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ANFIS-Based Prediction and Optimization of Hardness and Surface Roughness in FDM Printed PETG-Carbon Fiber Composites

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Abstract

Fused Deposition Modeling (FDM) is a widely used 3D printing process for producing prototypes and functional components, owing to its ability to rapidly fabricate geometrically complex parts without requiring specialized tooling or human intervention. FDM-fabricated components have numerous intriguing applications across diverse industries, including aerospace, automotive, medical, and personalized products. Nevertheless, the production of ready-to-use components by FDM is a formidable challenge. The processing factors, such as infill percentage, Layer thickness, extrusion temperature, and infill pattern, significantly influence the final component's design, quality, functioning, and mechanical qualities.

This study examines the impact of the material infill percentage, layer thickness, extrusion temperature, and infill pattern on the hardness and surface roughness of polyethylene terephthalate glycol carbon fibre (PETG CF). Nine test specimens are produced by varying the process parameters. This research utilizes an Adaptive Network-based Fuzzy Inference System (ANFIS) to forecast process parameters, utilizing both neural networks and fuzzy logic to establish a mapping between inputs and outputs.

Keywords: ANFIS; FDM; Mechanical Properties Enhancement; Prediction; PETG Carbon Fiber (PETG CF)

1.0 Introduction

Additive Manufacturing (AM), commonly referred to as 3D printing, has revolutionized the field of design and manufacturing by enabling the production of lightweight, customized, and functionally graded components with complex geometries. Among various AM processes, Fused Deposition Modeling (FDM) has gained significant attention due to its cost-effectiveness, material availability, and suitability for rapid prototyping and functional part production. However, the mechanical performance of FDM-fabricated components is highly

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dependent on process parameters such as infill percentage, layer thickness, extrusion temperature, and infill pattern, which directly influence mechanical properties including hardness, tensile strength, and surface quality.

Polyethylene Terephthalate Glycol (PETG), when reinforced with carbon fibers (PETG-CF), has emerged as a promising material in engineering applications because of its high strength-to-weight ratio, improved stiffness, and dimensional stability. The incorporation of carbon fibers not only enhances the structural integrity but also improves the tribological and thermal resistance properties of printed components, making them suitable for aerospace, automotive, and biomedical industries.

In recent years, predictive modeling techniques such as Artificial Neural Networks (ANN), Response Surface Methodology (RSM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been widely applied to estimate and optimize process outputs in AM. Among these, ANFIS provides a robust hybrid framework that combines the learning ability of neural networks with the reasoning capability of fuzzy logic, making it highly effective for handling nonlinear and uncertain process relationships. Several studies have demonstrated the superiority of ANFIS in predicting surface quality, wear behavior, and thermal performance in different material systems [1–4].

Therefore, the present study focuses on developing an ANFIS-based predictive model for evaluating the influence of key FDM process parameters on hardness and surface roughness of PETG-CF components. The outcomes are expected to provide valuable insights into process optimization and enhance the functional applicability of PETG-CF in critical engineering domains

Additive manufacturing, also known as 3D printing, has transformed mechanical engineering and nanotechnology by facilitating the production of intricate structures with exceptional accuracy. In mechanical engineering, it enables quick prototyping and manufacturing, minimising time and expenses while producing lightweight, high-strength components for aerospace and automotive uses. The attributes are predicted using the ANFIS technique, and the authors determined that the ANFIS prediction values closely align with the experimental values. Quantitative membership functions (MFs) for each input, coupled with a designated type of MF for each input, form the structural variables for grid partitioning and ANFIS. All MFs were evaluated using this approach, although several restrictions exist for each input [5]. Zhang et al. [6] optimized the thermo-physical process parameters of

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nanofluids, which are developed using hybridized methods. ANFIS is implemented using several clustering techniques, including partitioning of grids, cluster subtraction methods, and fuzzy methods. Zafar et al. [7] utilized Gaussian membership functions for each input variable (pH, adsorbent dose, starting concentration) in the context of Cr-VI adsorption data. Banza et al. [8] demonstrated that ANFIS outperforms both ANN and RSM as the most effective deterministic model for Cr-VI adsorption over cellulose nanocrystal-sodium alginates.

