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Improving the Finished Product's Quality and Mechanical Properties in Manufacturing of Prototyping Using Fused Deposition Modelling

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Abstract
In today's expanding market, customers prefer components with excellent mechanical properties and smooth surfaces. Additive manufacturing (AM) has been traditionally limited in full-scale manufacturing due to its mechanical strength and surface roughness. As a result, AM has been primarily utilized for prototyping and job shop production. Fused Deposition Modelling (FDM) involves the extrusion of wax or plastic materials through nozzles and layering them on a bed or platform to achieve the desired cross-sectional shape. There is a growing demand in industries for high-quality parts produced at a low cost and in a shorter time frame. It becomes crucial to optimize the machine's process parameters. However, it can be challenging to consistently achieve optimal values, even for a skilled operator. Understanding the FDM system parameters that affect the quality and mechanical properties of the final product is essential. Consequently, this study focuses on optimizing process variables to enhance the surface roughness of FDM products. The response surface methodology (RSM) has been utilized to determine the optimal FDM machining conditions. To plan and analyze experiments, a Design of Experiments (DOE) has been employed, considering factors such as layer thickness, printing temperature, and printing velocity. By integrating these parameters, we have determined the optimal layer thickness to be 0.20 mm, printing temperature to be 205.01 degrees, and printing velocity to be 50 mm/s, resulting in a surface roughness of 0.0510 microns. A confirmation test based on the optimal parameters has demonstrated good agreement with the predicted surface roughness result.

Keywords
Fused Deposition Modelling (FDM), Response Surface Methodology (RSM), Surface Roughnes.

Introduction

Additive manufacturing, also referred to as 3D printing, is the process of creating a physical object from a digital model by incrementally adding material layer by layer. As the 3D printer interprets the digital design file, it follows the instructions in the file to add successive layers of material, resulting in a physical object that faithfully replicates the characteristics and shape of the digital design. This capability allows for the production of intricate shapes and structures that would be difficult or even impossible to create using traditional manufacturing methods. Additive manufacturing has the potential to revolutionize how products are conceived, produced, distributed, and utilized in a wide range of industries, including aerospace, automotive, and healthcare (Abdulhameed et al., 2019; Kumar & Prasad, 2021). In the process of Fused Deposition Modeling (FDM), objects are built by extruding small strands of material one layer at a time. An FDM machine includes a print head that moves across a flat surface, depositing material from a heated nozzle. A digital design file guides the deposition of material onto the build platform as the nozzle moves. The material solidifies upon cooling and bonds with the layer below it, resulting in a sturdy object. FDM offers a cost-effective and straightforward method for manufacturing various parts and products, and is commonly used in prototyping and short-run

Manufacturing (Kumar & Prasad, 2021). However, the manufacturing components do not have the right mechanical properties and surface quality. The me-

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chanical properties and surface finish of FDM parts are affected by various factors, including the orientation of the part during printing, layer thickness, and platform temperature. By carefully controlling these factors, FDM parts can achieve satisfactory mechanical properties and surface finishes (Dey & Yodo, 2019). Post-processing techniques also improve AM product quality (Durgun & Ertan, 2014). The material utilized include ABS (Acrylonitrile Butadiene Styrene), polyamide, polycarbonate, polyethylene, and polypropylene (Penumakala et al., 2020). Surface roughness can be affected by the layer height and width used during printing. Smaller layer heights and widths can result in a smoother surface finish, which is less commonly reported. This research aims to enhance the surface roughness of Polylactic Acid (PLA) material using the RSM method. The focus on PLA material is important because of its biodegradability compared to conventional plastics, making it exceptional (Sandanamsamy et al., 2022).

