Prediction of Process Parameters Based on Stress–Strain Behaviour in 3D Printing Using Deep Neural Network

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***Abstract*—Material extrusion additive manufacturing enables the efficient fabrication of polymer components, yet modelling structures with internal complexity remains challenging. This study develops a deep neural network (DNN) model to predict printing parameters, specifically infill density and printing angles, based on pointwise stress–strain data from material extrusion printed polylactic acid (PLA) specimens. Unlike conventional methods applying a single angle per specimen, this work introduces the combination of three distinct printing angles within the same specimen, achieving in-sample angle compounding and greater structural complexity. Twelve experimental groups were designed using a Taguchi L12 orthogonal array, varying infill levels of 30, 50, 70, and 100 percent, and angle sequences. Tensile tests were conducted to obtain stress–strain curves, with extracted pointwise data used as model inputs. The DNN model achieved a coefficient of determination of 0.9481 and an MSE of 0.0518, demonstrating strong prediction performance. These results demonstrate that the proposed model not only captures the mechanical behaviour of compounded-structure material extrusion prints but also enables performance-driven design by recommending printing configurations that meet specific mechanical targets, reducing trial-and-error and expanding design efficiency.**

Keywords—Material extrusion, deep neural network, additive manufacturing, mechanical characterisation, data-driven modelling

I. Introduction

Material extrusion has become one of the most widely adopted additive manufacturing (AM) technologies, offering a cost-effective route to fabricate polymer components with tailored geometries. As a layer-by-layer fabrication method, AM enables the creation of complex internal features, custom mechanical behaviour, and lightweight structures that are difficult or impossible to achieve using conventional subtractive techniques [1]. Among various AM processes, material extrusion, commonly implemented as fused deposition modelling (FDM), is particularly attractive due to its simplicity, affordability, and compatibility with a wide range of thermoplastic polymers [2]. The mechanical performance of material extrusion printed parts, particularly tensile strength and deformation behaviour, is strongly influenced by process parameters such as infill density and printing orientation [3], [4]. Traditional experimental approaches for studying these relationships are often time-consuming and labour-intensive, limiting their scalability for process optimisation [5].

In recent years, machine learning (ML) techniques have increasingly been integrated into AM research to accelerate process–structure–property investigations [6], [7], [8]. Numerous studies have successfully applied ML models to predict mechanical properties based on various process parameters, often involving multiple variables such as print speed, temperature, infill density, and layer thickness [9], [10], [11]. While there has been progress in modelling intra-specimen parameter variations, most efforts have focused on combining different infill patterns, build orientations, or thermal conditions [12], [13]. A common limitation across these studies is the assumption of uniform printing parameters within each specimen, which does not reflect the complexity of real applications [14].

In practice, layer-wise heterogeneity is frequently introduced to achieve region-specific mechanical performance [15]. A notable example is the cyclic variation of printing angles across layers, used to enhance isotropy or reduce stress concentrations [16]. Such strategies are particularly relevant in functional and load-bearing components, where directionality of the internal structure has a direct impact on stiffness and failure behaviour [17]. Although such strategies are widely adopted, their influence on mechanical response has received limited attention in predictive modelling. Most studies involving print angles apply fixed values throughout a specimen or compare different angle sets between separate specimens, without addressing layer-wise directional changes within a single build.

To address this gap, the present study proposes a deep neural network (DNN) model that estimates printing parameters from experimental stress–strain data. Rather than predicting mechanical response from known settings, the model infers infill levels and cyclic printing angles directly from pointwise deformation curves, allowing reconstruction of the underlying process configuration. This inverse approach offers potential benefits for process validation, quality monitoring, and design analysis in material extrusion.

The framework is demonstrated using polylactic acid (PLA) specimens printed with three alternating printing directions per sample, forming a compounded internal structure that better reflects practical AM designs. The results enhance understanding of how internal directional variation affects mechanical behaviour and provide a basis for future data-driven strategies in the modelling and optimisation of printed components. The method may also inform future efforts to integrate layer-wise process planning with simulation-driven design, particularly in applications where spatially tailored mechanical response is required.

