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Parametric Prediction of FDM Process to Improve Tensile Properties Using Taguchi Method and Artificial Neural Network

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ABSTRACT

Fused deposition modeling (FDM) is a popular 3D printing technique that creates parts by heating, extruding, and depositing filaments made of thermoplastic polymers. The processing parameters have a considerable impact on the characteristics of FDM-produced parts. This paper focuses on the parametric prediction of the FDM process to predict ultimate tensile strength and determine a mathematical model using the Taguchi method and Artificial Neural Network. Five manufacturing variables, such as layer thickness, print speed, orientation angle, number of parameters, and nozzle temperature at five levels, are used to study the mechanical properties of PLA material to manufacture specimens using FDM 3D printer. The specimens are produced for tensile tests in accordance with ASTM-D638 standards, and the process parameters are established using the Taguchi orthogonal array experimental design technique. The results proved that the printing process parameters significantly impacted the tensile strength by changing the tensile test values between 37 MPa and 53 MPa. Also, the neural network predicted the tensile strength values, and the maximum error was equal to 8.91%, while the mathematical model had a maximum error equal to 19.96%.

Keywords: additive manufacturing; 3D printing; printing parameters, artificial neural network; fused deposition modeling.

INTRODUCTION

Using information from 3D models, additive manufacturing (AM), commonly referred to as 3D printing, is a technique for producing parts that is typically done layer-by-layer. This technology makes the design and producing process more swift and inexpensive. A complex shape requires a lot of time and cost using conventional manufacturing methods, so 3D printing machines are used in many industries to create parts during the design stage. AM can be classified into several different subfields, including fused filament fabrication (FFF), Stereolithography (SLA), direct jetting, photopolymer jetting, selective laser sintering (SLS), laser melting, electron beam melting, and hybrid processes. Fused deposition modelling (FDM), a kind of AM that employs layers of thermoplastic filament, is one of many several 3D printer designs. In an FDM machine, as shown in Figure 1, the head of the printer moves in X and Y axes. Up and down movement is made by the bed (Z-axis) where the filament or material is being melted and extruded by the nozzle and deposited on the film bed, layer over layer creating the required part. The first stage in using the FDM technique is to create a 3D design using CAD software. Then, the 3D model is divided using slicer software after being saved as an STL file. To start the 3D printing process, the finished sliced model is transferred to an FDM machine and saved as a G-code file.

The low maintenance cost of FDM is one of its key advantages over other AM technologies, environmentally friendly, and high flexibility. Also, 3D printing technology can reduce wasteful material use, labor requirements, and manufacturing times. FDM has a few drawbacks, including

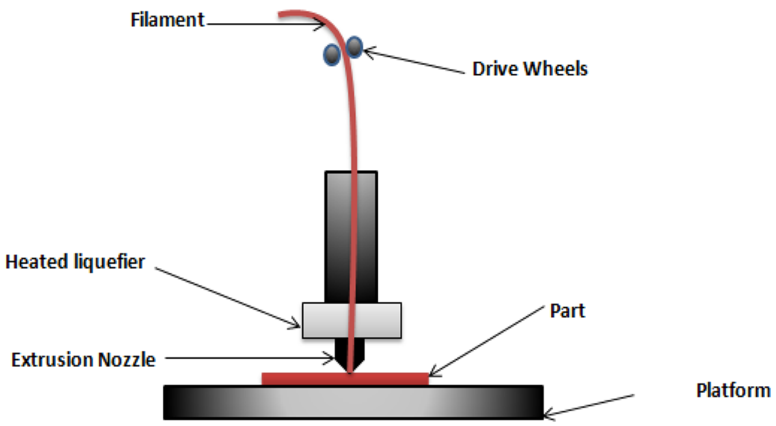

Figure 1. Schematic drawing of FDM system

a seam line between layers, the requirement for a support structure, a lengthy build time, and temperature-induced delamination. 3D printing parts are used in different fields, such as aerospace, civil engineering, automotive, biomedicine, and so on [1–7].

