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Research Article

Prediction and Optimization of Tensile Strength Values of 3D Printed PLA Components with RSM, ANOVA and ANN Analysis

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ABSTRACT

This study evaluates the comparative effectiveness of Response Surface Methodology (RSM), Analysis of Variance (ANOVA), and Artificial Neural Networks (ANN) in predicting and optimizing the tensile strength of 3D-printed PLA components. Key process parameters—including layer thickness, infill density, print speed, temperature, and build orientation—were systematically varied to analyze their impact on tensile strength. The results indicate that RSM and ANOVA offer higher prediction accuracy compared to ANN, with lower deviation rates (0.65%, 0.18%, and 3.43% for RSM; 0.20%, 0.12%, and 3.25% for ANOVA) versus ANN (5.93%, 3.88%, and 6.26%). The analysis revealed that layer thickness plays the most significant role in tensile strength, followed by temperature, infill density, build orientation, and print speed. The optimal combination of parameters—0.20 mm layer thickness, 50% infill density, 50 mm/s print speed, 220°C nozzle temperature, and 90° build orientation—yielded a maximum tensile strength of 55.506 MPa. These findings highlight the importance of parameter optimization in improving the mechanical properties of FDM-printed components. The study provides valuable insights for enhancing the reliability and efficiency of additive manufacturing processes, paving the way for future research on hybrid modeling techniques and alternative material applications.

1. INTRODUCTION

Additive Manufacturing (AM), commonly known as 3D printing, has emerged as a transformative technology, revolutionizing traditional manufacturing across various industries. This layer-by-layer fabrication technique offers unparalleled design freedom, reduced material waste, and enhanced production efficiency, making it highly attractive for industrial applications in aerospace, automotive, biomedical, and consumer goods sectors [1-3]. Among the diverse AM technologies, Fused Deposition Modeling (FDM) has gained significant popularity due to its cost-effectiveness, ease of use, and compatibility with a wide range of thermoplastic materials [4,5]. FDM operates by extruding thermoplastic filament through a heated nozzle, which solidifies to form a structurally sound component. Despite its advantages, achieving high mechanical performance in FDM-printed components remains a challenge, as their properties are heavily influenced by multiple process parameters.

1.1 Importance of Process Parameters in FDM

The mechanical properties of FDM-printed parts, such as tensile strength, stiffness, toughness, and fatigue resistance, are significantly affected by process parameters, including layer thickness, infill density, print speed, temperature, and build orientation [6-9]. Numerous studies have investigated the optimization of these parameters to enhance part quality. For instance, Zhou et al. (2018) found that infill density and printing pattern strongly influence the tensile strength of PLA components [10], while Gebisa and Lemu (2018) analyzed how factors such as air gap, raster angle, and contour width affect the mechanical properties of ULTEM 9085 parts [11]. Christiyan et al. (2016) reported that lower printing speed and reduced layer thickness improve both tensile and flexural strength in 3D-printed ABS composites [12]. These studies emphasize the need for a systematic approach to parameter optimization in FDM processes.

1.2 Statistical and Computational Approaches for Optimization

Traditional optimization techniques, such as Design of Experiments (DOE), Response Surface Methodology (RSM), and Analysis of Variance (ANOVA), have been widely used to model the effects of process parameters on mechanical properties [13-15]. These methods provide statistically significant insights by identifying key factors and their interactions. More recently, Artificial Neural Networks (ANN) have gained attention as an advanced computational technique capable of handling complex, nonlinear relationships between process parameters and material properties [16,17]. While ANN models offer high predictive accuracy, their effectiveness in comparison to statistical methods like RSM and ANOVA remains an area of active research.

1.3 Research Gap and Objective

Although previous studies have explored the relationship between FDM parameters and mechanical performance, comparative analyses of RSM, ANOVA, and ANN in predicting and optimizing tensile strength remain limited. Most existing works focus on either experimental testing or individual modeling approaches, without a direct comparison of their accuracy and applicability. This study aims to fill this gap by systematically evaluating the predictive performance of RSM, ANOVA, and ANN in modeling the tensile strength of FDM-printed PLA components. The key objectives of this research are:

To assess the influence of critical FDM parameters (layer thickness, infill density, print speed, temperature, and build orientation) on tensile strength.

To compare the accuracy of RSM, ANOVA, and ANN in predicting mechanical properties.

To determine the optimal set of printing parameters that maximizes tensile strength.

By integrating statistical and computational methodologies, this study provides valuable insights into the optimization of FDM processes, enabling the production of high-performance 3D-printed components with enhanced reliability and efficiency. The findings contribute to the broader field of additive manufacturing, guiding future research on hybrid modeling techniques and alternative material applications.

