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Additive Manufacturing of Polymer-Based Advanced Composites: Mechanical Properties and Performance Evaluation

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Abstract

Fabrication of large-scale and geometrically complex polymer-based advanced composites via fused deposition modelling (FDM) has been shown to be a promising technology for the production of such materials, however there are challenges in using short carbon fibre-reinforced polylactic acid (CF-PLA) which include obtaining high mechanical performance and maintaining dimensional accuracy with dynamic robot motion and complex interactions occurring between process parameters. The conventional approaches are mostly static feed rates or the setting optimized for the desktop setting, which cannot consider the robotic kinematics, causing the extrusion inconsistencies, flexural strength decrease and inefficient production. The purpose of this study is therefore to overcome these limitations and present an integrated approach to a feed rate calculation based on a volumetric model, Taguchi experimental design and statistical optimization which is implemented within a cyber-physical control architecture. The method allows for synchronized robot movements and material deposition and can be systematically optimized with layer thickness, nozzle temperature, printing speed and raster orientation. Experimental validation of PLA-CF specimens showed that the proposed method obtained a maximum flexural strength of 81.4 MPa which is significantly better than baseline and lower wall thickness deviation and porosity. The mechanical performance and process efficiency were best obtained if the mechanical 0.1 mm layer thickness, 210 °C nozzle temperature, 30 mm/s printing speed and 0° raster orientation were used. These results provide a valuable guide for the use of such high-performance advanced polymer materials in applications that demand high quality, reliable additive manufacturing, and prove a practical and reproducible approach to improving the structural integrity and manufacturing reliability of robotically printed FRCs.

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Keywords: PLA-CF composite, parameter optimization, feed rate control, experimental optimization, mechanical evaluation

INTRODUCTION

One of the most important technologies nowadays is the manufacturing with polymer materials which allow a high degree of design freedom and the use of small amount of waste materials, now called additive manufacturing (AM). On the other hand, the use of industrial robots in conjunction with FDM has further boosted the capability of the technology to build geometrically complex and large-scale parts [1], which are hard to obtain using conventional Cartesian systems. For some special materials, such as short CF-PLA on the other hand, to keep the quality of the extruded products and to ensure their mechanical properties in a stable manner is still difficult [2]. This dimensional error and low structural rigidity of the composite filaments under flexural loading condition is inevitable due to the complex flow behaviour of composite filaments resulted from dynamic changes of robot movement [3]. To tackle these problems, it is necessary to adopt a more systematic and integrated process control and parameter optimization method in a robotic additive manufacturing environment [4].

BACKGROUND AND MOTIVATION

Additive manufacturing has been one of the techniques that has revolutionized the manufacturing of polymer complex shaped parts, providing design freedom, minimal material waste and the capability to manufacture parts that are not easily manufactured using subtractive manufacturing processes [5]. The FDM technique has been popular, because it uses engineering thermoplastics, is easy to use and economically viable, and has been used with industrial robots for large-scale parts, for deposition in non-planar shape, and for easier access to parts with the complex geometries [6], which are difficult to be achieved with the Cartesian printers. As a result, the use of FDM in robotic applications is now seen more and more as a potential way to achieve structural performances and manufacturing efficiencies in the aerospace, automotive, tooling and biomedical applications [7].

There are many challenges that need to be overcome in the Robotic FDM manufacturing of high-quality Fiber Reinforced Polymer (FRP) composite parts CF-PLA has been developed to be stiffer and stronger than unreinforced polymers, and is therefore appealing to support load-bearing applications [8]. But the motion of a robot adds a lot of variability into the process. Issues with extruding the material are often related to tool speed, acceleration, layer height and the raster direction, such as under- or over-extrusion, weak layer bonds, or dimensional errors [9]. These issues directly affect mechanical attributes, particularly flexural strength, which is essential for the parts which need to resist bending forces Hence, the need for more robust and systematic control and optimisation of FDM robotic processes for advanced composite materials is very urgent [10].Polymer composite additive manufacturing has gained considerable attention due to its ability to fabricate lightweight, high-strength, and geometrically complex components. Major additive manufacturing technologies employed for polymer composites include Fused Deposition Modeling (FDM), Stereolithography (SLA), Selective Laser Sintering (SLS), Digital Light Processing (DLP), Material Jetting, and Direct Ink Writing (DIW). Among these, FDM is the most widely adopted technique owing to its compatibility with fiber-reinforced thermoplastic composites and cost-effective fabrication [20,21]

