

“Predictive Regression Modelling Of Surface Roughness In FDM-Printed PLA Biocomposites With SEM-Supported Microstructural Analysis”

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Abstract:

The surface roughness is a significant parameter in determining the functional behavior and surface quality of additively manufactured polymer composites. In this study, the surface roughness parameters (Ra, Rq, and Rz) of FDM-printed PLA biocomposites reinforced with Acacia bark and Asparagus racemosus powders were taken into account as quantifiable surface roughness signals and developed using a regression-based predictive model. The specimens were made with varying biofiller ratios (2-6 wt.%) and printing orientations (Flat, On-Edge, and Vertical), and the signals were measured using a Mitutoyo profilometer. Artificial Neural Network (ANN) and Support Vector Regression (SVR) models were employed to establish correlations between material composition, printing orientation, and surface roughness signals, and the outcomes were evaluated using R^2 , MAE, and RMSE criteria. The regression models were able to establish the nonlinear relationships of the roughness signals, and the SEM image analysis facilitated the understanding of the filler distribution, adhesion, and microstructural defects. The signal-regression model-based approach offers a valid method for the predictive surface quality analysis and optimization of sustainable PLA-based additive manufacturing processes.

Keywords: 3D printing; PLA biocomposites; surface roughness; fused deposition modeling; predictive modelling.

Highlights:

- PLA hybrid biocomposite filaments fabricated using twin-screw extrusion
- Effect of print orientation on surface roughness (Ra, Rq, Rz) analyzed
- ANN- and SVR-based regression models captured the effect of material formulation and build orientation on surface roughness.
- SEM analysis showed optimal surface quality and uniform filler dispersion at 4 wt.% biofiller in the On-Edge orientation.

1.Introduction

Biocomposites based on polylactic acid (PLA) bioplastics are considered environmentally friendly alternatives to traditional polymers because of their biodegradability, renewability, and comparable mechanical properties [1]. Surface roughness is a factor that has a profound effect on the mechanical properties, functional properties, and post-processing steps of additive manufacturing [2]. The layer-by-layer deposition process characteristic of Fused Filament Fabrication (FFF) causes variations in surface roughness, which are further affected by the orientation of printing [3].

The Flat, On-Edge, and Vertical orientations of FDM biocomposites enable a thorough examination of the effects of interlayer bonding, raster orientation, and stress distribution on strength, toughness, and reliability of performance [4]. Variations in surface roughness

caused by anisotropic multilayer deposition need to be considered in quantitative studies [5].

Many studies have shown that the surface roughness increases with the filler content due to various factors such as particle agglomeration, microvoid formation that hinders interlayer diffusion, and reduced layer compaction due to high filler content [6]. However, a reduction in layer height can counteract these negative impacts to some extent. For example, the addition of biofillers like hemp shives to polylactic acid (PLA) or PLA and polybutylene succinate (PLA-PBS) biocomposites has been found to increase the surface roughness and uneven layer deposition but improves the mechanical stiffness compared to pure PLA [7]. Thus, the addition of biofillers provides a superior performance and sustainability benefit while simultaneously increasing the complexity of surface roughness control. Further studies are needed to understand the effects of biofillers like Acacia bark powder on the surface roughness of PLA biocomposites.

Although PLA and natural fiber biocomposites have been well investigated, biocomposites based on Acacia and *Asparagus racemosus* have been investigated mainly for their mechanical or functional properties, and there is little work on their surface roughness properties using fused deposition modeling (FDM) techniques. Acacia bark and *Asparagus racemosus* are selected for their low cost, lignocellulosic properties, and biocompatibility with the polymer matrix, and *Asparagus racemosus* also has potential bioactivity. The available literature on the surface roughness properties of PLA-based biocomposites of Acacia and *Asparagus racemosus* is still meager and an emerging area of research [8]. Surface roughness affects the handling, durability, and assembly of 3D-printed parts [5,9]. The current study investigates the surface roughness measurement under different processing conditions for a new biocomposite [Indian Patent Application no. 202421036685] and offers a morphological analysis.