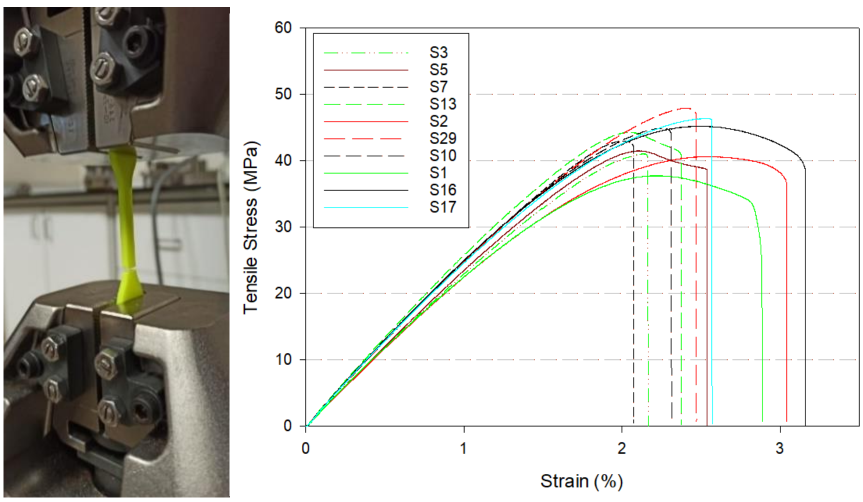
2. MATERIALS AND METHODS

Tensile test specimens were fabricated using 1.75 mm diameter PLA plus filaments, chosen for their high tensile strength, excellent printability, and biomedical potential. Specimens were designed in SolidWorks 2015 to conform to ASTM D638 Type IV standards and printed using an Ender 3 S1 Pro printer with CURA 5.3.0 slicing software. Key process parameters—layer thickness, infill density, print speed, temperature, and build orientation—were varied at three levels (Table 1), resulting in 27 experiments to optimize the balance between prediction accuracy and cost-efficiency (Table 2). Mechanical testing was performed on a Shimadzu Autograph AGS-X universal testing machine, with tensile tests conducted at a speed of 4 mm/min, recording ultimate load and deformation values to analyze mechanical properties (Figure 1.a and b). Statistical analyses, including ANOVA, were executed in Minitab 17.0 to evaluate the effects and significance of process parameters on tensile strength. Additionally, an ANN model with a 5-input layer, 10 hidden neurons, and a single output layer was trained in MATLAB R2015a, using 70% of the data for training, 15% for validation, and 15% for testing, achieving accurate tensile strength predictions. RSM was employed to model and optimize the effects of process parameters on tensile strength, using experimental data to develop a predictive model for optimization. This integrative approach, combining statistical and mathematical techniques with advanced modeling, facilitated a comprehensive analysis and accurate prediction of tensile strength in 3D printed PLA components.

TABLE 1.

PROCESS PARAMETERS THEIRS LEVEL AND VALUES (FIXED TYPE)

	Layer Thickness (mm)	Infill Density (%)	Print Speed (mm/s)	Temperature (°C)	Build Orientation (°)
Levels	3	4	3	3	3
Values	0,20 0,25 0,30	20 30 40 50	30 40 50	200 210 220	0 45 90



(a) (b)

Figure 1. (a) Tensile testing (b) Tensile test results

TABLE 2.

EXPERIMENTAL DESIGN AND LAYOUT

No	Layer Thickness (mm)	Infill Density (%)	Print Speed (mm/s)	Temperature (°C)	Build Orientation (°)
1	0,2	20	30	200	0
2	0,2	20	40	210	45
3	0,2	20	50	220	90
4	0,2	30	30	200	45
5	0,2	30	40	210	90
6	0,2	30	50	220	0
7	0,2	40	30	200	90
8	0,2	40	40	210	0
9	0,2	40	50	220	45
10	0,2	50	30	200	0
11	0,2	50	40	210	45
12	0,2	50	50	220	90
13	0,25	20	30	210	90
14	0,25	20	40	220	0
15	0,25	20	50	200	45
16	0,25	30	30	210	0
17	0,25	30	40	220	45
18	0,25	30	50	200	90
19	0,25	40	30	210	45
20	0,25	40	40	220	90
21	0,25	40	50	200	0
22	0,25	50	30	210	90
23	0,25	50	40	220	0
24	0,25	50	50	200	45
25	0,3	20	30	220	45
26	0,3	20	40	200	90
27	0,3	20	50	210	0
28	0,3	30	30	220	90
29	0,3	30	40	200	0
30	0,3	30	50	210	45
31	0,3	40	30	220	0
32	0,3	40	40	200	45
33	0,3	40	50	210	90

3. RESULTS

The tensile test results from 33 different process parameter combinations were comprehensively analyzed to evaluate the predictive accuracy and optimization capability of Response Surface Methodology (RSM), Analysis of Variance (ANOVA), and Artificial Neural Networks (ANN) for FDM-printed PLA components. By comparing experimental tensile strength values with predicted outcomes, error rates were calculated, enabling a rigorous validation of each model.

