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Optimization of FDM Process Parameters for Minimizing Specific Wear Rate Using a GA- ANFIS Hybrid Model

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This study investigates the optimization of tribological performance in Fused Deposition Modeling (FDM) fabricated components by focusing on the specific wear rate (SWR) of Polylactic Acid (PLA) specimens. A total of 30 samples were fabricated using a MakerBot Method X 3D printer following ASTM G99 standards, considering four key process parameters: nozzle temperature, infill density, layer height, and printing speed. Wear behavior was evaluated using a Pin-on-Disc apparatus under dry sliding conditions. To predict and minimize SWR, a hybrid GA-ANFIS (Genetic Algorithm–Adaptive Neuro-Fuzzy Inference System) model was employed. The ANFIS framework effectively captured nonlinear relationships among input variables, while GA optimized membership functions to improve prediction accuracy. Experimental results demonstrated that nozzle temperature and layer height had the most significant influence on SWR. The optimized parameter combination achieved a minimum SWR of 8.26×10^{-4} $mm^3/N{\bullet}m$, representing a 25.12% reduction compared to non-optimized settings. The proposed hybrid approach proved to be a robust tool for process parameter optimization, enabling enhanced wear resistance and mechanical integrity in FDM-printed parts.

Keywords: fdm, pin on disc, wear rate, ga-anfis

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1. Introduction

FDM is a three-dimensional printing (3D printing) technique which involves the process of building objects layer by layer, using a selected material, until the desired structure obtained. 3D printing is a cutting-edge manufacturing technology that constructs parts through a layer-by-layer deposition process. Fused Deposition Modeling, which uses thermoplastic filaments to construct things, is one of the most popular 3D printing methods. When compared to other quick prototyping in 3D-printed objects, a lot of work has been done to investigate tribological parameters, such as

wear resistance, wear strength, and coefficient of friction, which are crucial in evaluating the longevity and performance of a printed item. To improve wear resistance and other mechanical features, a large number of scientists and researchers from around the world have thoroughly examined the process factors related to FDM. To improve the wear resistance and other mechanical qualities of printed parts, a large number of scientists and researchers from across the world have thoroughly examined the process factors related to FDM. Singh et al., (2024) utilized Graphene- reinforced PLA (PLA-nGr) composite used to investigate the influence of critical FDM printing parameters—nozzle temperature, layer thickness, printing speed, and infill density on the wear performance of 3D-printed specimens. Using conventional pin-on-disc testing, a Taguchi L9 design of trials was used to methodically examine each factor's impact on wear rate and coefficient of friction. According to ANOVA results, the most important factors influencing wear resistance were nozzle temperature and layer thickness, with printing speed and infill density coming in second and third, respectively. When compared to prints that were not optimized, the wear loss was significantly reduced by using the ideal settings of high nozzle temperature, medium layer thickness, moderate speed, and moderate density. Phogat et al., (2022) conducted an extensive study on optimizing the parameters of the Fused Deposition Modeling (FDM) process, specifically raster angle, infill density, extrusion temperature, extrusion speed, and wall thickness, by utilizing a hybrid Genetic Algorithm-Artificial Neural Network (GA-ANN) approach. The research evaluated the wear resistance of FDM-printed samples made from PLA, ABS, and multi-material composites.

The findings revealed that PLA exhibited the lowest wear rate of 0.155371 mm^3/m under the best conditions, which included a raster angle of 89.26° and an infill density of 95.21%. Of all the parameters analyzed, infill density and extrusion temperature had the most significant impact on wear performance. The GA-ANN model showed a high level of predictive accuracy ($R = 0.9608$), demonstrating its effectiveness in optimizing process settings to reduce wear in FDM- printed materials. Wang et al., (2024) focused on assessing the mechanical and tribological characteristics of polyamide (PA), particularly Nylon-based materials, fabricated using FDM. The study identified nozzle temperature, print speed, layer height, infill density, and build orientation as critical parameters. Enhanced mechanical properties—including tensile strength, flexural modulus, and impact resistance—were associated with higher nozzle temperatures (≥250 °C) and reduced layer heights (0.1–0.2 mm), attributed to improved interlayer bonding. The research emphasized the importance of precise process control and noted that material modifications and

post-processing could further extend the application potential of PA parts in automotive, aerospace, and industrial sectors.

