PAPER • **OPEN ACCESS**

Experimental investigation and ANN prediction for part quality improvement of fused deposition modeling parts

To cite this article: A D Tura *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1201** 012031

Experimental investigation and ANN prediction for part quality improvement of fused deposition modeling parts

A D Tura [1, *], H B Mamo[1], Y D Jelila[2] and H G Lemu[3]

[1] Faculty of Mechanical Engineering, Jimma University, Jimma, Ethiopia
[2] Faculty of Transport and Aeronautical Engineering, Silesian University of Technology, Katowice, Poland
[3] Faculty of Science and Technology, University of Stavanger, N-4036 Stavanger, Norway

[*] Contact author: diriba.amanuel@ju.edu.et

Abstract. Fused deposition modeling (FDM) is the most prevalent thermoplastic additive manufacturing technology. Many input parameters and their settings have a significant impact on the quality and functionality of FDM parts produced. To enhance the quality of parts, it is critical to be able to predict surface roughness distribution in advance. The development of artificial neural network (ANN) models to forecast the impact of main FDM process factors on the part quality in terms of surface roughness while utilizing ABS (Acrylonitrile butadiene styrene) material is described in this work. Taguchi L9 orthogonal array was used to plan the experiments. Different printing input parameters such as layer thickness, orientation angle, and infill angle are used in the experiments. In terms of controllable input parameters, ANN is used to construct a predictive mathematical model. The effects of various printing settings on surface roughness were investigated using analysis of variance (ANOVA), main effect plots, and contour plots. Experiment findings and regression value are used to validate the models. The model has shown to be capable of adequately predicting responses within a maximum percentage error of 4.664 percent of arithmetic roughness average (Ra), which is a good agreement.

Keywords: Fused deposition modelling; artificial neural network; Surface roughness; process parameter

1. Introduction

Additive manufacturing (AM) is a cutting-edge technology that creates a product directly from a 3D CAD model using a layer-based manufacturing process. FDM is among rapid prototyping technologies that uses flexible thermoplastic filament extruded via a heated outlet to build components. It uses a range of process parameters throughout the part's production [1–4]. Acrylonitrile butadiene styrene, polylactic acid, polyetherimide (Ultem), Polyether Ether Ketone, polycarbonate, and fiber-reinforced thermoplastics are among the thermoplastics and reinforced thermoplastic materials that may be printed using FDM [5–8]. FDM offers a great deal of versatility when it comes to producing thermoplastic components with complex 3D geometry in a reasonable period of time, making it a viable option for applications in the aerospace, automotive, and medical industries [9–11]. Despite these advances, there is still an insufficient knowledge of the connections between manufacturing process factors and the final mechanical characteristics of such parts, which is hindering further progress and application of this technique.

Several studies have been conducted by various researchers to explored the role of printing factors on surface roughness. For instance, Pramanik et al. [12] conducted experimental study on improvement of surface roughness of ABS FDM printed components and identified substantial influencing factors such as print speed, extruder temperature, bed temperature, infill concentration, and layer thickness. To predict and analyze the electroplating effect on FDM components surface quality and size at various surface angles, Sugavaneswaran et al. [13] used NACA 0012 air foil methods. According to Huang et al. [14], layer resolution, fill mode, and processing material have a substantial impact on top surface roughness, whereas layer resolution has a considerable impact on side surface roughness. Surface roughness is mostly impacted by air gap and less influenced by raster angle, as detected by Mishra et al. [15], and raster width and chemical treatment successfully minimize surface roughness of FDM ABS built parts. According to Dezaki et al. [16], the build direction of FDM devices had a substantial effect on the surface texture, and the infill design and density of FDM objects manufactured with PLA materials had a direct effect on the part quality and mechanical characteristics [17].