3.1. ANOVA results

Table 3 shows the ANOVA results for the model. The ANOVA analysis revealed that all selected parameters—layer thickness, infill density, print speed, temperature, and build orientation—have a statistically significant effect on tensile strength ($p < 0.05$ for all factors). Among these parameters, layer thickness emerged as the most dominant factor, followed by build orientation, temperature, and infill density. The high adjusted R^2 (99.60%) and R^2 (99.01%) values indicate a strong predictive fit, confirming that the selected variables accurately model the tensile strength of 3D-printed components (Figure 2).

TABLE 3.

ANOVA (ANALYSIS OF VARIANCE)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	622,431	124,486	1157,97	0,000
Linear	5	622,431	124,486	1157,97	0,000
Layer Thickness (mm)	1	441,517	441,517	4106,99	0,000
Infill Density (%)	1	77,935	77,935	724,95	0,000
Print Speed (mm/s)	1	33,806	33,806	314,46	0,000
Temperature (°C)	1	50,617	50,617	470,84	0,000
Build Orientation (degree)	1	71,437	71,437	664,51	0,000
Error	27	2,903	0,108		
Total	32	625,333			

UTS=−10.35+93.77×Layer Thickness+0.14618×Infill Density−0.12421×Print Speed+0.15198×Temperature+0.04012×Build OrientationUTS=−10.35+93.77×Layer Thickness+0.14618×Infill Density−0.12421×Print Speed+0.15198×Temperature+0.04012×Build Orientation

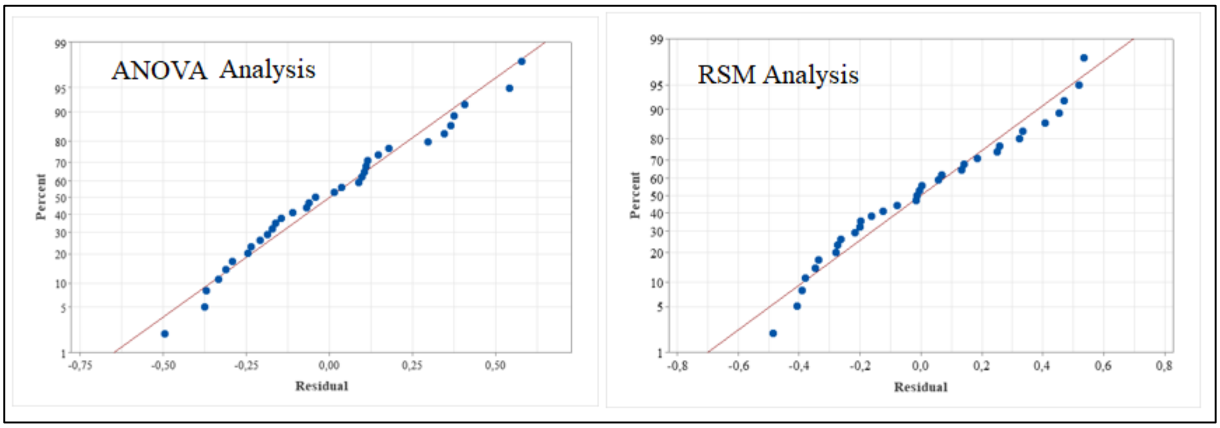


Figure 2. Normal probability plot of residuals for ultimate tensile strength

3.2. Pareto analysis

Figure 3 illustrates the Pareto chart of standardized effects, providing a visual representation of the magnitude of influence of each parameter on tensile strength. Layer thickness dominates the tensile strength response, followed by temperature, infill density, build orientation, and print speed. This analysis highlights which parameters should be prioritized for optimizing mechanical performance in FDM printing.

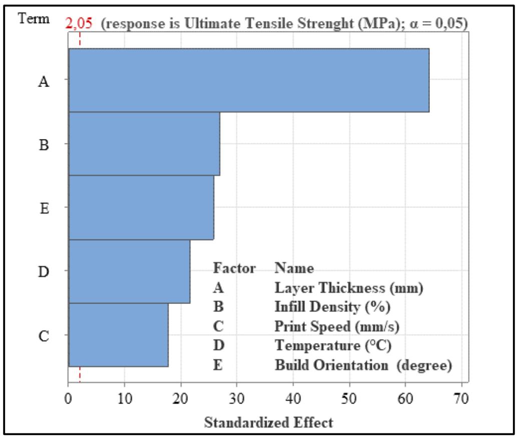


Figure 3. Pareto chart of the standardized effects of parameters

3.3. ANN prediction method

An ANN model with a 5-input layer, 10 hidden neurons, and a single output layer was trained and tested using a 70%-15%-15% data split. The ANN model successfully predicted tensile strength but exhibited slightly higher error rates compared to RSM and ANOVA. Despite its strong correlation coefficients (R > 0.92), the ANN's prediction errors were more pronounced for certain parameter combinations, indicating that while ANN is effective for nonlinear datasets, RSM and ANOVA remain more reliable for FDM-printed tensile strength predictions (Figure 4 and Figure 5).