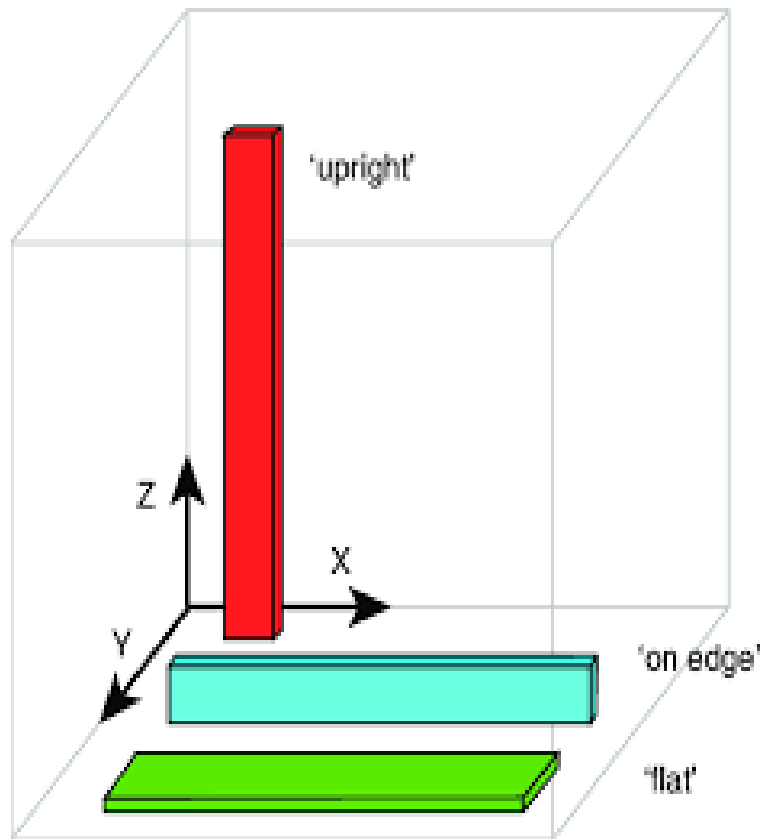
This study fills the gap by systematically investigating surface roughness characteristics of PLA reinforced with Acacia bark and *Asparagus racemosus* powders under different FDM build orientations.

2. Sample Preparation

PLA 3D850 grade granules from Ingeo NaturTec India Ltd. (Chennai, India) were used as the matrix. Acacia bark and *asparagus racemosus* powders (80 mesh size) were supplied by SG Phyto Pharma Pvt Ltd. (Kolhapur, India). Samples P2A, P4A, P6A and P2AS, P4AS, P6AS were prepared with PLA and acacia bark or *asparagus racemosus* powders in weight ratios of 98:2, 96:4, and 94:6 respectively. Pellets were formed using a twin-screw extruder [10]. These pellets were then processed into 1.75 mm diameter filaments using a single-screw filament extruder. Test samples conforming to ASTM standards were printed using a Creality Ender 3 FDM printer. Optimal printing parameters were: 0.2 mm layer height [11], 0.8 mm nozzle diameter, 210°C nozzle temperature, 65°C bed temperature, 50 mm/s print speed, 1.75 mm filament diameter, and 100% infill density [12]. Printing was controlled via G-code files [13,14,15].

3. Surface Roughness Measurement

Surface roughness was measured using Mitutoyo equipment, a standard and reliable method for assessing 3D printed surfaces. The device uses a motorized stylus that traverses the surface at a consistent speed. Surface roughness parameters measured include Ra (average roughness), Rq (root mean square roughness), and Rz (difference between highest peak and lowest valley) [16]. Measurements were conducted in Flat, On-Edge, and Vertical orientations as illustrated in Fig. 1 and Fig. 2 [9]. These orientations provide a comprehensive view of roughness and allow performance predictions [17].