Tianyun Yao et al. [6] investigated the ultimate tensile strength of 3D PLA materials manufactured using FDM method. The three layer thicknesses variable (0.1 mm, 0.2 mm, and 0.3 mm) were applied with different angles (0, 15, 30, 45, 60, 75, and 90°). The plastic multipurpose test specimens' standard ISO 527-2- 2012 designed the specimens. The specimens were analyzed using the transverse isotropic hypothesis, classical lamination theory, and Hill-Tsai anisotropic yield criterion. The outcomes demonstrated that at all angles and thicknesses, the theoretical model could successfully predict the final tensile strength of FDM materials. Additionally, it was discovered that as the printing angle or layer thickness increased, the final tensile strength decreased. Dezaki et al. [8] studied the impacts of infill density and patterned the effects on surface roughness (SR) and tensile strength using polylactic acid (PLA) material. Four tool paths, concentric, zig-zag, triangle, grid, and patterns, were used with varying densities that matched the FDM machine's structure. A finite element analysis (FEA) was also used to see how printing and simulation varied. The results showed that the surface quality of the grid and concentric tool path was the greatest. In contrast, according to a tensile strength test and microscopic analysis, the zig-zag pattern performed poorly due to its subpar design, weak adhesion, and lowest mechanical strength. D'Addona et al. [9] studied the optimization of FDM process parameters using polylactic acid (PLA) polymer. The selected printing parameters included layer thickness, printing speed, and infill percentage. The experiment's design was based on the L16 Taguchi array, which has three components, each with four levels. Additionally, the desirability function was used to optimize the process parameters of FDM operation. The results showed the best variables were 0.3 mm layer thickness, 81.5152 mm/s printing speed, 55% infill percentage, 2.10 m filament length, 5.68 g component weight, and 20.01 min printing duration. Abas et al. [2] investigated the effect of process variables on the dimensional deviation of fused deposition modeling of 3D printed parts. The parameters for the printing process that were chosen were layer height, number of perimeters, infill density, infill angle, print speed, nozzle temperature, bed temperature, and print orientation. The experimental runs were planned using a decisive screening design (DSD) with three levels. The findings indicated that infill density was the most important factor affecting length and breadth deviation. A layer height of 0.1 mm, six perimeters, 20% infill density, 90° fill angle, 70 mm/s print speed, 220 °C nozzle temperature, 70 °C bed temperature, and 90° print orientation were utilized as well to achieve the best results. Pang et al. [10] investigated the impact of printing temperature on bonding quality and tensile properties of FDM 3D-printed parts. The test specimens were made of PLA material and printed at temperatures between 180 °C and 240 °C, rising 10 °C at a time. At a strain rate of 1 mm/min, a five-times repeat of each variable's uniaxial tensile test under the ASTM D638-14 standard was carried out. Based on the results, it can be concluded that specimens printed at higher temperatures have better tensile characteristics. Also, the maximum tensile strengths measured for samples created at T = 240 °C and T = 180 °C were 36.97 MPa and 17.47 MPa, respectively.

The objective of the research is to study PLA a material for FDM-produced parts and to analyze how the process parameters affect tensile strength. Also, the ANN and mathematical model are used to predict ultimate tensile strength and the most remarkable error percentage between practical and predicted values.

MATERIALS AND PROCESS

One of the main points in the 3D printing process is the material selection process. Also, the material selection process depends on the type of application and the material's mechanical properties. The other essential point is the manufacturing process; it depends on the manufacturing variables because of affects the mechanical properties and the quality of the manufactured product. So, this part will talk about the selected material and the influencing printing variables on the manufacturing process.

Material

Polylactic acid, sometimes known as PLA, is one of the most frequently used materials for 3D printing. This biodegradable thermoplastic substance is made from renewable resources such as sugar cane, tapioca roots, corn starch, and potato starch. Printing with PLA is incredibly easy and doesn't emit any hazardous gases because it is non-toxic. It also requires a low nozzle temperature and does not warp easily. PLA can be used in surgical implants and medical suturing since it can degrade and produce lactic acid in the body. In 6 months to 2 years, these implants frequently dissolve within the body. Additionally, PLA is often utilized in dinnerware, disposable clothes and food packaging. It is normally not advised to use PLA for mechanical products because it is a little more fragile. PLA cannot be used in high-temperature situations due to its tendency to deform at temperatures exceeding 60 °C [11].