The tribological characteristics of 3D-printed items are affected by various important factors such as layer thickness, infill density, print speed, infill pattern, extrusion temperature, and nozzle diameter, which determine the material's overall performance. Current studies have not thoroughly investigated the interactions among these variables, indicating a need for a deeper understanding to optimize the FDM process effectively. Although traditional optimization techniques like Design of Experiments (DOE), Response Surface Methodology (RSM), and Taguchi's technique are frequently applied, advanced computational methods, including Machine Learning (ML), Artificial Intelligence (AI), and genetic algorithms, have not been fully employed for FDM optimization. The incorporation of AI-based models, particularly for real-time process adjustments and automating the optimization process across varying material types and intricate geometries, remains largely underexplored. Furthermore, the integration of real-time monitoring and adaptive algorithms into the optimization framework is a crucial area for ongoing research.

In particular, the hybrid GA-ANFIS system enables a systematic investigation of the intricate interactions between essential FDM process parameters—such as nozzle temperature, infill density, layer height, and printing speed—and their impact on wear resistance. By optimizing performance at the interface between material and process, the suggested approach aids in enhancing the capabilities of additive manufacturing, ensuring improved component durability and production efficiency.

2. Materials and Methods

In today's world, there are various types of materials available for 3D printing, such as Acrylonitrile Butadiene Styrene (ABS), Nylon, Polycarbonate, High-Density Polyethylene (HDPE), High Impact Polystyrene (HIPS), and Polylactic Acid (PLA). Of these, PLA has become a popular choice for 3D printing as a result of its lower melting point (150–160 °C), which leads to lower energy usage during the printing process. PLA is a biodegradable thermoplastic polyester characterized by a chemical structure made up of repeating units of (C3 H4 O2) or [–C(CH3)HC(=O)O–] , where "n" indicates the degree of polymerization.

Table 1: Material Properties

PLA Material properties	
Specific Gravity(g/cm3)	1.2–1.4
Impact Strength (KJ/m2)	6.5–7.0
Tensile Strength(MPa)	55–60
Tensile Modulus (MPa)	3.2–3.5
Elongation at Break (%)	5.5–6.0
Softening Temperature (◦C)	50–55

2.1 Methods and Test Specimen Printing

The wear test specimens were produced using a MakerBot Method X 3D printer in line with ASTM G99 standards and then tested for wear resistance using a Pin-on-Disc apparatus. The fabrication process utilized the sophisticated MakerBot Method X printer, illustrated in **Figure 1(a).** The primary input factors for Fused Deposition Modeling (FDM), such as nozzle temperature, infill density, layer height, and print speed, are being adjusted to enhance the wear resistance of the test samples. A total of thirty wear test specimens were produced based on the FDM parameter matrix presented in Table 2, with the experimental plan outlined in Tables 3, and the wear testing specimens illustrated in **Figure 1(b).**

The specimens were designed using AUTOCAD software, and the resulting .dxf AutoCAD file was converted into a stereolithographic (STL) file format. This generated STL file was then uploaded to the 3D printer's software to define the tool path and set all process parameters according to the experimental design matrix for the fabrication of parts. These input parameters were modified at three different levels while other parameters remained unchanged. To reduce the number of experimental runs, a 2k factorial design was utilized through Design Expert 13 software.