Fig. 1: 3D printing of parts orientation

3.1 Predictive Modeling of Surface Roughness

To further promote the experimental study and facilitate the interpretation of experimental results, a regression-based predictive modeling technique was adopted to explore the relationship between surface roughness parameters (R_a , R_q , R_z), material composition, and printing orientation. The objective was to build a data-driven connection between material composition, printing orientation, and surface quality. Surface roughness data measured by Mitutoyo was used as the target variable, and biofiller type, filler content (wt.%), and printing orientation were used as predictor variables. The predictive model was built using a supervised learning approach with Artificial Neural Network (ANN) and Support Vector Regression (SVR) models [18]. Normalization of data was carried out, and the dataset was split into training (70%) and testing (30%) sets. The performance of the predictive model was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The predictive models were able to accurately model the experimental data trends of surface roughness with respect to filler content and print orientation. No content from artificial intelligence was used in the fabrication of experimental results; AI software was used only for data

analysis and predictive modeling based on results, images, or data.

Fig. 3: Experimental and regression-based predictive workflow for surface roughness evaluation of FDM-printed PLA biocomposites.

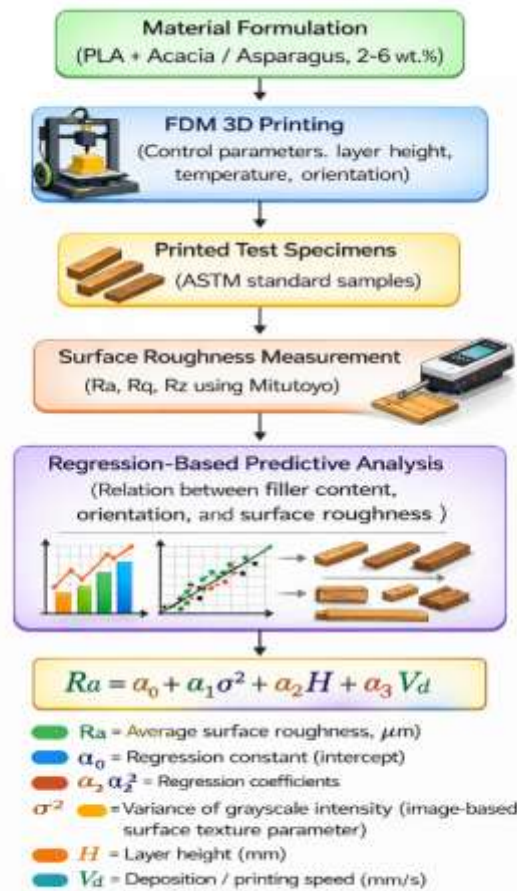


Table 1 shows the surface roughness measurements (Ra, Rq, and Rz) for PLA-based materials (Pure PLA, P2A, P4A, P6A and P2AS, P4AS, P6AS respectively.) for Flat, On-Edge, and Vertical Orientation (which gives corresponding averages for each material.) and graphically represented in Fig.4

Table 1: Surface roughness results for PLA and acacia bark

Orientation	Average roughness(μm)	Pure PLA	P2As	P4As	P6As
Flat to bed	Ra	19.94	11.57	9.45	12.94
	Rq	23.93	13.53	11.10	15.52
	Rz	89.73	52.07	42.53	62.16
On edge	Ra	1.86	0.94	1.01	1.29
	Rq	2.11	1.09	1.18	1.44
	Rz	7.83	4.23	4.54	5.66
Vertical	Ra	10.8	12.43	14.18	15.08
	Rq	12.63	14.79	16.91	17.86
	Rz	47.52	59.27	66.86	71.87