Process parameters

Layer thickness is a feature parameter that significantly affects printing time and the precision and mechanical properties of printed materials. Increases in layer thickness lead to decreased elastic modulus, tensile strength, and elongation at break. A low layer thickness will produce an excellent surface finish, whereas a large layer will create a bad surface finish. The surface roughness increases when the number of layers increases [12]. The best printing speed in FDM is determined by the material, extrusion temperature, and resolution. The amount of space covered by the nozzle tip in one second (mm/s) during printing is referred to as printing speed. Additionally, the material's dynamic cooling and thawing rates are strongly impacted by the printing speed, which has an undesirable effect on layer bonding. Setting a fast printing speed could result in poor layer bonding and reduced mechanical strength of the printed items. Larger voids and worse layer bonding are the results of faster printing rates [13]. However, using a low printing speed increases the manufacturing process time, and therefore the appropriate printing speed that gives the desired result must be determined. The printing path with respect to the X-axis on the platform, which is connected to the interior design of the finished printed product, is represented by the raster

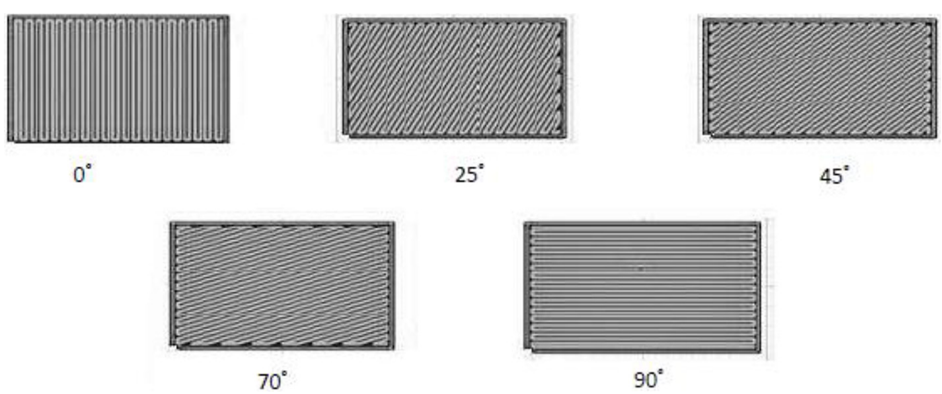

Figure 2. Represents different types of 3D printing raster angles

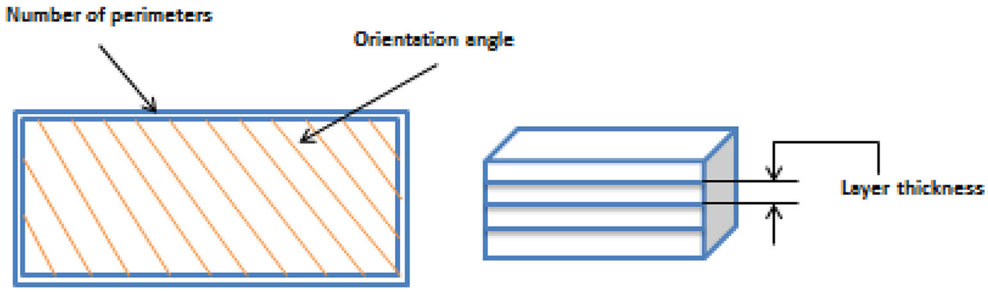

Figure 3. 3D printer's process parameters

angle. The raster angle influences the surface roughness and mechanical strength, and the typically allowed raster angles are from 0° to 90° [14], as shown in Figure 2.

Nozzle temperature is used to melt the solid filament before the extrusion process, and The filament material's melting point must be set. It changes the printing material's viscosity, changing the part's properties. The ideal temperature must be maintained because changing it could change how fluid the filament material is, impacting the manufactured component. Also, the temperature extrusion is influenced by the type of material and printing speed. The perimeter is the number of shells used for the part's outer covering. The tensile strength is constantly increased by increasing the number of perimeters [14]. A schematic of the FDM 3D printer and some of the procedures abovementioned are shown in Figure 3.

EXPERIMENT DESIGN

In the study, some parameters have been considered for studying their effect on tensile strength. In contrast, few parameters have been kept constant such as infill density 100, infill pattern Zig-Zag, and bed temperature 60 °C. The layer thickness (height), print speed, nozzle temperature, orientation angle, and the number of perimeters have been selected for the present study with five levels. Table 1 shows the levels and values of the selected process parameters.