II. EXPERIMENTAL DESIGN AND DATA COLLECTION

A. Materials

The material used in this study was tough polylactide filament (Ultimaker, Geldermalsen, the Netherlands) with a nominal diameter of 2.85 mm. The filament exhibited an impact strength of 9 kJ/m², a thermal resistance up to 58 °C, a hardness of 80 Shore D, and a melting temperature of 152 °C.

B. Sample Preparation and Experimental Design

PLA specimens were fabricated using an Ultimaker 3s printer (Ultimaker, Geldermalsen, the Netherlands). Test specimens were designed in SolidWorks 2023, sliced with Cura 4.13.1, and saved in STL format, as shown in Fig. 1. The models were printed according to ISO 527-1BA (75 mm) specifications [18].

During printing, the PLA filament was fed into the extrusion head, where it was heated, melted, and deposited onto a pre-heated build plate. The printer's head moved along the XY plane while the platform adjusted along the Z-axis to construct the specimen's layer by layer.

The detailed process parameters are summarised in Table I.

This study investigated the influence of infill density and printing angle on the tensile properties of material extrusion printed PLA specimens. A controlled variable approach was adopted, varying the infill rate and the printing angles. The printing direction followed a cyclic layer-by-layer pattern, with angles alternating every three layers. Twelve experimental groups were established using the Taguchi method, as shown in Table II [19]. For each experimental group, five identical specimens were printed and subsequently subjected to tensile testing, with the average tensile response of the five specimens used for further analysis.

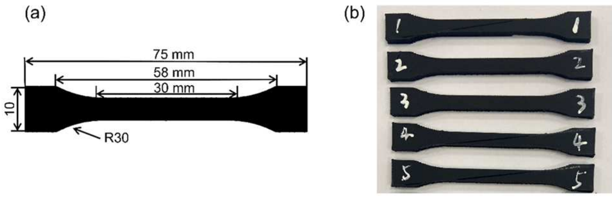

Fig. 1. Geometry and fabricated specimens of the standard tensile test sample: (a) schematic of the ISO 527-1BA specimen dimensions; (b) material extrusion printed PLA specimens prepared for mechanical testing.

TABLE I. PRINTING PROCESS PARAMETERS USED FOR MATERIAL EXTRUSION PRINTED PLA SPECIMENS

Printing Parameter	Numerical Values
Print temperature	200°C
Print speed	30mm/s
Build plate temperature	60°C
Layer height	0.2mm
Flow	100%
Infill pattern	Lines
Infill rates	30%, 50%, 70%,100%
Print angles	(0°, 0°, 0°), (0°, 60°, 120°), (45°, 90°, 135°)

TABLE II. EXPERIMENTAL DESIGN MATRIX FOR CYCLIC PRINTING ANGLE AND INFILL RATE VARIATIONS

Group Number	Fill Rate	Print Angle
1	30%	0°, 0°, 0°
2	30%	0°, 60°, 120°
3	30%	45°, 90°, 135°
4	50%	0°, 0°, 0°
5	50%	0°, 60°, 120°
6	50%	45°, 90°, 135°
7	70%	0°, 0°, 0°
8	70%	0°, 60°, 120°
9	70%	45°, 90°, 135°
10	100%	0°, 0°, 0°
11	100%	0°, 60°, 120°
12	100%	45°, 90°, 135°

The corresponding top surface structures of representative samples from the three printing angle groups are shown in Fig. 2. These images were acquired using a Zeiss Axio Imager microscope (Carl Zeiss AG, Germany), providing high-resolution optical characterisation of the printed surface structures. It is noted that although the (0°, 0°, 0°) group was printed with identical layer-wise deposition angles, the internal structure in the optical micrograph appears bidirectional. For reference, a perfectly unidirectional pattern would exhibit parallel raster lines aligned in a single direction across the entire layer, without crosshatching or alternating paths. This discrepancy is attributed to the infill path