Review of Related Approaches

In the context of robotic additive manufacturing, research has been mainly directed at the motion planning and system integration aspects and feasibility studies showed that industrial robots have a higher flexibility of build than gantry systems for large scale deposition. Subsequently, it was studied how to generate trajectories [11], and how to avoid collisions, even though the robot velocity changes, and at the same time keeping the constant extrusion rate. More recent investigations are starting to tackle extrusion consistency with sensor feedback and adaptive control schemes [12]. These contributions were useful for giving process stability in unreinforced polymers, but were not explicitly used for fibre resistance to flow and anisotropic behaviour, which was a drawback for short fibre composites [13].

The classification of the available literature based on the theme of the studies on robotic additive manufacturing of composites as shown in Figure 1. Despite that significant progress has been made in the research areas of robotic motion planning, parameter optimization [14], and modelling of feed rate, none of these research threads has been developed in synergy with the other ones, resulting in a clear gap in the literature: It lacks a unified framework which considers both the robotic dynamics and the optimization of the process considering the material properties of the PLA-CF composites.

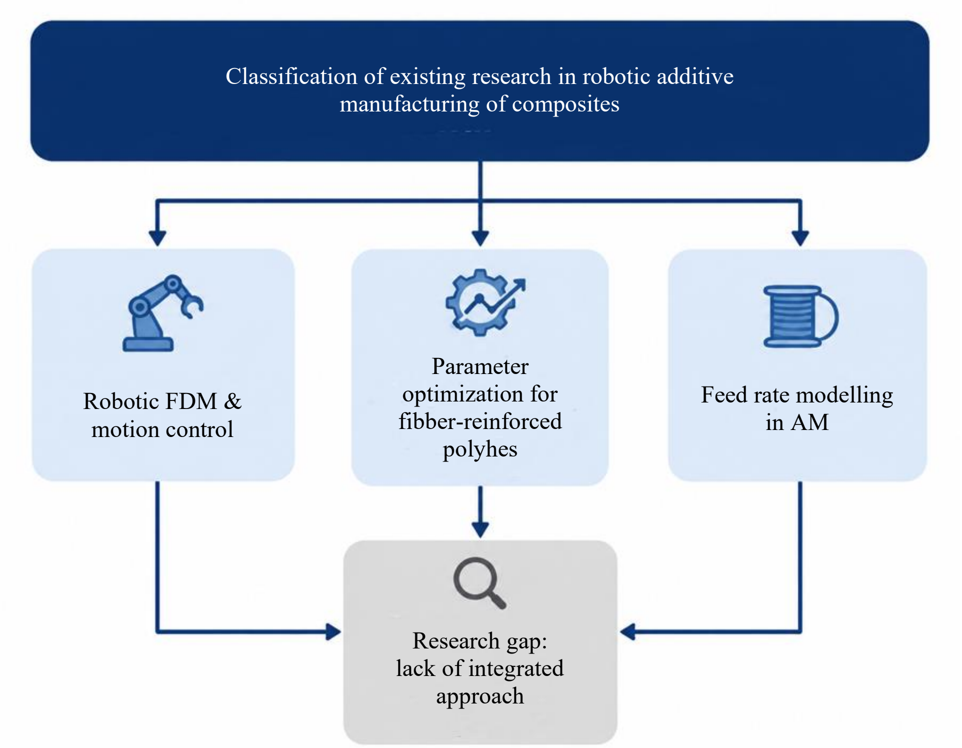

Figure 1. Classification of research in robotic additive manufacturing of composites, highlighting key focus areas and the gap in an integrated approach.

