

INTEGRATING PARAMETRIC OPTIMIZATION AND MACHINE LEARNING TO IMPROVE DIMENSIONAL ACCURACY IN ADDITIVE MANUFACTURING

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ABSTRACT:

Additive Manufacturing (AM) continues to transform rapid prototyping and low-volume production, particularly for applications requiring complex geometries and fast iteration cycles. However, its broader adoption in precision engineering remains constrained by dimensional accuracy and mechanical reliability limitations. These challenges are especially critical in producing components such as gears for mechanical and electromagnetic counters, where tight tolerances and functional durability are essential.

This study explores using Artificial Intelligence (AI) to optimize AM-produced precision components, focusing on gear applications. Utilizing vat photopolymerization (VPP) or Stereolithography Apparatus (SLA), technologies widely available at the Philippines' Advanced Manufacturing Center (AMCen), this study evaluates how various print parameters and material choices affect dimensional deviation and mechanical durability.

Artificial neural networks (ANNs) train the data from experimental prints and performance tests. Results show training, validation, and test R^2 values ranged from 0.75 to 0.86, 0.74 to 0.94, and 0.79 to 0.93. The total R^2 is consistent across 10 K-folds. The lowest MSE was observed in Folds 4, 6, and 7, aligning with the highest test R^2 values, with Fold 7 achieving the best performance at an MSE of 9.38×10^{-4} and an R^2 of 0.92. The overall model performance remains consistent regardless of data partitioning, indicating model stability and reliability.

The experimental results showed that the optimal parameter setting was achieved with a 0.05 mm layer height, 22.5° angle, 15-minute curing time, and 60 °C curing temperature, with curing temperature and layer height exerting the most decisive influence on performance. The prediction profiler identified 0.075 mm layer height, 22.5° angle, 30-minute curing time, and 60 °C curing temperature as the optimal settings, achieving an S/N ratio of 9.51 with a desirability of 0.8435.

KEYWORDS: 3D printing, Additive manufacturing, Artificial Neural Network, Dimensional accuracy, Machine learning

1) INTRODUCTION:

Additive Manufacturing (AM), also widely known as 3D-printing, is a relatively new and promising technology that has seen tremendous growth in researchers' interest in the past few years. In the Philippines, the Advanced Manufacturing Center (AMCen) under the Metals Industry Research and Development Center, Department of Science and Technology (MIRDC-DOST), aims to be the nation's technological hub for additive manufacturing. DOST-AMCen houses multiple 3D-printing technologies that support different research and development projects, locally and internationally.

Currently, there are seven (7) major 3D printing technologies per ISO/ASTM standards, namely material extrusion, vat photopolymerization, material jetting,

Table 1. Printing parameters DOE using the L9 Taguchi Method

Case No.	Layer Height/ Thickness (mm)	Angle (degrees)	Curing (minutes)	Time	Curing Temp (°C)
1	0.1	0	15		30
2	0.1	22.5	30		45
3	0.1	45	45		60
4	0.075	0	30		60
5	0.075	22.5	45		30

6	0.075	45	15	45
7	0.05	0	45	45
8	0.05	22.5	15	60
9	0.05	45	30	30

binder jetting, powder bed fusion, laminated object manufacturing, and direct energy deposition [1]. The general process for AM is first to create a Computer-Aided Design (CAD) and process it to generate machine code that will fabricate the part layer-by-layer. This creates advantages compared to conventional manufacturing (subtractive manufacturing and formative manufacturing), which includes the following: (i) the fabrication of complex geometry, which is challenging when using traditional manufacturing, (ii) the production of novel material properties, and (iii) reduced material surplus and costs, especially for prototyping. However, 3D printing can have defects and faults that are absent in conventionally manufactured parts and products. Some of these defects include deflection and distortion in parts, dimensional deviation, porosity, surface roughness, and material anisotropy, mainly because of the manner of creation of parts in AM.

Dimensional accuracy in 3D-printed parts refers to assessing how closely the manufactured dimensions match the nominal values of the original model. Since accuracy is a critical aspect of manufacturing, dimensional accuracy should be extensively studied to ensure reliability and quality in production. Hanon & Ma [2] investigated the accuracy of 3D printed PLA, with different colors and process parameters, while Tungcel [3] investigated 3D printed objects using PLA, ABS, and PETG. Furthermore, Okamoto & Ura [4] measured accuracy using an image processing system.