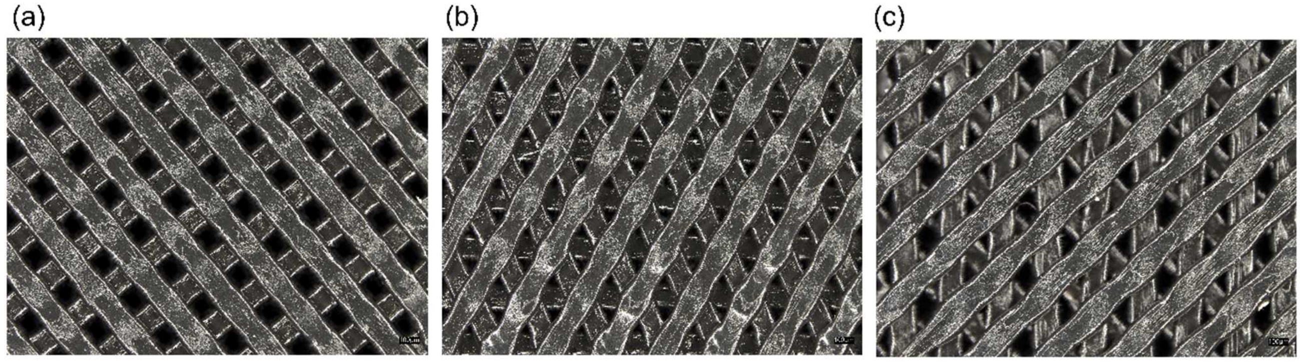

Fig. 2. Top surface optical micrographs of specimens fabricated with different cyclic printing angle configurations: (a) (0°, 0°, 0°), (b) (0°, 60°, 120°), and (c) (45°, 90°, 135°).

alternation automatically generated by the slicing software, which introduces alternating deposition directions even under uniform nominal angle settings. This behaviour is intended to reduce internal stress and is not a deviation from the defined printing parameters. Therefore, the printing angle input for this group remains consistent with the nominal (0°, 0°, 0°) setting used in model training.

C. Mechanical Testing

Tensile tests were performed using a Shimadzu AG-X Plus machine following ISO 527-1BA standards. Samples were printed along the XY plane, with layer-wise variation in the YZ plane according to the specified printing angles, to capture the anisotropic behaviour.

D. Deep Neural Network Modelling

A deep neural network was developed to infer the printing parameters of material extrusion printed PLA specimens based on pointwise mechanical test data. The model takes two input features, strain and stress, and outputs four process parameters including infill density and three cyclic printing angles. All features were numerically encoded and normalised to improve training stability and convergence.

Prior to model development, the raw dataset was pre-processed by removing duplicate entries and transforming the printing angles, initially recorded as comma-separated strings, into numerical arrays. Normalisation was applied to both input features and output values to improve convergence during training.

The DNN architecture consisted of three fully connected hidden layers containing 64, 128, and 64 neurons, respectively. Each hidden layer employed the rectified linear unit (ReLU) activation function to introduce non-linearity into the model [20]. The output layer comprised four neurons corresponding to the predicted printing parameters. The structure of the model is illustrated in Fig. 3.

Model training was conducted using the Adam optimiser with a learning rate of 0.001, and mean squared error (MSE) was selected as the loss function [21], [22]. The dataset, comprising 477,640 data points, was randomly divided into training and validation sets in an 80:20 ratio. The model was trained over 100 epochs with a batch size of 512.

III. Results and Discussion

To construct the training dataset, each strain–stress pair from the full mechanical curves was treated as an individual training instance, with the associated printing parameters used as the target outputs. This approach allowed the model to learn from the entire deformation behaviour, rather than relying on aggregated or single-point features.

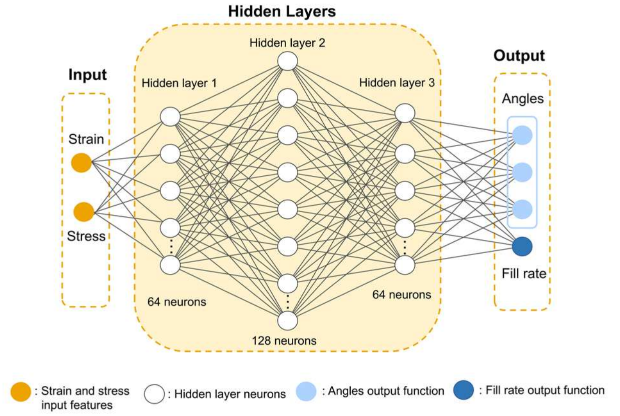

Fig. 3. Architecture of the deep neural network model for inverse prediction of printing parameters based on strain and stress input.