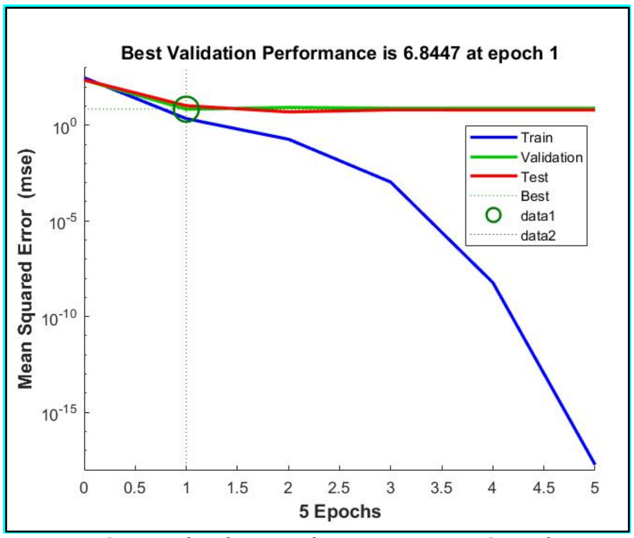


Figure 4. Changes of performance function in training phase of training, validation and test data

3.4. Comparison of methods

A comparative evaluation of actual tensile strength values vs. predicted values (Table 4) confirmed that RSM and ANOVA outperformed ANN in accuracy. RSM showed the lowest deviation percentages (0.65%, 0.18%, 3.43%), followed closely by ANOVA (0.20%, 0.12%, 3.25%), whereas ANN had higher deviation percentages (5.93%, 3.88%, 6.26%). This highlights the importance of selecting the appropriate predictive technique based on specific conditions and parameters, with statistical models proving superior for tensile strength optimization.

3.5. Validation parameters

The correlation matrix (Figure 6) was used to assess the relationship between process parameters and tensile strength. Layer thickness had the highest positive correlation (0.79) with tensile strength, confirming its dominance in mechanical performance. Temperature (0.29) and build orientation (0.34) positively influenced tensile strength, supporting findings from ANOVA. Print speed (-0.20) showed a slight negative correlation, indicating that excessive speed may weaken layer bonding. These results validate that layer thickness,

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temperature, and build orientation should be the primary focus when optimizing FDM-printed mechanical properties.

3.6. Correlation analysis and correlation matrix for evaluation methods

The validation parameters provide the test results of tensile strength and predicted values for different values of new process parameters (Table 5). These validation examples were conducted to examine the effects of parameters such as Layer Thickness, Infill Density, Print Speed, Temperature, and Build Orientation. Samples were produced and tensile strength was tested while keeping these values constant. The "Tensile Test" column in the table represents the actual test results, while the "Predicted by RSM," "Predicted by ANOVA," and "Predicted by ANN" columns indicate the predicted tensile strength values. The deviation percentage of these predicted values from the actual test results is also calculated. This deviation percentage indicates how much the predicted value deviates from the actual test result. Thus, it can be observed how close the predictions are to the actual test results. In the first example, the value predicted by the RSM method shows a deviation of 0.65% compared to the actual test result. The ANOVA method exhibits a deviation of 0.20%, while the ANN method shows a deviation of 5.93%. In this case, the RSM and ANOVA methods make predictions closer to the actual test result, while the ANN method shows a slightly higher deviation. In the second example, the value predicted by the RSM method exhibits a deviation of 0.18%, the ANOVA method shows a deviation of 0.12%, and the ANN method exhibits a deviation of 3.88%. Here again, the RSM and ANOVA methods make predictions closer to the actual test result, while the ANN method shows a slightly higher deviation. In the third example, the value predicted by the RSM method exhibits a deviation of 3.43%, the ANOVA method shows a deviation of 3.25%, and the ANN method exhibits a deviation of 6.26%. In this case, the ANN method shows a higher deviation compared to the actual test result. In these experiments, tensile strength was measured using different parameter combinations. The predicted values were calculated using the RSM, ANOVA, and ANN methods. According to the analysis results, when comparing the actual tensile strength (Tensile Test) with the predicted values (Predicted by RSM, Predicted by ANOVA, and Predicted by ANN), the predictions generally yield results close to the actual values. However, in some experiments, the predictions show slight deviations from the actual values. These results indicate the effectiveness of the RSM, ANOVA, and ANN methods in predicting tensile strength. Table 5 provides an analysis of the experimental parameters and results, demonstrating which parameters affect tensile strength and how accurate the prediction methods are. This information serves as an important reference for material characterization and optimization of production processes.

