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Statistical Modeling and Optimization of Surface Roughness for PLA and PLA/Wood FDM Fabricated Items

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A B S T R A C T

During last decades fused deposition modeling (FDM) has emerged as a widely applied additive manufacturing technology for numerous engineering applications. The present work investigates the effects of two independent variables during FDM fabrication of conventional polylactic acid (PLA) and organic biocompatible composite material with coconut flour (PLA/w) on mean surface roughness (Ra) of fabricated items. The parameter optimization adopts a customized response surface (RSM) design, based on an L9 orthogonal array. The independent variables investigated, were nozzle temperature, NT (oC) and layer thickness, LT (mm) whilst regression models for Ra concerning both materials; PLA and PLA/W, were developed to correlate the independent parameters. Proper analysis was preceded, based on response surface analysis through contour plots. The regression models were further utilized as objective functions to minimize Ra for both filament materials with the use of grey-wolf optimization genetic algorithm (GWO).

1. INTRODUCTION

Globalization and keener competition among manufacturing industries has imposed the necessity to produce high-quality and low-cost products at the same time. Such volatile and competitive processing scenarios found in industry, have already drawn the interest of researchers to develop and deploy automation technologies in almost all branches of manufacturing engineering. To develop new products, it is mandatory to produce prototypes from solid models and examine their properties. This can be done through additive manufacturing (AM) technologies. AM employs operations where physical models are built by selectively adding material in the form of thin cross-sectional layers.

Currently, additive manufacturing technologies are applied not only on communicating ideas and inspecting several design aspects but also on large-scale production of medical, biomedical and aeronautical models. Some technologies available for supporting additive manufacturing are fused deposition modeling (FDM); selective laser sintering (SLS); stereolithography (SL) and laminated object manufacturing (LOM) [1].

PLA mixed with wood flours (PLA/W) is an organic biocompatible composite for which research efforts have been made to examine mechanical properties with regard to material synthesis and FDM parameters [2-8].

This paper studies the effect of nozzle temperature and layer thickness as crucial FDM parameters, on mean surface roughness Ra (μm) for PLA and PLA/w tensile specimens, designed as per the ASTM D638-10 (2015) standard; see also [9]. A custom response surface design based on an L9 orthogonal array was set to print the tensile specimens and statistically analyze mean surface roughness Ra (μm) results with regard to the continuous experimental domain. This enables the generation of higher order model development for regression and prediction. Finally a grey-wolf optimization algorithm (GWO) was applied using the regression models referring to PLA and PLA/w materials for minimizing Ra (μm).

2. EXPERIMENTAL

Test specimens were fabricated according to ASTM D638 (2015) standard by applying 3D-printing technology. All 9 specimens were fabricated having 4 mm thickness and exported in *.STL format in *Solidworks*®. A *Craftbot*® *Plus* 3D printer equipped with a 250 x 200 x 200 mm table was used for fabricating the specimens (Fig. 1).

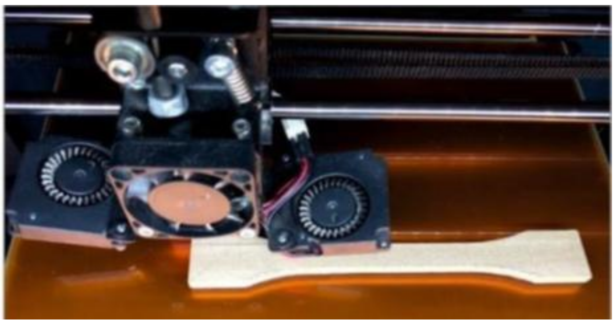


Fig. 1. 3D-printed test specimen.

This work examines the influence of two FDM process input variables on mean surface roughness, Ra (μm) of PLA and PLA/w experimental items with standard shape for tensile testing reported previously in [9]. The FDM variables read as follows:

- Nozzle temperature (NT/^{o}C): It refers to the amount of heat generated by the extruder's nozzle (also known as extruder temperature or extrusion temperature).
- Layer thickness (LT/mm): It defines the thickness of a layer (layer height) deposited by the extruder's nozzle and is related to nozzle type.

The selection for the levels of FDM parameters was realized with reference to work material properties and technical recommendations accompanying the equipment (3D printer and related software). Other process-related parameters for FDM were kept constant in order to focus only on nozzle temperature and layer thickness for the time being. Such parameters were bed temperature (60^{o}C), printing speed (40 mm/sec), raster angle (45deg.), number of top and bottom layers (1 layer) and infill density (100 %).

