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Artificial Neural Network for Benchmarking the Dimensional Accuracy of the PLA Fused Flament Fabrication Process

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ABSTRACT: Fused Deposition Modeling (FDM) is an additive manufacturing technique that uses a 3D printer to extrude molten filament through a nozzle, which moves along the X, Y, and Z axes to create parts with the desired geometry. FDM offers numerous advantages, especially for producing parts with complex shapes, due to its ability to enable rapid and cost-effective manufacturing compared to traditional methods. This study implemented an Artificial Neural Network (ANN) to optimize process parameters aimed at minimizing dimensional inaccuracies in the FDM process. Key parameters considered for optimization included the number of shells, infill percentage, and nozzle temperature. The ANN utilized three algorithms: Scaled Conjugate Gradient, Bayesian Regularization, and Levenberg-Marquardt. Model performance was evaluated based on dimensional deviations along the X and Y axes, with a hidden layer of 25 neurons. Among the algorithms, Scaled Conjugate Gradient provided the most accurate results in minimizing dimensional errors.

KEYWORDS: Fused deposition modeling; artificial neural network; scaled conjugate gradient; Bayesian regularization; Levenberg-Marquardt

1. Introduction

The FDM process, commonly referred to as 3D printing or Fused Filament Fabrication (FFF), has gained widespread adoption in the industrial sector due to its ease of use, versatility, and cost-effectiveness. FDM constructs physical objects by depositing material layer by layer, offering distinct advantages such as the ability to produce complex shapes quickly and at a lower cost compared to traditional manufacturing [1]. As an additive manufacturing process, FDM works by extruding molten filament material through a nozzle, which moves along the X, Y, and Z axes to build parts layer by layer. This method is especially advantageous for producing parts with complex geometries that would be difficult or expensive to manufacture using conventional methods.

Despite these benefits, a primary limitation of FDM is its lack of dimensional accuracy [2], which directly impacts the product's tolerance and usability. This shortcoming limits broader industrial application, as dimensional precision is crucial for ensuring manufactured parts meet design specifications. When parts deviate from specified tolerances, especially in assemblies involving components like holes and shafts, the result can be unusable or difficult-to-fit products. Improving dimensional accuracy in FDM has therefore become a key area of research in the field.

Several factors affect the dimensional accuracy and surface quality of FDM-manufactured parts, including material type, infill percentage, number of shells, nozzle temperature, and layer thickness, which all impact material flow through the nozzle [3]. Traditionally, researchers have employed statistical design approaches to identify optimal process parameters to enhance dimensional accuracy. However, advancements in machine learning, particularly with Artificial Neural Networks (ANNs), have opened new avenues for optimization.

Previous studies have explored various approaches to optimize FDM parameters. For example, Aslani et al. [4] applied the Grey Taguchi method to benchmark the dimensional accuracy of PLA filaments, while Mohamed et al. [5] focused on optimizing FDM parameters for ABS to improve mechanical properties using statistical methods. Other studies, such as Beniak et al.'s work [6], examined the effects of layer thickness and printing temperature on part accuracy. Dey and Yodo [7] reviewed factors influencing dimensional accuracy, surface quality, and mechanical properties, revealing that smaller layer thickness, a higher number of shells, and optimal extrusion temperature improve dimensional accuracy.

Additional studies by Turner and Gold [8] highlighted the importance of controlling material flow from the print head and minimizing warping and shrinkage caused by heat. Valerga et al. [9] studied FDM PLA filaments, identifying extrusion temperature, material pigments, and environmental humidity as key factors affecting dimensional accuracy, surface quality, and mechanical strength.

Moza et al. [10] found that dimensional accuracy on the XY plane is mainly influenced by print material, infill rate, number of shells, and layer thickness. PLA was found to provide better dimensional accuracy than ABS. Alafaghani’s study on six process parameters concluded that build orientation, extrusion temperature, and layer height most significantly impact dimensional accuracy. Sudin et al. [11] found that FDM machines struggle to maintain accuracy when producing circular components, exceeding tolerance limits in parts like cylinders and holes.