A common method frequently used in engineering research is the study of some factors. However, This type of methodology has several drawbacks, including ambiguous conclusions, the need for many trials, the inability to explore factor interactions fully, and others. A design of experiments (DOE) can be used to get around these difficulties. DOE is a subfield of statistics that enhances experiment output by assisting in efficient experiment planning, organization, and execution. Most studies use Taguchi analysis to minimize the experiments number. So, L25 Taguchi orthogonal array has been used in this research to analyze the impact of chosen parameters; Table 2 shows samples of PLA have been printed.

SPECIMENS FABRICATION

The design is the most essential factor in the manufacturing process; SolidWorks software was used to design the specimen. After that, the CAD file is transformed into an STL file. Ultimaker CURA software is used to configure the settings of the printing parameters to start printing the required part. The specified characteristics and size may affect the time, but the complexity of the design has no bearing on it. Tensile specimens were produced using a 3D printer-Creality Ender6. The specimens were built according to the ASTM standard D638 type, as shown in Figure 4.

Table 1. Printing process parameters and their levels

Parameters	Level 1	Level 2	Level 3	Level 4	Level 5
Layer thickness (mm)	0.2	0.22	0.24	0.24	0.26
Print speed (mm/s)	45	50	55	60	65
Nozzle temperature °C	200	205	210	215	220
Orientation angle	0°	25°	45°	70°	90°
Number of perimeters	2	3	4	5	6

Table 2. Matrix of experimental printing parameters

Experiment number	Layer thickness (mm)	Print speed (mm/s)	Nozzle temperature (°C)	Number of Perimeters	Orientation angle (degree)
1	0.2	45	200	2	0
2	0.2	50	205	3	25
3	0.2	55	210	4	45
4	0.2	60	215	5	70
5	0.2	65	220	6	90
6	0.22	45	205	4	70
7	0.22	50	210	5	90
8	0.22	55	205	6	0
9	0.22	60	220	2	25
10	0.22	65	200	3	45
11	0.24	45	210	6	25
12	0.24	50	215	2	45
13	0.24	55	220	3	70
14	0.24	60	200	4	90
15	0.24	65	205	5	0
16	0.26	45	215	3	90
17	0.26	50	220	4	0
18	0.26	55	200	5	25
19	0.26	60	205	6	45
20	0.26	65	210	2	70
21	0.28	45	220	5	45
22	0.28	50	200	6	70
23	0.28	55	205	2	90
24	0.28	60	210	3	0
25	0.28	65	215	4	25

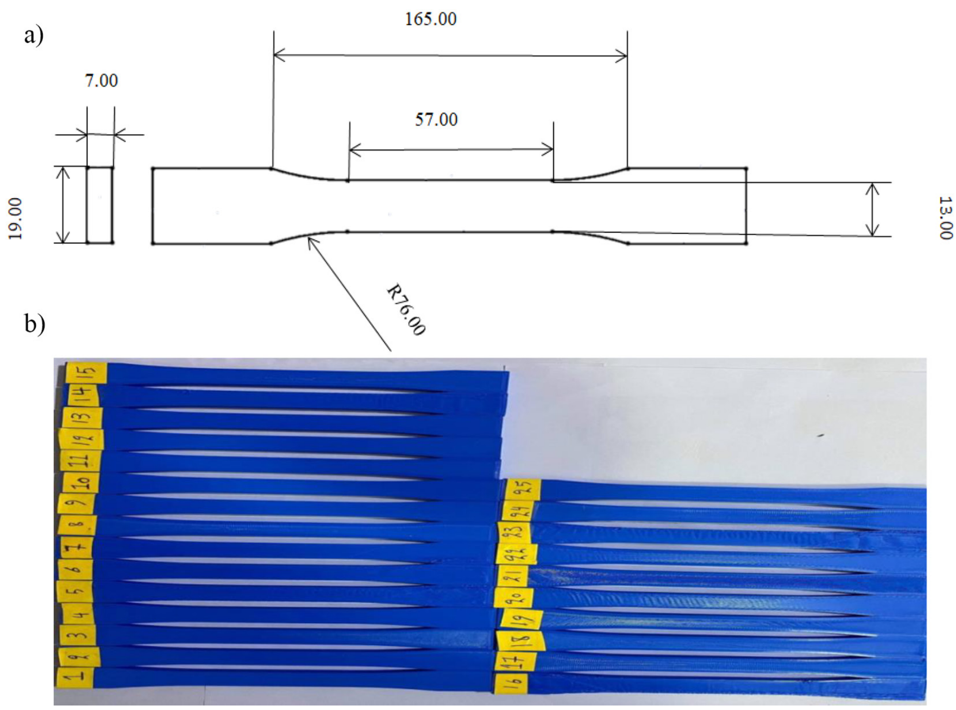

Figure 4. Sample dimensions and printed samples (a) Dimensions according to ASTM D638 standard (b) Fabricated specimen