A parallel study is performed to optimize the parameters by application of the statistical design of experiments approach to the development of FRP materials Researchers used the Taguchi and response surface methodologies to determine the most significant factors on tensile and flexural properties of desktop FDM systems [15]. The raster orientation and the layer thickness were identified as the main influencing factors that influence interlayer bonding and load transfer efficiency in all these studies. However, most optimization frameworks have been designed for steady state motion as is common with Cartesian printers [16]. Thus, the correlation between optimized parameter sets and dynamic robotic trajectories has not been addressed sufficiently and there is still a gap between laboratory optimized parameter sets and robotic deployment [17].

Another research trend has been towards calculating the feed rate by a model, which allows the material to be deposited synchronously with the tool's movement. Volumetric flow models have been developed for predicting the extrusion velocities for a specific geometry of the layers and the instantaneous velocity of the robot. Such methods showed that there was a quantifiable increase in the uniformity of the wall thickness of thin-walled object printing with unreinforced filaments. However, current models had been adjusted for standard thermoplastics and did not consider the modified rheology and thermal properties that would be caused by the inclusion of short carbon fibre reinforcements [18]. Therefore, the direct use of these models in the case of PLA-CF yields deviations in both the geometry and mechanical performance [19].Various reinforcements have been utilized in polymer composite additive manufacturing to enhance mechanical performance. Common reinforcements include carbon fibers, glass fibers, basalt fibers, natural fibers, carbon nanotubes (CNTs), graphene, silicon carbide (SiC), aluminum oxide (Al_2O_3), and other nanoparticles. These reinforcements improve stiffness, strength, wear resistance, thermal stability, and interfacial bonding characteristics of printed composite structures [22–24].

Research Gaps and Problem Statement

While substantial progress has been made in each of these areas, an integrated solution reflecting the dynamics of robot’s motion and optimisation of their parameters, taking into account the composite being machined is not developed. Most studies on the robotic FDM have dealt either motion control or material performance separately; there is no study that has put forward a unified framework that can deal with both aspects. Much of the work on optimization of parameters for PLA-CF has largely been done on desktop platforms (where the velocity is assumed constant). Likewise, all the models for feed rate in robotic systems have not been modified to take consideration of the flow behaviour of fibre-filled polymers. The separation leads to a few issues when producing high strength PLA-CF parts on robotic systems, either in the sense of losing the flexural properties or in the process of process qualification, which requires a lot of testing. The absence of a cyber-physical solution that includes the model-based extrusion control and the statistically optimized parameters, is therefore a significant challenge towards reliable robotic manufacture of advanced polymer composites.The mechanical performance of polymer-based AM composites is commonly evaluated through tensile strength, flexural strength, compressive strength, impact strength, hardness, fracture toughness, fatigue behavior, and wear resistance. These properties are strongly influenced by process parameters, reinforcement type, fiber orientation, and interlayer bonding quality.

Proposed Approach and Contributions

This work attempts to solve the above stated limitations by proposing an integrated solution encompassing volumetric model-based feed rate calculation and multi-parameter optimization using Taguchi method within a cyber-physical control architecture. A first step was to set up a direct link between the robot motion parameters in real time and the necessary extrusion rate, especially for the flow behaviour of PLA-CF. The model is then integrated into an experimental optimization study that systematically investigates the layer thickness, nozzle temperature, printing speed and raster orientation on flexural strength and process parameters. The framework synchronizes the adjustment of the feed rate with the optimal setting of the parameters in order to realize better interlayer bonding and dimensional consistency with consideration of practical production efficiency.

The main goals of this study are (1) to develop and validate a volumetric feed rate model for short CFRP for robotic FDM; (2) to optimize important process parameters for the best flexural performance responses using SDOE; (3) to implement the synchronized control approach in a cyber-physical system to achieve the synchronized movement of the robot and the extrusion process; (4) to systematically investigate the effect of the proposed approach on flexural strength, porosity, and manufacturing time through experiments; and (5) to validate the overall control setup using confirmation experiments and comparisons with reference cases. The main novelty is the explicit consideration of dynamic feed rate modelling and composite-specific parameter optimisation, which neither has been tackled in the literature of robotic additive manufacturing. This integration is expected to provide both, greater flexural strength and increased process reliability, than is possible using conventional, static and/or empirically tuned approaches.