Literature Review

The following literature review focuses on optimizing the properties of FDM-manufactured parts through optimization techniques. The Taguchi method was employed to study the effect of technical parameters on the quality of components manufactured using fused deposition modeling (Anitha et al., 2001). The study found that the layer thickness had the most considerable impact on component quality, making it the most suitable process parameter. In order to attain the desired quality traits in the parts, optimization of the layer thickness was put into practice. A genetic algorithm (GA) was employed to enhance the surface quality and decrease build time by optimizing the build orientation of additively manufactured parts. The investigation also considered the support material's impact on these outcomes, establishing that optimal build orientation involves minimizing the weighted sum of surface roughness and build time (Thrimurthulu et al., 2004). This methodology proposes to optimize the build orientation for parts with intricate geometries, suggesting significant potential for improving surface quality and reducing the build time in various additive manufacturing applications. Employing the Taguchi technique and grey relational analysis (GRA), another study aimed to optimize outputs of additive manufacturing systems. This research highlighted how the Z-axis orientation substantially affects tensile strength, while layer thickness is closely related to dimensional accuracy and surface roughness. The findings, analyzed with ANOVA and corroborated using the TOPSIS method, underline that through these methodologies, process parameters can be optimized to yield parts with superior tensile strength, dimensional accuracy, and surface finish (Wang et al., 2007). In further research, Design of Experiments (DOE) was employed to determine the optimal combinations of temperature, layer thickness, and part fill styles for achieving the best surface finish. It was discovered that layer thickness plays the most critical role in the quality of the surface finish, where thinner layers resulted in smoother surfaces. Additionally, it was noted that higher temperatures aid in achieving a smoother surface finish. Leveraging DOE to meticulously adjust and optimize process parameters enables the production of parts with superior surface finishes through additive techniques (Horvath et al., 2007). Zhang and Chou (2008) utilized the FEA method to study part distortion in fused deposition modeling (FDM) parts, considering scan speed, layer thickness, and model temperature across three levels. The outcome showed that scan speed and layer thickness significantly influence the stresses and deformations in parts. By applying FEA, the interplay between process parameters and part distortion can be understood, facilitating the optimization of design and manufacturing processes to minimize distortion and achieve desired dimensional accuracy and mechanical performance. Furthermore, examining the impact of deposition parameters on surface roughness revealed that slice height and raster width are pivotal factors. Regulating and optimizing these parameters allows for the production of parts with satisfactory surface finishes, thus reducing manufacturing time and costs while delivering components that meet functional and aesthetic requirements (Zhang & Chou, 2008). The use of the surface roughness angle was introduced as a means to quantify the surface roughness of FDM components. This approach was employed to explore how various factors, such as the angle of the filament, the thickness of the layer, and the cross-sectional shape, affect surface roughness (Sung-Hoon et al., 2002). The study utilized the FDM Prodigy Plus machine to examine the quality of Fused Deposition Modeling (FDM)-manufactured components with regard to surface finish and dimensional accuracy. Optimal parameters for these characteristics were identified by varying process parameters (Bakar et al., 2010). Employed the Taguchi method to explore the impact of layer thickness, road width, raster angle, and air gap on the surface quality and dimensional accuracy of FDM parts. Findings highlighted the significant influence of these parameters on the mentioned characteristics (Nancharaiah, 2011). A 2^5 factorial design encompassing 32 experiments was utilized to optimize build time and the volume of support material for fused deposition modeling (FDM) parts. The research findings indicated that several input parameters, namely layer thickness, raster angle, orientations, and raster width, considerably influenced these aspects (Gurrala & Regalla, 2014). The effects of build orientation, material type, and other process parameters on the mechanical properties and other attributes of FDM parts were investigated by Jami et al. (2013). They concluded that build orientation significantly impacted the tensile strength, bending strength, and total cost of FDM parts (Raut et al., 2014). Similarly, N. Kumar et al. (2018) employed the ANOVA method to analyze the impact of barrel temperature, platform temperature, build orientation, and raster angle on the tensile properties of FDM parts made from EVA material, identifying raster angle as the most significant factor. Jiang et al. (2019) utilized polyetherimide (PEI) material for producing additively manufactured parts via the FDM process. They assessed the mechanical properties of these parts by varying input parameters such as nozzle temperature and printing orientations, highlighting the potential to produce FDM parts with desirable mechanical properties for various applications. However, literature suggests that less attention has been given to surface finish improvement, particularly for biodegradable materials in the context of FDM. PLA is a preferred material in additive manufacturing due to its low energy consumption, non-toxic emissions, and biodegradability. It is also recognized for its stability and consistent performance over extended periods, making it suitable for a wide range of applications (DeStefano et al., 2020; R. Kumar et al., 2018). However, there has been relatively little research on using PLA filament materials in the fused deposition modelling (FDM) process and optimizing process parameters to produce high-quality parts with this material. This lack of research might be due to the challenges associated with processing PLA filament materials using FDM, such as the material's tendency to shrink and warp during the cooling process. Further exploration into the use of PLA filament materials in FDM and optimizing process parameters could help address these challenges and ensure the production of high-quality, high-performance parts.