Reddy et al. [18] approved that layer height and build inclination, rather than material infill, were the most critical parameters impacting printing quality of FDM components. Print orientation angle had the main effect on FDM produced PLA components, as reported by Buj-Corral et al. [19]. Bintara et al. [20] conducted research on the surface quality of FDM printed components using Polylactic Acid material and found that surface roughness was prominently influenced by layer height, i.e. the higher layer height, the rougher the surface is. According to Sammaiah et al. [21], the optimal output of the surface quality of a FDM printed component is founded at higher infill concentration and lower layer height, with rising layer height also result in increased surface roughness. The layer height has a substantial effect on the surface texture and dimensional tolerances of printed items utilizing the FDM 3D Ultimaker printer PLA thermoplastics according to Mendricky et al. [22]. Rendering to Altan et al. [23], layer height was determined to be the most significant element in improving ultimate tensile and lowering surface roughness of PLA products manufactured by FDM.

Rajesh et al. [24] used the Taguchi S/N ratios optimization technique to improve the quality characteristics in terms of ultimate tensile and surface roughness for ABS products printed using FDM, and found that when surface roughness is considered, temperature plays an essential role, with the lower the temperature, the smoother the surface texture. Manoharan et al. [25] compared experiment and predicted tensile strength during FDM printing components utilizing RSM and ANN approaches. The authors concluded the RSM approach predicted less improvement than the ANN approach. Pazhamannil and his research fellows [26] used an ANN to estimate the ultimate tensile of produced components using FDM at various nozzle temperatures, layer height, and infill rates.

Several pieces of research used various prediction approaches to enhance the feature of FDM printed components. However, few studies have observed at the effect of printing settings and the application of ANN to forecast FDM component quality. Based on a literature review, this study aims to enhance the performance of FDM printed products using experimental and ANN prediction with three input factors such as layer height, orientation angle, infill angle, and surface roughness as the output response.

2. Materials and methods

2.1 Sample preparation

The quality of built part attributes as well as their manufacturing efficiency is heavily influenced by printing settings. It is important to investigate the impact of inputs, printed parameters, and out variables on the quality of printed components. The adjustable input parameters in this study were layer thickness (mm), orientation angle (˚), and infill angle (˚).

Table **1** illustrates the three input variables of the experiment, and their actual level values. As indicated in Figure 1, the test specimen utilized in this experiment was constructed using Solid works CAD modelling software based on the American steel testing and manufacturing (ASTM) D638 standard [27].

Table 1. Controllable input parameters and their levels.

Input parameters	Levels 1	Levels 2	Levels 3
Layer thickness (mm)	0.1	0.2	0.3
Orientation angle (˚)	0	15	30
Infill angle (˚)	0	30	30

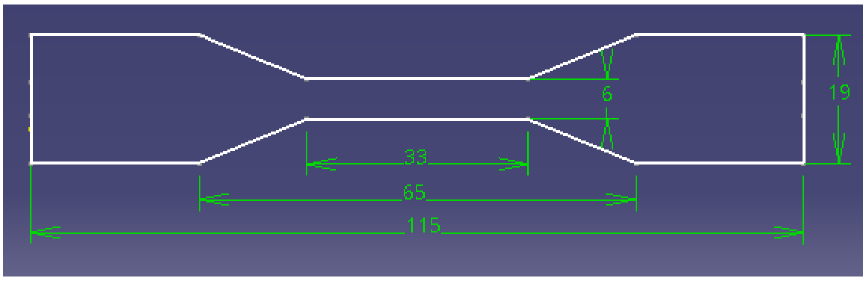
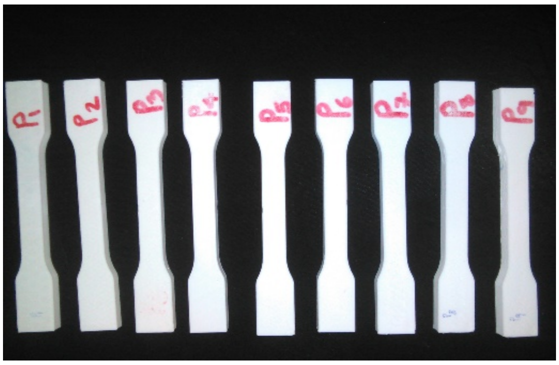