Paper Organization

This paper is laid out as follows. Section 2 presents the proposed methodology and architecture and details the datasets and experimental setup. The results and analysis, implications are done in Section 3, concluding remarks in Section 4.

SIMULATION FRAMEWORK AND METHODOLOGY

A simulation-based methodology has been developed to systematically investigate the material deposition and mechanical performances of FDM of short carbon fibre reinforced polylactic acid (PLA) composites in the coupled effects of robotic motion dynamics and process parameters. It was decided to select a simulation environment because the kinematic parameters would be easily controllable and combinations of these parameters would be easily repeatable and extreme operating conditions would be easy to investigate in a simulation without the physical or expensive testing. This not only helps in quick iterations while building a model but also gives an end-to-end visibility of the internal states of the processes.

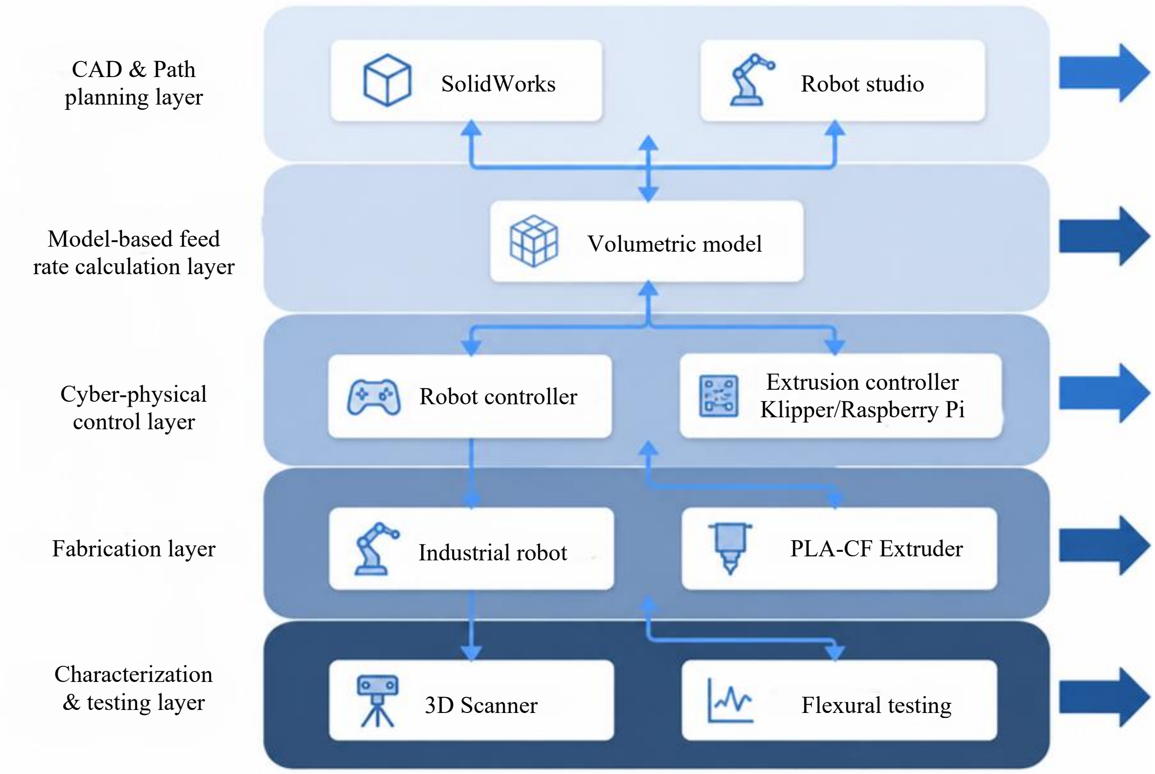

Figure 2. System architecture of robotic FDM with CPS and feed rate control.