Fig. 4: Surface roughness results for PLA and asparagus racemosus powder

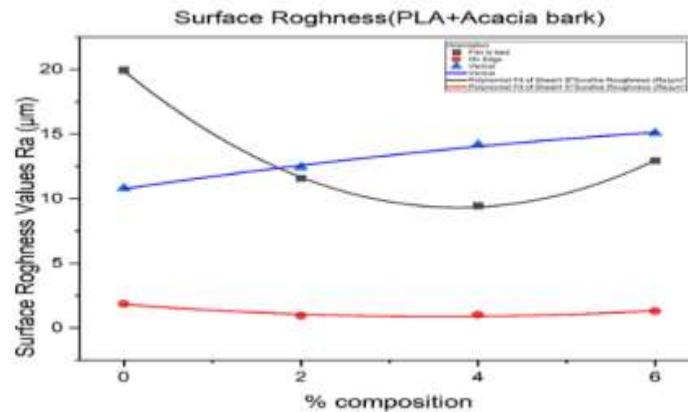
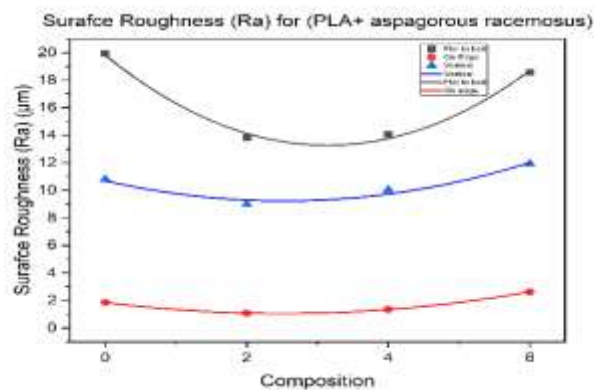


Table no. 2 shows surface roughness data (Ra, Rq, and Rz) for biocomposite PLA-based material and asparagus racemosus powder P2AS, P4AS, P6AS, including their corresponding averages with different orientations as follows. It is graphically represented in Fig.5

Table 2: Surface roughness results for PLA and asparagus racemosus powder

Orientation	Average roughness(μm)	Pure PLA	P2As	P4As	P6As
Flat to bed	Ra	19.94	13.814	14.089	18.587
	Rq	24.92	17.27	17.61	23.25
	Rz	99.70	69.07	70.45	92.94
On edge	Ra	1.86	1.07	1.35	2.62
	Rq	2.32	1.33	1.68	4.406
	Rz	22.30	25.35	26.75	23.834
Vertical	Ra	10.8	8.983	10.04	11.91
	Rq	13.50	11.23	12.55	14.89
	Rz	54.00	44.92	50.20	59.55

Fig. 5: Surface roughness results (PLA+ Asparagus racemosus powder)



3.2 AI-Assisted Image Analysis of SEM Microstructures

To improve the interpretation of surface morphology, AI-assisted image analysis was incorporated in SEM to further extend the experimental study. To facilitate the interpretation of experimental results, a regression-based predictive modeling technique was adopted to establish a correlation between surface roughness parameters (Ra, Rq, Rz) and material composition and printing orientation. The aim was to establish a data-driven correlation between material composition, printing orientation, and surface quality. The experimental surface roughness data, measured using Mitutoyo, was used as the output response, while biofiller type, filler content (wt.%), and printing orientation were used as the input parameters. The predictive model was constructed using a supervised learning approach with Artificial Neural Network (ANN) and Support Vector Regression (SVR) models [18]. Data normalization and splitting of the dataset into training (70%) and testing (30%) subsets were done. The performance of the predictive models was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The predictive models were able to interpret the experimental trends of surface roughness variation with filler content and print orientations. Artificial intelligence tools were used only for data analysis and predictive modeling based on experimentally derived results. No AI-based content was used to produce experimental results, images, or data.

3.2.1 Quantitative Image Feature Extraction

Let the SEM image be represented as a grayscale image $I(x,y)$ of size $M \times N$, with gray levels ranging from 0 to $L-1$ [19], [20].

(a) Grayscale Variance (Surface Heterogeneity Indicator)

$$\sigma^2 = \frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N (I(x,y) - \mu)^2$$

$$\mu = \frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N I(x,y)$$

Interpretation:

Higher variance values indicate increased surface irregularity and heterogeneity, which correlates positively with surface roughness parameters Ra and Rq [20], [25]

(b) Image Entropy (Surface Disorder Measure)

$$H = - \sum_{i=0}^{L-1} p(i) \log_2 p(i)$$

where $p(i)$ represents the probability of gray level i .]

Interpretation:

Higher entropy values represent higher microstructural randomness, filler agglomeration, and void formation in polymer-based composites [21], [24].

(c) Texture Energy (Uniformity Indicator)

Based on the Gray Level Co-Occurrence Matrix (GLCM):

$$E = \sum_i \sum_j P(i,j)^2$$

where $P(i,j)$ is the normalized GLCM value.