Machine learning (ML), a subset of artificial intelligence (AI), utilizes algorithms to analyze data, construct models, and make predictive inferences [5]. From reviewing literature, Artificial Neural Network (ANN) has been integrated into 3D printing to investigate the impact of printing parameters on produced parts [6], identification of intricate 3D printed patterns [7], and help evaluate the relationship between the process and output parameters [8].

ANN comprises interconnected mathematical neurons arranged in a structured network. Input signals of varying intensities are processed through these neurons, as shown in Figure 1, where they are combined to produce a net input transmitted to the next layer. The output layer, which represents the dependent variables, is determined by the weights and biases assigned to the connections between neurons [5].

This study uses an ANN to predict the dimensional accuracy of 3D printed gears fabricated using Stereolithography Apparatus (SLA), in partnership with Line Seiki Philippines Inc. (LSPI), a globally recognized company specializing in producing a wide range of electronic, electromagnetic, mechanical counters, switches, thermometers, and sensors. Research aims to enhance 3D-printed parts by integrating artificial intelligence (AI) to produce LSPI products, particularly in developing high-precision gears.

The Taguchi experiment design is used to provide a systematic experiment run using different variables crucial for SLA to identify the most influential factors affecting the quality of the 3D printed gear.

2) METHODS AND METHODOLOGY:

(a) Design of Experiment

Stereolithography Apparatus (SLA), or Vat Photopolymerization (VPP), is the AM technology adopted in this study. SLA is a resin-based 3D printing technology that utilizes a UV laser to selectively cure liquid photopolymer resin layer by layer, forming highly detailed and precise parts.

Parameters crucial in SLA include the layer thickness, print orientation angle, curing time, and curing temperature. These four (4) parameters underwent design of experiments (DOE), which was formulated using the Taguchi L9 orthogonal array to systematically explore the impact of key printing parameters on dimensional accuracy and mechanical reliability. Layer height varies from 0.1, 0.05, and 0.075 while the angle ranges from 0, 22.5, and 45. Curing durations were 15 minutes, 30 minutes, and 45 minutes, while curing temperatures used were 30 °C, 45 °C, and 60 °C, respectively. The parameters studied for VPP were layer thickness, print orientation angle, curing time, and curing temperature, as detailed in Table 1. The DOE was generated using the JMP Statistical software.

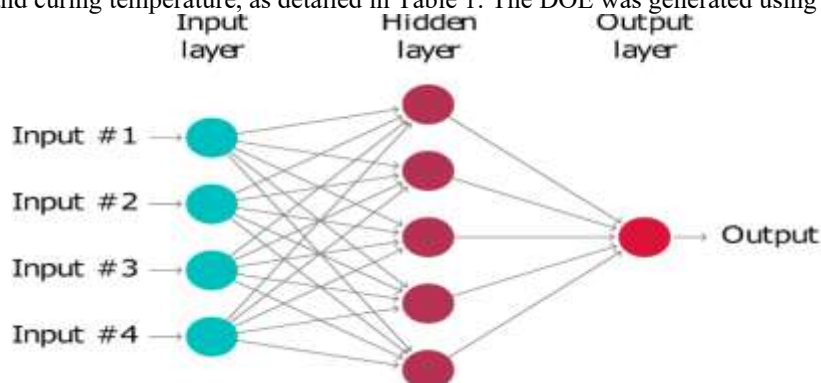


Figure 1. Neural Network Architecture

$$\frac{S}{N} = -10 \log \left(\frac{1}{n} \sum_i Y_i^2 \right) \quad \text{Equation 1}$$

The result analysis follows the smaller-the-better performance criterion, as shown in Equation 1. This approach is appropriate since a lower response value signifies better performance. In this study, the objective is to achieve a percentage error as close to zero as possible.

(b) Fabrication

Nine (9) experiment runs were developed and were fabricated using a VPP-based 3D printer available at the DOST-AMCen, as illustrated in Figure 2. After fabrication, the dimensions of the printed samples were assessed using a Coordinate Measuring Machine (CMM), as shown in Figure 3. Additionally, micrometers, calipers, and pin gauges were also utilized to gather supplementary dimensional data.