ARTIFICIAL NEURAL NETWORK MODELING

Artificial neural networks (ANNs) are a paradigm for information processing inspired by the operation of biological nervous systems, such as the brain. An ANN comprises several layers of fundamental processing units called neurons. The neuron performs two functions collects inputs and generates an output. Predictive modeling using neural networks has the advantage of implicitly recognizing complex nonlinear correlations and any potential interactions between the independent variables. This is accomplished through multi-layered ANNs, which act as a prediction model in a black box. Since ANNs are data-driven, self-adaptive methods, they can adapt the system's model. However, they see fit without explicitly specifying the model's functional form [16, 17]. Function Artificial Neural Network technique is used to predict the output. The neural network has three layers: an input layer, an output (or target) layer, and a hidden layer. ANN model has been trained between input and output parameters. The input matrix (5×25) and output data (1×25) have been imported into the neural fitting tool, as shown in Figure 5.

Table 3 shows three methods used to represent the paramount results for discrete regression values, such as (Levenberg Marquardt (LM), scaled conjugate gradient (SCG), and Bayesian regularization (BR)). The network training is represented by updating the weights, and it is recommended to use LM or BR because they are efficient algorithms for adapting nonlinear systems in both simulated and actual practical data and reducing squared errors and weights. Also, based on the regression results, all values are equal or close to one. As for BR, despite its good results, it requires more time commensurate with the depth of the problem. Additionally, given the training of the data set and the relationship between the input and the target, the LM algorithm was chosen to analyze the data. In addition, 70% of experimental data has been used for training, 15% of the sample for testing, and 15% for cross-validation.

The ANN has been trained with 25 sets of five input process parameters (layer thickness, print speed, nozzle temperature, number of perimeters, orientation angle) and output response (tensile strength). Different regression values are evaluated to establish the connection between outputs and targets. Several regression values are assessed to determine the relationship between outputs and targets. Regression R values close to 1 indicate a best fit and strong correlation between the variables, whereas values close to 0 indicate a random relationship. Figure 6 shows four plots training data is a set of data that is used to train the model, validation data is a set of data separated from training which is used to investigate the performance of a model during training, test data is a set of data that is separately used to test a model after completion of training, and all's plot provides an unbiased final model performance metric in terms of accuracy, which indicates the possibility of using this product in the future. The dashed line in each drawing represents the best values between the outputs and the target, while the solid line represents the linear regression of the ratios between the outputs and the target. The R-value indicates the relationship between the outputs and the target. If R = 1, this shows an accurate linear relationship between the outputs and

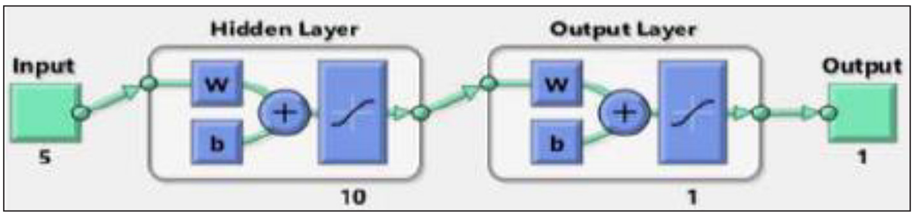

Figure 5. Schematic of the neural network

Table 3. ANN algorithms with regression values

No.	Data training algorithm	Coded As	Training: R	Validation: R	Test: R	All: R
1	Levenberg-Marquard (LM)	Trainlm1	0.99389	0.97451	0.98755	0.98055
2	Scaled-Conjugate-Gradient (SCG)	Trainscg	0.78646	0.97051	0.9457	0.8607
3	Bayesian Regularization backpropagation (BR)	Trainbr	1	-	1	1