Further research, including Alafaghani et al.'s work [12] using Taguchi DOE, indicated that low infill percentage, specific infill patterns, and thin layers enhance dimensional accuracy, while strength improves with higher values and a triangular pattern. Mahmood et al. [13] examined ABS filament geometric characteristics and found that the number of shells is the most critical factor affecting dimensional accuracy, followed by inset distance multiplier, shell spacing, and ambient temperature.

Minetola and Galati [14] studied low-cost 3D printers and found that enhancing structural stiffness and reducing noise significantly improves print quality. Vishwas et al.'s [15] optimization of process parameters for FDM printing with ABS and nylon concluded that specific combinations of layer thickness, orientation angle, and shell thickness yield the best dimensional accuracy and tensile strength.

From the literature, several conclusions can be drawn. First, improving printer stiffness and reducing noise are essential for high-performance FDM prints. Second, the geometry and deposition angle of the STL model strongly influence the quality of 3D-printed parts. Third, layer thickness plays a limited role in XY-plane dimensional accuracy at a zero-degree deposition angle, but smaller layer thicknesses improve accuracy as the angle increases. Fourth, the number of shells, infill rate, and infill pattern significantly impact the final product quality.

Several studies have explored machine learning models to predict dimensional deviation in FDM. Sharma et al. [16] used a Decision Tree algorithm to model dimensional accuracy across various geometries such as cylindrical shafts and rectangular slots, achieving an R^2 score of 0.67. Mohamed et al. [17] introduced a novel approach combining definitive screening design (DSD) with an ANN to evaluate and predict dimensional deviations in FDM-produced cylindrical parts, effectively minimizing experimental efforts while optimizing fabrication conditions.

Charalampous et al. [18] employed regression-based machine learning algorithms to create predictive models for dimensional deviations, providing insights into process conditions and demonstrating machine learning's potential to enhance FDM precision in complex, real-world applications. Joshi et al. [19] examined dimensional accuracy through classification methods using K-Nearest Neighbors (KNN), Kernel Approximation, and Stochastic Gradient Descent (SGD) algorithms. Their approach, based on supervised machine learning classifiers, showed that Kernel Approximation and SGD outperformed KNN, underscoring the utility of these algorithms for categorizing deviations and informing parameter selection to enhance part accuracy. Other methods used for dimensional accuracy prediction in FDM include fuzzy inference systems [2], logistic regression [20], Gaussian Naïve Bayes [20], linear regression with interactions [21], Response Surface Methodology [22], and recurrent neural networks [23].

ANN was selected for this study due to its capacity to model nonlinear relationships between input parameters (number of shells, infill percentage, nozzle temperature) and dimensional deviations in the FDM process. The ANN's architecture, with a hidden layer of 25 neurons, effectively captures complex interactions among parameters, leading to more accurate predictions of dimensional errors. Additionally, ANNs offer flexibility in adjusting model depth, making them suitable for both smaller and larger datasets.

This study aims to address the critical issue of dimensional accuracy in the FDM process by using an ANN to optimize key process parameters. Despite FDM's growing popularity in industrial applications for its cost-effectiveness and ability to produce complex geometries, dimensional inaccuracies continue to hinder its broader adoption for precision parts. The goal of this research is to identify the optimal combination of parameters—such as the number of shells, infill percentage, pattern, and nozzle temperature—to minimize dimensional errors in FDM-produced parts. By leveraging experimental data and machine learning techniques, this study seeks to advance FDM technology, ensuring higher accuracy and reliability in manufacturing and expanding its applicability in industries that demand tight tolerances and high precision.

2. Materials and Methods

This section describes the methods used in the study, including analytical approaches. An Artificial Neural Network (ANN) was employed to investigate the effect of 3D printing process parameters on the dimensional error of 3D-printed PLA plastic. The fitting method was chosen for the ANN due to its suitability for the data used and its capability to provide numerical output. Three types of training algorithms were applied, resulting in diverse outcomes for comparative analysis. The algorithms included the Scaled Conjugate Gradient (SCG), Bayesian Regularization, and Levenberg-Marquardt.