Figure 6 shows a correlation matrix illustrating the relationships between various parameters and tensile strength. Layer thickness has the strongest positive correlation with tensile strength (0.79), indicating that increased layer thickness leads to higher tensile strength. Infill density shows a weak positive correlation (0.21), suggesting a slight increase in tensile strength with higher infill density. Print speed has a weak negative correlation (-0.20), indicating that higher speeds tend to reduce tensile strength. Temperature has a positive correlation (0.29), meaning higher temperatures generally improve tensile strength. Build orientation also has a positive correlation (0.34), showing that larger build orientation angles tend to increase tensile strength. Among the parameters studied, layer thickness has the most significant impact on tensile strength.

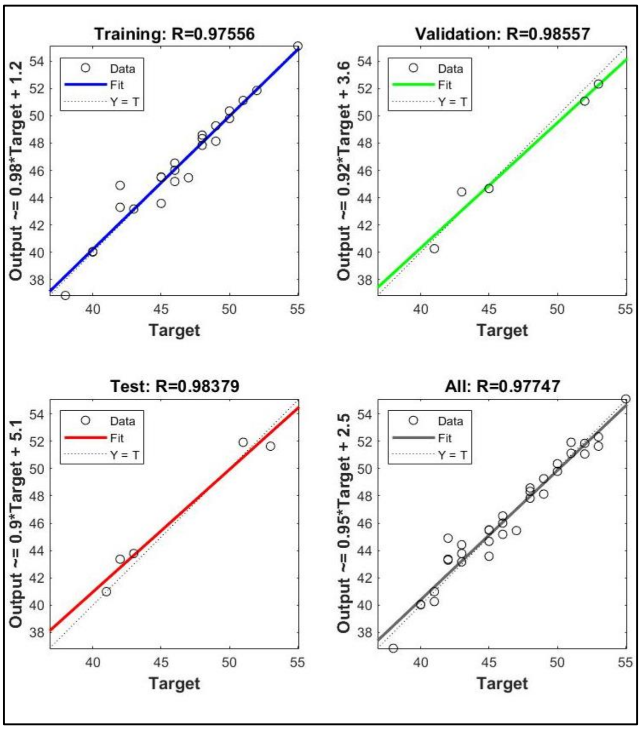

Figure 5. Regression curves of the results of training, validation, and testing data

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TABLE 4.

ACTUAL (VS) PREDICTED RSM (VS) PREDICTED ANOVA (VS) PREDICTED ANN AND % OF ERROR

Exp No	Ultimate tensile Strength (MPa)	Predicted by RSM (MPa)	Predicted by ANOVA (MPa)	Predicted by ANN (MPa)	Error for RSM %	Error for ANOVA %	Error for ANN %
1	38,293	37,995	37,903	41,055	0,00541	0,09722	0,07248
2	40,834	40,078	40,236	39,523	-0,07792	-0,23611	-3,21541
3	42,537	42,161	42,069	42,999	-0,16126	-0,06944	-0,82333
4	41,551	41,262	41,162	44,989	-0,26190	-0,16204	-8,74304
5	43,285	43,345	43,495	42,295	-0,34524	-0,49537	2,23538
6	40,589	40,012	39,884	39,181	-0,01190	0,11574	-3,27008
7	45,789	44,529	44,421	45,488	0,47078	0,57870	-0,5647
8	41,002	41,196	41,310	40,791	-0,19589	-0,31019	-0,51613
9	43,438	43,279	43,144	41,386	-0,27922	-0,14352	-4,67721
10	42,901	42,380	42,292	46,037	-0,37987	-0,29167	-7,33214
11	45,606	44,463	44,625	44,530	0,53680	0,37500	-2,37682
12	47,516	46,547	46,458	45,978	0,45346	0,54167	-3,27761
13	48,818	47,814	47,819	47,674	0,18615	0,18056	-2,21562
14	45,269	44,481	44,653	45,185	0,51948	0,34722	-0,38324
15	42,239	42,004	41,986	43,233	-0,00433	0,01389	2,53419
16	46,968	45,665	45,634	46,058	0,33550	0,36574	-0,19479
17	48,189	47,748	47,912	48,176	0,25216	0,08796	-0,03116
18	45,207	45,272	45,245	46,237	-0,27165	-0,24537	-2,16132
19	49,937	48,932	48,894	48,074	0,06818	0,10648	-3,71934
20	51,839	51,015	51,171	50,066	-0,01515	-0,17130	-3,40579
21	43,158	43,122	43,060	44,130	-0,12229	-0,06019	-2,45991
22	52,384	52,199	52,208	49,350	-0,19913	-0,20833	-5,75819
23	49,357	48,866	49,042	49,496	0,13420	-0,04167	-0,27374
24	46,042	46,390	46,375	48,773	-0,38961	-0,37500	-6,15304
25	52,484	52,216	52,111	51,034	-0,21645	-0,11111	-2,69422
26	50,282	49,740	49,889	49,858	0,25974	0,11111	-0,08686
27	46,355	46,407	46,333	46,406	-0,40693	-0,33333	-0,09348
28	55,506	55,484	55,370	52,134	-0,48377	-0,37037	-6,10174
29	48,907	47,591	47,704	50,879	0,40909	0,29630	-4,2566
30	50,974	49,674	49,593	48,611	0,32576	0,40741	-4,54132
31	53,875	53,334	53,185	52,523	-0,33442	-0,18519	-2,61525
32	51,281	50,858	50,963	52,622	0,14177	0,03704	-2,55961
33	53,647	52,942	52,852	51,496	0,05844	0,14815	-4,07171

