



Design and Performance Enhancement in 3d Printed Structures

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Abstract

The study aims at investigating the design and performance improvement of 3D printed structures using Fused Deposition Modelling (FDM) and the PLA+, ABS and carbon-fibre-reinforced nylon (PA-CF) materials. The paper analyses the influence of some of the major parameters of the process to the tensile strength, surface roughness, wear rate and dimensional accuracy: layer thickness, raster angle, and infill density. Experimental tests were performed in the ASTM specifications and the observations were determined using Response Surface Methodology (RSM) and hybrid Artificial Intelligence (AI) optimization methods such as GA-ANN, GA-ANFIS, GA-Fuzzy model. PA-CF had the greatest tensile strength (62.8 MPa) and wear resistance, whilst PLA+ had the greatest surface finish. The hybrid optimization model has shown to be highly predictive ($R^2 = 0.95$) and minimized error (under 1.5%), which proves the efficiency of the integrated statistical and AI-based modelling as a method to enhance the performance and reliability of the FDM components.

Keywords: Additive Manufacturing, Fused Deposition Modelling, Optimization, Artificial Intelligence, Mechanical Performance

1. Introduction

Manufacturing technologies have also developed into additive manufacturing (AM) that adds material layer by layer directly out of CAD models, whereas manufacturing methods were earlier subtractive, meaning that the desired shape is created by removing material. The change has resulted in waste minimization of materials, an increase in flexibility on designs and a speed of prototyping in various industries like aerospace, automotive, and biomedical engineering. Fused Deposition Modelling (FDM) has also become one of the most affordable and available approaches among other AM techniques, which employs thermoplastic strands such as PLA and ABS to form functional structures. But the mechanical characteristics of FDM components are highly determined by process variables which include layer thickness, raster angle, and infill density. In order to assess and improve the quality of the printed structures, optimization methods such as Weibull distribution, genetic algorithm and artificial neural network are commonly used to compute the propensity of failure, forecast material performance, and identify the optimal printing settings. A combination of such design and statistical optimization solutions allows achieving a considerable performance improvement and structural efficiency in 3D printed components.

2. Literature Review

Valizadeh *et al.* (2021) ^[4] conducted a study on how surface roughness impacts 3D printed components in terms of functionality and quality. Their research objective was to identify the best parameters in the input in order to reduce the surface roughness with the help of a hybrid artificial neural network (ANN) and a particle swarm optimization (PSO) method. A 3D printer was used to carry out three level tests with five parameters in mind including material density, printing speed, nozzle size, and nozzle temperature. There were 43 flat specimens that were printed by the use of the Central Composite Design (CCD). The roughness of the surfaces of the samples was measured and the results trained a multilayer perceptron ANN (7-4-1) with high correlation coefficient (0.95). The PSO algorithm was then used to determine the most suitable combination of parameters to obtain a low surface roughness.

Menderes and Ahmet (2021) ^[2] analysed the effect of filament material type, raster angle, and layer thickness on the mechanical performance of 3D printed parts. ABS, PLA and PET-G filament materials were used to test the raster angle of 30, 45, and 60 degree and the layer thickness of 0.15, 0.2 and 0.25 mm were taken into account. The Taguchi method was adopted to reduce the number of

experiments and establish the best values of mechanical strength, printing time, and weight reduction. They used Signal-to-Noise ratio and regression and ANOVA to determine that the optimum printing parameters to use to achieve strength include PET-G filament, raster angle of 45 degrees and 0.25 mm layer thickness. It was found that the 45 raster angle was always giving good mechanical behaviour than any other angle and analysis of printing time also confirmed the results.

Saed *et al.* (2020) [3] investigated the application of Poly-L-Lactic Acid (PLLA) in the creation of hard tissue scaffolds by Digital Light Processing (DLP) 3D printing. PLLA was selected because of its biocompatibility, biodegradability, and strength; therefore, it can be used in biomedical application. The properties of the porous scaffold models under the influence of light exposure time and dye concentration on compressive strength and morphology were studied (pore size 600 μm , porosity 70%). It was found that scaffolds were easily printed with complex structures, with the highest compressive strength being 2.2 MPa at the longest exposure time and the lowest dye concentration. The *in vitro* testing showed that there is no cytotoxicity and therefore it can be used biologically.

Elkaseer *et al.* (2020) [1] studied the influence of the process parameters of Fused Filament Fabrication (FFF) on the quality of parts and their manufacturing efficiency. They investigated the effect of surface inclination angle, printing speed, temperature, layer thickness, and infill percentage on energy consumption, surface roughness and dimensional accuracy using a Taguchi L50 orthogonal array. The most critical factors were identified by the Statistical and ANOVA analysis. As it was noted, dimensional accuracy was most affected by thick layers and high printing speed, because of the spread of the material. The roughness of the surface was largely influenced by surface inclination angle, thickness of the layer and temperature which determined the viscosity of the material. In addition, the fastest printing speed and the thickness of the layers the most significant impact on the reduction of the energy consumption and the productivity of the process.