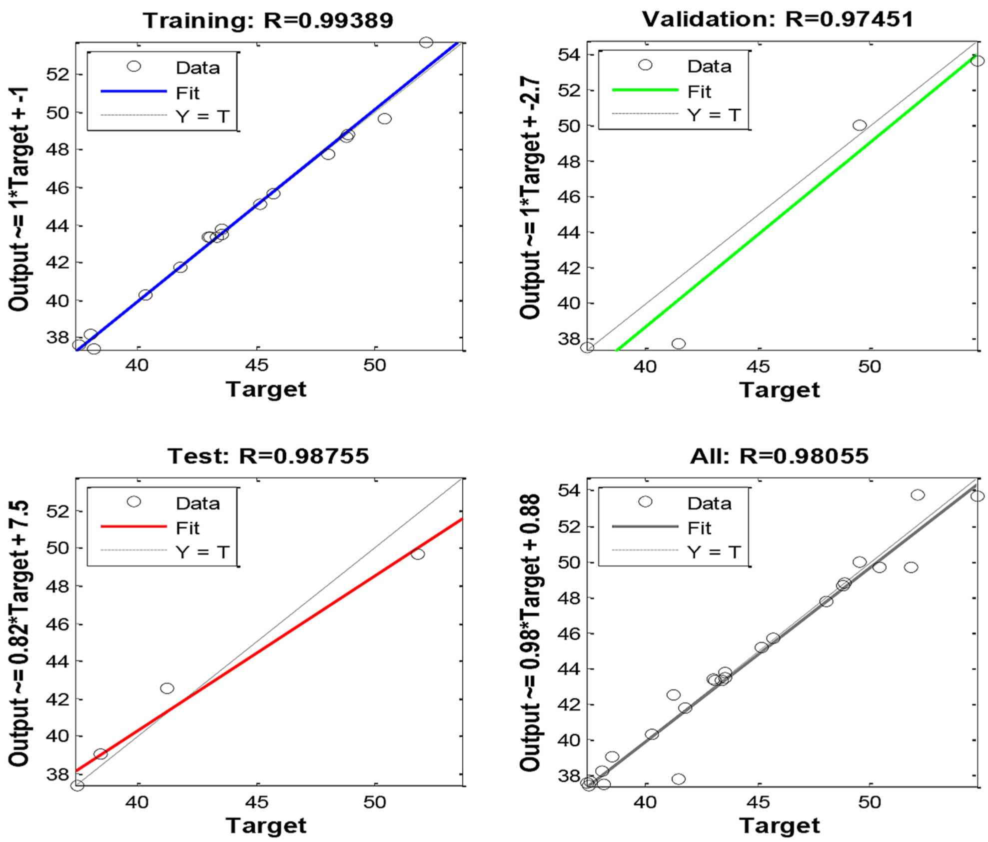

Figure 6. Regression plots for ultimate tensile strength were obtained using artificial neural networks

Table 4. Comparative evaluation of predictive models

EXP	Tensile test values (MPa)	ANN Predicted values (MPa)	Error percentage of ANN	Mathematical Model values	Error percentage of mathematical model
1	38.13	37.42	1.86	36.35	4.67
2	37.34	37.49	-0.41	40.44	-8.30
3	42.99	43.37	-0.88	43.99	-2.33
4	51.79	49.65	4.13	48.08	7.16
5	48.78	48.64	0.29	51.63	-5.84
6	54.74	53.65	1.98	46.35	15.33
7	52.13	53.74	-3.08	49.91	4.26
8	41.78	41.76	0.04	41.31	1.12
9	38.04	38.20	-0.41	40.06	-5.31
10	43.08	43.34	-0.59	42.34	1.72
11	40.3	40.27	0.08	44.18	-9.63
12	37.51	37.63	-0.31	41.89	-11.68
13	49.52	50.00	-0.97	45.97	7.17
14	45.69	45.64	0.11	48.25	-5.60
15	41.42	37.73	8.91	40.17	3.02
16	45.17	45.12	0.10	47.80	-5.82
17	37.44	37.36	0.21	39.72	-6.09
18	41.25	42.51	-3.05	42.53	-3.10
19	43.53	43.47	0.13	46.08	-5.86
20	48.88	48.81	0.14	44.32	9.33
21	48.04	47.72	0.67	45.63	5.02
22	50.44	49.64	1.58	48.44	3.97
23	38.47	39.04	-1.48	46.15	-19.96
24	43.34	43.34	0.01	38.07	12.16
25	43.52	43.76	-0.55	42.15	3.15

the target, and if the R values are close to Zero, there is no linear relationship between the output and the target. Additionally, the regression values of training, validation, test, and all were 0.99389, 0.97451, 0.98755, and 0.98055, which indicates a significant fit between target ad output.