Through ANFIS, it is forecasted that the quantity of Cr-VI to be removed from textile water waste using activated carbon [9]. Without a systematic methodology, an analysis was also carried out for all types of MFs with 1 to 2 input variables. Yusuff et al. [10] forecasted Cr-VI adsorption over activated eucalyptus charcoal utilising ANFIS-bell-shaped membership functions and three membership functions for every input (concentration, pH, and time). It is predicted that adsorption of Cr-VI over mesoporous CeO_2 utilizing ANFIS, without specifying information regarding ANFIS characteristics, such as membership function type and quantity [11]. In investigations concerning chromium adsorption prediction, a systematic method for identifying optimal ANFIS parameters is absent. Kuyakhi [12] developed experimental inputs with ANFIS variables, integrating the particle swarm optimization (PSO) algorithm alongside ANFIS to construct a model for the elimination of Cr-VI using NiO nanoparticles.

2.0 Experimental procedure

The material used in this study is PETGCF, with filament thicknesses of up to 1.75 mm. The mechanical properties are listed in Table 1. The characteristics of the 3D printer utilized for printing these materials are detailed in Table 2. The subsequent elements were selected as the process variables for the printing samples, as enumerated in Table 3. In this study, the optimization of selected process parameters, including infill percentage, layer Thickness, infill pattern, and temperature, aims to achieve the highest hardness and better surface finish characteristics.

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Table 1. Properties of PETGCF

Property	PETG+CF
Ultimate Tensile Strength (MPa)	35.3
Young's Modulus (MPa)	2430

Table 2. Characteristics of the FDM printer.

Characteristics	Value
Filament (mm)	1.75 PETGCF
Layer height (microns)	50–400
Nozzle diameter (mm)	0.4
Max extruder temperature (°C)	250
Print speed (mm/s)	30−150
Maximum printing volume (mm^3)	170(x) × 150(y) × 160 (z)

Considering the four factors and three levels, optimized the number of experiments using the Taguchi DOE parameter combination, which is listed in Table 4.

Table 3. Taguchi variables and Levels

Sno	Variables	Level 1	Level 2	Level 3
1	Infill Percentage	20	40	60
2	Layer Thickness	0.1	0.15	0.2
3	Temperature	230	235	240
4	Infill Pattern	Line	Hor	Tri

2.1 Measurement of Shore D Hardness

Shore D hardness evaluates the hardness of materials such as rubber, elastomers, and plastics. To ascertain the extent to which a pointed item may penetrate a material under a specified constant force. The Shore D scale employs a durometer. The apparatus utilized for the Shore D hardness assessment is seen in Figure 1. Polymer-based elastomers, stiff plastics, and other hard rubbers may undergo testing for Shore D hardness. The material's hardness is assessed by measuring the penetration depth of a diamond-tipped indenter according to the

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Shore D hardness scale. The material testing is illustrated in Figure 2. The test findings are presented in Table 4.

Figure 1. Shore-D Hardness Equipment

Figure 2. While testing

2.2 Measurement of Surface Roughness

A surface roughness assessment is performed using PETG CF specimens. Surface roughness is quantified via the Talysurf surface measurement device. Surface roughness refers to the inherent irregularities resulting from the manufacturing process. Surface roughness is defined by the variations of an actual surface's normal vector from its ideal state. Figure 3 illustrates the apparatus employed for surface roughness assessment, namely a Talysurf surface measuring device. Figure 4 illustrates the testing and operational procedure. The test results are presented in Table 4

Figure 3. Surface roughness tester

Figure 4. Measurement of surface roughness

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Table 4. Taguchi OA and responses

Experimental Run.	Infill percentage	Infill pattern	Layer thickness	Temperature	Hardness	Surface Roughness
1	20	H	0.10	230	79	10.66
2	20	T	0.15	235	78	16.33
3	20	L	0.20	240	84	13.18
4	40	H	0.15	240	87	14.17
5	40	T	0.20	230	82	12.71
6	40	L	0.10	235	82	10.94
7	60	H	0.20	235	87	13.39
8	60	T	0.10	240	84	10.08
9	60	L	0.15	230	86	13.54

3.0 Prediction using ANFIS

ANFIS architecture integrates Fuzzy Logic (FL) with Artificial Neural Networks (ANN), employing a mapping relationship among input and output data to ascertain the optimal distribution of MFs. The adaptive network frameworks incorporate both FL theory and ANN. Fuzzy Logic theory was employed to construct the Fuzzy Inference System (FIS), and iterative techniques were utilized to develop the FIS MFs. An ANN method is used by ANFIS to build the FIS model. This lets the neural network use training data from the given dataset. The Surgeon category IF-THEN rule framework has been used to represent the findings.