Experimental Work

The surface roughness of additively manufactured parts can be systematically studied using the design of experiments (DOE) method, and factors that significantly affect this characteristic can be identified. This research investigated the correlation between process parameters and surface roughness by conducting experiments and measurements utilizing a surface roughness tester, such as the MGW surface roughness tester. It optimized the process and design of the parts to achieve the desired surface finish.

Material

PLA material was taken for this work as it is biodegradable and environmentally friendly. There are several solvents that can dissolve PLA, including chlorinated solvents, hot benzene, tetrahydrofuran, and dioxane (Farah et al., 2016; Sin et al., 2013). Table 1 outlines the physical and thermal properties of the PLA material filament utilized for the experimental procedures.

Table 1
Properties of PLA Material in Terms of Physical and Thermal Characteristics

Property	Value
Physical	
Density	1.24 g/cm^3
Melt mass flow rate	6 g/10min
Thermal	
Melting point	135°C
Glass transition temperature	55–60°C

Experimental Setup

The experiment utilizes the Accucraft i250+, an FDM machine which employs fused deposition modelling (FDM) to create 3D-printed components through the sequential deposition of material layers. This machine is known for its simple design and low noise level and can operate at a maximum printing velocity of 200mm/sec. It is also compatible with a different type of filament materials, including ABS, PETG, HIPS, carbon fibre, polycarbonate, PLA, and wood infill, allowing users to choose the most suitable material for their specific application. The Accucraft i250+ is also equipped with a closed chamber that helps to stabilize the internal temperature and ensure uniform consistency of the printed parts. It can be connected to various external devices, such as SD cards, Ethernet, USB, and Wi-Fi, which can help transfer data and control the machine remotely. Additionally, it has a semi-automatic bed that is useful for fast production. The Accucraft i250+ is a versatile and reliable FDM machine well-suited for many applications.

Design of Experiment

The literature review suggests that producing FDM parts with the desired surface roughness is possible by controlling and optimizing parameters. In a study, the independent variables (i.e., the variables being controlled or manipulated) are typically chosen based on their known or suspected impact on the dependent variable (i.e., the variable is being measured or observed). In this case, the independent variables comprise the thickness of the layers, printing temperature, and printing speed, while the dependent variable is the surface roughness of the final product. DOE suggests optimal parameter settings for producing FDM parts for the desired surface roughness.

Experimental work as per the DOE

CATIA and Ultimaker CURA serve as pivotal software tools utilized in this project to design and manufacture 3D-printed components. CATIA enables users to create 3D models of parts in STL format, which is essential for computer-aided design and manufacturing purposes. Following the exportation of files to Ultimaker CURA, a specialized 3D printing software, the model undergoes slicing into layers, with G-code instructions generated for the 3D printer. Ultimaker CURA also offers control over various input parameters of the FDM process, such as layer thickness, printing temperature, and printing velocity, facilitating optimization for desired surface roughness.

In the experimental work, independent variables, including layer thickness, printing temperature, and printing velocity, were manipulated following the design of experiments (DOE) approach. Subsequently, the resultant cubic blocks' surface roughness was measured using an MGW surface roughness tester. Visualization of the 3D model simulation within the FDM machine and the production capacity of PLA blocks are depicted in Figures 1 and 2, respectively. Moreover, Table 2 illustrates the DOE design with the dependent variable of surface roughness. Analyzing relationships between independent variables and surface roughness can identify potential optimal parameter settings for achieving the desired surface finish in FDM parts.