The predictive performance of the developed DNN model was evaluated based on key validation metrics. As summarised in Table III, the model achieved an MSE of 0.0518 and a coefficient of determination (R^2) of 0.9481 on the validation dataset. These results demonstrate that the model accurately captures the relationships between mechanical response and printing parameters under cyclic layer-wise angle variations. The high R^2 indicates strong agreement between predicted and actual values, while the low MSE reflects the model's ability to minimise prediction errors. Overall, the performance metrics confirm the robustness and effectiveness of the proposed DNN framework for parameter inference in material extrusion printing.

Existing studies applying machine learning to additive manufacturing have mostly focused on forward prediction, using models such as linear regression, support vector machines, or shallow neural networks, and typically report R^2 values between 0.80 and 0.92 with MSE values above 0.1 under uniform or single-angle parameter settings [23] [24] [25]. These approaches do not address inverse prediction from full stress–strain curves, nor do they consider multi-angle parameter combinations within a single specimen. In contrast, the present model demonstrates superior performance while handling increased structural complexity, indicating its capability to generalise across more realistic printing scenarios.

TABLE III. PERFORMANCE METRICS OF THE DEEP NEURAL NETWORK MODEL

Metric	Value
Mean squared error	0.0518
Coefficient of determination	0.9481

The training and validation loss histories are shown in Fig. 4. Both curves exhibit a clear decreasing trend over the training epochs, indicating that the model converges effectively. The training loss decreases gradually from approximately 0.055 at the beginning to below 0.045 by the end of the training. The validation loss, while exhibiting more noticeable fluctuations, follows a similar downward trajectory, generally remaining within the range of 0.045 to 0.065. Although the validation curve shows higher variance, particularly in the early and middle stages of training, the overall trend remains aligned with the training loss curve. The proximity between the two curves throughout the training process, and particularly towards the later epochs, suggests that the model maintains stable learning behaviour and achieves good generalisation without significant overfitting. The absence of divergence between training and validation performance confirms that the model is capable of learning meaningful patterns in the data and applying them to unseen samples. These consistent trends further reflect the suitability of the network structure and training settings for inverse modelling tasks involving stress–strain data.

Fig. 5 shows the comparison between the true and predicted values for the four printing parameters: (a) infill density, (b) printing angle A, (c) printing angle B, and (d) printing angle C. Printing angle A, B, and C correspond to the first, second, and third layer orientations in each cyclic sequence. For infill density (Fig. 2a), the predicted curve accurately follows the true step changes between 30%, 50%, 70%, and 100%, with deviations generally within ±5%. For the printing angles (Figs. 2b–d), the model captures the overall cyclic trend, although small local deviations, typically within ±10°, are observed, particularly near transition points. These results indicate that the model reliably tracks both discrete and cyclic parameter variations, despite minor errors at rapid transitions. The high visual overlap between true and predicted curves across all four subplots demonstrates the model's effectiveness in multi-output regression. Although the angular predictions exhibit more fluctuation than those of infill density, the predicted curves successfully preserve the periodicity and magnitude of the true signals. This consistency suggests that the model has learned the underlying mapping between stress–strain patterns and corresponding process parameters, even in cases of frequent directional alternation and irregular sampling intervals.