3.1 Hardness prediction using ANFIS

ANFIS architecture and network framework, depicted in Figure 5 (a) and Figure 5 (b), were employed to assess the hardness of a PETGCF printed sample. MFs are employed to finalize training in Sugeno-type fuzzy inference systems. In this study, the FIS evaluates four 3d printer parameters: infill percentage, infill pattern, layer thickness and temperature.

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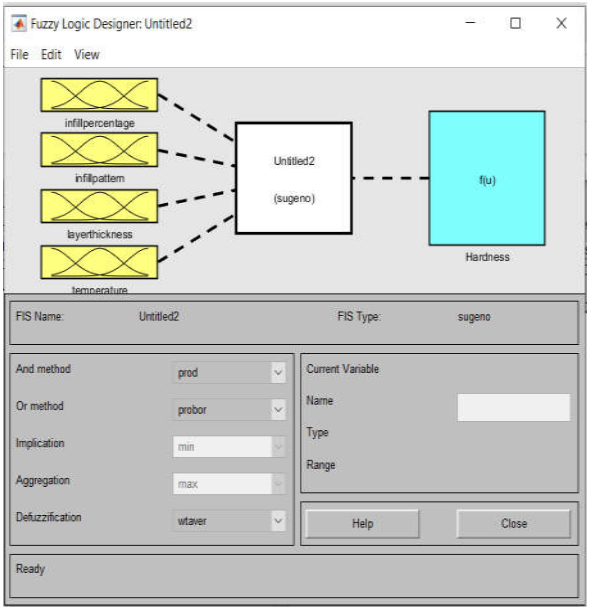

Figure 5(a). Established ANFIS Structure

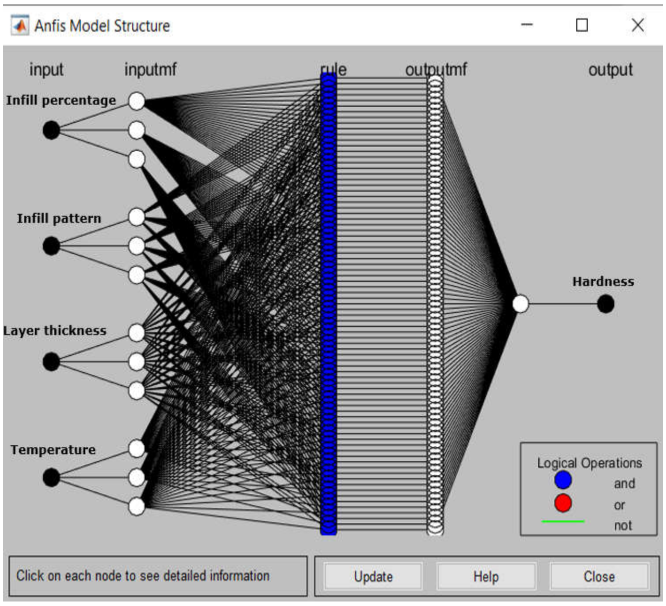

Figure 5(b). Generated model for Hardness prediction

The dataset presented in Table 5 is utilized for training the ANFIS model. The predictive capability of the associated model is evaluated utilizing dataset presented in Table 6. Figure 6 (a) and Figure 6 (b) illustrate the process of loading training and testing data into the generated ANFIS model.

Table 5. Training dataset for hardness

Sno	Infill Percentage	Infill Pattern	Layer Thickness	Temperature	Hardness
1	20	2	0.15	235	78
2	20	3	0.2	240	84
3	40	1	0.15	240	87
4	40	3	0.1	235	82
5	60	1	0.2	235	87
6	60	2	0.1	240	84

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Table 6. Testing datasets for hardness

Sno	Infill Percentage	Infill Pattern	Layer Thickness	Temperature	Hardness
1	20	1	0.1	230	79
2	40	2	0.2	230	82
3	60	3	0.15	230	86

