Fused Deposition Modeling of 3D Printed Part

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Fused deposition modeling (FDM) is the most economical additive manufacturing (AM) technology available for fabricating complex part geometries. Dimensional instabilities are challenges of FDM that depends on printing parameters. The selected printing parameters include layer height, number of perimeters, infill density, infill angle, print speed, nozzle temperature, bed temperature, and print orientation. Three-level definitive screening design (DSD) was used to plan experimental runs.

Keywords: fused deposition modeling ; polylactic acid (PLA) ; dimensional deviation ; definitive screening design

1. Introduction

Among the AM technologies, fused deposition modeling (FDM) is one of the most widely used additive manufacturing technologies because of its economy and ability to process a diverse range of materials, including polymers and metals [1]. However, the use of FDM printing for part fabrication is still a challenge because of the involvement of numerous process parameters and because the choice of materials affects the part quality, mechanical strength, and development time [2][3]. Depending on the application, careful consideration of process variables and material selection is necessary. According to the published reports, the process parameters can be divided into three major sets [4]. The first set of parameters includes the process-related parameters, such as infill speed, number of shells, thickness of shells, bed temperature, fill density, layer height, nozzle temperature, print speed, air gap, and raster angle. The second set of parameters includes the machine-specific parameters, such as nozzle diameter, filament width, bed adhesion type, and filament diameter. The third set of parameters is related to part geometry, such as the part's orientation and special features.

To achieve good dimensional accuracy in FDM-printed parts, the optimal process parameter settings are crucial, as they vary according to material, complexity of part geometry, material type, and chemical composition [5][6]. Therefore, finding the optimal settings and combination of parameters can be challenging and laborious. Additionally, most of the polymers used in FDM are semi-crystalline and prone to part distortion due to crystallization [7]. Therefore, the process requires trial and error experimental procedures, or application of the design of experiments (DoE), to achieve excellent quality prints with desirable mechanical properties. The most common semi-crystalline polymers are polylactic acid (PLA), polypropylene (PP), polycaprolactone (PCL), polyethylene (PE), and polybutylene terephthalate (PBL). Moreover, the dimensional specifications may vary for the same material as well as for varied materials. For instance, in PLA, positive deviation (expansion) is observed in the width and thickness direction, while negative deviation (shrinkage) is observed in the length direction [8].

PLA is considered a green material because it is made through the polymerization of lactic acid by the fermentation of renewable resources. There are four different forms of crystals, namely α, β, and γ [9]. The α crystals show two disordered modifications i.e., α′ and α″ [9]. The α crystal is obtained through cold, melt, or solution crystallization at a higher temperature (i.e., above 120 °C) [10], while α′ is produced at a lower temperature (i.e., below 100 °C) by mixing α and α′ between 100 °C and 120 °C [11]. The α″ crystal is obtained through crystallization at a temperature (0 °C to 30 °C) under high-pressurized CO_2 [12]. The α′ crystal forms the chain conformation of the PLA chain, which is more disordered than in the α form crystal [13]. Therefore, the α form provides lower elongation at break, higher Young's modulus, and better preservation against water vapor than the α′ form. The α″ crystal produces poor chain packing and the lowest crystal density compared to α and α′ [14]. The published studies have shown that the α form crystal is more stable compared to its other forms [9]. The β form crystal is obtained through α crystal deformation and through annealing or stretching at elevated temperatures [15]. The γ form is obtained by epitaxial growth on a hexamethyl benzene substrate [16].

The physical and mechanical properties of PLA are influenced by the degree of crystallinity. Mechanical properties can be improved by thermal annealing to increase the degree of crystallinity [17]. In FDM printing, the degree of crystallinity in the bottom layers is higher than in the top and side layers because of the bed temperature, which causes the layer to cool down slowly, thus rendering the printed part dimensionally unstable [18].