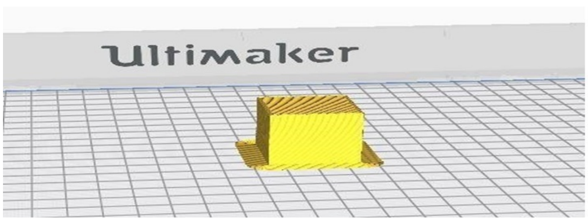

Fig. 1. Slice view of 3D model

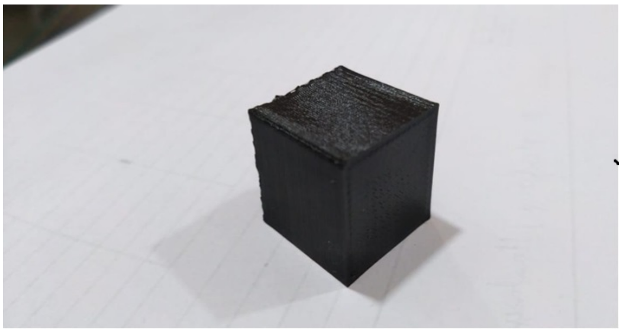

Fig. 2. PLA specimen

Table 2
Design of experiment

Model no.	Layer thickness (mm)	Printing velocity (mm/sec)	Printing temperature (°C)	Surface roughness, Ra (μm)
Exp. 1	1	1	1	4.765
Exp. 2	1	1	2	4.824
Exp. 3	1	2	3	5.064
Exp. 4	2	2	1	12.12
Exp. 5	2	3	2	6.938
Exp. 6	2	3	3	6.3
Exp. 7	3	1	1	9.052
Exp. 8	3	2	2	9.052
Exp. 9	3	3	3	8.852

Result analysis & discussion

Response Surface Methodology (RSM) is a statistical and mathematical engineering technique utilized to forecast and enhance the efficiency of manufacturing procedures. It is commonly applied in optimizing the performance of manufacturing processes, including parts produced through fused deposition modelling (FDM) in additive manufacturing (de Oliveira et al., 2019). In this study, RSM mathematical model was developed that describes the relationship between the dependent responses (such as surface roughness) and the critical input parameters (layer thickness, printing temperature, printing velocity) (Aydar, 2018; Hanrahan & Lu, 2006; Myers, 2010). A mathematical model should be based on reactions and factors to optimize the machine input parameters.

Generally, the relationship between the response variable Y and independent variables ξ_1, $\xi_2, \ldots, \xi_k$ can be expressed as:

$$Y = f(\xi_1, \xi, \ldots, \xi_k) + \varepsilon(i) \tag{1}$$

Here, the variables $\xi_1, \xi_2, \ldots, \xi_k$ are measured in natural units such as degrees Celsius, millimeter per second, and millimeters, termed natural variables. The successful application of Response Surface Methodology (RSM) relies on conducting experiments to develop a suitable approximation model, typically of first-order or polynomial nature. In RSM, the independent variables are transformed into coded variables denoted as $x_1, x_2, \ldots, x_k$. Thus, the equation can be represented as:

$$\eta = f(x_1, x_2, \ldots, x_k) \tag{2}$$

The first-order model of the approximation model takes the form:

$$\eta = \beta_0 + \beta_1 \times 1 + \beta_2 \times 2 \tag{3}$$

This first-order model is called the main effect model since it encompasses only the main variables x_1 and x_2. If an interaction exists between variables x_1 and x_2, it is incorporated into the first-order model. Estimation of the parameters β_0, β_1, and β_2 requires experimental data.

This study employed response surface methodology (RSM) to investigate the potential relationship between the machining parameters of fused deposition modelling (FDM) and the surface roughness of printed parts. The variables considered included printing temperature, printing velocity, and layer thickness. Analysis was conducted using a third-order response surface model. The high R-squared value (0.96) and adjusted R-squared value (0.95) indicate a strong alignment between the model and the data, suggesting a good fit.

$$\begin{aligned} &\text{Ra(Surface roughness)} = 493.7 + 2719A \\ &- 6.265B - 0.7163C - 1921A \times A \; + 0.01923B \times B \\ &+ 0.000099C \times C - 12.29A \times B + 4.731A \times C \end{aligned} \tag{4}$$

the context where A represents the layer thickness, B represents the printing temperature, and C denotes the printing velocity.