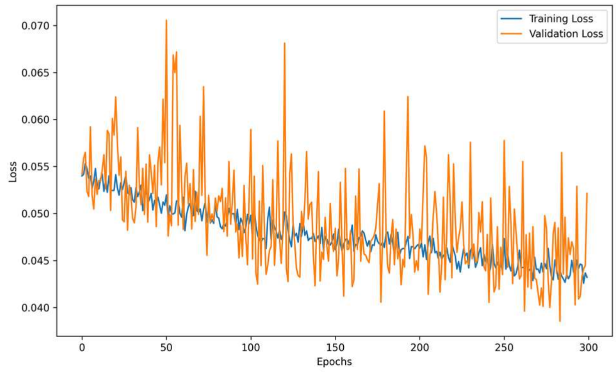

Fig. 4. Training and validation loss curves for the deep neural network model.

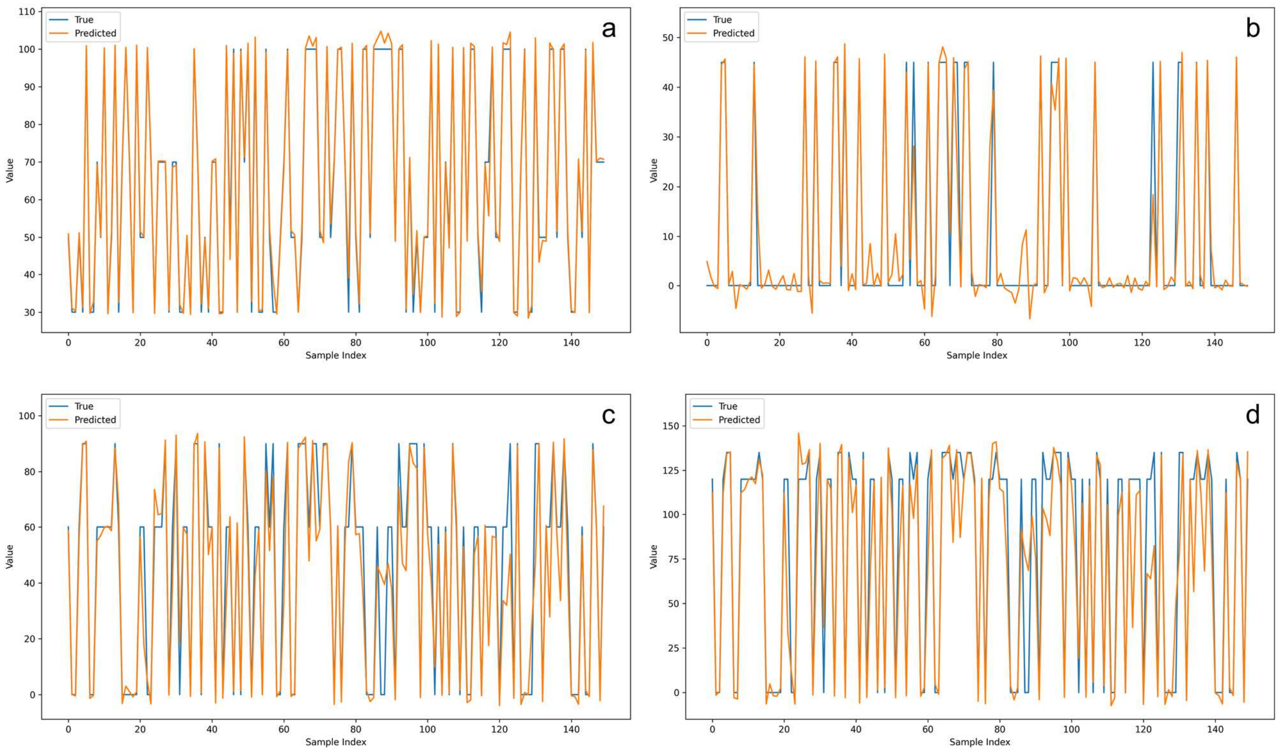

Fig. 5. Comparison of true and predicted values for printing parameters: (a) infill density (30%, 50%, 70%, 100%), (b) printing angle A (first layer orientation), (c) printing angle B (second layer orientation), and (d) printing angle C (third layer orientation).