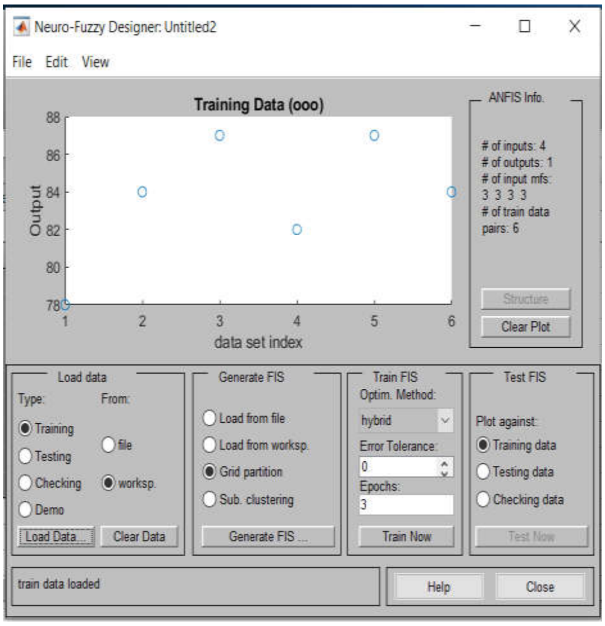

Figure 6 (a). Loading Training Data

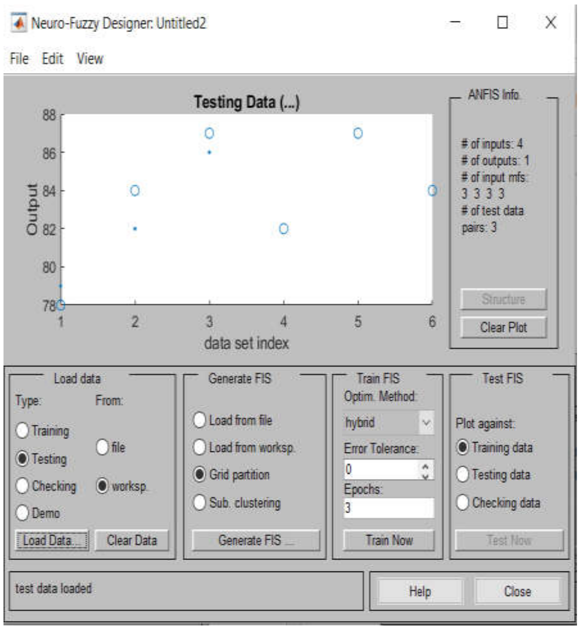

Figure 6 (b). Loading Testing Data

The ANFIS model was trained with the training data and later evaluated using the test data to measure its performance. The input dataset is repeatedly plotted throughout the training process of the ANFIS model to decrease the chance of inaccurate predictions. The count of epochs required for mapping is expressed as the number of iterations. Figure 6 (a) illustrates the loading of training data, and Figure 6 (b) illustrates the loading of testing data into the created fuzzy model. This model requires 3 epochs (iterations) across 6 datasets. . The results were tabulated in Table 9.

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3.2 Surface roughness prediction using ANFIS

The estimation of surface roughness for a PETGCF printed sample was conducted using generated ANFIS structure and generated network model, as depicted in Figure 7 (a) & Figure 7 (b). MFs are utilized to enhance training in Sugeno-type fuzzy inference systems. This research includes evaluation of four parameters related to 3D printing by the FIS: temperature, infill pattern, layer thickness, and infill percentage.