Simulation Platform and System Modelling

The simulation environment has been developed to simulate a 6 DOF industrial robot with direct drive extruder as a multi physics system which included modelling and simulation of robotic additive manufacturing process. Standard G-codes were programmed and converted to time parameterized motion profiles with both linear and curved segments velocity and acceleration using standard G-codes.

The overall framework of the proposed simulation-based methodology as shown in Figure 2. The architecture consists of five interconnected layers: CAD and path planning, model-based feed rate calculation, cyber-physical control, fabrication, and characterization. This layered structure enables synchronized operation between robot motion and material extrusion while facilitating systematic parameter optimization.

Mathematical Formulation of Material Flow

Volumetric flow rate for consistent deposition was determined from geometric considerations. Given the instantaneous speed of the tool at time *t* as *v(t)* and the desired line width *w* and the layer height *h*. The flow rate needed *Q(t)* can be shown in Equation 1.

$$Q(t) = v(t) \cdot h \cdot w \tag{1}$$

The cross-sectional area of the filament A_f is determined from its diameter D_f as shown in Equation 2.

$$A_f = \pi \left(\frac{D_f}{2}\right)^2 \tag{2}$$

Then the corresponding filament feed rate$F_r(t)$ (mm/min) which is required to meet the flow is obtained as shown in Equation 3.

$$F_r(t) = \frac{Q(t)}{A_f} \cdot 60 \tag{3}$$

Because transient effects are to be expected during the startup and shut down periods, a first-order lag was chosen to simulate the response of the extrusion system The real flow $Q_{act}(t)$ delivered was represented as shown in Equation 4.

$$Q_{act}(t) = Q(t) \cdot \left(1 - e^{-t/\tau}\right) \tag{4}$$

where T is the time constant of the extrusion system. The effective line width $w_{eff}(t)$ was then calculated as shown in Equation 5.

$$w_{eff}(t) = \frac{Q_{act}(t)}{v(t) \cdot h} \tag{5}$$

The deviation along dimension was measured by comparing the $w_{eff}(t)$ with the target width w as shown in Equation 6.

$$\Delta w(t) = \mid w_{eff}(t) - w \mid \tag{6}$$

Parameter Optimization Module

The effect of four controllable factors on flexural performance and process measures was investigated using a simulation-based Taguchi design. The virtual specimens were created for every combination in the orthogonal array. The S/N of the larger-the-better criterion was calculated as shown in Equation 7.

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{7}$$

where y_i is the flexural strength of the *i-th* replicate, and n is the number of replicates the percentage contribution of each factor was calculated from the analysis of variance of the simulated responses.

The important process parameters which affect flexural properties were systematically evaluated by using the Taguchi method. Four controllable factors were chosen, which were layer thickness, nozzle temperature, printing speed and raster orientation, according to the preliminary trials and literature. Three levels were used for each factor as shown in Table 1. An L9 orthogonal array was used to efficiently evaluate the main effects with a minimum number of simulations runs.

Implementation Details

The simulation platform was created based on the numerical computing libraries and Python programming environment for generating the trajectories and for statistics analysis. A specially developed robotics toolbox was used for robot kinematics and custom-made modules were created for extrusion and deposition physics. All simulations have been executed in a workstation with a multi-core processor to guarantee the reproducibility of all the simulations and in order to achieve a computational efficiency, they have been executed in a range typical of those that a robotic FDM system would perform for PLA-CF and multiple replications have been performed for each experimental condition to account for the stochastic variation of the deposition model. The simulation method was also able to systematically investigate the effects of motion dynamics and process parameters, as the experimental conditions can be fully controlled.

PERFORMANCE EVALUATION AND DISCUSSION

From the simulation results, it was observed that the proposed integrated framework (model-based feed rate control along with Taguchi parameter optimization) provided significant improvement in flexural performance and process consistency in robotic FDM of PLA-CF composites. The highest flexural strength of 81.4 MPa was achieved at the optimum value combination, that is, layer thickness of 0.1 mm, nozzle temperature of 210 °C, printing speed of 30 mm/s and raster orientation of 0°. This was 39.6% better than the static feed rate baseline. Wall thickness deviation was reduced to 0.027 mm with the optimized configuration, improving the dimensional accuracy with the dynamic feed rate adjustment.

