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Multi-objective prediction and optimization of 3D-printed polymer properties using neural networks and desirability functions

Layth Fadhil Shakir[1], Hameed Sarhan Ismael[2], Mostafa Adel Abdullah[3*], Abdullah Faraj Hauyier[3], Safaa Kadhim Ghazi[3]

[1] Engineering Department of Materials Engineering,University of Al-Qadisiyah, Al Diwaniyah, Iraq
[2] Civil Engineering Department, University of Technology, Baghdad, Iraq
[3] Department of Production Engineering and Metallurgy, University of Technology, Baghdad, Iraq
* Corresponding author's e-mail: mostafa.a.hamed@uotechnology.edu.iq

ABSTRACT

The industry uses fused deposition modeling (FDM) in the manufacture of the final products through the additive manufacturing method (AM). Due to this approach, one can construct a prototype and other components with complicated geometry, which not only translates into the saving of expensive dollars but also makes the project more flexible. Printing and material type, as well as other processing settings, affect the nature of parts, in terms of mechanics as well as other aspects. This paper attempts to develop a model to predict the mechanical capabilities and surface quality of FDM-printed ABS objects based on artificial neural networks. Taguchi design of experiments is applied with an L27 orthogonal array coupled with a two-layer neural network (NN) with 15 neurons. The impact of the characteristics of the layer height, the orientation angle, and the nozzle temperature on the strength and finish of parts was investigated by means of the analysis of variance (ANOVA). Layer thickness seemed to be the major variable in the analysis because it was identified to create over 43.67% variation in ultimate tensile strength and 46.38% variation in surface roughness. The predicted results by the model were just a little different compared with the actual results. The highest percent error in the tensile strength and the surface roughness are 2.346 and 1.876, respectively, which arises when comparing the experimental and predicted values as calculated using the ANN model. With such a model, different parameters selected are able to achieve the requirements of a particular application.

Keywords: ABS, FDM, ANN, tensile strength, surface roughness.

INTRODUCTION

Additive manufacturing (AM) is transforming the manufacturing industry by radically changing the centuries-old production models. This new technology is very flexible, customized, and efficient. AM works by printing layer by layer on the basis of the digital designs of objects, allowing the production of models and prototypes, and functional final products. The wide use and enormous potential of 3D printing have been enabled by the fact that it can process a wide variety of materials such as plastics, metals, ceramics, and even living cells [1]. The transformational ability of AM can be traced in several industries that make use of its unique benefits to innovate. AM can be applied in the aerospace sector to produce lightweight complex components, which create fuel-efficient and better structural designs, making aircraft more advanced. On the same note, the application of AM in medicine is applied in the production of patient-specific implants, prosthetics, and biological structures that match specific requirements. In addition to these fields, automotive corporations are openly using AM in quick prototyping, tailored automobile materials, and lean supply chains [2]. Its capabilities are ventured into by architects and designers in designing complex structures and models that stretch the limits of 3D design and construction [3]. Even the food sector tries to utilize AM to create something new in the world of food and individual nutrition [4]. Conventional manufacturing tends to produce waste due to the usually subtractive method of production, whereas AM allows the manufacturing of objects with high levels of precision, utilizing only the required amount of materials, hence facilitating sustainability [5, 6]. The development of AM keeps extending boundaries by bringing next-level materials science and scale-up. Its introduction into the current production ecosystems equates to a paradigm shift of decentralized, on-demand manufacturing, which will result in the advent where complex designs quickly manifest into real-life products, and lead to the maximization of innovation in international industries [7].

It is done by heating the material in the liquefier head until it is molten, where it is then precisely extruded into a nozzle. This nozzle travels along the particular geometry of the various cross-sections of the item under fabrication. Both the construction and support materials are supplied as filaments with a diameter of 1.75 mm, rolled into spools. These filaments are provided to the extrusion head through a flexible tube with ease and continuous supply. The spools are also normally fixed on a spindle situated on the side or the backside of the machine so as to keep them steady and within easy reach of the operator in the course of reaching them. This arrangement allows controlling the deposition of materials with high precision needed to generate parts with complicated geometry and low features. This research involves making parts on the basis of the FDM printing method, by using ABS filament. As a very common thermoplastic polymer in 3D printing, ABS could be called a tough and impact-resistant material suitable for functional prototypes and end-use pieces.