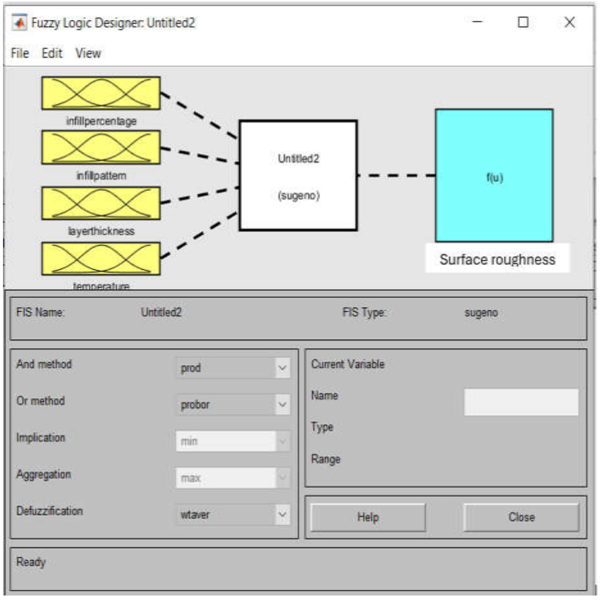

Figure 7(a). Established ANFIS Structure

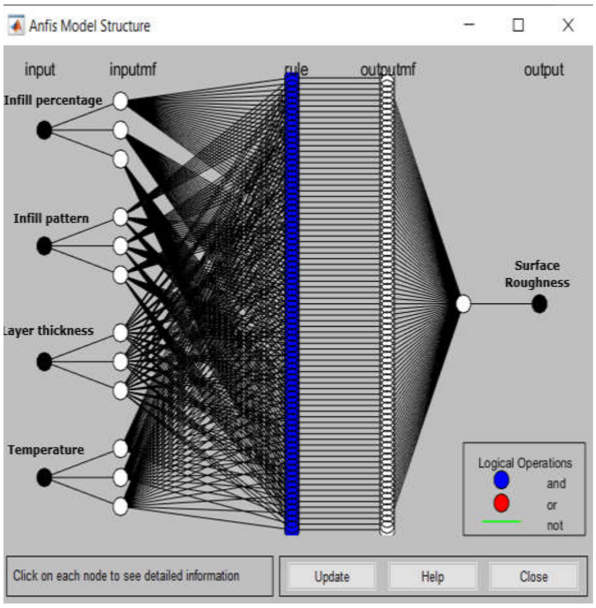

Figure 7(b). Generated model for Surface roughness prediction

ANFIS model is trained utilizing the dataset presented in Table 7. Predictive capability of the associated model is evaluated using the dataset presented in Table 8. Figure 8 (a) & Figure 8 (b) illustrate the input of training & testing data into the model.

Table 7. Training dataset

Sno	Infill Percentage	Infill Pattern	Layer Thickness	Temperature	Surface Roughness (Ra) µm
1	20	2	0.15	235	16.330
2	20	3	0.2	240	13.180
3	40	1	0.15	240	14.170
4	40	3	0.1	235	10.940
5	60	1	0.2	235	13.390
6	60	2	0.1	240	10.080

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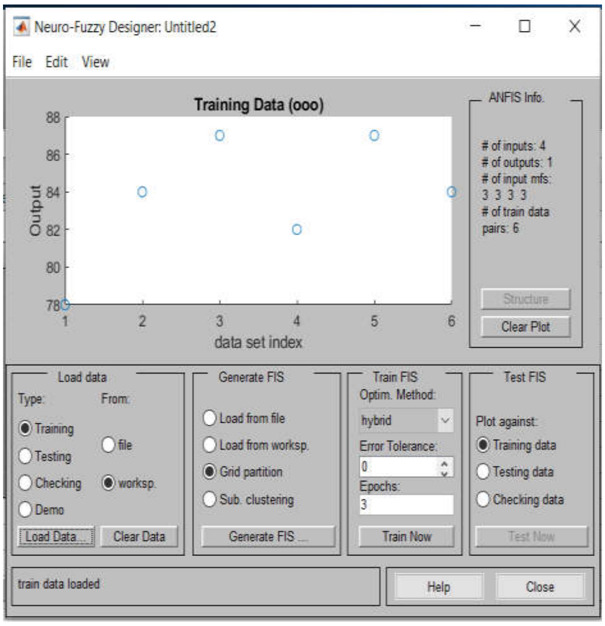
Table 8. Testing dataset

Sno	Infill Percentage	Infill Pattern	Layer Thickness	Temperature	Surface Roughness (Ra) µm
1	20	1	0.1	230	10.660
2	40	2	0.2	230	12.710
3	60	3	0.15	230	13.540



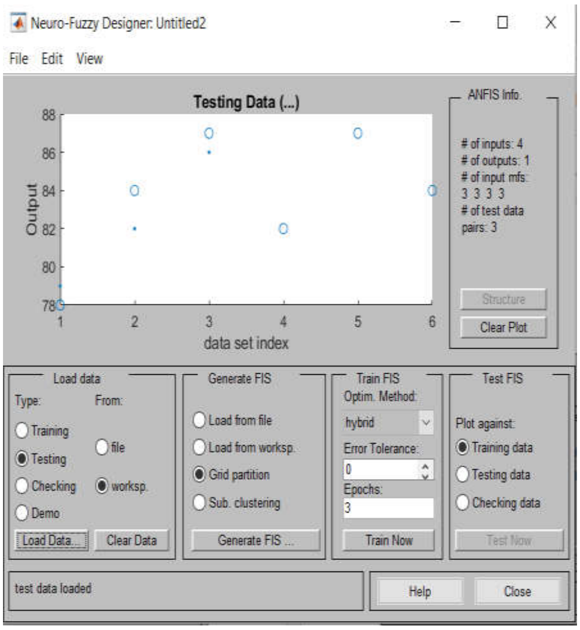


Figure 8 (a). Loading Training Data

Figure 8 (b). Loading Testing Data

Figure 8 (a) illustrates the loading of training data, and Figure 8 (b) illustrates the loading of testing data into the created fuzzy model. This model requires 3 epochs (iterations) across 6 datasets. Pimf's prediction is selected for both hardness and surface roughness testing because to its minimal prediction error compared to other membership functions [3]. The results were tabulated in Table 9.