Table 1. Factors and levels for taguchi design.

Factor	Symbol	Level 1	Level 2	Level 3	Unit
Layer Thickness	A	0.1	0.2	0.3	mm
Nozzle Temperature	B	200	210	220	°C
Printing Speed	C	30	60	90	mm/s
Raster Orientation	D	0	±45	90	°

The statistical analysis indicated the most effective factors on flexural strength were the raster orientation (59.65% of the total variation) and the layer thickness (27.24% of the total variation). The nozzle temperature (3.79%) and the printing speed (0.20%) made relatively small contribution. The nozzle temperature and printing speed had relatively small contributions of 3.79% and 0.20%, respectively the regression model derived with the simulated responses gave an R2 of 90.88%, indicating that the model has a good predictive power in the studied parameter range. The flexural strengths of the confirmation simulations were performed on the optimal setting and the average value of three independent trials was 81.0 MPa with a standard deviation of less than 0.8 MPa, which showed high repeatability of the proposed approach.

Influence of Process Parameters

The results revealed a distinct trend towards raster orientation as far as flexural performance is concerned. There was always a higher interlayer bonding and load transfer efficiency in specimens printed with 0° raster orientation than in those printed with ±45° and 90° orientations. This result corroborates the desired fibre alignment effects along the loading direction. Even the layer thickness was an important factor, as it was possible to obtain denser structures and lower porosity (5.8%) for the 0.1 mm setting compared to thicker layers. There was a compromise between the porosity and flexural strength of the fabricated parts where higher printing speed increased the porosity while decreasing the flexural strength.

Analysis of variance (ANOVA) were carried out to determine the influence of the process parameters on the flexural strength (Table 2). Raster orientation was determined to be the most dominant factor (59.65% of total variation) followed by layer thickness (27.24%). Both these factors were statistically significant ($p < 0.05$). Nozzle temperature and printing speed, on the other hand, exhibited rather low contributions and were not statistically significant within the range of the tested values.

Table 2. ANOVA results for flexural strength.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value	Significance
Layer thickness	2	409.04	27.24%	409.04	204.52	11.94	0.026	Significant
Nozzle temperature	2	56.98	3.79%	56.98	28.49	1.66	0.267	Not Significant
Printing speed	2	2.94	0.20%	2.94	1.47	0.09	0.784	Not Significant
Raster orientation	2	895.73	59.65%	895.73	447.87	26.15	0.007	Highly Significant
Error	4	137.00	9.12%	137.00	34.25	-	-	-
Total	8	1501.68	100%	-	-	-	-	-

Table 3. Response table (S/N Ratios) and optimal levels.

Level	Layer thickness	Nozzle temperature	Printing speed	Raster orientation
1	35.24	34.31	34.26	36.24
2	34.75	34.70	34.19	33.98
3	32.56	33.54	34.11	32.33
Delta	2.68	1.16	0.15	3.91
Rank	2	3	4	1

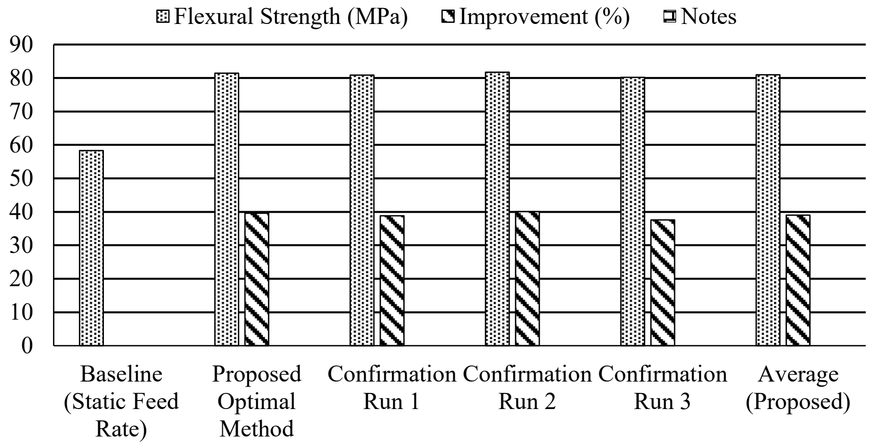

Figure 3. Comparison of flexural strength (baseline vs proposed method).