Unlike PLA, ABS demands a hot bed and higher extrusion temperature, but it is much tougher and temperature resistant. Despite the fact that ABS is harder to print because of the warping and smell problems, it is widely used in areas that require a stronger mechanical stiffness and resistance to heat. Every FDM parameter has a considerable influence on the quality of printed ABS parts. It is necessary to optimize these parameters so as to enhance print quality as well as reduce the effort put into printing. Parameters in the FDM processes are usually determined either by the machine manuals or by the individual operator's experience, and yet it is not always optimal to suit a given system or an environment. When this happens, an alternative is the Taguchi that makes the whole experiment simple and predicts the interaction and effects of FDM parameters [9].

To have the best production outcome, that too at the most reasonable production cost, is the unending task to get the best process parameters. Among the most essential performance parameters in the FDM process, mechanical properties and surface quality provide an instant impact on efficiency and the cost level of production [10]. Recently, outcomes and optimisation of 3D printing parameters have been predicted through techniques such as artificial neural networks (ANNs), genetic algorithms, simulated annealing, and grey relational analysis. ANNs, especially, are good at modeling complex interactions between the inputs and the outputs.. They have the abilities of generalization, self-organization, and association, just like the human brain functions. ANNs are appropriate in modeling the FDM process because they can be efficiently used to approximate non-linear functions. Due to their excellent learning and generalization capabilities, they can observe complex input-output relations during ABS 3D printing. Picking up the ideas formulated in works similar to that one, the present research provides a detailed report on the performance properties of FDM technology. More studies are required to completely comprehend the impact of different FDM settings on part strength. It is important, therefore, to be thorough in examining the weaknesses of the print-out parts before giving any application recommendation. Samykano et al. [11] investagated were done on the impact of the three most significant process parameters that control the mechanical features of acrylonitrile butadiene styrene (ABS), a common thermoplastic used in many industrial applications of the FDM technology, namely, the raster angle, the layer height, and infill density. They planned experiments to scan the effects of these factors on major mechanical properties, such as ultimate tensile strength, elastic modulus, yield strength, fracture strain, and toughness. The findings indicated that all of the parameters taken into consideration greatly influenced the mechanical performance of the printed ABS parts. Using response surface methodology will allow them to generate a mathematical model that can correlate process parameters with mechanical products. In this manner, they concluded that the best suited 3D printing ABS parameters were 80% percent infill parameter, the layer thickness of 0.5 mm, and the raster angle of 65. In such circumstances, the experimental results yielded a tensile strength of 31.57 MPa, an elastic modulus of 774.50 MPa, a yield strength of 19.95 MPa, a fracture strain of 0.094 mm/mm, and the toughness (energy absorption) of 2.28 Jm-3. As studied by Tianyun et al. [12], the ultimate tensile strength of the 3D-printed ABS materials manufactured using FDM was examined when variable layer thicknesses were applied to different angles. They prepared a universal plastic test sample by the ISO 527-2-2012 standard. Their theoretical model was able to predict the tensile strength correctly at all printing angles and layer thicknesses. The research established that the utmost tensile strength is minimal when the printing angle is maximized and also when the layer thickness is maximized. Polylactic acid (PLA) was also exploited in the research. [13] studied the, different tool-path patterns-concentric, zigzag, triangular, grid, and so on, but at particular densities Chinchanikar et al. [14] proposed an ANN model that could be applied to predicting surface roughness on parts printed with FDM. The factors used were print speed, nozzle temperature, and infill density, the presence of hidden layers, the layer height, and the number of neurons in the model. Their research established that two concealed unit trails of 150 nodes were better at