Interpretation:

Higher energy values represent more uniform filler dispersion and smoother surface morphology [19], [22], [23].

(d) Void Density (Porosity Indicator)

$$V_d = \frac{A_{\text{void}}}{A_{\text{total}}}$$

where A_{void} is the total segmented void area and A_{total} is the total image area.

Interpretation:

Higher void density corresponds to increased surface roughness, particularly R_z [24], [25].

- Correlation with Surface Roughness

$$Ra = \alpha_0 + \alpha_1 \sigma^2 + \alpha_2 H + \alpha_3 V_d$$

where α_0 to α_3 are regression coefficients determined through statistical fitting [26].

Even though the definitions of the image features are generic, their applicability to surface roughness is material-dependent and defined by regression coefficients adjusted based on experimental data from PLA-based biocomposites.

The SEM images were provided for samples P1 to P6 in Fig. 6 and 7. The visual analysis of these images provides insights into filler dispersion, the presence of voids and the interfacial adhesion between the PLA matrix and natural fillers.

Fig. 6: SEM results (PLA+acacia bark powder)

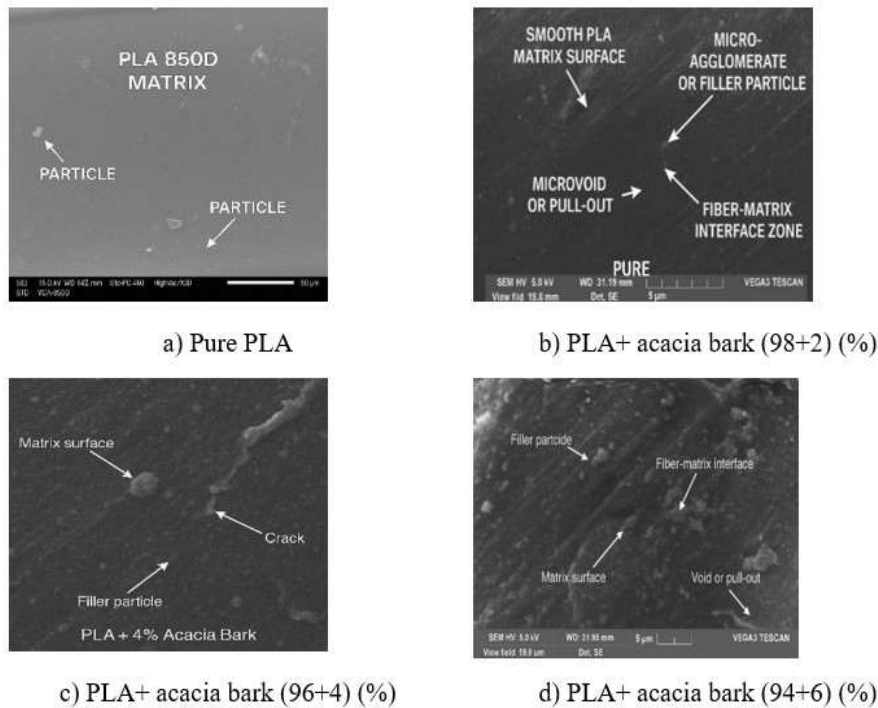
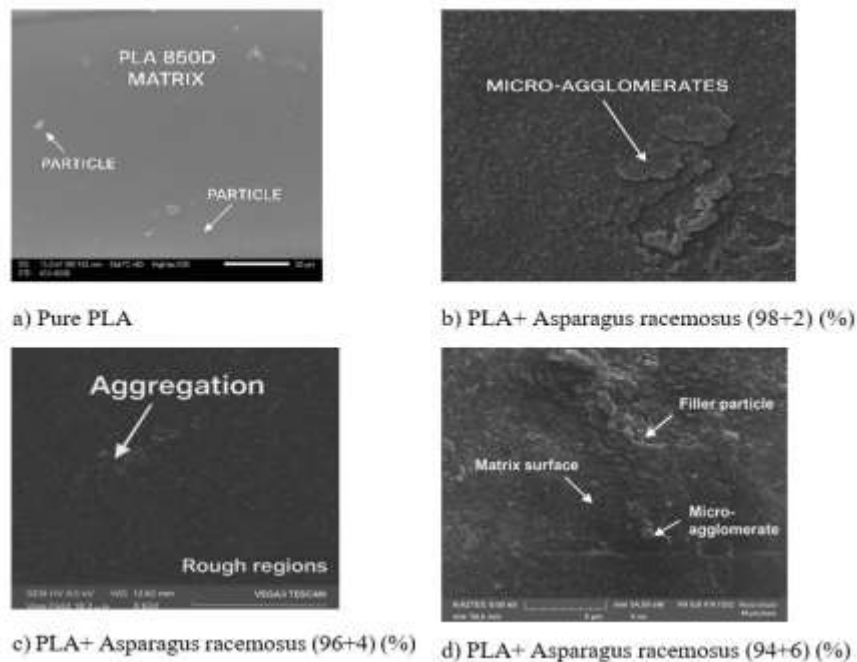