Figure 1(a): MakerBot Method X printer

Figure 1(b): ASTM standard 3-D printed wear test samples at various input parameters setting

Table 2: FDM parameters matrix along with their range

S no	Parameter	Unit	Level				
			min(m-)	-1	0	1	max(m+)
1	Nozzle Temp	°C	200	205	210	215	220
2	Infill Density	%	55	65	75	85	95
3	Layer Height	mm	0.2	0.25	0.3	0.35	0.4
4	Printing Speed	mm/s	40	50	60	70	80

Table 3: Experimentation design as per design of experiment (DOE)

Sample No	Parameter Level							
					Temp. (°C)	Infill Density (%)	Height (mm)	Speed (mm/s)
	Temp. (°C)	Density (%)	Height (mm)	Speed (mm/s)				
1	1	0	0	0	215	75	0.3	50
2	-1	1	-1	1	205	85	0.25	60
3	m+	0	0	0	220	75	0.3	50
4	m-	0	0	0	200	75	0.3	50
5	0	m-	0	0	210	55	0.3	50
6	0	m+	0	0	210	95	0.3	50
7	-1	-1	1	-1	205	65	0.35	40
8	1	-1	-1	1	215	65	0.25	60
9	0	0	0	0	210	75	0.3	50
10	1	1	-1	1	215	85	0.25	60
11	1	1	-1	0	215	85	0.25	50
12	0	-1	-1	0	210	65	0.25	50
13	0	-1	-1	1	210	65	0.25	60
14	0	-1	1	-1	210	65	0.35	40
15	1	1	1	1	215	85	0.35	60
16	0	0	m-	0	210	75	0.2	50
17	0	1	-1	0	210	85	0.25	50
18	0	0	0	0	210	75	0.3	50
19	0	0	m+	0	210	75	0.4	50
20	0	0	0	0	210	75	0.3	50

2.2 Pin-on-Disc Wear Testing and Determination of Specific Wear Rate

The performance of the developed PLA part test specimens in dry sliding wear was evaluated using a pin-on-disc apparatus. Cylindrical samples, measuring 30 mm in diameter and 3 mm in thickness, were produced using a 3-D printer. The wear tests were performed under dry sliding conditions over a distance of 3000 m, with a sliding speed set at 1.5 m/s and a load applied of 25N. The specific wear rate (SWR) for the samples was determined through a structured method based on the parameters of the wear test and the data on material loss. The diameter of the wear track (d) was established at 0.1 meters, and the tests were carried out at a rotational speed (N) of 500 rpm for a period (t) of 10 minutes.

2.3 GA-ANFIS Approach for Process Parameters Training and Optimization

In this study, a hybrid modeling approach called GA-ANFIS was employed to enhance process parameters with the goal of minimizing the specific wear rate (SWR) of PLA (Polylactic Acid) parts. This method integrates two intelligent systems: ANFIS (Adaptive Neuro-Fuzzy Inference System), which fuses neural networks with fuzzy logic to identify complex relationships between inputs and outputs derived from data, and the Genetic Algorithm (GA), an optimization method inspired by natural selection. ANFIS is particularly useful for modeling nonlinear systems where traditional techniques may fall short. It processes information through five distinct stages: converting input values into fuzzy sets, utilizing fuzzy rules, evaluating rule strengths, amalgamating outputs, and producing a final crisp numerical result.

In this scenario, the ANFIS model was trained using experimental data with four key FDM process parameters as inputs: nozzle temperature, layer height, infill density, and print speed. These parameters significantly influence the tribological properties of the printed PLA components. After the initial training, the Genetic Algorithm optimized the internal configurations of the ANFIS model, which included the shapes and positions of the membership functions and the weights assigned to the fuzzy rules. This optimization helps in avoiding local minima and enhances the model's prediction accuracy. As a result, the GA-ANFIS model effectively forecasted the specific wear rate of PLA components and identified the optimal combination of process parameters for improved wear resistance. This validates the GA-ANFIS method's effectiveness as a reliable tool for optimizing processes and predicting performance in FDM-based additive manufacturing.

2.4 Experimental Data Training and Results through GA-ANFIS Hybrid Modelling

The Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out among other hybrid approaches that combine neural networks and fuzzy logic frameworks. It gives smooth interpolation due to its fuzzy control (FC) capabilities and ensures model adaptability and learning efficiency through neural network-based backpropagation.