Various plots were obtained in MINITAB software for result and analysis purposes.

Figure 3 illustrates the correlation between FDM input parameters (layer thickness, printing temperature, and printing velocity) and the surface roughness of printed parts. The plot indicates both layer thickness and printing temperature have a noticeable impact on surface roughness while printing velocity does not affect it significantly. Moreover, the relationship between surface roughness and layer thickness shows an initial increase until a certain point, followed by a decrease with further increases in layer thickness. Conversely, the curve for printing temperature suggests that surface roughness decreases initially with temperature, reaching an optimal point before increasing with higher temperatures. This suggests that optimal layer thickness and printing temperature values could lead to minimal surface roughness. Additionally, the negligible effect of printing velocity on surface roughness implies that adjustments to printing velocity may not significantly alter surface roughness. Utilizing this information could aid in optimizing the FDM process to achieve desired surface finishes in produced parts.

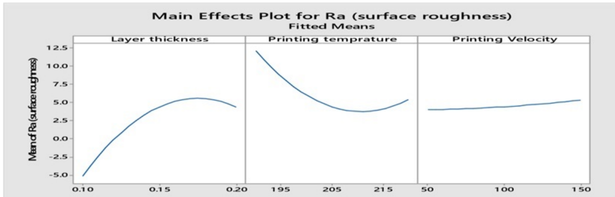

Fig. 3. Main effects plot

Figure 4 is a contour plot illustrating the correlation between layer thickness and printing temperature concerning the surface roughness observed in FDM-printed components. The plot includes several different colours, each representing a range of surface roughness values. It appears that the black region of the plot represents an area where it is impossible to achieve rough surface values of less than −5 micrometers, while the light blue region represents a range of surface roughness values from 0 to 5 micrometres. This suggests that specific combinations of layer thickness and printing temperature may result in surface roughness values within this range. The analysis acknowledges that the speed of printing has minimal impact on surface roughness, hence it is

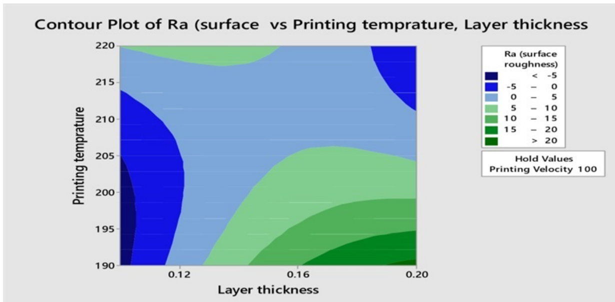

Fig. 4. Contour plot

omitted from the contour plot. This information may be beneficial for optimizing the FDM method and producing components with the desired surface finish.

Figure 5 illustrates the relationship between the surface roughness of FDM printed parts and printing temperature alongside layer thickness. This graph provides a visualization of roughness values corresponding to different printing temperatures and layer thicknesses, allowing us to identify the optimal settings for achieving the lowest surface roughness. It's evident from the plot that specific combinations of printing temperatures and layer thicknesses yield the minimum surface roughness. Utilizing this data can assist in optimizing the FDM process to manufacture parts with the desired surface finish.

The optimization plot (Fig. 6) is a graphic representation of an optimization process based on response surface methodology (RSM). The process parameters (printing temperature, printing velocity, and layer thickness) were analyzed to identify the optimal values, resulting in 190°C for printing temperature, 141.39 mm/sec for printing velocity, and 0.1264 mm for layer thickness. These optimized parameters yielded a surface roughness of 0.50 micrometers.