predicting than one concealed unit trail of 150 nodes. Also, they noted that as infill density was increased, surface roughness decreased. Arivazhagan Selvamet et al. [15] focused on optimizing the fused filament fabrication (FFF) printing parameters in an attempt to improve surface quality and printing time of ABS polymer. Analysis of variance (ANOVA) was employed by the researchers to statistically examine the influence of layer thickness, printing speed, and nozzle temperature on surface roughness and printing time. They used a central composite design under response surface methodology (RSM) to organize the tests and established mathematical regression models to encapsulate the interactions among the input parameters and output reactions. Having confirmed the correctness of these models, they used them together with particle swarm optimization (PSO) as well as RSM to propose optimum printing parameters. The weighted aggregated sum product assessment (WASPAS) algorithm was used in proving the two optimization methods, whereby it is indicated that PSO provided better optimal values. The ideal parameters forecasted by PSO melting speed of 125.6 mm/sec, a nozzle temperature of 221 degrees Celsius, and a layer offset of 0.29 mm. The settings resulted in excellent surface quality of about 3.92 microns on both upper and lower surfaces, as well as about 1.78 microns on other surfaces, and a printing time of only 24 minutes. Al-Duroobi et al. [16] made an experimental study on ANN model, parametric optimisation, and PEEK 3D printing. They studied four parameters of the process. The parameters they arrived at were a 4-12-2 ANN network system, lower speeds during printing, and an increase in infill density, to achieve better strength and surface quality. A l-Bdairy AM et al. [17] stood out to establish how the orientation of the part and parameters of the process used in 3D printing affect the tensile strength. They produced a neural network (NN) to set the relationship between input parameters and output results. A concealed layer of 12 neurons performed the finest when it was introduced with optimum component orientation and process parameters to receive the most study on the tensile strength. In the present paper, the ANN was used as a fitness criterion of the genetic algorithm (GA) in the optimization process. The results proved the efficiency of the method applied to improving the 3D printing process, and its possible application in different engineering disciplines. Abdullah et al. [18] suggested that ANNs can be used in a new way to model part strength and minimize the errors when predicting the strength of 3D printed parts to improve the accuracy of those predictions. Mahdi et al. [19] made an attempt to learn more about the surface roughness of three main process variables, which are printing speed, layer thickness, and extrusion temperature. A Taguchi L27 orthogonal array experimental design was used in carrying out the investigation. Post-processing and any further surface finishing processes were not used on the samples. An Alti surf device was used to obtain 3d images and 2d profiles of surface peaks and valleys with abundant surface measurements to be fed to the subsequent statistical analysis. Quantitatively, the values of arithmetic roughness (Ra) were between 7.18 and 13.4 µm. The best surface finishes were reported at the highest scan speed of 4000 mm/min, whereas the smoother the surfaces were related to the thinner the layer of 0.1 mm. Moreover, the thicker the extrusion temperature was, the better the surface finishes. The ANOVA of a multiway type was used to determine the most influential conditions and interactions between them. It was found out that the works of both RSM and ANN could make the process easier to implement, lessen the amount of tests needed, and enhance parameter settings of MEAM processes. FDM requires further studies, even though a literature review on numerous additive manufacturing processes has been conducted. The problem that is addressed via the work is the lack of knowledge on the sensitivity of layer height, orientation angle, and nozzle temperature to the mechanical properties and surface roughness of fused deposition modeling (FDM)-printed specimens. The objective is to develop a feed-forward artificial neural network using a backpropagation algorithm in order to extrapolate ultimate tensile strength and surface roughness on the basis of these input parameters and introduce a system of continuous and multi-parameter control in order to maximize mechanical properties and surface quality of FDM-printed specimens.