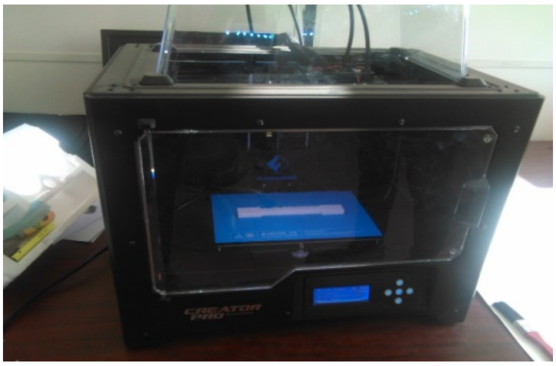
Figure 1. The geometry of the test specimen

2.2 Experimentation setup: Design of experiment and specimen fabrication

Taguchi's experiment design gives an effective method for studying the experiments with the least number of experimentation. A Taguchi L9 (3^3) orthogonal array was used to create an experimental design matrix (Table 2) based on specified process parameters and their levels. As indicated in Figure 1, the test specimen utilized in this experiment was constructed using Solid Works CAD modelling software per the ASTM D638 standard [27] with 3.2 mm thickness. The design format, which was initially in .SLDPRT file format, is changed to .STL file format once the specimen is designed. Additionally, the STL file is imported into CURA, a process control software for Ultimaker 3D printer. This program is used to slice a CAD model into layers, build support structures, change process parameter values, and virtually alter the parts location in the 3D printer's bed. For printing samples (Figure 2(a)), which were generated using design of experiment (DOE) method, an FDM Flash forge creator pro is utilized as shown in Figure 2(b). Each fabricated part's surface roughness was measured at five separate locations on the top and bottom surfaces, with the average results utilized for analysis. The surface roughness of the manufactured items was measured using laser scanning microscopy (VK –X 200 K, Keyence, Japan).



(a)



(b)

Figure 2. (a) Parts fabricated by FDM machine; (b) FDM Flash forge creator pro

Table 2. L9 orthogonal array design of experiments (DOE) and results

Exp. trials	Layer thickness (mm)	Orientation angle (˚)	Infill angle (˚)	Surface Roughness (Ra) (μm)
1	0.1	0	0	0.3265
2	0.1	15	30	0.5925
3	0.1	30	60	0.5988
4	0.2	0	30	1.0545
5	0.2	15	60	1.2165
6	0.2	30	0	1.2095
7	0.3	0	60	1.3375
8	0.3	15	0	1.3425
9	0.3	30	30	1.6542

2.3 ANN modelling

ANNs are inspired by biological neural systems. In this approach, the weighted sum of inputs coming at each neuron is processed through an activation function to create an output signal. To increase or decrease the net input to the activation function, the weighted sum is given an extra bias input. The network design and connections between the processing units play a big role in the functions synthesized this way [28]. The majority of ANN designs are feed-forward networks, which are usually trained using the error back-propagation method from input data. The independent variables are represented by each input node, while the dependent variables are represented by the output nodes. Hidden layers are utilized for computing and are used to execute nonlinear changes on the input space [29].

The independent factors in this study are layer thickness, orientation angle, and infill angle, whereas the dependent variable is surface roughness. The data used to train the network is taken from Table 2. Figure 3 shows the three inputs, ten hidden layer, single output layer, and output (surface roughness) of a three-layer feed-forward network. Table 3 shows the ANN design and learning variables used in this investigation, and the neural network model was generated using the neural network toolbox (version 6.0) in the MATLAB R2019a computational environment.