Three input parameters were utilized, with nine data points for each parameter (resulting in an input matrix of size 9x3). The input parameters were the number of shells, nozzle temperature, and infill percentage, as shown in Table 1. The output consisted of two parameters, each with nine data points (output matrix size 9x2), representing deviations along the X-axis and Y-axis, as shown in Table 2. Prior to training, the data were normalized to a range of 0-1. The dataset was then split, allocating 70% for training, 15% for validation, and 15% for testing.

In the prediction model, a single hidden layer with 25 neurons was used. The input layer contained three neurons corresponding to the inputs—number of shells, temperature, and infill—while the output layer contained two neurons, representing deviations in the X and Y directions. Figure 1 provides an illustration of the architecture of the developed prediction model.

Table 1. Input data.

Exp. No.	Original value				Normalized value		
	Number of Cells (-)	Temperature (°C)	Infill (%)	Pattern (-)	Number of Cells (-)	Temperature (°C)	Infill (%)
1	2	210	10	E	0	0	0
2	2	220	15	D	0	0.5	0.5
3	2	230	20	R	0	1	1
4	3	210	15	R	1	0	0.5
5	3	220	20	E	1	0.5	1
6	3	230	10	D	1	1	0
7	2	210	20	D	0	0	1
8	2	220	10	R	0	0.5	0
9	2	230	15	E	0	1	0.5

Table 2. Output data.

Feature	Nominal dimension (mm)		Measured dimension (mm)				Normalized value	
	X-dir	Y-dir	X-dir		Y-dir		X-dir	Y-dir
			Avg.	Dev.	Avg.	Dev.		
A	5	20	5.063	0.063	19.940	0.060	0.224	0.357
			5.063	0.063	19.850	0.150	0.224	1
			5.040	0.040	19.890	0.110	0.132	0.714
			5.113	0.113	19.990	0.010	0.424	0
			4.963	0.037	19.930	0.070	0.12	0.428
			5.090	0.090	20.030	0.030	0.332	0.143
			5.070	0.070	19.920	0.080	0.252	0.5
			5.257	0.257	19.890	0.110	1	0.714
			5.007	0.007	19.920	0.080	0	0.5

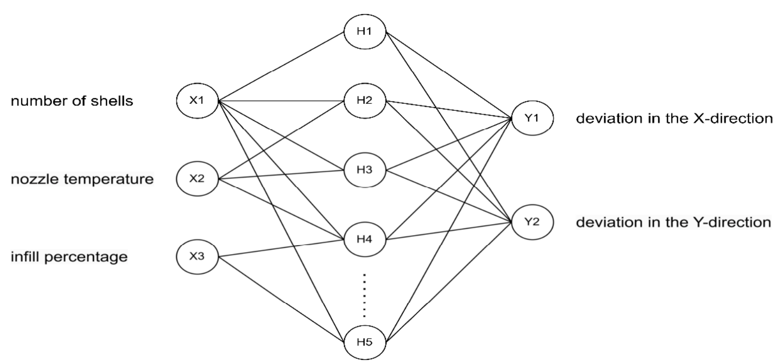

Figure 1. ANN architecture.

3. Results and Discussion

Figure 2 illustrates the Mean Squared Error (MSE) plot throughout the training process. For the Scaled Conjugate Gradient algorithm, training halted after 14 iterations. A continuous decrease in MSE was observed in the training data with each iteration, while the validation and test data maintained relatively stable MSE values, reaching their lowest point at the 8th iteration with an MSE of 0.00043918. In the training state plot, a gradient of 0.00011141 was noted, with 6 validation checks at the 14th epoch. The error histogram plot shows that errors during the test and validation phases remained somewhat distant from zero, indicating residual inaccuracies. However, the regression plot displayed an R-value close to 1, suggesting a strong correlation.