The overall predictive performance of the model is illustrated in Fig. 6, which shows the scatter plot of true versus predicted values for all printing parameters. Data points for infill density are tightly clustered along the diagonal line, with most falling within a ±5% relative error band. For the printing angles, the scatter is slightly wider, with most points within ±10° and a few isolated deviations beyond this range. Greater dispersion is particularly evident at lower angle values, especially below 60°, where the predictive accuracy tends to decrease. This increased prediction deviation at lower angles may be attributed to the reduced anisotropy in mechanical response. At such angles, the corresponding stress–strain curves display less distinctive variation across parameter groups, which limits the model's ability to accurately differentiate between underlying printing configurations. Overall, the points are well aligned along the diagonal without significant systematic bias, indicating balanced predictive accuracy across different parameters. These observations are consistent with the high R^2 and low MSE reported in Table III, confirming the model's capability to infer complex cyclic printing configurations from mechanical data.

The ability of the model to predict parameters from mechanical test data demonstrates the feasibility of machine learning approaches in decoding complex process–structure–property relationships in additive manufacturing. In particular, the model successfully handles the challenges posed by the cyclic variation of printing angles within a single specimen, a condition that has rarely been addressed in previous studies. While the model performance for fill rate prediction is highly accurate, the slightly greater prediction error in the printing angles highlights an area for future improvement, potentially through the introduction of more refined angle encoding methods or enhanced mechanical testing protocols. Nevertheless, the results confirm the potential of deep learning frameworks to assist in process monitoring, quality assessment, and ultimately the optimisation of parameter design for material extrusion processes involving complex internal structures.

IV. Conclusion and Future Work

This study investigated the influence of cyclic layer-wise printing angles combined with varying infill densities on the mechanical behaviour of material extrusion printed PLA specimens. Unlike conventional approaches that apply different printing angles across separate specimens, this work implemented multiple printing directions within the same specimen to more accurately replicate the complex internal structures encountered in practical applications. Tensile tests were conducted to characterise the stress–strain responses under different process conditions. Based on the experimental data, a DNN model was developed to predict the associated printing parameters from mechanical test results. The model achieved an R^2 of 0.9481 and an MSE of 0.0518, demonstrating high predictive accuracy. These results highlight the feasibility of using machine learning techniques to capture the intricate relationships between printing strategies and mechanical performance in material extrusion manufacturing.

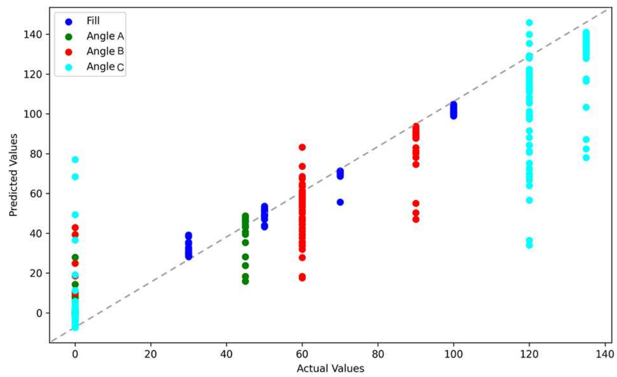

Fig. 6. Scatter plot of predicted versus true values for all printing parameters, showing overall model accuracy.

Beyond predictive modelling, the insights gained from this study can support the development of data-driven design frameworks for additive manufacturing. By elucidating how layer-wise orientation and infill strategies influence mechanical behaviour, this approach enables designers to optimise internal structures to achieve targeted performance characteristics, thereby reducing reliance on empirical trial-and-error methods. Furthermore, integrating machine learning models into the design process could facilitate the automatic recommendation of optimal printing parameters based on predefined mechanical requirements, improving design efficiency and expanding the design space for complex and functional AM components. In addition to direct parameter recommendation, the inverse prediction capability demonstrated in this study may also support integration with simulation-driven design frameworks. By linking target mechanical responses derived from numerical simulations with feasible process parameters, this approach can support performance-guided process planning. This offers a potential pathway for layer-wise control in cases where spatially varying mechanical performance is required.

Future work will focus on expanding the dataset by incorporating additional process parameters, such as printing speed and layer thickness, and on further refining the modelling framework to enhance its generalisation capabilities across different material systems and more complex geometrical structures.

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