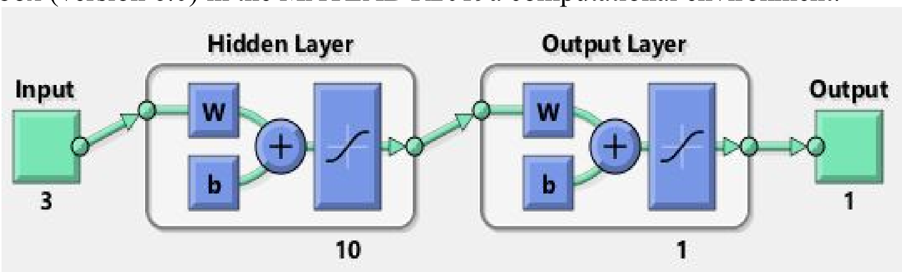


Figure 3. Schematic of the neural network

Table 3. Learning factors selected for ANN

Network type	Feed forward neural network
Training function	Train levenberg-Marquardt(LM)
Adaption Learning function	LEARNGD (Gradient descent)
Performance function	Mean square error
Network topology	3-10-1
Transfer function	TANSIG
Number of Hidden Layers	1
Number of Neurons	10
Training method	Back-propagation
Number of Epochs	100

3. Results and discussion

3.1 Effect of process parameters on surface roughness

The research looks at three FDM process factors. Surface roughness experimental data (Table 2) were evaluated via analysis of variance (ANOVA) to find out the key factors influencing performance metrics. The mean surface roughness was studied using an ANOVA with a 95% certainty interval. The F – value and P-value from the ANOVA table are utilized to verify for significance. The F-test and P-test work on the concept that the bigger the F value and the smaller the value for a given process parameter, the significant the influence on the performance characteristic owing to that process parameter modification. Table 4 shows the ANOVA table with comprehensive analysis. Factors with a very modest probability (Prob > F value less than 0.05) are considered significant in the ANOVA table and are included in the regression model, whereas factors with a probability (Prob > F value) higher than 0.1 are considered unimportant and are omitted from the model.

Table 4. ANOVA tables of surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value (Prob > F)	Remark
Regression	3	1.42681	0.47560	25.18	0.002	Significant
Layer thickness (mm)	1	1.32202	1.32202	69.99	0.0001	Significant
Orientation angle (˚)	1	0.09226	0.09226	4.88	0.078	insignificant
Infill angle (˚)	1	0.01254	0.01254	0.66	0.452	insignificant
Error	5	0.09444	0.01889			
Total	8	1.52126				

3.1.1 Effect of layer thickness. Figure 4 shows the main effects plot of process parameters on surface roughness. It was observed that layer thickness has a substantial impact on responses than orientation angle and infill angle. In Figure 3, when comparing equivalents with low-level and high-level layer thickness, it is obvious that the low-level layer thickness enhances the material's surface roughness. Table 4 shows that layer thickness has a substantial influence on surface roughness since P-value is less than 0.05. Figure 5(a) illustrates Ra contour plots against layer thickness and orientation angle (30° infill angle), while Figure 5 (b) shows Ra contour plots against layer thickness and infill angle (15° orientation angle). The plots in the figure show the interaction analysis between layer thickness vs. orientation angle and infill angle. As illustrated, the lowest surface roughness is achieved at a layer thickness of 0.10 mm to 0.15 mm, as shown in this plot. We also noticed that when layer thickness enlarged, the surface roughness increased.

3.1.2 Effect of orientation angle. In Figure 4, the impact of the orientation angle on the material's surface roughness can be observed in the second plot from the left. This parameter has a negligible impact on part quality. The low-level orientation angle, in contrast, enhances the surface roughness of printed components. As given in Table 4, because the p-value is greater than 0.05, the orientation angle has a minimum effect on surface roughness. The plots in Figure 5(a) and (b) also indicate that optimum surface quality is achieved between 0° and 5° orientation angle. Surface roughness was also shown to be larger at high orientation angles.

3.1.3 Effect of infill angle. The outcome of infill angle on the surface roughness can be seen in the third plot from the left in Figure 4. This parameter has a negligible effect on part quality. The surface roughness of printed components is improved by the lower level infill angle. The infill angle has a minimum effect on surface roughness than the other two factors, as seen in Table 4. The plots in

Figure 5(b) and Figure 5 (c), with 0.2 mm layer thickness, indicate that acceptable surface quality is attained between 0° and 5° orientation angle.