METHODOLOGY

Material and method

The design of the part or component using design software is the first step that is taken in the 3D printing process. The SOLIDWORKS program is used to produce the CAD file. After the 3D model is ready, scaling should be done to a common format, with the most popular file format being the STL file format since it is widely compatible with the various platforms and devices in the market. After this, it is converted into the desired 3D printing language, which is normally G-Code on an FDM printer. This program indicates how the printer needs to move, flow faster or slower, what a printing temperature should be, integrated cooling systems, and other working processes. As shown in Figure 1, the workflow that the study would follow begins with the selection of FDM parameters and ends at the determination of the percentage error between the anticipated and the measured values. The STL file created in SolidWorks was edited in Cura 4. 13. 1, which further allows it to be readable by the machine to be used and 3D-printable. Figures 2a and 2b characterise the solid model and its sliced model which was made regarding ASTM D638 Type 4.

Selection of process parameters also plays a major role in the determination of the quality of the parts produced by FDM. The parameters observed in this study are layer height, nozzle temperature, and the orientation angle. Alteration in such FDM settings immensely influences process products like tensile strength and surface roughness. Thus, the outcome of the overall process could be improved by selecting the best FDM parameters. In Table 1, the selection and value of

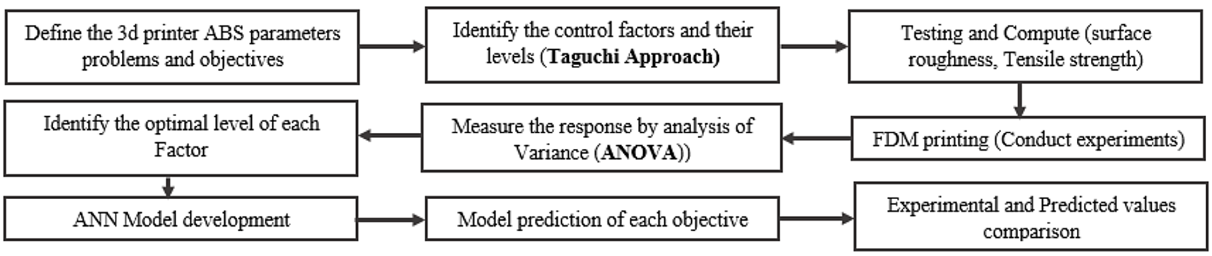


Figure 1. Outline of the methodology workflow

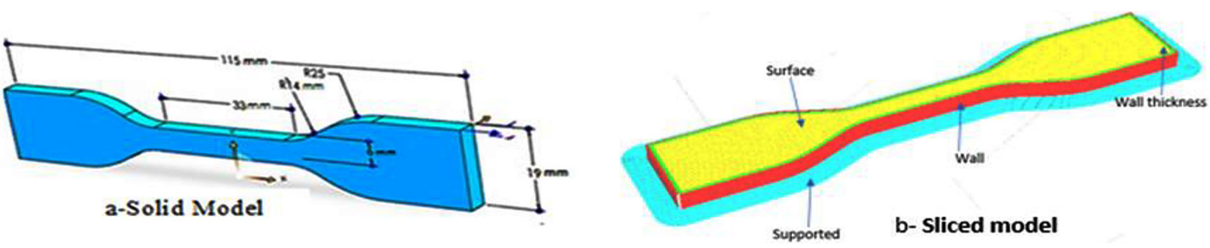


Figure 2. The sliced 3D models are shown with sliced models

Table 1. Selection of process parameters with its level

FDM parameters	Units	Levels		
		1	2	3
Layer thickness	(mm)	0.2	0.25	0.3
Orientation angle	degree	0	45	90
Nozzle temperature	°C	230	240	250

Table 2. The constant parameters

FDM parameters	value	Units
Infill pattern	Line	-
Wall thickness	1.2	mm
Printing speed	55	mm/s

the process parameters in printing the parts have been presented, and Table 2 gives other FDM parameters that remained unchanged throughout the course of the experiment. Here, the experimental tasks in this part of the study are explained in detail as shown in Figure 3.

The rationale in choosing the levels of the FDM parameters was based on experience, literature review, the importance of the identified parameters that were significant and relevant after the preliminary experiments, and the recommended acceptable high and low levels that were given by the equipment's manufacturers. The parameter levels of three or more levels are desirable to capture the behavior of the response variables. The Taguchi method was applied to design the experiments. A tensile test was performed under the standard ASTM D638 Type 4. The Taguchi method uses the signal-to-noise (S/N) ratio to determine the extent to which a performance attribute is off the desired level. During the S/N ratio analysis, the performance characteristics are categorized into three-headed groups of nominal-the-best, higher-the-better, and lower-the-better characteristics. This division assists in the choice of the best parameters to get a better performance of the system [20]. In this experiment, the response variable of the maximization of tensile strength and the minimization of surface roughness was aimed to be achieved (high-the-better; low-the-better). The calculations of S/N ratios concerning higher-the-better performance characteristics are indicated by Equation 1, whereas Equation 2 indicates calculations of the S/N ratio of the smaller-the-better performance characteristic.

- Larger is better:

$$S/N = -10\ log(\ 1\ n \sum 1\ yk\ 2\ n\ k=1\ ) \quad (1)$$

- Smaller is better:

$$S/N = -10\ log(\ 1\ n \sum 1\ yk\ 2\ n\ k=1\ ) \quad (2)$$

In which n is the number of tests, and yk is the value of the performance characteristic.

Tensile test with a WDW200E computer operated electronic universal testing machine was applied according to ASTM D638 Type IV to obtain the mechanical properties of the specimens which were fabricated. Figure 3 represents the tensile properties of the specimens. They were tested at room temperature under constant