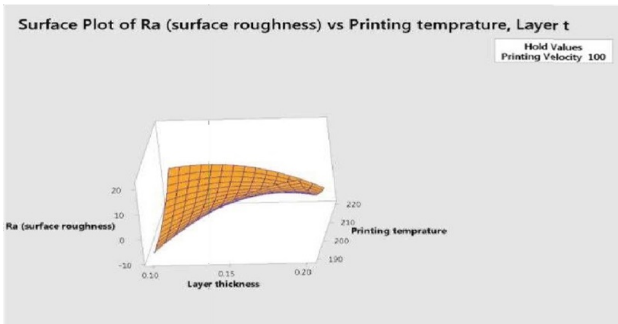

Fig. 5. Surface plot

It is important to acknowledge that while our optimization process yielded specific values for printing temperature, velocity, and layer thickness, the practical application of these parameters in industrial settings requires careful consideration of inherent variabilities and limitations. The response surface analysis, particularly evident in Figures 3 and 5, reveals a relatively flat region near the optimum, especially for printing temperature. This "saddle" shape suggests that small variations in these parameters around the optimum may not significantly impact surface roughness, offering a degree of robustness beneficial for industrial applications. Consequently, rather than adhering strictly to single optimal values, we propose operational ranges: 185–195°C for printing temperature, 0.12–0.14 mm for layer thickness, and 130–150 mm/sec for printing velocity. These ranges account for normal variations in industrial settings while still achieving near-optimal surface roughness. Factors contributing to such variations include material property fluctuations between PLA batches, equipment limitations in maintaining precise control, and environmental influences. Manufacturers should be prepared to fine-tune parameters within these ranges based on their specific PLA source and equipment capabilities. Furthermore, implementing real-time monitoring of key parameters and surface roughness could help maintain quality within acceptable limits despite these variations. Future research should focus on quantifying the impact of parameter variations on surface roughness within these proposed ranges, potentially leading to the development of adaptive control systems for maintaining optimal surface quality in dynamic industrial environments. This nuanced understanding of parameter optimization and its practical implications enhances the applicability of our findings in real-world manufacturing scenarios.

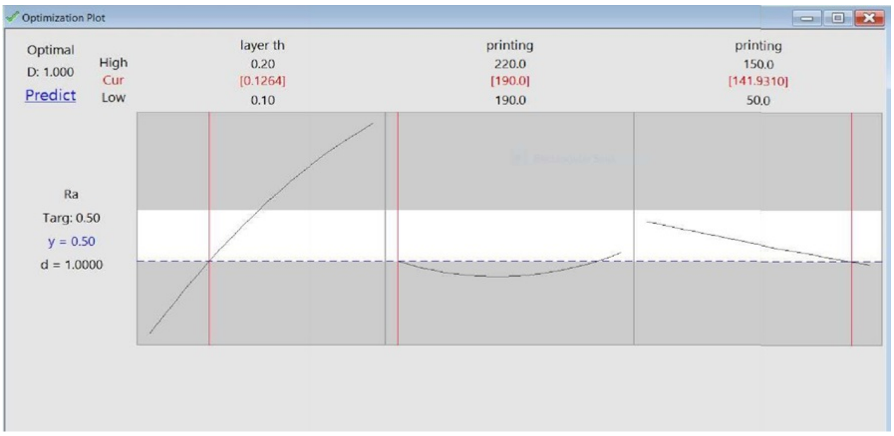

Fig. 6. Optimization plot

Conclusion

In conclusion, our experimental investigation into the impact of input process factors on the surface roughness of PLA material has yielded valuable insights. We successfully identified optimal process parameters – printing temperature of 190°C, printing velocity of 141.39 mm/sec, and layer thickness of 0.1264 mm – that minimize surface roughness in PLA components manufactured via FDM techniques. Leveraging a third-order response surface model and response surface methodology (RSM), we accurately predicted PLA component surface roughness. This methodology shows promising potential for broader application across various materials and additive manufacturing processes. Exploring multi-objective optimization could unlock further enhancements, considering process time, material strength, quality, and energy consumption factors. While our study primarily focused on surface roughness optimization, it is crucial to consider other factors like part strength, dimensional accuracy, and production efficiency in future research endeavors. The impact of our findings extends across social, managerial, and sustainability realms. Advancements in additive manufacturing technology facilitated by our research could revolutionize industries such as healthcare, consumer goods, and education, offering smoother, higher-quality parts for various applications. Manufacturers stand to benefit from optimized FDM processes, leading to improved product quality, reduced production costs, and enhanced competitiveness in the market. Moreover, by minimizing surface roughness, manufacturers can mitigate material waste and energy consumption associated with post-processing efforts, contributing to sustainability efforts and reducing environmental impact.

Disclosure statement

The author did not report a potential conflict of interest.

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