For training purposes, a dataset comprising 30 samples was loaded from the MATLAB workspace in .mat format, structured as a 30×4 matrix. This dataset includes three input parameters—Nozzle temperature (°C), infill density (%), and layer Height and printing speed (mm/s)—along with one output variable UCS, A Sugeno-type fuzzy inference system (FIS) was initially generated using the grid partitioning method. Each input variable was assigned three linear-form membership functions (MFs), with default configuration settings such as zero tolerance, hybrid optimization (a combination of least squares and backpropagation), and a rule base consisting of 27 fuzzy rules and training was performed over three iterations. To explore the impact of different membership functions on system performance, various FIS models were created using alternative MFs. ANFIS supports 11 built-in membership functions, and allows integration of custom MFs.

3. Results and Discussion

The wear testing specimens were fabricated in accordance with ASTM G99 standards, utilizing 30 unique combinations of four key process parameters. These combinations were systematically determined through the Face-Centered Central Composite Design (FCCCD) methodology. Specific wear rate measurements conducted for each specimen, and the final value was derived by averaging the results from three individual tests. **Table 4** summarizes the input parameters and the corresponding output responses (SWR).

Table 4: Wear analysis results at different parametric combinations

Experiment No.	Nozzle Temperature	Infill Density	Layer Height	Printing Speed	SWR (mm3 /Nm)(10^{-4})
1	215	75	0.3	50	25.6
2	210	85	0.25	60	28.05
3	225	75	0.3	50	29.18
4	205	75	0.3	50	32.14
5	215	55	0.3	50	21.67
6	215	95	0.3	50	21.45
7	220	65	0.35	40	14.77
8	220	65	0.25	60	11.03
9	215	75	0.3	50	26.62
10	220	85	0.25	60	12.23
11	220	85	0.25	40	18.23
12	210	65	0.25	40	29.53
13	210	65	0.25	60	29.62
14	210	65	0.35	40	14.84
15	220	85	0.35	60	29.62
16	215	75	0.2	50	15.33
17	210	85	0.25	40	28.15
18	215	75	0.3	50	20.23
19	215	75	0.4	50	25.12
20	215	75	0.3	50	14.23

3.1 Experimental Data Learning and Training through Developing GA-ANFIS Model

The Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out among other hybrid approaches that combine neural networks and fuzzy logic frameworks. It gives smooth interpolation due to its fuzzy control (FC) capabilities and ensures model adaptability and learning efficiency through neural network-based backpropagation. For training purposes, a dataset comprising 30 samples was loaded from the MATLAB workspace in .mat format, structured as a 30×4 matrix. This dataset includes three input parameters—Nozzle temperature (°C), infill density (%), and layer Height and printing speed (mm/s)—along with one output variable SWR, A Sugeno-type fuzzy inference system (FIS) was initially generated using the grid partitioning method. Each input variable was assigned three linear-form membership functions (MFs), with default configuration settings such as zero tolerance, hybrid optimization (a combination of least squares and backpropagation), and a rule base consisting of 27 fuzzy rules and training was performed over three iterations. To explore the impact of different membership functions on system performance, various FIS models were created using alternative MFs. ANFIS supports 11 built-in membership functions, and allows integration of custom MFs. Each modified FIS configuration then saved in a separate file in the working directory and subsequently incorporated into a Genetic Algorithm (GA) for optimizing process parameters. **Figure 2(a)** shows the predicted output from the FIS with the actual training data. The blue circular markers represent the experimental training data, while the red stars indicate the FIS model output. A significant deviation between these two sets is clearly visible, highlighting that the model did not achieve a perfect fit. Figure **2(b)** depicts the training error progression of the ANFIS model over three epochs. The Y-axis represents the training error, while the X-axis denotes the number of **epochs**. This minimal and nearly constant error suggests that the chosen number of epochs was sufficient for learning the underlying patterns in the data without overfitting. **Figure 2(c**) illustrates the convergence behavior of the Genetic Algorithm (GA) used to optimize process parameters for minimum SWR.

While**, Figure 3** represent the Implication framework for Sugeno-fuzzy network.