Asadollahi-Yazdi *et al.* (2018) [5] analyzed the valuable advantages and disadvantages of Advanced Manufacturing Techniques (AM). The Fused Deposition Modelling (FDM) one of the common AM techniques, was used to determine the best production conditions of AM objects. This is the purpose with which an FDM technology analysis based multi-optimization problem was created. These decision factors of the problem were the thickness of the layer, and part orientation which are two important production features. Material mechanical behavior and roughness of the surface of FDM outputs were constraints functions, whereas end functions were production time and mass of material. Different methods were being formulated to replicate the AM criterion with regards to these decision variables. The An algorithm of non-dominated sorting genetic algorithms, NSGA-II was used to find the most beneficial manufacturing solutions. Finally, a case study demonstrated the reliability of the offered method.

3. Materials and Methods

a. Composition of Materials Used in Research

Three thermoplastics were employed, such as PLA+, ABS and carbon-fibre-reinforced nylon (PA-CF).

Polylactic Acid Plus (PLA+) is a renewable material (based on corn starch) that has improved toughness and thermal resistance compared to regular PLA because it has polymeric stabilizers and additives. ABS (Acrylonitrile Butadiene Styrene) is an acrylonitrile terpolymer with butadiene and styrene that has rigidity, surface finish, and impact, which could be used with a temperature of [?] 20 degC to 80 degC. PA-CF (Polyamide containing 20% Carbon Fibre) gives nylon more strength, stiffness and resilience to wear, making it useful in high-performance industrial elements.

b. Research Methodology

Preparation of Specimen: The printing of specimens was done on a Geeetech FDM 3D printer (300 x 300 x 400 mm, ± 0.1 mm accuracy). CAD models were designed and then exported in STL files and cut in Cura 3.4.1 to come up with G-codes. Central Composite Design (CCD) under Response Surface Methodology (RSM) was used to determine the printing parameters such as the layer thickness, raster angle, and infill density.

Experiment Setup: A dimensional accuracy test, tensile strength test, roughness test (surface) and wear test were conducted as per the applicable standards of ASTM.

- Primary measurements were taken with the help of a micrometer (± 0.01 mm) to measure dimensional accuracy.
- Tensile (ASTM D638- V) was measured on a UNITEK-94100 UTM at a rate of 5 mm/min.
- The roughness of the surface was measured on a Mitutoyo SJ-210 Talysurf.
- The wear (ASTM G99) was analyzed with the help of a pin-on-disc test on an EN-31 steel disc (RC 62 hardness).

Optimization Method Used

RSM, ANN, ANFIS and Fuzzy Logic hybrid framework were adopted together with a combination of Genetic Algorithm (GA). Regression models were set up by RSM, whereas AI-based models (ANN, ANFIS, GA-hybrids) forecasted and optimised the outcomes like tensile strength and surface roughness. This methodology allowed the correct modeling of the 3D printed parts related to the optimal FDM process parameters to be identified.

4. Results

In the research, the hybrid computational and experimental methods were used to evaluate the performance of FDM-fabricated components fabricated using PLA+, ABS, and PA-CF. Dimensional accuracy, tensile strength, surface roughness and wear resistance were the key response parameters that were optimized using RSM and AI-based hybrid models (GA-ANN, GA-ANFIS, GA-Fuzzy).

a. Experimental Results

The ASTM standard test was carried out using the CCD

matrix design. Table summarises the mean experimental results of the three materials.

Table 1: Experimental results of FDM parameters and material performance

Material	Layer (mm)	Raster (°)	Infill (%)	Tensile Strength (MPa)	Surface Roughness (μm)	Wear Rate (mm ³ /m)	Dimensional Error (mm)
PLA+	0.20	45	80	51.2	4.85	0.013	0.09
ABS	0.25	45	70	44.6	5.31	0.018	0.11
PA-CF	0.20	60	90	62.8	3.92	0.010	0.07

b. Model and Optimization Performance

The RSM model had good predictive power with $R^2 = 0.95$. The hybrid models also reduced the amount of errors and increased the accuracy in prediction of responses.

Table 2: Comparison of experimental and predicted results.

Model	Response	Experimental	Predicted	Error (%)
RSM	Tensile Strength	51.2	50.6	1.17
GA-ANN	Surface Roughness	4.85	4.78	1.44
GA-ANFIS	Wear Rate	0.013	0.0129	0.77
GA-Fuzzy	Dimensional Error	0.09	0.089	1.11

Findings affirmed that material composition and process parameters have a significant effect on mechanical and surface properties of 3D printed parts. PA-CF was found to be better in tensile strength and wear resistance, whereas PLA+ produced a more smooth surface finish. Hybrid optimization methods were successful to minimize the error to less than 1.5% and proved the accuracy of the combined RSM-AI model to modify the FDM part performance.

5. Conclusion

This paper has shown that a combination of experimental analysis and hybrid optimization can be important in improving the performance and reliability of the FDM-produced 3D printed structures. Out of the tested materials, PA-CF had the best tensile strength and wear resistance, which is caused by the presence of carbon fibre as a reinforcing material, whereas PLA+ had better surface smoothness. The study established that the layer thickness, raster angle, and infill density are very important parameters that affect mechanical and surface properties. The application of the integrated RSM-AI optimization framework with the GA-ANN, the GA-ANFIS, and the GA-Fuzzy models showed very high accuracy of predictions ($R^2 > 0.95$) and reduced errors to less than 1.5%. All in all, the hybrid strategy was efficient in streamlining the parameters of FDM processes to enhance the efficiency of structural functionality and proving the high potential of the intelligent computational methods in promoting the development of additive manufacturing design and performance.

6. References

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