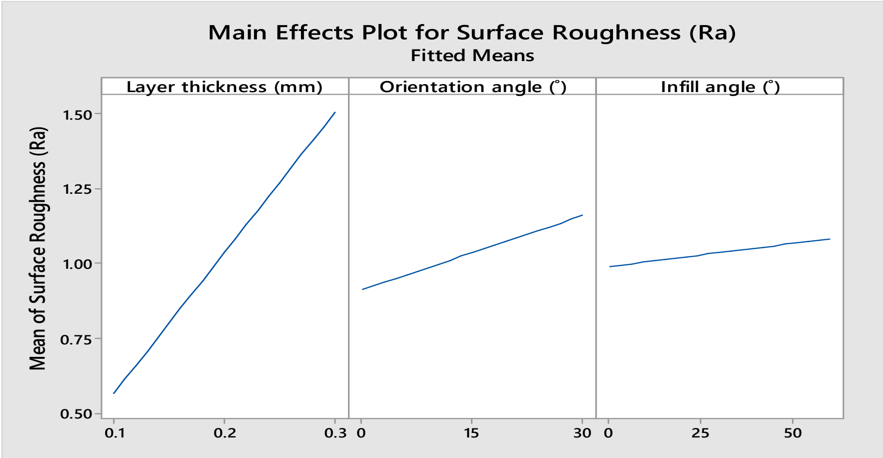


Figure 4. Plots of main effects showing influence of process parameters on Ra

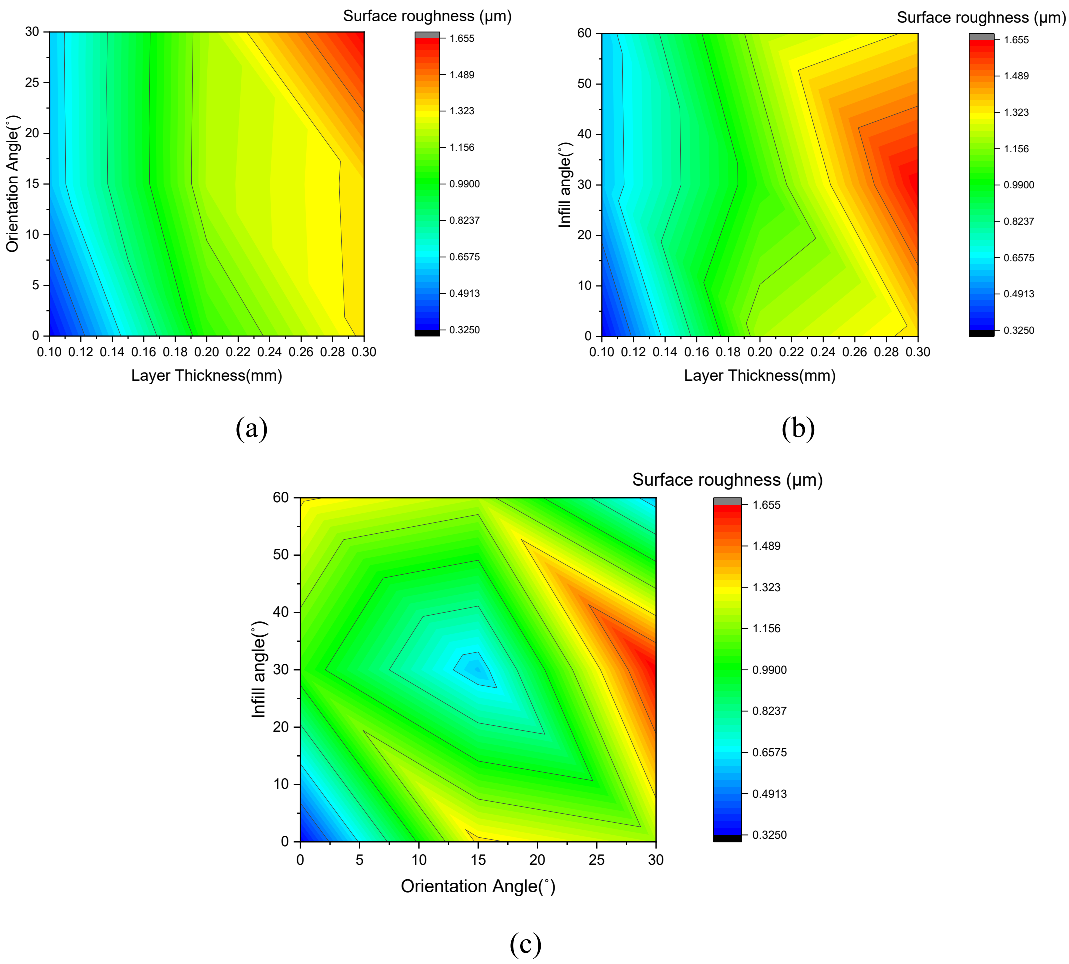


Figure 5. Contour plots of Ra against (a) layer thickness and orientation angle, (b) layer thickness and infill angle, and (c) orientation angle and infill angle

3.2 ANN prediction result

To obtain a good regression value range, the network is trained by modifying the default training settings. When the error, or the gap between the expected and predicted output, is below a given threshold value, or when the number of iterations or epochs is over a designated threshold value, the ANN is stopped training. The regression value (R) near to 1 specifies that relationship is close and value near to 0 represents random relationship. Figure 6 shows the regression plots generated using ANNs, with R = 0.99915 indicating the best fitness after repeated training. This shows that the predicted results of the ANN model appear to be in agreement with the experimental findings. Figure 7 shows comparison graphs between observed and ANN predicted values. Error percentage for ANN was computed individually by associating the predicted values with the test results. As demonstrated in Table 5, the ANN model performed satisfactorily, with all forecasts falling within 5% of the experimental value, indicating its potential for future use.