The commercially available material *NEEMA3D™ WOOD PLUS* consisting of 30% wooden fibers of coconut and additives and 70% pure PLA polymer was examined and compared to pure PLA. Filament diameter was 1.75 mm while specific gravity was 1.2 g/cc (ASTM D1505). Melting point for this material is between 140 and 150^{o}C. Nozzle diameter was equal to 0.4 mm. Table 1 summarizes the FDM inputs as well as their three levels; "low", "mid" and "high".

Table 1. Design of experiments.

Parameters	Levels		
Nozzle temperature, NT (^{o}C)	180	200	220
Layer thickness, LT (mm)	0.1	0.2	0.3

Roughness measurements were performed using a *DIAVITE*® profilometer (4 mm sample length, ±0.001 μm accuracy). A special fixture device was prepared to properly clamp the test specimens. All specimens were measured five times and the average result was finally considered as the response output for each of the specimens examined. Table 2 summarizes the series of experimental runs accompanied with their corresponding indicative results of mean surface roughness Ra (μm) for both PLA and PLA/w materials. Note that results for surface roughness is the average value of five independent roughness measurements.

Table 2. Series of experiments and corresponding results for Ra (μm).

No.	NT(°C)	LT(mm)	Ra (μm) PLA	Ra (μm) PLA/w
1	180	0.1	1.89	9.86
2	180	0.2	11.20	9.48
3	180	0.3	15.25	9.90
4	200	0.1	6.82	9.75
5	200	0.2	12.30	8.72
6	200	0.3	11.59	10.46
7	220	0.1	6.26	9.89
8	220	0.2	10.61	8.57
9	220	0.3	11.08	10.16

3. EXPERIMENTAL RESULTS AND STATISTICAL ANALYSIS

From the results presented in Table 2 it is evident that Ra is strongly affected by the inclusion of wooden flour in the pure PLA material since it is dramatically increased in the composite material. Such a result indicates that PLA/w material should not be used in applications where smooth surfaces are needed. Moreover it is observed that the Ra variation in the case of PLA/w is constrained to a narrower region, i.e., from 8.57 μm to 10.46 μm as compared to the range from 1.89 μm to 12.30 μm referring to pure PLA.

For PLA the lowest value of 1.89 μm is achieved for nozzle temperature (NT) equal to 180°C and layer thickness (LT) equal to 0.1 mm. (1st experiment, Table 2). In the case of PLA/w material its lowest Ra value equal to 8.57 μm is observed for nozzle temperature (NT) equal to 220°C and layer thickness LT equal to 0.2 mm. (8th experiment, Table 2).

Experimental results of Ra for PLA and PLA/w have been investigated through analysis of variance (ANOVA) by selecting the full quadratic regression model. ANOVA decomposes the error per each variable on the overall error when a mathematical model is fitted on the results. MINITAB® R17 statistical analysis environment was used for interpreting the results in terms of percentage contribution, significance checking and model fitting. According to ANOVA for Ra of PLA material it was found that square terms of NT and LT parameters hold 69.03% of total contribution, square terms hold 11.42% of total contribution and 2-way interactions hold 14.30%. In the case of PLA/w linear terms hold 7.61% of total contribution, square terms hold 74.17% and finally 2-way interactions hold 0.40% of the overall contribution. Fig. 2 illustrates the plots for main effects of NT and LT parameters on Ra response for PLA and PLA/w filaments.

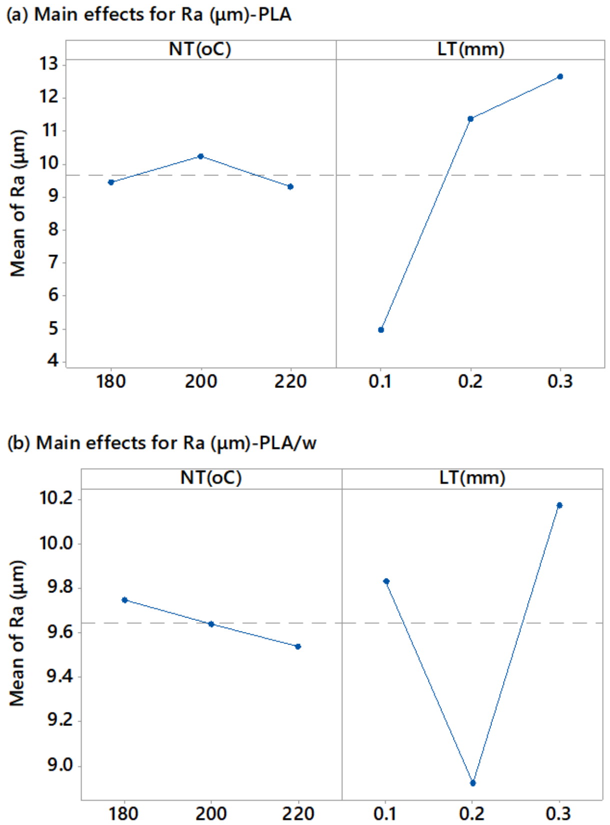


Fig. 2. Main effects plots of mean surface roughness Ra: (a) PLA, (b) PLA/w.