Dimensional deviations, such as shrinkage or expansion were quantified and documented for each set of parameters. The test model featured different patterns of cylindrical and rectangular holes and embosses, serving as a reference for measurement. These varied geometric features were strategically selected to evaluate dimensional accuracy comprehensively and effectively.

(c) Machine Learning

The collected experimental data were screened to develop the ANN algorithm. The dataset includes the printing parameters (layer height, angle, curing time, and temperature) and the measured dimensions. This was used to develop predictive models specifically targeting dimensional accuracy, enabling optimization of print parameters for enhanced precision.

In designing the neural network, the hidden layers were structured progressively with neuron counts of 10, 7, 5, 3, and 2. This gradual reduction in the number of neurons allows the model to capture complex patterns in the early layers while compressing and refining information as it moves deeper into the architecture. The dataset was divided into three subsets to support training and evaluation. The data was allocated for training, validation, and testing, following 50:25:25. The hyperbolic tangent sigmoid activation function was employed for the hidden layers. At the same time, purelin (linear) was used for the output layer. These combinations use nonlinearity to model complex patterns, ensuring the final predictions are realistic and unrestricted. K-fold cross-validation was also included to provide an unbiased estimate of model performance.

Coefficient of determination (R^2) and mean-square error (MSE) were used as the evaluation metric. R^2 provides the variable distribution in response to the predicted variables. Value is from 0 to 1, where 1 shows perfect prediction accuracy. MSE reflects the model's performance using the squared average difference between the predicted and actual values. The lower the value, the more accurate the prediction.

Additionally, statistical analysis was performed on the collected data to determine the significance of each printing parameter and its interactions. Analysis of Variance (ANOVA) was used to identify parameters contributing most significantly to dimensional deviations. This statistical evaluation provided essential insights into the process sensitivity, ensuring optimized printing parameters were statistically robust and practically applicable.

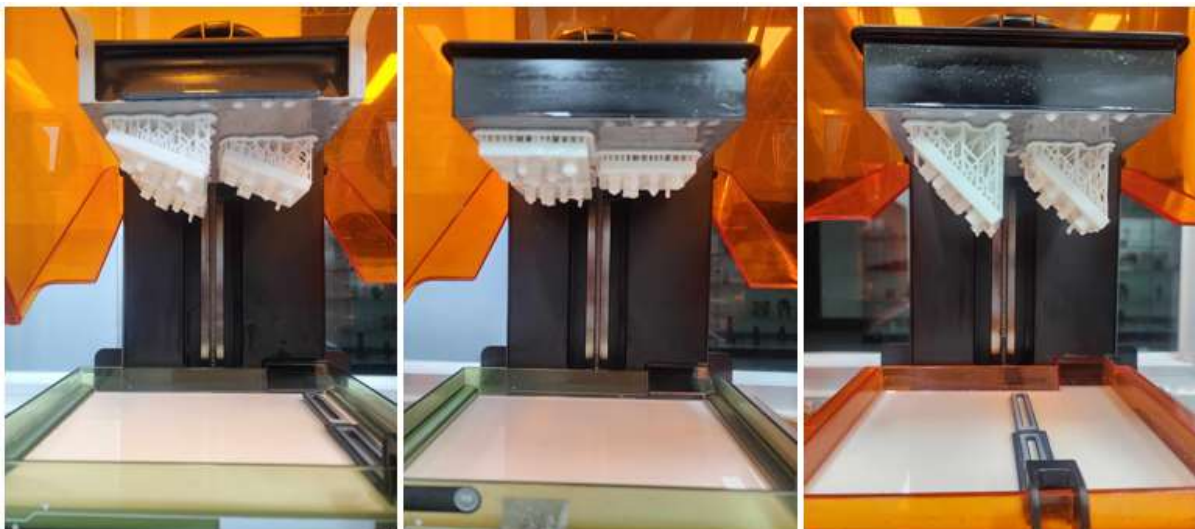


Figure 2. 3D-Printing of a model with different parameters from Taguchi DOE using Vat Photopolymerization (VPP)



Figure 3. Actual 3D-printed parts and dimensional inspection using a Coordinate Measuring Machine (CMM)

3) RESULT:

(a) Prediction of Dimensional Accuracy

The results of the ANN model training are summarized in Table 2. The training R^2 values ranged from 0.75 to 0.86, with the highest performance observed in Fold 1. The model fits the training data, with only slight variations across folds, but no extreme overfitting is observed.