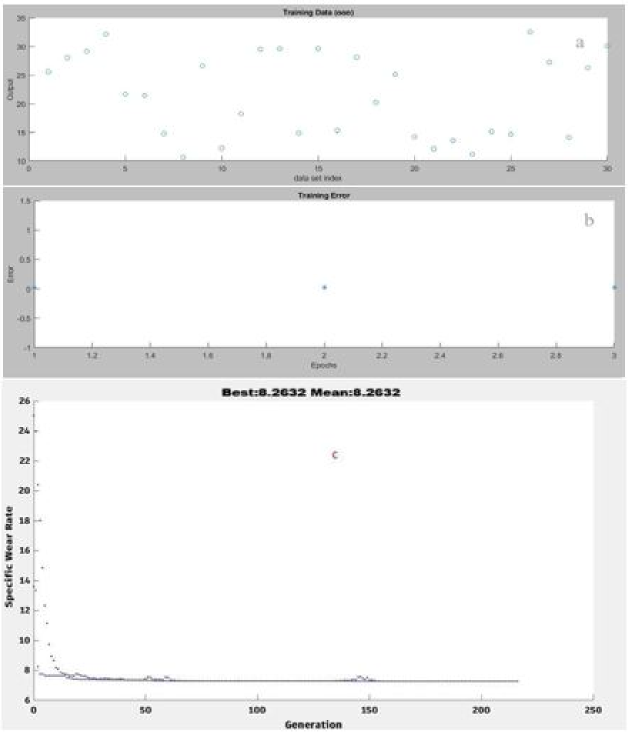

Figure 2: (a) Training error vs epochs plot, (b) training-FIS output demonstration, (c) assimilation results of GA-ANFS for tensile strength optimization

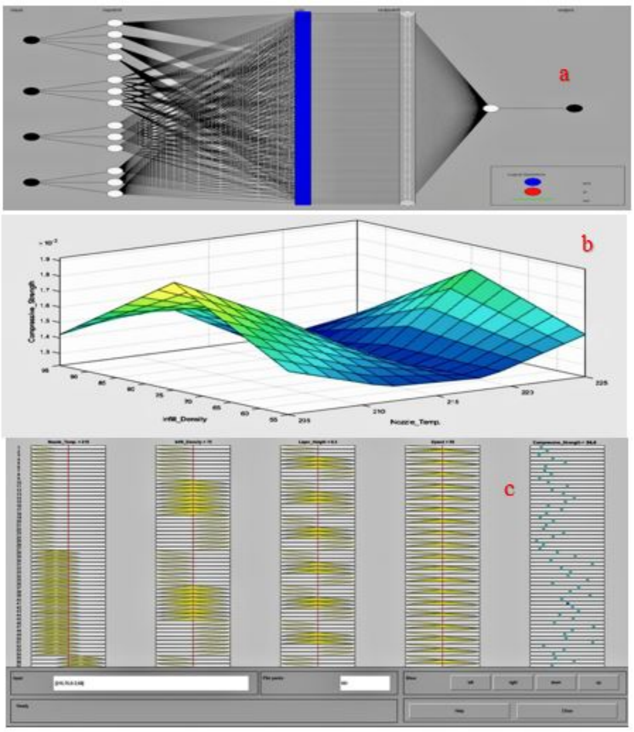

Figure 3: Implication framework for Sugeno-fuzzy: (a) representation of ANFIS construction, (b) surface plot of ANFIS response, (c) training schedule representation of ANFIS training system.

Table 5 presents the comparative analysis of various ANFIS models configured with different types of membership functions (MFs), optimized using GA. Each model was trained using the Grid Partitioning method and the Hybrid learning algorithm**,** with a consistent training error of

0.086 across all configurations during Epoch 3. Among the various membership functions, the trimf-linear ANFIS model demonstrated superior performance in predicting the SWR. Achieved SWR value of 8.26 (mm3 /Nm)(10^{-4}) with optimized parameters: Nozzle Temperature = 210°C**,** Infill Density = 75%**,** Layer Height = 0.3 mm and Speed = 40 mm/s**.** Gauss2mf (Gaussian Membership Function - Type 2) achieved a SWR of 8.27 (mm3 /Nm)(10^{-4}), very close to trimf, demonstrated high predictive capability with smooth, differentiable MFs.