To further examine interaction effects on Ra for both filament materials contour plots were constructed to investigate the regions under interest where Ra response is minimized according to a set of recommended parameter settings for NT and LT. Fig.3 illustrates the interaction effects corresponding to the process-related independent parameters, LT and NT in the form of contour plots. Fig.3a refers to the interaction effect among LT and NT on Ra for PLA material. According to the graphical area where advantageous results are obtained for minimizing Ra (i.e. dark blue color) LT should be set to 0.1 mm provided that NT is kept low and equal to 180°C. Fig.3b shows the NTxLT effect on Ra for PLA/w. According to the graphical area where advantageous results are obtained for minimizing Ra (i.e. pale green color) roughness may be reduced when nozzle temperature NT (°C) is increased from 200°C and above, provided that layer thickness LT (mm) is to be set with a value between 0.15 mm and 0.25 mm.

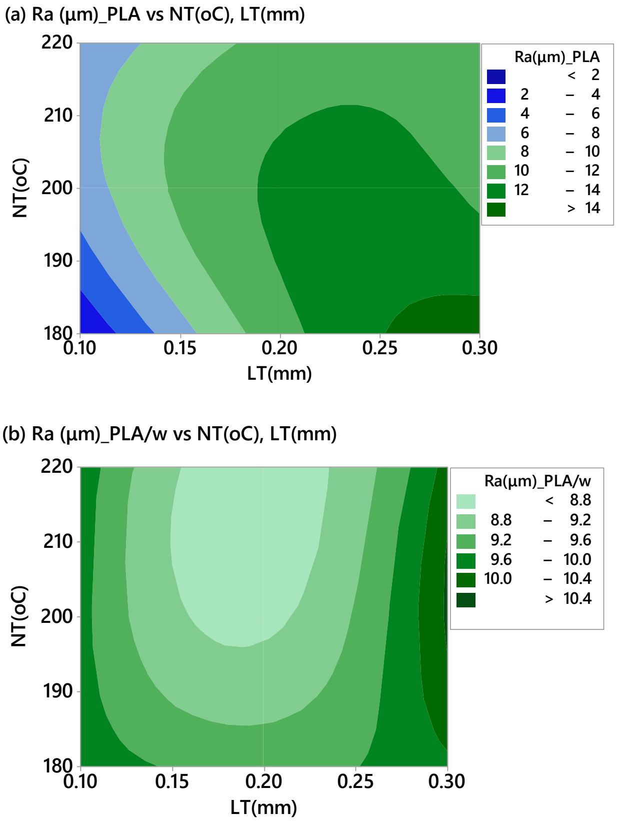


Fig. 3. Contour plots for Ra versus LT and NT parameters: (a) plot for PLA, (b) plot for PLA/w.

Coefficient of determination R^2 may not always specify whether the coefficient estimates and predictions are biased. Therefore the residual plots should be assessed to extract additional information for model adequacy. To check significance, F and p indicators are examined during ANOVA. Probability of F greater than computed F owing to noise is indicated by p-value. A result less than 0.05 for p-value suggests that the corresponding independent variable is significant. When it comes to lack of fit, p-value has to be greater than 0.05. Note that an insignificant lack of fit is preferred which means that any term excluded by the model is insignificant and thus the model fits well. Anderson–Darling normality test has been used to validate the generated models' suitability referring to Ra for both materials tested. In such a test, if p is lower than the selected significance level (usually 0.05) the data fails to follow the normal distribution.

Fig.4 summarizes the probability plots of residuals for the two quadratic models generated to predict Ra response for PLA and PLA/w materials. It is shown that the models are definitely suitable for predicting Ra and this outcome is verified by p-value which is less than 0.05 in both cases. Fig.4a shows a p-value equal to 0.765 whilst Fig.4b shows a p-value equal to 0.529. These results are far beyond 0.05 and therefore it is concluded that residuals follow a normal distribution and predictions by the regression models are in very good agreement with experimental results.