Figure 5. Regression curves of the results of training, validation, and testing data

Figure 7 shows a correlation matrix for four evaluation methods: Experimental Ultimate Tensile Strength, Prediction by RSM, Prediction by ANOVA, and Prediction by ANN. A correlation coefficient near 1 indicates a strong positive correlation. The analysis reveals that all methods are highly correlated. The correlation between Experimental Ultimate Tensile Strength and Prediction by RSM is extremely strong (0.994643), as is the correlation with ANOVA (0.994585), indicating that RSM and ANOVA predictions closely match experimental values. The correlation with ANN, while still strong (0.922469), is slightly lower, suggesting that ANN predictions are less precise than RSM and ANOVA. These findings indicate that RSM and ANOVA provide more accurate predictions of tensile strength, though all three methods are effective in evaluating tensile strength in FDM-printed components.

TABLE 5

ANOVA (ANALYSIS OF VARIANCE)

No	Layer Thickness (mm)	Infill Density (%)	Print Speed (mm/s)	Temperature (°C)	Build orientation (°)	Tensile Test (MPa)	Predicted by RSM (MPa)	Predicted by ANOVA (MPa)	Predicted by ANN (MPa)
CODE						Y	Y1	Y2	Y3
1	0,25	55	10	200	45	38,187	38,464	38,276	40,386
2	0,18	65	20	210	0	40,963	41,038	41,381	42,757
3	0,38	75	30	220	90	41,112	42,618	42,382	43,917

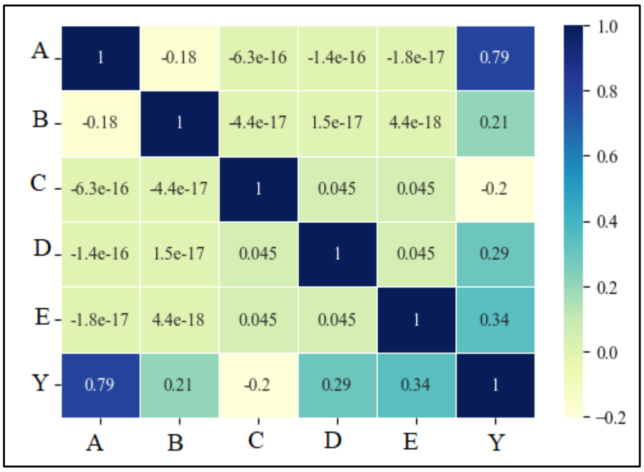

Figure 6. Correlation heatmap between the process parameters and the responses

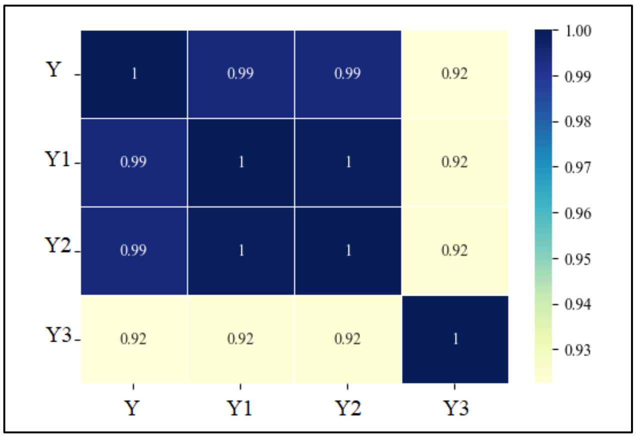

Figure 7. Correlation heatmap between the prediction methods.