The MSE plot highlights a discrepancy between the training curve and the validation and test curves, suggesting possible underfitting. This may be attributed to the limited dataset, as the training set contained only nine data points. Complete training and testing results for the prediction model using the Scaled Conjugate Gradient algorithm are shown in the gradient plot in Figure 3, the error histogram plot in Figure 4, and the regression plot in Figure 5. Subsequently, results for the Bayesian Regularization Algorithm are provided in Figures 6 and 7, while results for the Levenberg-Marquardt algorithm are presented in Figures 8 and 9

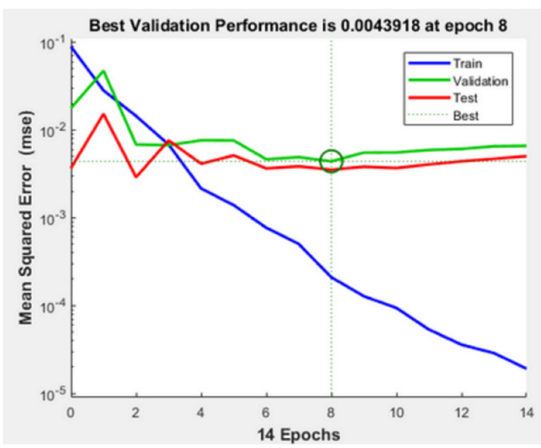

Figure 2. Mean squared error plot.

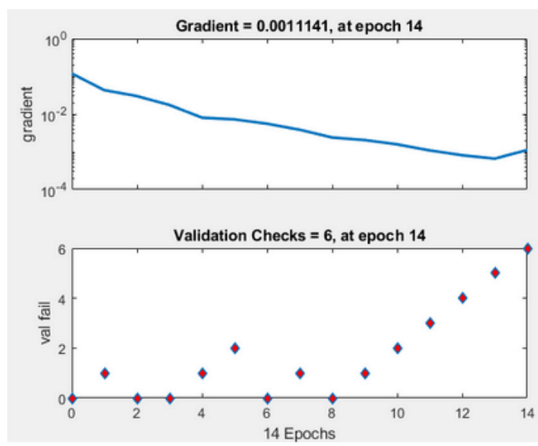

Figure 3. Gradient model plot using scaled conjugate gradient.

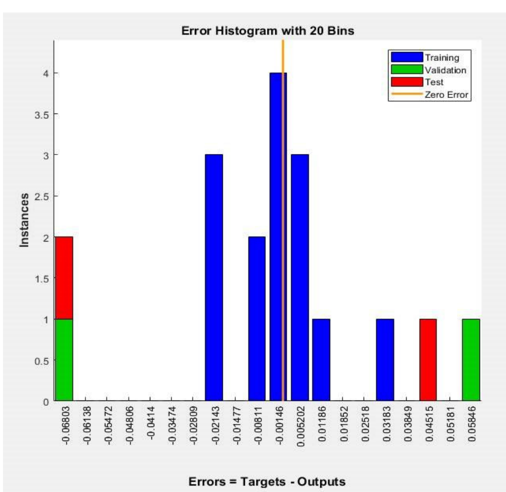

Figure 4. Error histogram graph model using scaled conjugate gradient.

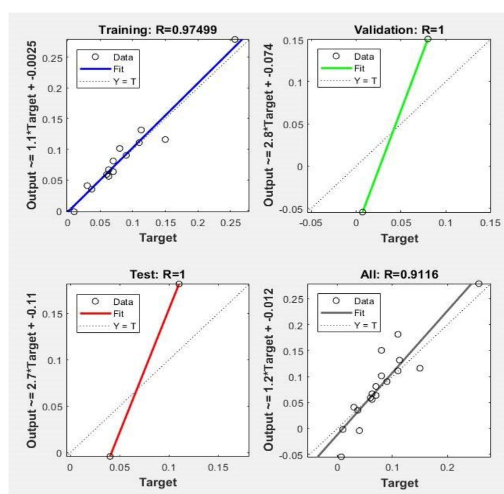

Figure 5. Plot regression model using scaled conjugate gradient.