Table 5: Different used ANFIS MFs and GA obtained optimize results

Sr. No	MF Type	Epoch 3: error	Method adopted to generate FIS	Train FIS Method	Optimized GA Value				SWR (Best)	SWR (Mean)
					Nozzle Temp.	Infill Density	Layer Height	Speed		
1	Linear gauss2mf	0.786	Grid-Partition	Hybrid	210	60	0.3	40	8.27	8.27
2	Linear trimf	0.786	Grid-Partition	Hybrid	210	75	0.3	40	8.26	8.26
3	Linear pimf	0.786	Grid-Partition	Hybrid	215	95	0.35	70	10.25	10.25
4	Linear dsigmf	0.786	Grid-Partition	Hybrid	215	95	0.2	50	10.21	10.21

3.2 Validation of Wear Resistance Predictions

Table 6 compile the comparative analysis to evaluate the effectiveness of an optimization technique (GA-ANFIS) in reducing the Specific Wear Rate (SWR) of 3D-printed components. The table compares the specific wear rate optimization using two methods—pin on disc testing and a hybrid genetic algorithm-artificial neural network (GA-ANFIS) approach—based on input factors: temperature (℃), infill density (%), speed (mm/s), and layer height (mm). It includes predicted SWR (in 10^{-4} mm^3/nm), experimental SWR (in 10^{-4} mm^3/nm), and percentage accuracy. The best experimental sample was fabricated under conventional conditions using a nozzle temperature of 220 °C**,** 65% infill density**,** 0.25 mm layer height**,** and a print speed of 60 mm/s**,** which resulted in an experimental SWR of 11.03 × 10^{-4} mm^3/Nm**.** The GA-ANFIS optimized settings—210 °C nozzle temperature, 75% infill density**,** 0.30 mm layer height, and 40 mm/s print speed—produced a significantly reduced SWR of 8.26 × 10^{-4} mm^3/Nm, amounting to a 25.12% reduction in wear rate.

The results highlight the effectiveness of GA-ANFIS in identifying optimal process parameters to enhance the tribological performance of 3D-printed parts. These findings are particularly valuable for applications where component durability and wear resistance are critical.

Table 6: Detailed output results obtained via different optimization tools

Sr. No	Optimization Tool	Optimized input factors				Predicted SWR (mm^3/Nm)(10^{-4})	Experimental SWR (mm^3/Nm)(10^{-4})	Reduction in SWR (%)
		Temperature (°C)	Infill Density (%)	Layer Height (mm)	Speed (mm/s)			
1	Pin on Disc-testing	220	65	0.25	60	11.03	11.03	---------
2	GA-ANFIS	210	75	0.3	40	8.26	8.26	**25.12%**

4. Conclusions

1. This study comprehensively investigated the wear characteristics of FDM-fabricated PLA specimens by optimizing key process parameters—nozzle temperature, infill density, layer height and printing speed using a hybrid artificial intelligence The combined use of Genetic Algorithm (GA), Adaptive Neuro-Fuzzy Inference System (ANFIS)**,** demonstrated high predictive accuracy and effective minimization of the specific wear rate. The principal findings are The integration of GA and ANFIS techniques proved highly effective in refining FDM process parameters, leading to substantial enhancements in tribological performance. The optimized configuration achieved a minimal specific wear rate of 8.26×10^{-4} mm^3/Nm, with reduction in SWR by 25.12 %, experimental validation results yielding an excellent prediction accuracy.

2. The results highlighted that nozzle temperature is the dominant factors affecting wear resistance, printing speed also demonstrated an appreciable influence. Layer height have comparatively smaller impacts on specific wear rate. The infill density variable shows the least impact.

3. The results affirm that the hybrid GA-ANFIS model significantly surpassed traditional optimization techniques in modeling complex, nonlinear interactions within the FDM process. This approach not only minimized the need for extensive experimental work but also provided a robust framework for achieving superior mechanical performance with reduced material and time expenditure.

These conclusions validate the application of advanced hybrid optimization techniques in addressing challenges associated with FDM processes, paving the way for improved material performance and broader industrial adoption.

Conflict of Interest

The authors reported no potential conflict of interest.

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Data Availability Statements

All data generated or analyzed during this study are provided in the manuscript.

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