difficult to explain. Likewise, PSO has emerged as a globally efficient optimization strategy, which can be used to find an optimum combination of process parameters with keeping computational effort used to a minimum. For multi-objective optimization problems with conflicting responses, such as maximizing the mechanical strength and minimizing surface roughness while also requiring a minimal printing duration, PSO can effectively be used by PSO. Its optimization performance relies on the proper tuning of the parameters; however, the optimization can be very fast if search diversity is not preserved.

Table 3: Critical Comparison of Optimization Techniques Used for FDM Process Parameter Optimization

Technique	Best Application	Strengths	Limitations	Industrial Suitability
Taguchi	Preliminary optimization	Fewer experiments, low cost	Limited nonlinear modelling	High
RSM	Mathematical modelling	Models' interactions, optimization	Regression assumptions	High
GRA	Multi-response optimization	Simple, efficient	Limited predictive capability	Medium
ANN	Nonlinear prediction	High prediction accuracy	Requires large datasets	High
PSO	Global optimization	Efficient search capability	May converge prematurely	High
Hybrid ANN–PSO	Multi-objective optimization	High accuracy and robustness	Higher computational cost	Very High

Hybrid optimization models of ANN and PSO along with other evolutionary algorithms are more developed with the increasing studies in this area. In these methods, ANN predicts the performance of the process, and PSO is used to learn how to choose the optimal combination of parameters. This kind of hybrid techniques substantially lessen number of experimental trials, enhance the model prediction real-life precision and effectively address multiple conflicting objectives. Thus, hybrid applications of AI-driven optimization methods are gaining traction in the context of smart manufacturing and Industry 4.0 and have become very attractive. In general, classical statistical methods still can perform for experimental design, screening of factors and preliminary optimization, due to their simplicity and small computation demand. Other optimization techniques based on AI and hybrid offer more advanced predictive capability, the ability to manage complex nonlinear parameter interaction, and better performance of multi-objective optimization, however. The addition of statistical methodologies with AI is likely to be the most popular solution in intelligent/autonomous AM production lines to achieve good, efficient and adaptive FDM process optimization in the coming years. A comparison of widely adopted optimization techniques for FDM process optimization, including their best applications, strengths, limitations, and industrial suitability, is provided in Table 3.

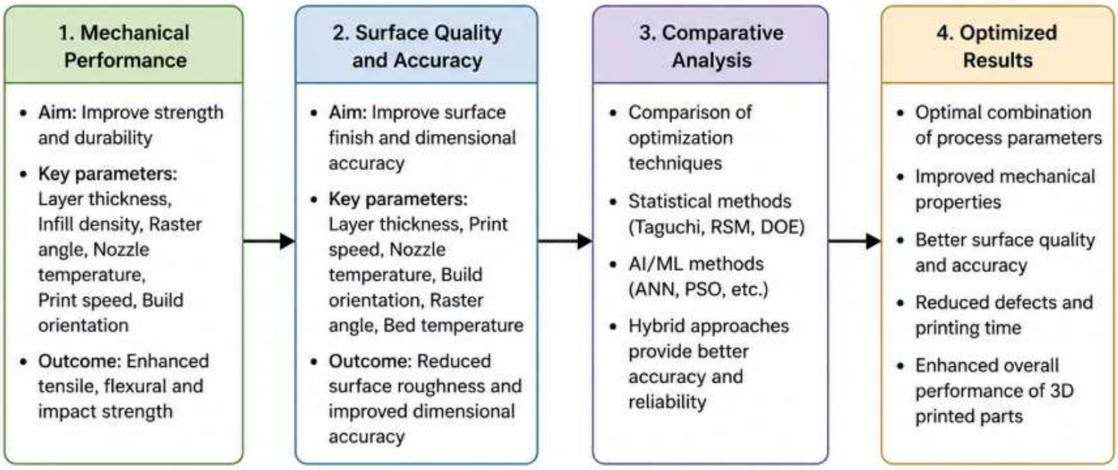

Figure 4: Summary of Research Findings in 3D Printing Optimization

The various research results obtained from the literature reviewed on optimization of FDM process parameters are concluded in the form of a summary as shown in Figure 4. The figure shows that there are four major factors that are mostly focused on while optimizing a product; mechanical performance, surface quality, dimensional accuracy, and manufacturing efficiency. The reviewed studies on process parameters consistently show that layer thickness, print speed, nozzle temperature, bed temperature, infill density, raster angle and build orientation play a significant role in these quality characteristics. The Taguchi method, RSM, GRA and DOE are among the many conventional statistical methods used to establish combinations of optimal parameters for requiring only a limited number of runs. The use of AI and ML techniques, especially ANN and PSO, are more recently emerging as superior methods for modelling the complex, non-linear relationship between variables and performing multi-objective optimisation. The reviewed studies showed that, among the various techniques that have been proposed for integrating statistical and AI-based optimization techniques, it is possible to make significant improvements in the quality of the product, reduce manufacturing defects and material waste and improve the efficiency and reliability of FDM-based AM in general.

To facilitate comparison among representative studies, Table 4 summarizes the materials investigated, optimization methods employed, process parameters considered, principal findings, and reported limitations.