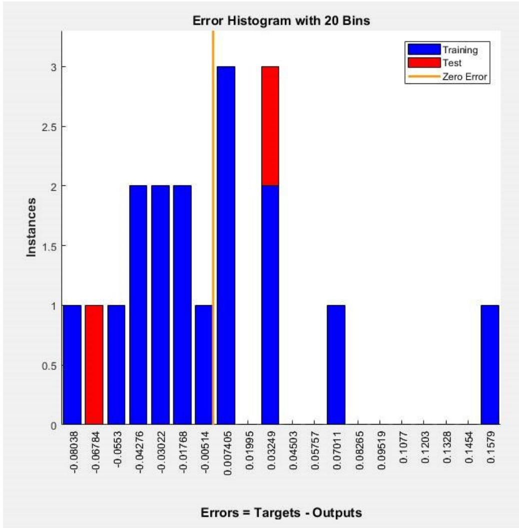

Figure 6. Error histogram graph model using Bayesian regression.

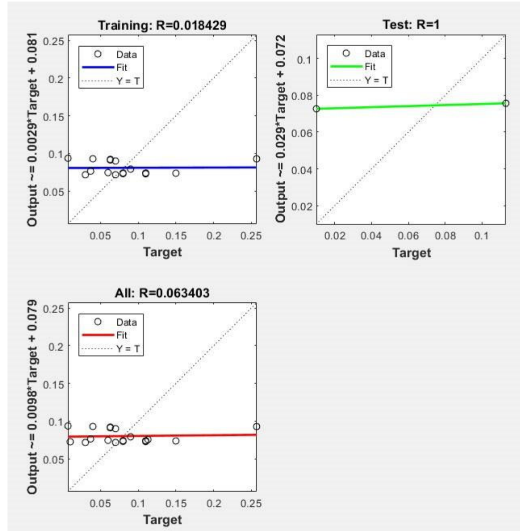

Figure 7. Plot regression model using Bayesian regression.

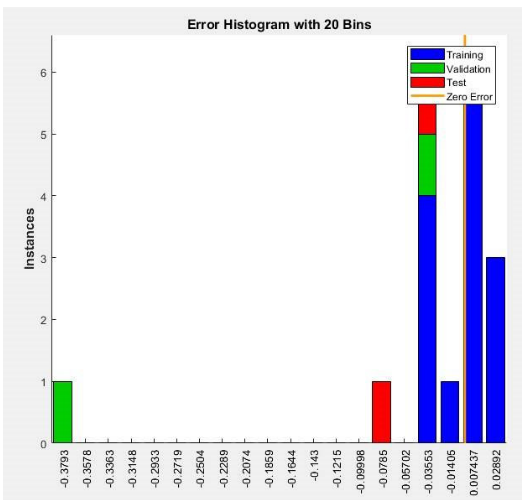

Figure 8. Error histogram graph model using Levenberg-Marquardt.

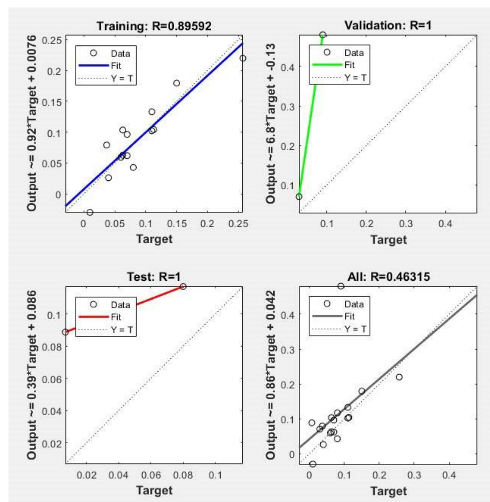

Figure 9. Plot regression model using Levenberg-Marquardt.