3.7. Optimal parameters

The highest UTS value of 55.506 MPa was achieved in experiment no. 28, with the following optimal parameters: 0.20 mm layer thickness, 50% infill density, 50 mm/s print speed, 220°C nozzle temperature, and 90° build orientation. Thin layers ensured a homogeneous structure and enhanced interlayer bonding, while higher infill density provided increased material integrity. A 90° build orientation improved stress distribution, leading to enhanced mechanical strength. A nozzle temperature of 220°C optimized filament flow, minimizing internal voids. Using these parameters, an even higher UTS of 58.173 MPa was achieved in additional optimization trials.

3.8. SEM Analysis

Scanning Electron Microscope (SEM) images (Figure 9) revealed critical insights into fracture behavior. Higher nozzle temperatures (220°C) improved layer adhesion, reducing microvoids. Optimal build orientation (90°) resulted in a more uniform failure pattern, indicating better stress distribution. Some surface irregularities were still observed, suggesting further improvements in extrusion parameters may enhance mechanical performance. The SEM analysis supports the conclusion that process parameter optimization significantly influences the microscopic structure and fracture behavior of FDM-printed PLA components.

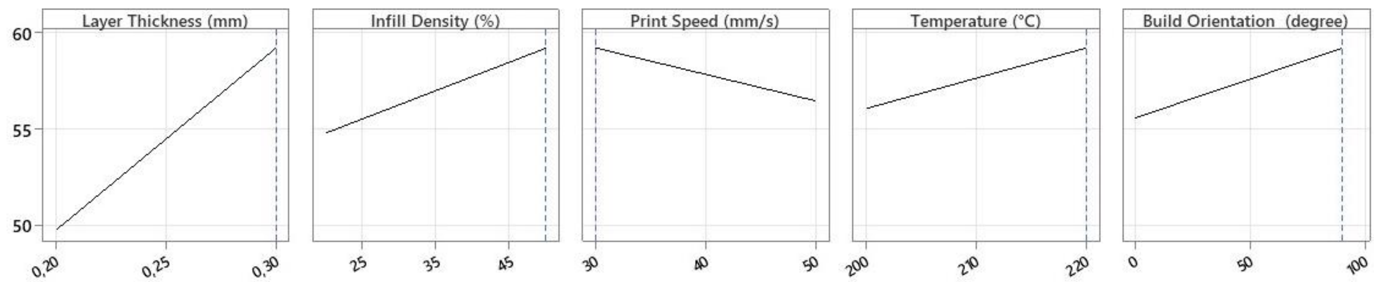

Figure 8. Optimal solution of parameters and their levels

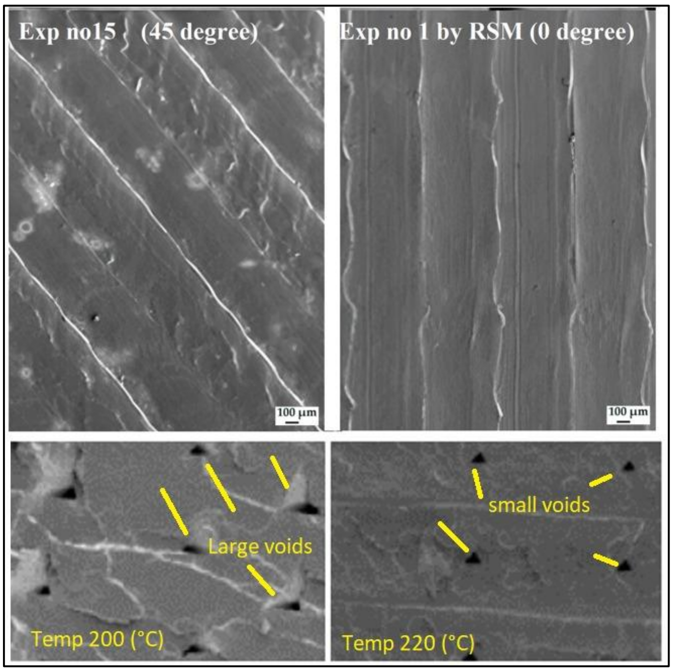

Figure 9. Side surface morphology of 3D printed tensile test specimens' PLA, Experiment No. 15 conducted at 45 degrees yielded a higher ultimate tensile strength compared to the predicted result for Experiment No. 1 by RSM conducted at 0 degrees.