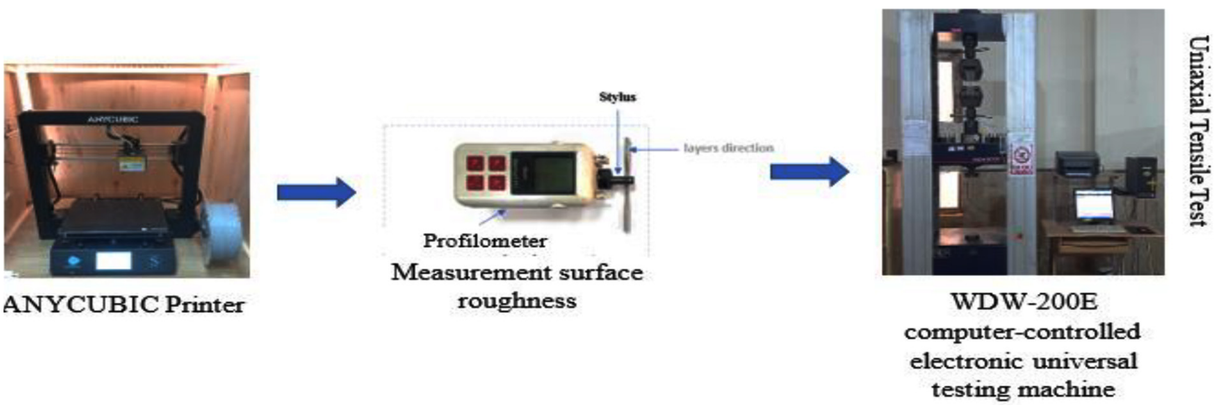


Figure 3. Experimental workflow

crosshead speed of 1.5 mm/min. During the experiment, it recorded three data types of load, deformation, stroke, as well as time. The ultimate tensile strength was calculated using peak load values that were recorded same, which corresponded to the actual dimensions of specimens (and not the parameters of their CAD models). These experimental findings were then applied in computing the values of stress as well as the mechanical properties, and also in the estimation of the tensile strength of each of the ABS test specimen based on Equation 3.

$$\sigma = F/A \tag{3}$$

where: σ – Tensile stress (N/mm^2); F – Applied Force (N); A – Cross section area (mm^2).

The roughness of the surfaces of tensile test samples in this work was determined with the use of the Pocket Surf profile measurement device (illustrated in Figure 3). To determine the roughness value, three measurements of the roughness normal to the layer's orientation were taken at three different points on the sample, and then the Ra parameter was calculated three times for each specimen. Lastly, the three values were averaged to obtain the resulting measured surface roughness value of each printed component.

Artificial neural network prediction model

An artificial neural network is a computational model based on the biological neural networks found in the human brain. It comprises a set of interconnected so-called neurons or nodes, usually as an input layer, one or several hidden layers, or as an output layer [21]. Information runs through the network, and the weights between the connections of the neurons are adapted during the training process. The input data is presented to the network with many iterations, and then the weights are altered depending on the error between the modeled output and the actual output. In the present work, the number of the input neuron in the neural network model is 3 (layer height, orientation angle, and nozzle temperature) with a (3 × 27) input data matrix and the number of the output neuron is also 2 (tensile strength and surface roughness) with a (2 × 27) output data matrix. In the model, the Hebbian learning rule is used. These input and output neurons were processed by the neural fitting tool, and it was presented in Figure 4.

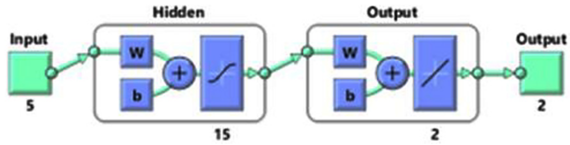


Figure 4. Illustration of the employed ANN structure

Desirability analysis

Desirability analysis (DA) is an advanced statistical technique used to simultaneously evaluate and optimize multiple responses or parameters. Its versatile framework is widely implemented in manufacturing, process optimization, and product design to achieve balanced and improved outcomes. It improves decision-making and general performance by giving a common platform for describing how desirable particular outcomes are and determining the best combinations of input parameters to operate on several objectives. A desirability function is allocated to each objective, whose values are scaled into values between 0 and 1, where 0 denotes undesirable levels and 1 denotes desirable levels. These individual desirability values are combined to form an overall desirability function with each set of input parameters. A desirability value (Di) of 1 denotes that it is possible to optimize the response, whereas a value of 0 depicts that the response is in the range of desirability [22]. The desirability values are defined by whether a 'lower the better' or 'higher the better' decision criterion is needed in the responses; in this case, value 'y is supposed to be either maximised or minimised. The value of desirability Di is between 0 and one, where it grows to 1 over a threshold value and declines to 0 over a threshold value.

RESULTS AND DISCUSSION

Analysis the results

Table 3 shows measurements of tensile strength and surface roughness of 27 FDM-printed specimens that have been made after the printing procedure. The Minitab was used to analyze the data obtained in the experiment to allow the prediction of the best level of each parameter based on the outcome of the tensile strength and the surface roughness. They further conducted a statistical ANOVA to determine the relative contribution of different parameters on the ratio of