Validation R^2 values varied between 0.74 and 0.94, with the best result achieved in Fold 9. The result shows a higher value than training, indicating that the model generalizes well. The result also achieved a higher value (0.94), indicating stability.

Meanwhile, the test R^2 values ranged from 0.79 to 0.93, with the highest accuracy recorded in Fold 4. The result remains close to validation, confirming a robust and not overfitted model. The total R^2 values are 0.81 and 0.84, which show a very stable model. The overall model

performance remains consistent regardless of data partitioning. This stability in total R^2 is a strong indicator of model reliability. The lowest MSE was achieved at Fold 4, 6, and 7, aligning with the highest test R^2 results. As observed, the lowest MSE is at Fold 7 at 9.38×10^{-4} with the highest R^2 at 0.92. The graphical illustration of Fold 7 is shown in Figure 4.

(b) Signal-to-Noise Ratio

Table 3 presents the results of the Taguchi design of experiments. The highest S/N ratio of 6.14 was obtained in Case No. 8, corresponding to the factor combination of a 0.05 mm layer height, 22.5° angle, the shortest curing time of 15 minutes, and the highest curing temperature of 60°C . This combination represents the optimal parameter settings, yielding the greatest accuracy and overall performance.

Table 2. Results of K-fold Validation

K-fold Validation	Train	Validate	Test	Total	MSE
	R^2	R^2	R^2	R^2	
1	0.86	0.74	0.79	0.81	3.1×10^{-3}
2	0.77	0.90	0.81	0.81	1.96×10^{-3}
3	0.75	0.91	0.88	0.81	1.54×10^{-3}
4	0.82	0.89	0.93	0.84	9.98×10^{-4}

5	0.82	0.85	0.86	0.84	1.93×10^{-3}
6	0.82	0.85	0.92	0.84	1.30×10^{-4}
7	0.80	0.90	0.92	0.84	9.38×10^{-4}
8	0.84	0.88	0.83	0.84	4.38×10^{-3}
9	0.82	0.94	0.84	0.84	1.88×10^{-3}
10	0.83	0.89	0.86	0.84	2.45×10^{-3}