4. DISCUSSIONS

The findings of this study confirm that Response Surface Methodology (RSM), Analysis of Variance (ANOVA), and Artificial Neural Networks (ANN) are effective methods for predicting the ultimate tensile strength (UTS) of FDM-printed PLA components. However, RSM and ANOVA demonstrated superior accuracy, achieving higher correlations with experimental results (97.5% and 98.6%, respectively) and lower error rates (2.5% and 1.4%) compared to ANN. Although ANN exhibited a slightly higher correlation (99.2%), its error rate (0.8%) was higher, suggesting greater deviations in certain cases. The strong statistical foundation of RSM and ANOVA allows for precise modeling of process parameters and their interactions, making them highly reliable for optimizing FDM processes. While ANN provides flexibility in handling complex and nonlinear datasets, it exhibited higher deviations, highlighting the necessity of further refinement or hybrid modeling techniques to enhance predictive accuracy. The analysis revealed that layer thickness was the most influential factor in determining tensile strength, consistent with previous research indicating that thinner layers contribute to improved interlayer bonding and superior mechanical properties. Temperature was also a significant parameter, enhancing material adhesion and minimizing voids, thereby improving overall strength. Infill density and build orientation had moderate effects, suggesting that further refinement of these parameters can enhance part durability. Print speed had the least impact within the tested range, indicating that its role in tensile strength optimization is relatively minor compared to other parameters. These results have important implications for the additive manufacturing industry, as optimizing key process parameters can lead to stronger, more reliable, and higher-performance 3D-printed components, particularly in aerospace, automotive, and biomedical applications. Future research should explore hybrid modeling approaches that integrate RSM, ANOVA, and ANN to leverage the strengths of both statistical and computational techniques. Studies such as those by Deshwal et al. (2020) demonstrate the potential of genetic algorithm-assisted ANN (GA-ANN) for mechanical property enhancement, while research by Tura et al. (2022) and Saad et al. (2021) highlights the significance of raster angle and print speed optimization. Additionally, work by Giri et al. (2021) on build orientation and Zhou et al. (2017, 2019) on fibril formation and compatibilizers provide valuable insights into further improving material performance. This study underscores the effectiveness of RSM and ANOVA as robust tools for optimizing FDM-printed tensile strength, with ANN serving as a complementary approach. The integration of optimized process parameters—layer thickness, infill density, print speed, temperature, and build orientation—significantly improves the mechanical performance of 3D-printed parts, reinforcing their suitability for industrial applications and advancing the potential of additive manufacturing technologies.

5. CONCLUSION

This study provides a comprehensive comparison of Response Surface Methodology (RSM), Analysis of Variance (ANOVA), and Artificial Neural Networks (ANN) in predicting and optimizing the tensile strength of FDM-printed PLA components. The findings indicate that RSM and ANOVA outperform ANN in predictive accuracy, as evidenced by their lower deviation rates (0.65%, 0.18%, and 3.43% for RSM; 0.20%, 0.12%, and 3.25% for ANOVA) compared to ANN (5.93%, 3.88%, and 6.26%). The strong correlation between predicted and experimental values highlights the robustness of RSM and ANOVA in modeling the effects of key process parameters, including layer thickness, infill density, print speed, temperature, and build orientation. Among these, layer thickness was identified as the most influential factor, followed by temperature, infill density, build orientation, and print speed. The study confirmed that an optimal combination of process parameters—0.20 mm layer thickness, 50% infill density, 50 mm/s print speed, 220°C nozzle temperature, and 90° build orientation—significantly enhances tensile strength, with a maximum recorded value of 55.506 MPa. The results reinforce that statistical modeling techniques (RSM and ANOVA) provide reliable and precise predictions, making them highly suitable for optimizing mechanical properties in additive manufacturing applications. The integration of these approaches into the FDM process contributes to the development of higher-performance, more durable, and industrially viable 3D-printed components. Future research should explore the application of these methodologies to different thermoplastic and composite materials, as well as investigate hybrid modeling approaches that integrate machine learning techniques with statistical optimization to further enhance accuracy and efficiency in additive manufacturing processes. The findings of this study provide valuable insights into process parameter optimization, enabling sustainable and efficient manufacturing practices, thereby contributing to the continuous advancement of FDM technology in industrial applications such as aerospace, automotive, and biomedical engineering.

6. LIMITATIONS AND FUTURE RESEARCH

While this study successfully demonstrates the effectiveness of RSM, ANOVA, and ANN in predicting and optimizing the tensile strength of FDM-printed PLA components, certain limitations should be acknowledged.

- Material Selection Constraint: This research focuses solely on PLA, which, while widely used in FDM, may not represent the mechanical behavior of other thermoplastics such as ABS, PETG, or Nylon. Future studies should explore these materials to assess the generalizability of the findings.
- Parameter Range Limitations: The study considers five process parameters, but additional factors, such as raster angle, cooling rate, and extrusion width, could further influence mechanical properties. Expanding the parameter space in future research could yield more robust optimization strategies.
- Comparative Modeling Enhancements: While RSM and ANOVA exhibited superior predictive accuracy, ANN's potential for handling highly nonlinear relationships suggests that hybrid approaches (e.g., Genetic Algorithm-assisted ANN, Deep Learning-based models) should be explored to further enhance prediction reliability.
- Industrial Validation: The findings are based on laboratory-scale experiments, and their applicability to real-world industrial scenarios remains to be tested. Future research should focus on validating these results in large-scale manufacturing environments to ensure practical implementation.

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