Table 3. The experimental results

Exp. No.	Layer thickness (mm)	Orientation angle (degree)	Nozzle temperature °C	Tensile Strength (MPa)	Surface roughness (μm)
1	0.20	0	230	40.02	2.2943
2	0.20	0	240	44.2	2.158
3	0.20	0	250	43.07	2.341
4	0.20	45	230	45.33	2.27
5	0.20	45	240	42.64	2.485
6	0.20	45	250	44.46	3.501
7	0.20	90	230	41.42	2.1473
8	0.20	90	240	41.94	2.139
9	0.20	90	250	41.33	2.3653
10	0.25	0	230	42.72	2.366
11	0.25	0	240	**47.34**	2.602
12	0.25	0	250	38.81	3.274
13	0.25	45	230	45.59	3.473
14	0.25	45	240	43.68	1.933
15	0.25	45	250	40.29	2.141
16	0.25	90	230	38.98	2.233
17	0.25	90	240	40.98	4.105
18	0.25	90	250	42.29	2.569
19	0.30	0	230	36.89	3.486
20	0.30	0	240	44.81	2.854
21	0.30	0	250	44.98	3.337
22	0.30	45	230	28.46	6.673
23	0.30	45	240	42.55	5.879
24	0.30	45	250	39.24	2.423
25	0.30	90	230	40.02	2.2943
26	0.30	90	240	39.32	2.214
27	0.30	90	250	38.88	**1.677**

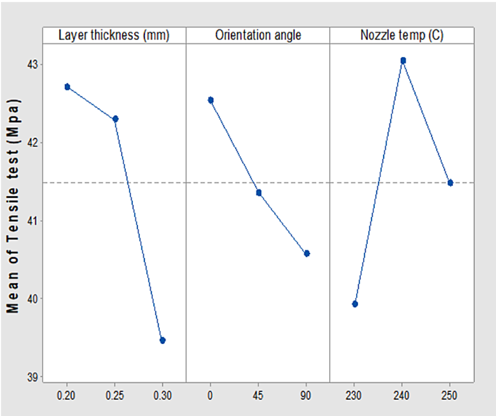
factors that considered which aspects have a significant contribution to the performance characteristics and the interactions among them.

Table 3 shows that as a result of the experiment, tensile strength improved from 7.45 to 10.45 MPa to 47.34 MPa of the same specimen with the layer thickness of 0.25 mm (level 2), an orientation angle of 0 (level 1) and a nozzle temperature of 240 °C (level 2). Interestingly, the reference [23] records that the anticipated highest tensile strength of the specimen should be 23.1 MPa. Conversely, the surface roughness went down to 6.673 to 1.677 in experimental specimens that had a printed layer thickness of 0.30 mm (level 3), an oriented angle of 90 (level 3), and a printed nozzle temperature of 250 (level 3). The importance of this outcome is seen in the fact that Reference [24] predicted a minimum surface roughness of 2.792 μm, and thus it can be seen that the actual result was much lower than expected [25]. The ANOVA using the data of the experimental results given in Table 3 has been done to determine the main parameters and interactions that influence tensile strength and reduce the level of surface roughness, the outcomes of which are highlighted in Table 4.

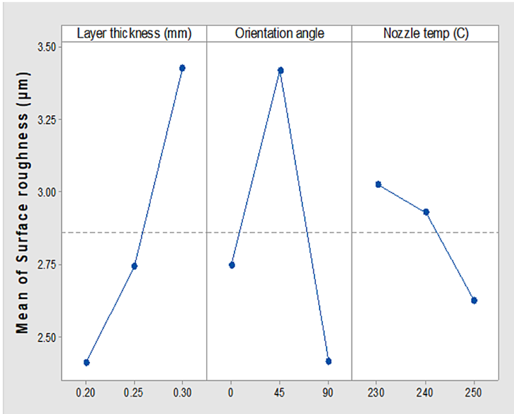
Table 5 shows the layer thickness (mm) as the most contributing factor in determining the tensile strength and surface roughness using a 95 percent level of confidence and the P-values of 0.109 and 0.158, respectively, as shown in Figure 5 (a and b). The reason behind this is that the layer thickness has direct effects on the bonding between the layers, and also the surface finish, which then influences the mechanical strength and quality of the printed parts. The impact of any given parameter was also measured by the percentage contribution it made in terms of the overall variation in

Table 4. The significance and ideal values for every parameter

ANOVA for TS						
Source	DF	Adj SS	Adj MS	F-Value	P-Value	Percentage contribution
Layer thickness (mm)	2	150.36	75.18	2.49	0.109	43.67%
Orientation angle	2	44.6	22.3	0.78	0.474	12.95%
Nozzle temp (C)	2	130.65	65.325	1.93	0.172	37.94%
Error	20	18.69	9.345			5.42%
Total	26	344.30				
ANOVA for Ra						
Source	DF	Adj SS	Adj MS	F-Value	P-Value	Percentage contribution
Layer thickness (mm)	2	15.8222	7.9111	2.03	0.158	46.38%
Orientation angle	2	14.7107	7.35535	1.98	0.164	43.12%
Nozzle temp (C)	2	3.025	1.5125	0.33	0.722	8.86%
Error	20	0.543	0.2715			1.59%
Total	26	34.1142				



a)



b)