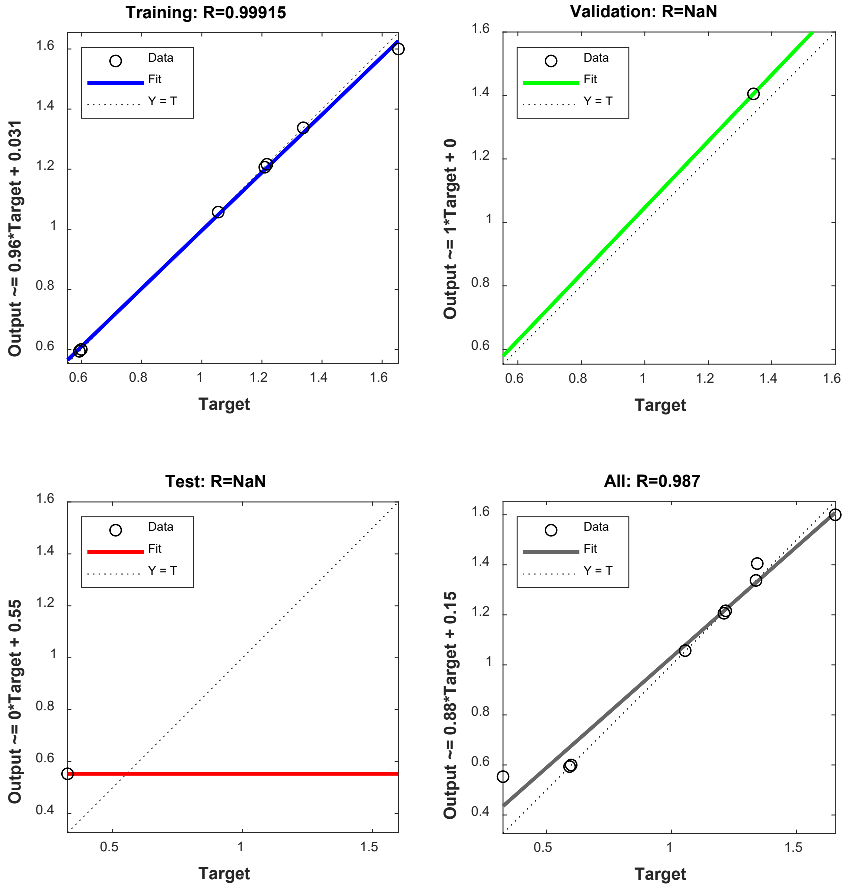


Figure 6. Regression plots for surface roughness obtained using ANN

Table 5. Experimental (vs) predicted ANN and % of error

Exp. trails	Experimental results of Ra (µm)	ANN predicted results of Ra (µm)	% Error for ANN
1	0.3265	0.33201	1.688
2	0.5925	0.59356	0.179
3	0.5988	0.59986	0.177
4	1.0545	1.05707	0.244
5	1.2165	1.21627	0.019

6	1.2095	1.20642	0.255
7	1.3375	1.33770	0.015
8	1.3425	1.40512	4.664
9	1.6542	1.60008	3.272

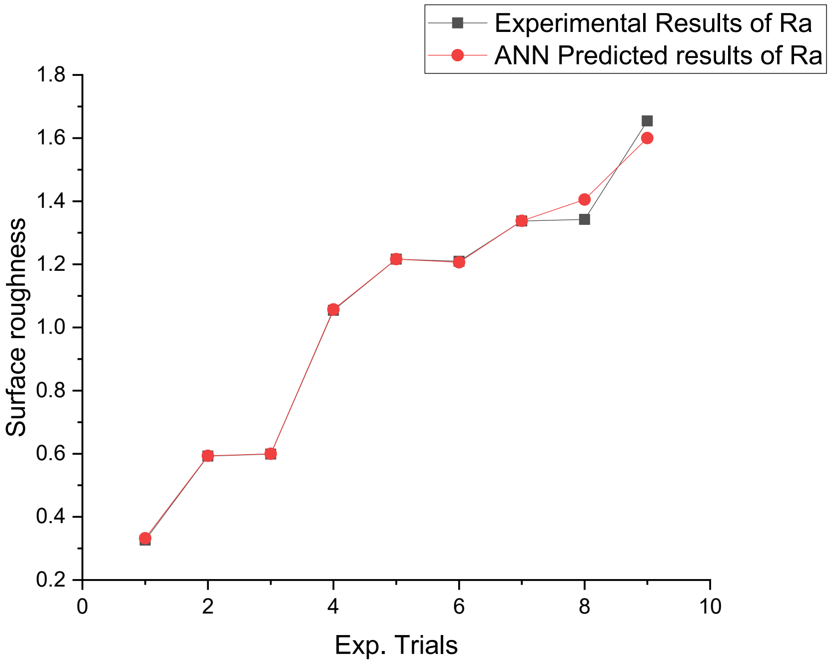


Figure 7. Comparative plots of experimental and prediction result for Ra

4. Conclusion

An experimental investigation and ANN model prediction was presented in this study to estimate surface roughness for the influence of layer thickness, orientation angle, and infill angle on FDM produced ABS components. The DOE L9 orthogonal array was used in all of the tests to alter the input parameters at various levels. The neural network toolbox in MATLAB R2019a was utilized to create the ANN model. The experimental results were used to train and test the developed ANN model. In terms of relative error and quality of fit, the model's prediction performance was found to be adequate. As a result, the suggested model may be used to fabricate FDM parts. From this research, the following findings may be drawn:

- The thickness of the layer has the greatest impact on surface roughness (Ra). The orientation angle and infill angle, in contrast, have mainly minor on Ra.
- The lowest surface roughness is obtained with a layer thickness of 0.10 mm to 0.15 mm, an orientation angle of 0 to 5°, and an infill angle of 0 to 5°.
- Low layer height, orientation angle, and infill angle are all effective ways to get a smooth surface.
- The maximum error percentage (4.664%) and goodness of fit 0.994 (R= 0.99915) in training were found in the statistical study of the ANN result for surface roughness, which is acceptable accord with the experimental data.

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