ANN utilizes sample data that are available in the system to make quick predictions, saving both time and cost. The mathematical model was obtained based on the samples data results of the ANN to predict the tensile strength values of the samples after compensating the variables in the mathematical model-Equation 1, where X1 is layer thickness, X2 is printing speed, X3 is the number of perimeters, X4 is orientation angle named, and X5 is nozzle temperature.

$$\begin{aligned} \mathrm{UTS-ANN} &= 23.7 - 0.1\,X1 + 0.003\,X2 + \\ &+ 1.169\,X3 + 0.1058\,X4 + 0.051\,X5 \end{aligned} \quad (1)$$

Table 4 shows practical tensile test values; the output parameter values were predicted using the ANN technique-levenberg Marquard training algorithm and mathematical model results. The experimental tensile test values determined using tensile test devices were between 37.34 MPa and 54.74 MPa. Also, the tensile test values can be predicted by the ANN technique using the LM algorithm, and the results were close to the practical values of the tensile test, which range between 37.36 MPa and 53.74 MPa. In addition, the mathematical model is used first degree for predicting the tensile values, and the results were between 36.35 MPa and 51.63 MPa. Furthermore, The error values for ANN were between -3.08 and 8.91 percent, and the error values for the mathematical model were between 15.33 and -19.96 percent. Besides that, Error percentages for ANN and mathematical model were computed individually.

Figure 7 shows the relationship between experiments and tensile test values for practical tensile test values, ANN, and Mathematical model results. The artificial neural network results were close to the results of the practical tensile test, in contrast to the values of the mathematical model.

CONCLUSIONS

This work investigated the influence of printing parameters layer thickness, print speed, nozzle temperature, perimeters number, and orientation angle for fabricating PLA specimens on tensile strength, and the results of the specimens have been analyzed using ANN and mathematical models to determine and predict better printing parameters that give maximum tensile strength.

The tensile strength values obtained were between 37.34 MPa and 54.74 MPa; through the large variance between the values obtained, it was concluded that the parameters of the printing process significantly impact tensile strength. The best variables that give the maximum tensile strength were 0.22 mm layer thickness, 45mm/s print speed, 205 °C nozzle temperature, 70° orientation angle, and 4 perimeter numbers.

The tensile test results were compared with those predicted using the ANN and the mathematical model. The maximum error of the ANN and the mathematical model was 8.91% and 19.96%, respectively. This indicates that the values of the ANN are close to the values of practical experiments compared to the mathematical model.

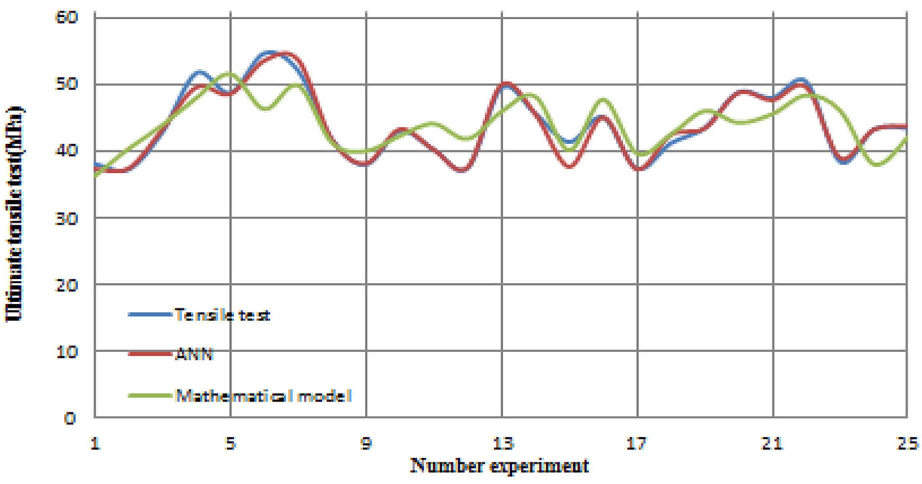

Figure 7. Relationship between tensile test values and predicted values

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