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4.0 Results and Discussions

4.1 Hardness & Surface roughness prediction using ANFIS

Table 9. ANFIS predicted values

Sno	Infill Percentage	Infill Pattern	Layer Thickness	Temp	Hardness	ANFIS Predicted Hardness	Surface Roughness (Ra) µm	ANFIS Predicted SR
1	20	1	0.1	230	79	80.93	10.660	12.060
2	20	2	0.15	235	78	78.00	16.330	16.330
3	20	3	0.2	240	84	84.00	13.180	13.180
4	40	1	0.15	240	87	87.00	14.170	14.170
5	40	2	0.2	230	82	82.28	12.710	12.982
6	40	3	0.1	235	82	82.00	10.940	10.940
7	60	1	0.2	235	87	87.00	13.390	13.390
8	60	2	0.1	240	84	84.00	10.080	10.080
9	60	3	0.15	230	86	84.08	13.540	13.356

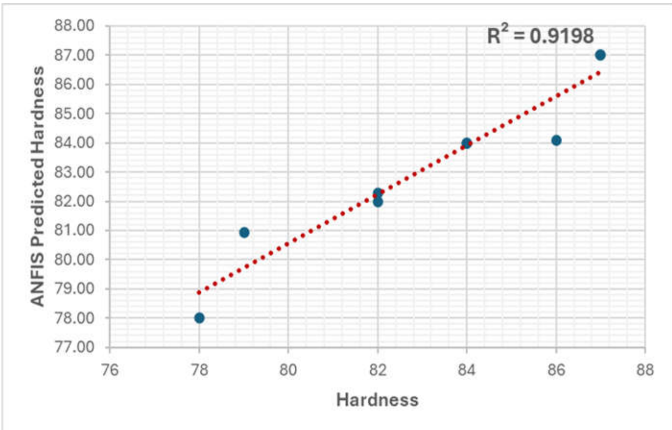

Figure 9. Analysis of Experimental outcomes in relation to ANFIS predicted values for Hardness.

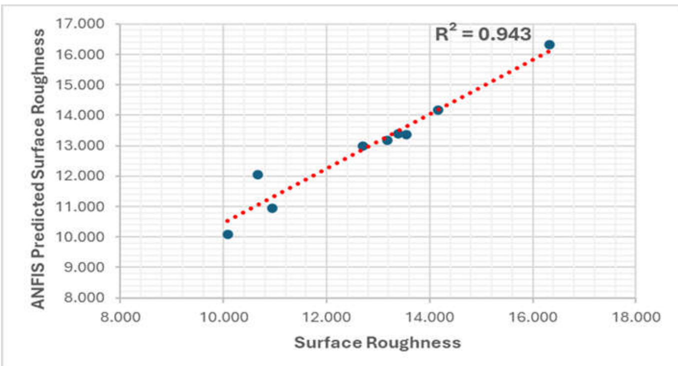

Figure 10. Comparison of Experimental results with ANFIS predicted values for Surface Roughness

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Table 9. shows the ANFIS predicted values. Figure 9 and Figure 10 demonstrate a strong correlation between experimental results and ANFIS predicted values, with R-squared values of 0.9198 and 0.943 for hardness and surface roughness, respectively, which are satisfactory.

Conclusions

This study systematically investigated the effects of key FDM process parameters—namely infill percentage, layer thickness, extrusion temperature, and infill pattern—on the hardness and surface roughness of PETG-CF components. The ANFIS predictive model demonstrated excellent agreement with experimental data, achieving R^2 values of 0.9198 for hardness and 0.943 for surface roughness, confirming its effectiveness as a reliable predictive tool.

The findings clearly indicate that optimization of process parameters plays a vital role in enhancing the mechanical performance of PETG-CF parts, thereby broadening their potential applications in high-performance engineering sectors such as aerospace, automotive, and biomedical implants. Furthermore, the hybrid capability of ANFIS highlights its advantage over conventional predictive approaches like RSM and ANN, particularly in capturing nonlinearities and parameter interactions. Overall, this study establishes ANFIS as a powerful tool for advancing material-process-property relationships in additive manufacturing and paves the way for the development of next-generation functional 3D-printed composites.

Conflict of Interest

All authors declare that they have no conflicts of interest.

All data is included in the article

All data generated or analysed during this study are included in this published article

Ethics

This study was conducted in accordance with ethical standards.

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