Table 4: Comparative Summary of Previous Studies on 3D Printing Process Optimization

Author & Year	Material	Optimization Method	Output Response	Process Parameters	Major Findings	Study Limitation
Mushtaq et al. (2023)	PLA	DOE	Surface quality, Dimensional accuracy	Layer thickness, Print speed	Improved print performance and dimensional quality	Limited to selected parameters
Shirmohammadi et al. (2021)	PLA	ANN + PSO	Surface roughness	Layer thickness, Nozzle temperature, Print speed	Significant reduction in surface roughness	High computational cost and large training dataset required
Yasmin et al. (2024)	PLA	Taguchi Method	Tensile strength	Infill density, Print settings	Enhanced mechanical strength through parameter optimization	Limited interaction analysis
Marković et al. (2024)	PLA/ABS	Process Parameter Optimization	Mechanical performance	Layer thickness, Build orientation, Nozzle temperature	Improved tensile and structural properties	Validation limited to selected materials
Panico et al. (2025)	Polymer materials	DOE + ML	Multi-objective optimization	Multiple FDM process parameters	Increased optimization accuracy and prediction capability	Industrial-scale validation required
Yadav et al. (2020)	Multi-material FDM	ANN-Based Optimization	Mechanical and dimensional properties	Multi-material process parameters	Improved prediction capability	Performance depends on training data quality
Kechagias (2024)	PLA	Taguchi Design	Process optimization	Layer thickness, Print speed, Raster angle	Effective identification of optimum process parameters	Limited multi-response optimization
Sharma et al.	PLA	Taguchi Method	Tensile strength	Layer thickness, Infill density, Print speed	Improved mechanical performance	Experimental validation limited

Table 4 presents a comparative summary of representative studies on FDM process parameter optimization. It highlights the materials investigated, optimization techniques employed, process parameters considered, response variables evaluated, key findings, and limitations of each study. This comparison enables readers to identify current research trends and the suitability of different optimization approaches for specific manufacturing objectives.

4.4 Research Gaps in Existing Literature

Although significant progress has been made in optimization of 3D printing process parameters, several research gaps still exist in AM studies. Most previous investigations mainly concentrate on limited characteristics of the process, such print speed, & nozzle temperature, while combined interaction of multiple parameters remains insufficiently explored.

Many optimization studies are conducted under laboratory-scale conditions and lack industrial-scale validation. In addition, optimization techniques often vary depending on material type, machine configuration, and printing conditions, resulting in the absence of universally accepted optimization standards.

Another important limitation is the limited implementation of real-time monitoring & adaptive control systems in FDM printing. Existing optimization approaches are primarily based on offline experimental methods rather than intelligent automated systems. Furthermore, comparatively fewer studies have focused on multi-material printing, sustainable materials, and energy-efficient manufacturing processes. Although AI & ML techniques have shown promising results, their industrial implementation and integration with Industry 4.0 technologies are still at an early stage. Therefore, future research should focus on intelligent real-time optimization systems, hybrid optimization approaches, and large-scale industrial applications for improving the efficiency and reliability of AM processes.

5. Challenges, Future Scope, and Conclusion

5.1 Current Challenges in Process Optimization

Although rapid developments have been made in the field of 3D printing technologies, there are a number of challenges to still be addressed with the optimization of 3D printing process parameters. Complexity of the relationship between process parameters like layer thickness, nozzle temperature & build orientation represent one of the great challenges. The variation of these can have a major impact on the mechanical properties, dimensional accuracy & surface quality. One of the other big issues is the inability of the optimisation procedure to be the same for other materials and printing technologies. Optimum parameters for one material/machine may not yield the same results on varying operating conditions. This makes it difficult to obtain uniformity of product quality in different applications. Process optimization is also affected by limitations in the material. Top plastic materials, like thermoplastic (PLA & ABS) can have serious warping, shrinkage and poor inter-layer bonding problems. Likewise, composite and resin material, they should have controlled environment and processing conditions to ensure reliable performance. Furthermore, the application of many optimization techniques necessitates a lot of experimentation, computational power and expertise. There is a lack of development of real-time monitoring & adaptive process control systems in industrial applications. Thus, enhancing the reliability of the processes and minimizing manufacturing uncertainties are still significant research issues in AM.

5.2 Future Research Directions

By studying and developing intelligent and automated manufacturing systems, future 3D printing process optimization research and development will utilize its advantages. Predictive and self-optimizing manufacturing processes are expected to be developed using the AI, ML and DL algorithms. Certain sensing and IoT technologies can be used to monitor the processes in real time, capture defects and automatically correct them during production. Such adaptive manufacturing systems can help to enhance the product quality, material utilization, and production efficiency. Another key research area would be the manufacturing of sustainable and environmentally friendly materials for 3D printing. The research focus is growing on biodegradable polymers, recycled materials, and composite materials for better environmental sustainability.

A few hybrid optimization approaches covering statistical techniques and ML models are also expected to be more mainstream owing to their accurate predictions and efficient decision-making power. Moreover, the future studies should emphasize large industrial-scale printing, multi-material printing, high-speed printing systems. Industry 4.0 technologies combined with AM are going to be a gamechanger for the traditional production systems to create 'smart manufacturing environments', more flexible and automated.

5.3 Conclusion

The present paper reviews and summarizes the process parameter optimization in 3D printing by covering the recent research done on the FDM based AM. The study talked about the effects of certain of the key process parameters of the printer – layer thickness, & infill density – on print quality & performance. Various optimization methods such as Taguchi method, RSM, GRA, ANN, PSO and DOE were studied and compared. Mechanical strength, surface quality, dimensional accuracy and production efficiency have been substantially increased under the results discussed, which show that appropriate process parameter optimization have positive effects. Review also identified present constraints namely complex parameter interactions, material constraint, lack of standardization in optimization methods and more. The future of AM will see further improvements in capabilities, such as the use of more sustainable materials, real-time monitoring and ML & AI technologies. In general, process Parameter optimisation is an important aspect to enhance the reliability, productivity and industrial applicability of 3D printing systems. Research and technological innovations on a continuous basis will help in the maturation of smart and very efficient processes of AM.

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