In the prediction model trained with the Bayesian Regularization Algorithm, Figure 6's error histogram plot reveals that errors during the test phase remained considerably distant from zero. Additionally, Figure 7's regression plot indicates suboptimal outcomes, as the R-value for both training and testing across all data was substantially below 1. In the prediction model trained using the Levenberg-Marquardt Algorithm, Figure 8's error histogram plot shows that errors did not converge close to zero. The regression plot in Figure 9 shows an overall R-value that remains far from 1, though the R-values for the training and test sets were close to 1.

Table 3. Comparison of R-values.

	Training	**All**
Scaled Conjugate Gradient	0.97	0.91
Bayesian Regression	0.02	0.06
Levenberg-Marquardt	0.89	0.46

Table 3 presents a comparison of R-values for the three algorithms. The results reveal notable differences in the performance of the Scaled Conjugate Gradient (SCG), Bayesian

Regression, and Levenberg-Marquardt (LM) algorithms, evaluated by their accuracy in both training and overall testing. The SCG algorithm excelled, achieving an impressive 97% accuracy on the training set and a robust 91% accuracy overall. This consistency indicates that SCG not only effectively learned patterns within the training data but also generalized well to new data. Its strong performance across both measures suggests SCG's suitability for this application, providing reliable predictions for similar datasets.

In contrast, Bayesian Regression performed poorly, reaching just 2% accuracy during training and only slightly improving to 6% overall. These low scores indicate that Bayesian Regression failed to capture meaningful relationships within the data, making it ineffective for this predictive task. This may reflect an incompatibility between the requirements of this application and the assumptions or structure of Bayesian Regression. The LM algorithm produced mixed results, achieving a high 89% accuracy on the training set but dropping sharply to 46% overall. This decline suggests that LM overfitted the training data; while it captured specifics of the training set well, it struggled to generalize effectively to new data. This pattern of overfitting indicates that further adjustments, such as regularization or parameter tuning, may be needed to improve its generalizability. The SCG algorithm demonstrated the best overall performance, proving both accurate and consistent. While LM showed some potential, it would require refinement to avoid overfitting, whereas Bayesian Regression did not prove effective for this application.

4. Conclusions

The training results from the three different algorithms still showed suboptimal outcomes and did not fully represent actual data conditions due to the limited dataset available from the journal. Nevertheless, among the three algorithms, the Scaled Conjugate Gradient (SCG) method demonstrated relatively better results than the others. When applying an Artificial Neural Network (ANN) to minimize dimensional errors in 3D-printed PLA plastic, this approach proved effective in identifying optimal parameters to reduce these errors. By improving parameter selection, ANN has the potential to contribute to producing more accurate and higher-quality products in additive manufacturing, as it can identify the ideal conditions for the 3D printing process. A key limitation of this study, however, was the insufficient amount of data. A larger dataset would enhance the accuracy of the model's learning process. Additionally, incorporating other intelligent algorithms, such as backpropagation neural networks or learning vector quantization, could further improve the results. The author believes that using the SCG method could yield more accurate predictions of dimensional errors in 3D-printed PLA plastic. Based on the experiments, SCG consistently produced better results compared to the other methods. This ANN approach could also be extended to Fused Deposition Modeling (FDM) with other PLA variants, such as carbon fiber PLA or wood PLA, by adjusting or modifying the process parameters accordingly.

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Author Contribution

Conceptualization: N. M. E. Normasari, A. P. Rifai; Methodology: K. S. Setiawan, I. P. Tanaji, A. Permana, H. N. Akbar, D. A. A. Prihatmaja., A. P. Rifai; Data Collection: K. S. Setiawan, I. P. Tanaji, A. Permana, H. N. Akbar, D. A. A. Prihatmaja; Data Analysis: K. S. Setiawan, I. P. Tanaji, A. Permana, H. N. Akbar, D. A. A. Prihatmaja ;Writing: K. S. Setiawan, I. P. Tanaji, A. Permana, H. N. Akbar, D. A. A. Prihatmaja., A. P. Rifai, P. D. Pamungkasari; Supervision: N. M. E. Normasari, A. P. Rifai; Funding: A. P. Rifai, P. D. Pamungkasari.

Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the data and the paper are free of plagiarism.

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