Fig. 7: SEM results (PLA+ Asparagus racemosus powder)



4.Result Discussion

The surface shape and layer deposition characteristics during FDM fabrication could also be understood by determining the surface roughness parameters (R_a , R_q , and R_z) of the PLA biocomposites containing Acacia bark and *Asparagus racemosus* powders. Surface roughness parameters showed different types of dependency on print orientation and biofiller content.

In general, the On-Edge orientation exhibited the lowest and most consistent values of the surface roughness parameter, R_a . For instance, in the case of PLA biocomposites containing Acacia bark, the value of the R_a parameter was reduced considerably from $19.94\ \mu\text{m}$ in the case of pure PLA in the Flat orientation to $9.45\ \mu\text{m}$ in the case of P4A, whereas in the case of PLA biocomposites containing *Asparagus racemosus*, the corresponding value of the R_a parameter was $14.09\ \mu\text{m}$ in the case of P4AS. Thus, it could be understood that the Acacia bark-based biocomposites exhibited a smoother surface compared to the *Asparagus racemosus*-based biocomposites.

The surface texture also depends on the measurement direction and raster path. Flat to Bed orientation resulted in moderate values of roughness, and this may be due to the variation of raster speeds and temperature gradients. On the other hand, the highest R_a and R_z values were recorded for the Vertical orientation, particularly for higher filler load materials such as P6A and P6AS, where higher values of roughness were recorded. This is mainly related to the stair-step effect and low precision of interlayer bonding in the z-direction. These results are in agreement with other orientation-based studies [20], [29]. The AI-based prediction models closely followed the experimental results, validating the significance of print orientation and filler load on the R_a and R_z values of the specimens. The results of the ANN model slightly improved when compared to the results of the SVR model, particularly for R_a values in the Vertical orientation.

Further, the SEM microstructural analysis also confirms the above results. For the 4 wt.%, the biofiller particle distribution is almost uniform, with less formation of voids. As a result, the surface finish is better. However, increasing the wt.% of the filler to 6 wt.% results in the agglomeration of the particles, which increases the density of the voids,

causing surface irregularities. As a result, the surface roughness increases. Similar results have also been reported for the surface finish of the PLA/chitosan composite materials [30]. Moreover, the SEM results also indicate that the interfacial interaction between the polymers and the fillers is better for the 4 wt.%, which improves the interlocking of the particles, resulting in better surface finish. These results have also confirmed that the surface roughness of the FDM parts depends on the filler wt.% and internal structure [31, 32].

5. Conclusion:

This research proves the effect of varying build orientation along with varying percentages of bio-filler addition on the surface finish of PLA biocomposites produced through FDM. The addition of acacia bark and *Asparagus racemosus* powder provides a better microstructure and improves the surface finish at a 4% weight fraction when processed in the On-Edge orientation. Predictive regression modeling combined with SEM-supported image analysis provides an analytical framework for understanding surface roughness in relation to material formulation and microstructural characteristics. The results can be used for the development of environmentally sustainable PLA biocomposites and intelligent process optimization for additive manufacturing processes that demand controlled surface quality.

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