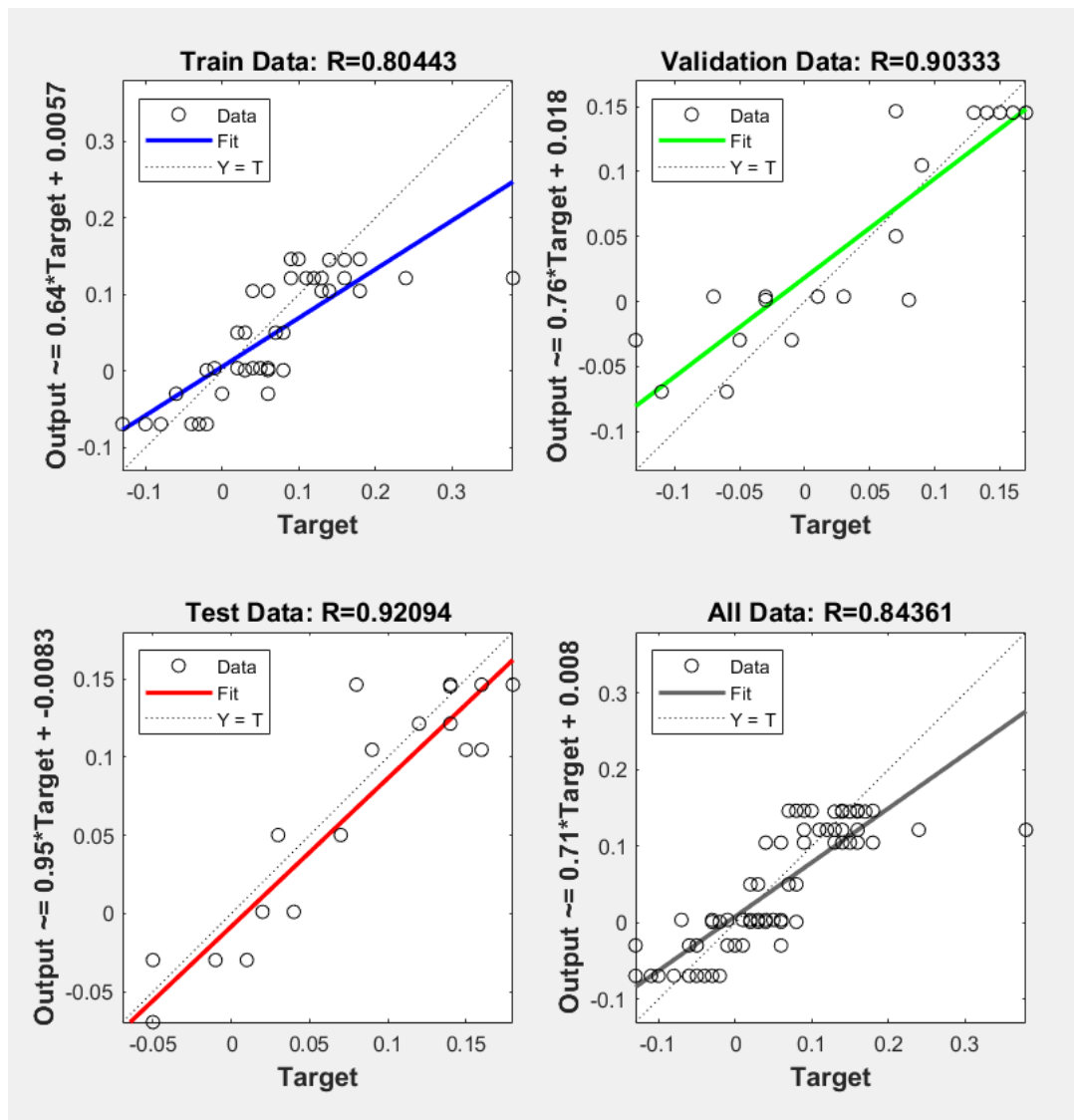


Figure 4. Plot of K-fold 7

Table 3. Taguchi Design of Experiment

Case No.	Layer Height/ Thickness (mm)	Angle (degrees)	Curing Time (minutes)	Curing Temp ($^{\circ}\text{C}$)	Mean	S/N Ratio
1	0.1	0	15	30	1.59	-4.57
2	0.1	22.5	30	45	1.40	-3.01
3	0.1	45	45	60	1.22	-2.02
4	0.075	0	30	60	0.44	5.93

5	0.075	22.5	45	30	0.59	3.77
6	0.075	45	15	45	1.11	-1.27
7	0.05	0	45	45	1.81	-5.19
8	0.05	22.5	15	60	0.40	6.14
9	0.05	45	30	30	0.66	3.21