Figure 5. Main effect plot for (a) tensile strength, (b) surface roughne

Table 5. ANOVA results for tensile strength (TS) and surface roughness (Ra)

Parameters	Layer thickness (mm)	Orientation angle (Degree)	Nozzle Temperature (°C)	Significant
Optimized Ts	0.25	0	240	Layer thickness
Optimized Ra	0.3	90	250	Layer thickness

the experiment results. The research also identifies the layer thickness as the greatest influencing factor since it contributed 43.67% to tensile strength and 46.38% to the surface roughness at 95 percent confidence of the layer thickness. Table 4 shows the best values and importance of every parameter.

Results of the developed ANN

To allow comparison with experimental data, predictive models based on an artificial neural network (ANN) were generated. The experimental database was used to train the ANN, after which a training dataset was used to test the ANN. The data were trained with almost 70 percent, tested with 15 percent, and validated with 15 percent. The output response sample observation is proposed in Table 6. Figure 6 indicates that the best solution to the current study occurred at epoch 0, when the data recording provided the least average absolute error in predicted output, which was 3.7023e^{-06}.

Levenberg-Marquardt also came up with the best overall results, the correlation coefficient (R)

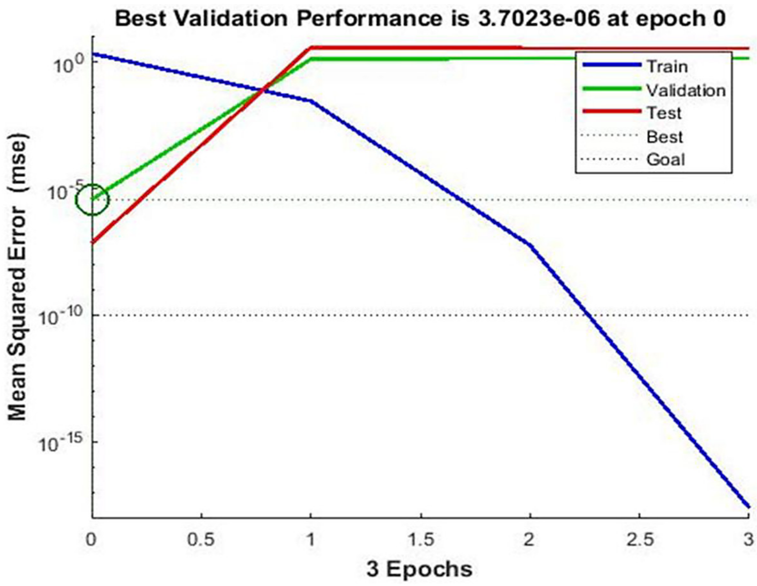


Figure 6. Tensile and surface roughness performance plot

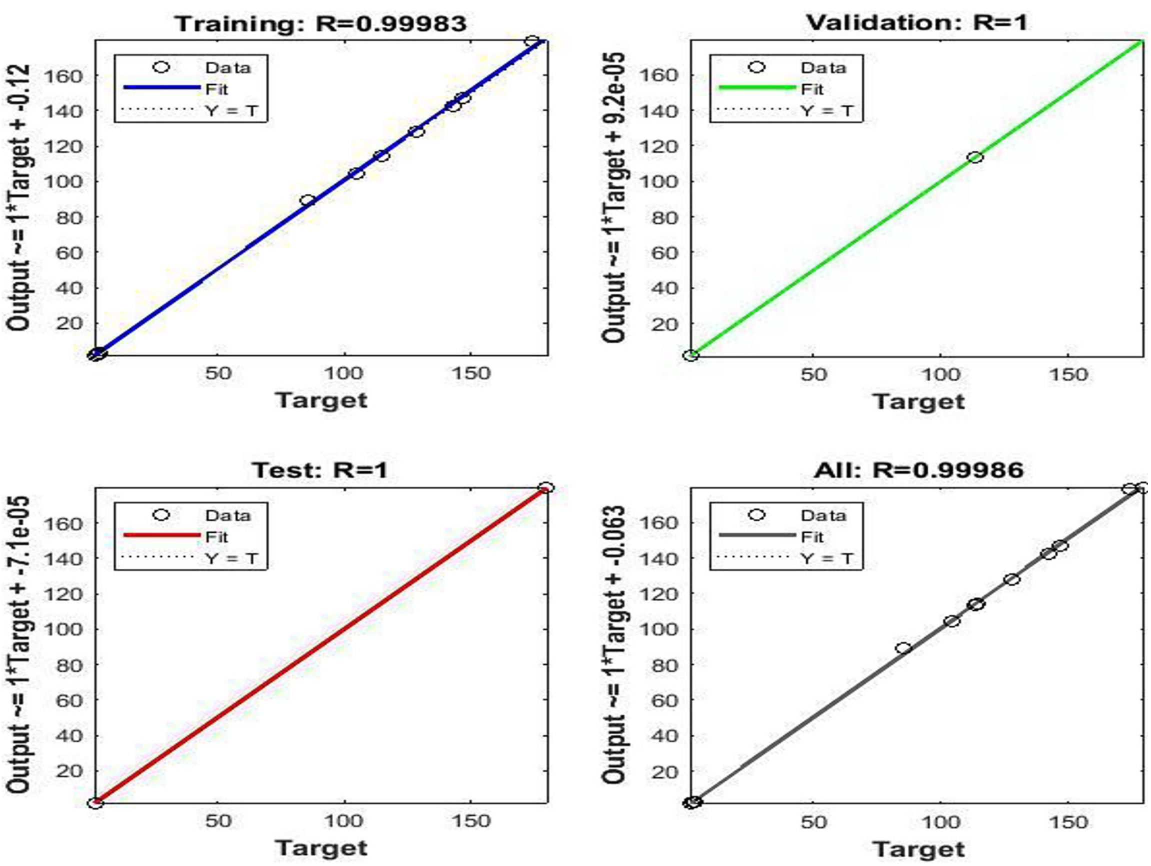


Figure 7. The proposed network graphical representation

of 0.99986 as illustrated in Figure 7. The validation dataset has an even larger regression coefficient of 1, which means that there was a high correlation in relation to both the ANN predictions and the experimental data.