2. Fused Deposition Modeling of 3D Printed Parts

Numerous studies have been reported that investigated the effect of FDM process parameters on quality characteristics, mechanical properties, physical properties, energy consumption, and build time for diverse types of materials. For instance, Galetto et al. [4] investigated the effect of process parameters on the process efficiency and quality of PLA printed parts. Quadratic models were developed for surface roughness and dimensional accuracies. For maximizing dimensional accuracy, the design features of parts play a significant role. Kitsakis et al. [19] studied the dimensional accuracy of FDM-printed parts for medical applications. In the study, they considered different parameters, including the material type (PLA and ABS), layer height, infill rate, and the number of shells, as well as studying the dimensional accuracy. The study revealed that the best dimensional accuracy for PLA material was attained at an infill rate of 50%, with one shell, and a layer height of 0.3 mm. The study of Aslani et al. [20] showed that the extrusion temperature significantly affects the dimensional accuracy and surface roughness of PLA printed parts. The study proved that by applying grey relational analysis, high extrusion temperature (230 °C) combined with medium wall thickness values (2 mm) optimized both surface roughness and dimensional accuracy. Nathaphan and Trutassanawin [21] concluded that for good dimensional accuracy and compression strength, the layer height and print speed must be set at a low level, the nozzle temperature at a high level, while the bed temperature must be above the glass transition temperature of ABS material. Further, shrinkage occurs in the diameter of the cylinder because of the cooling and solidification of molten polymer. However, expansion was noticed in height of the cylinder due to the rounding of the number of layers to the higher integer number. Basavaraj and Vishwas [22] found that layer thickness affects the tensile strength, manufacturing time, layer thickness, shell thickness, and orientation angle. Further, the study concluded that tensile strength and dimensional accuracy decrease with an increase of the layer thickness and increase with increases of the orientation angle and shell thickness. The study of Lalegani Dezaki et al. [23] revealed that surface quality and mechanical properties are directly affected by the type of patterns. Concentric and grid patterns exhibit good surface quality and tensile strength while the zigzag pattern produces the worst surface roughness and mechanical properties. Padhi et al. [24] noted that shrinkage occurs along the width and length directions, while the thickness increases in parts printed from acrylonitrile-butadiene-styrene (ABSP 400). The shrinkage may develop inner stress upon solidification. Further, the formation of inner layer cracks and weak interlayer adhesion decrease the dimensional accuracy of final parts. Vahabli and Rahmati [25] improved the surface quality of FDM-printed parts for medical devices using artificial neural networks based on the feed-forward back propagation (FFBP) algorithm. Parts were printed from ABSplus material. The successful fabrication of medical devices such as a molar tooth, femur, skull, and stem further confirms the performance of FFBP. Deswal et al. [8] worked on FDA process parameters by applying an approach integrated with a response surface methodology, artificial neural network-genetic algorithm (ANN-GA), genetic algorithm (RSM–GA), and artificial neural network (ANN) for improving the dimensional accuracy of ABS parts. The adaptive neuro-fuzzy inference system (ANFIS) model and whale optimization algorithm (WOA) was applied by Sai et al. [26] to optimize the process parameters for printing PLA implants. Their study concluded that layer thickness followed by raster angle and infill density significantly affects the surface roughness, while layer thickness and raster angle at low level and infill density at medium level provides good surface quality. The findings of Vyavahare et al. [27] revealed that layer thickness and build orientation have a significant effect on fabrication time and surface roughness, while for dimensional accuracy, in addition to these two parameters, Camposeco-Negrete [28] optimized the process parameters to improve the dimensional accuracy, energy consumption, and the production time of FDM 3D printed acrylonitrile styrene acrylate (ASA) parts. The study showed that printing plane is the most significant parameter that helps in reducing production time and energy consumption. For dimensional accuracy, the infill pattern influences the width of the part, and layer thickness affects the length of the part significantly. Mohamed et al. [29] applied a deep neural network to analyze and optimize the dimensional accuracy of FDM PC-ABS printed parts. In the study, a total of 16 experiments were planned based on a definitive screening design (DSD). The part profile for dimensional accuracy was considered as the percentage variation in diameter and length. The quadratic model was found to be significant for both length and diameter variation. Slice thickness, print direction, interaction of print direction, and deposition angle were found to be significant for length variation. Mohanty et al. [30] applied the hybrid approach of a Taguchi- MACROS- nature-inspired heuristic optimization technique to optimize parameters affecting the dimensional precision of ABS M30 FDM-printed parts. Their results showed that part orientation significantly affected dimensional precision. All of the nature-inspired algorithms considered in the study provide comparable results for minimizing dimensional error. Garg et al. [31] studied the dimensional accuracy and surface roughness of ABS P430 FDM-printed parts under the cold vapor technique using acetone. The results revealed that chemical treatment reduces surface roughness and improves the dimensional accuracy of the final part. This may be attributed to softening of the external layer, because acetone causes rupturing of a secondary bond between the chains of ABD polymers and reaches a more stable position.

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