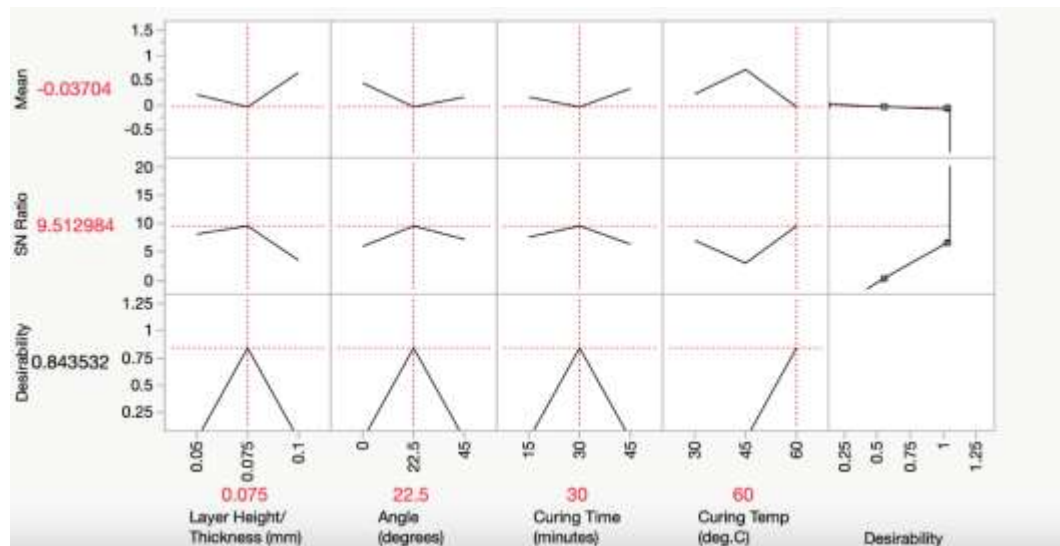


Figure 5. Maximized Desirability

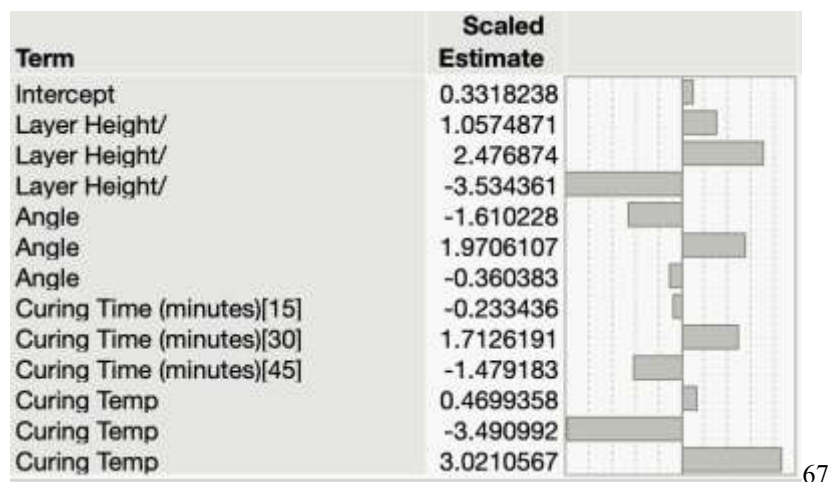


Figure 6. Scaled Estimates

Figure 5 identified the combination of a 0.075 mm layer height, 22.5° angle, 30 minutes curing time, and 60 °C curing temperature as the optimal settings, yielding an S/N ratio of 9.51 and a desirability value of 0.8435. The scaled estimates in Figure 6 further confirm that curing temperature and layer height significantly influence performance. At the same time, angle and curing time are secondary factors contributing to minimizing error.

4) CONCLUSION:

This study successfully demonstrated the capability of ANN models to accurately predict dimensional deviations of AM-produced components, particularly with VPP technology. The ANN model was trained using the Taguchi L9 orthogonal array and validated with a comprehensive statistical analysis, which provided a reliable predictive tool for optimizing AM print parameters. The high correlation between actual and predicted dimensional accuracy and excellent training convergence indicated by error metrics affirms the robustness and practical applicability of the developed ANN framework.

The ANN model achieved training R^2 values between 0.75 and 0.86, with the best result in Fold 1, while validation R^2 ranged from 0.74 to 0.94, peaking in Fold 9. Test R^2 values were consistent at 0.79–0.93, with the highest

accuracy in Fold 4, confirming robustness and absence of overfitting. The lowest MSE was recorded in Fold 7 at 9.38×10^{-4} , paired with a high R^2 of 0.92, highlighting the model's reliability.

The result of the Taguchi design of the experiment indicates that curing temperature and layer height significantly affect the achievement of dimensional accuracy. From the experiment, Case No. 8, with a 0.05 mm layer height, 22.5° angle, 15-minute curing time, and 60 °C curing temperature, was identified as the optimal parameter setting, achieving the highest accuracy and overall performance. Furthermore, the prediction profiler identified the combination of a 0.075 mm layer height, 22.5° angle, 30 minutes curing time, and 60 °C curing temperature as the optimal settings, yielding an S/N ratio of 9.51 and a desirability value of 0.9986.

This research significantly enhances dimensional accuracy in additive manufacturing, particularly for precision engineering applications, by identifying critical parameters and interactions. The findings not only enhance AMCen's capability for accurate and reliable AM practices but also provide a viable approach to broaden AM adoption in precision-driven industries, facilitating further innovations and economic efficiencies in the broader manufacturing sector.

5) FUTURE WORK:

Future work will extend the research by exploring dimensional accuracy optimization using other Additive Manufacturing technology. Furthermore, integrating Finite Element Analysis (FEA) simulation data into ANN training datasets will be explored to develop physics-informed AI models. This approach aims to further enhance predictive accuracy by incorporating physical principles into the model training process, improving the reliability and applicability of ANN predictions in practical AM scenarios.

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