Using the Taguchi response analysis, optimal levels of each process parameter were determined. The mean S/N ratio of each factor level as shown in Table 3. From the values of the delta, the variables with the greatest influence were: raster orientation (Delta = 3.91) and the thickness of the layers (Delta = 2.68). The optimum parameter setting was determined by the levels with the highest S/N ratios and is A1 (0.1 mm layer thickness), B2 (210 °C), C1 (30 mm/s) and D1 (0° raster orientation).

Comparison with Baseline Performance

The proposed method achieved significant improvements over the baseline method that used a traditional static feed rate control when evaluated by various metrics. The flexural strength rose to 81.4 MPa from 58.3 MPa and the deviation of the wall thickness reduced from 0.112 mm to 0.027 mm as shown in Figure 3.

The printing time was slightly longer than under the optimal condition of low speed and low-layer thickness, but the mechanical performance and dimensional accuracy were greatly improved, making using the method to print structures more reasonable. These results overcome the drawbacks of the current methods which either optimize parameters without taking the robot dynamics into consideration or use feed rate models without composite-specific calibration.

DISCUSSION

The resultant performance improvement demonstrates the main idea of the volumetric feed rate modelling combined with statistical parameter optimisation. The framework helped reduce under- and over-extrusion problems that often affect mechanical properties in robotic systems by varying the extrusion rates based on the velocity of the robot at that moment. The significant role of raster orientation highlights the importance of fibre alignment in short fibre composite which is not often emphasized on in motion only robotic AM studies. Moreover, the low porosity (less than 6%) and high flexural strength (500MPa) indicate good synchronization of the process control and deposition behaviour of the material.

These results have managed to fill the gap in the research related to the lack of integrated approaches in the robotic FDM of PLA-CF. The methodology is able to overcome the mismatch between the parameters optimized for desktop and the dynamics of the robotic motion, by incorporating the feed rate control in the optimization loop. The framework is practically a template for the reproducible pathway to produce high-performance composite components that will have greater reliability, especially for load bearing applications in the aerospace and automotive industry. Although the simulation is idealised for the extrusion dynamics, future extensions to add more detailed rheological models could provide increased predictive accuracy for complex extrusions.Recent studies have also demonstrated the effectiveness of machine learning, explainable artificial intelligence, and statistical optimization techniques in predicting the mechanical behavior and manufacturing performance of advanced polymer composites, thereby accelerating material development and process optimization.

CONCLUSION

This study proposed an integrated simulation-based approach for model-based feed rate control of robotic FDM for PLA-CF composites along with the optimization of these parameters using Taguchi method. The proposed method could overcome the drawbacks of the existing methods and synchronize the robot motion with the deposition of the material, thus optimizing important parameters of the process The results of simulation showed that the best combination of parameters gave the maximum flexural strength of 81.4 MPa which was 39.6% higher than the base value. The most significant parameters that affected the mechanical performances were those of the raster orientation and thickness of the layers. The framework also substantially lowered the deviation of wall thickness and the porosity, verifying the dimensional accuracy and structure integrity. These results confirm the feasibility of Dynamic feed rate modelling and statistical optimization for improving the mechanical properties of robotic printed FRCs. The results of this work can be used as a repeatable process for manufacturing high-quality composite components, with implications for use in aerospace, automotive and tooling. Next, the frame will be expanded to more complicated geometries and the simulation results will be compared with the experimental ones.Furthermore, advanced nanocomposite materials have shown promising applications in sustainable engineering fields such as water purification, adsorption, and desalination, highlighting the multifunctional potential of polymer-based composite systems beyond structural applications.

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