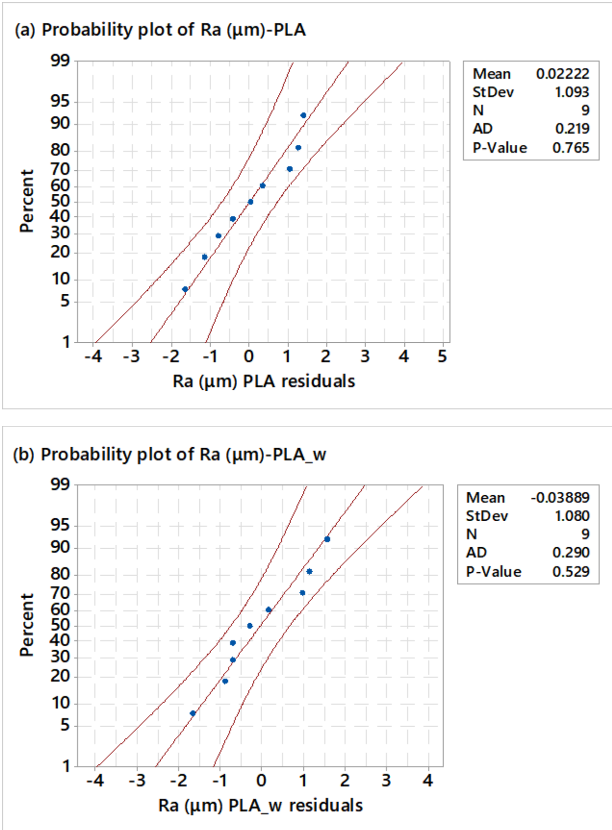


Fig. 4. Probability plots of residuals for assessing quadratic model fitting adequacy: (a) Ra for PLA, (b) Ra for PLA/w.

4. SURFACE ROUGHNESS OPTIMIZATION USING THE GREY WOLF OPTIMIZATION (GWO) ALGORITHM

Once the regression models are validated for their adequacy of predicting surface roughness Ra, next step, typically, is to investigate the optimization region for finding out the "optimal" combination of input parameters capable of minimizing the response [10]. In the present study the algorithm implemented to minimize surface roughness was the Grey wolf optimization algorithm (GWO). GWO mimics the leadership hierarchy and hunting mechanism of natural grey wolves [11]. Four types of grey wolves such as alpha, beta, delta, and omega are applied to simulate their social hierarchy and leadership. Moreover, the major steps of hunting, searching for prey, encircling prey, and attacking prey, are computationally simulated.

The single-objective optimization problem formulated according the response of surface roughness and the experimental range of the two process parameters LT and NT is mathematically described in Eq.1:

$$\min Ra\ (LT, NT) \tag{1}$$

subjected to constraints:

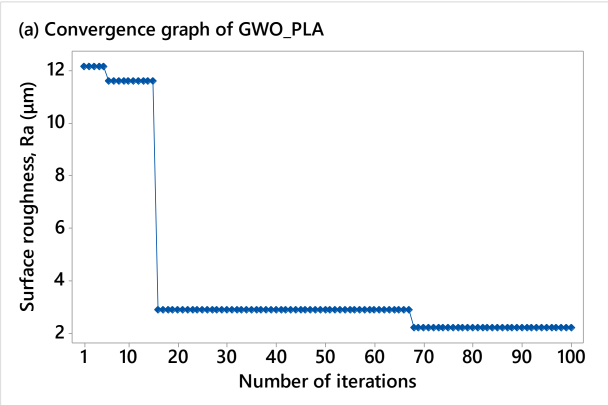
$$NT_{min}=180^{o}C \leq NT \leq NT_{max}=220^{o}C \tag{2}$$

$$LT_{min}=0.1mm \leq LT \leq LT_{max}=0.3mm \tag{3}$$

Minimum and maximum values appeared in Eq.2 and Eq.3 corresponds to the experimental ranges for the settings of control factors with regard to Table 1. To apply the GWO algorithm for minimizing surface roughness Ra for both materials studied; initialization of algorithm-related parameters was first conducted. The number of grey wolves (candidate solutions) was set to 10, while the number of iterations was set to 100. The repository size for storing the non-dominated solutions by the algorithm was set to 50. “Attacking prey” parameter (exploitation operator) was set to the range [-2*a*, 2*a*] where *a* is an algorithm-specific variable decreasing from 2 to 0 over the iterations. “Search for prey” (exploration operator) was determined by using a vector *A* taking random values such that $-1>A>1$ (greater than 1 and less than -1) to force the search agent to diverge from the prey and allow the algorithm to perform a global search [11].

The algorithm was simulated many times to examine the algorithm’s operational behavior and robustness in terms of avoiding local trapping, attaining the “global” maximum and maintaining a fast convergence to reduce computational cost. The algorithm was applied in *Mathworks MATLAB® R2014b* see [9] for details. Two of the many convergence graphs obtained during the simulation studies of this work for PLA and PLA/w materials are presented in Fig.5.

By examining the convergence curve obtained by GWO algorithm it is observed that the algorithm maintains a reasonable convergence speed for both simulations with regards to PLA and PLA/w materials. According to Fig.5a, four convergence regions are distinguished before reaching best solution for Ra which is 2.220 μm. The first region starts from 12.146 μm and is maintained for the next five iterations. The algorithm escapes and reaches the value of 11.600 μm from the 6th to 15th iteration. The next best value is equal to 2.886μm and is maintained from 16th to 67th iteration. Finally the algorithm escapes and reaches its optimal result of 2.220 μm from the 68th iteration until the end.



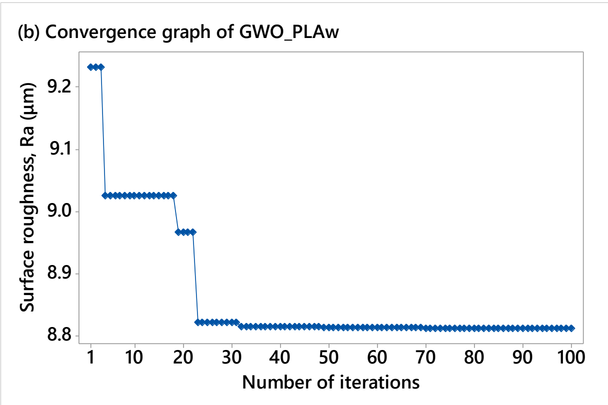


Figure 5. Convergence graphs obtained by GWO algorithm: (a) PLA; (b) PLA/w.

In the case of PLA/w (Fig.5b), seven convergence regions are noticeable towards the recommended optimal value for mean surface roughness, Ra which was found equal to 8.812. The first region refers to the value of 9.231μm that the algorithm maintained from the 1st to the 3rd iteration. Thereby the algorithm escapes from this value and obtains the value of 9.025 μm the 4th iteration. This result is maintained up to the 18th iteration where the algorithm escapes again and reaches the result of 8.967 μm at the 19th iteration. This new result is maintained until the 22nd iteration. Convergence continues from the 23rd iteration up to 31st iteration by maintaining the value of 8.822 μm. The next two values obtained by the algorithm are equal to 8.814 μm 8.813 μm. Finally the algorithm arrived to its optimal value equal to 8.812μm for minimum surface roughness at the 70th iteration. This result is maintained until the algorithm's convergence and is considered as the global optimum.

Table 3. Optimal settings for parameters accompanied with the best response value for mean surface roughness, Ra (μm).

Material	FDM parameters		Ra (μm)
	NT (°C)	LT (mm)	
PLA	180	0.1	2.220
PLA/w	220	0.18≈0.2	8.812

Table 3 summarizes the optimal settings for input parameters for achieving the minimum surface roughness for both FDM materials examined; PLA and PLA/w. By comparing the two results of the best experimental outputs (1.89 μm and 8.57 μm for PLA and PLA/w respectively) and the optimal values obtained by GWO algorithm can be considered the same from a practical perspective.

5. CONCLUSION

This study examined the effect of two important process parameters related to fused deposition modeling (FDM), namely Nozzle temperature NT (°C) and Layer thickness LT (mm), on mean surface roughness Ra (μm). Two filament materials were examined; PLA and PLA/w (organic biocompatible composite material with coconut flour). The two parameters were first assigned to an L9 orthogonal array to obtain results related to Ra that further analyzed by building a continuous search domain. This was achieved using response surface methodology. Thereby, statistical analysis was conducted to study the effects of the two parameters while regression analysis was followed next to generate full quadratic equations that will correlate the independent variables NT and LT with the response of Ra.

Finally the regression models (full quadratic equations) were implemented as objective functions to be iteratively evaluated by the grey-wolf algorithm aiming at minimizing mean surface roughness for both filament materials PLA and PLA/w. By considering the main effects it was shown that the coconut flour when added to pure PLA can maintain surface roughness variation in terms of parameter settings despite the high values, i.e., larger than 6 to 7 μm. The problem's non-linearity justifies the implementation of a modern intelligent algorithm like GWO to minimize the response of Ra. GWO algorithm managed to obtain practically the same low results as those obtained from the experiments.

Looking further ahead, the authors are to extend the research to other responses such as compressive strength, vibration and tribological properties, as well as to other population or swarm-based intelligent algorithms to test and compare efficiency and applicability to additive manufacturing technologies. In addition more mechanical and tribological tests will be performed to investigate the effect of FDM input variables for different materials.

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