The comparison of Equation 4, ANN-predicted and experimental values on the tensile strength and the surface roughness of the ABS parts is given in Table 6. The table shows that the tensile strength and the surface roughness recorded the highest percentage deviations between the measured and the predicted value by 2.346 and 1.876%, respectively.

Figures 8 and 9 illustrate the differences between the experimental results and the predictions of the ANN model.

Table 6. Experimental versus ANN values for tensile strength and surface roughness.

No.	Ts (MPa)	ANN predicted Ts (MPa)	% Error	Ra (μm)	ANN predicted Ra (μm)	% Error
1	40.02	40.2059	0.464	2.2943	2.2622	1.399
2	44.2	44.3204	0.272	2.158	2.16582	0.362
3	43.07	43.1126	0.098	2.341	2.36133	0.868
4	45.33	45.0281	0.666	2.27	2.25616	0.609
5	42.64	42.1426	1.166	2.485	2.43979	1.819
6	44.46	44.5748	0.258	3.501	3.4353	**1.876**
7	41.42	41.2415	0.430	2.1473	2.13252	0.688
8	41.94	41.3559	1.392	2.139	2.13614	0.133
9	41.33	41.7881	1.108	2.3653	2.33165	1.422
10	42.72	42.7915	0.167	2.366	2.35499	0.465
11	47.34	46.9059	0.9169	2.602	2.60861	0.254
12	38.81	38.3381	1.215	3.274	3.23412	1.218
13	45.59	45.6137	0.051	3.473	3.46895	0.116
14	43.68	43.7281	0.110	1.933	1.93258	0.021
15	40.29	40.1604	0.321	2.141	2.16808	1.264
16	38.98	38.827	0.392	2.233	2.26531	1.446
17	40.98	41.9415	**2.346**	4.105	4.16893	1.557
18	42.29	42.3737	0.197	2.569	2.56444	0.177
19	36.89	36.7548	0.366	3.486	3.4775	0.243
20	44.81	44.7693	0.090	2.854	2.88112	0.950
21	44.98	44.7015	0.619	3.337	3.37663	1.187
22	28.46	28.577	0.411	6.673	6.59146	1.221
23	42.55	42.8915	0.802	5.879	5.79508	1.427
24	39.24	39.3237	0.213	2.423	2.45059	1.138
25	40.02	39.9904	0.073	2.2943	2.28782	0.282
26	39.32	39.1048	0.547	2.2145	2.25144	1.668
27	38.88	38.537	0.882	1.67778	1.64695	1.837

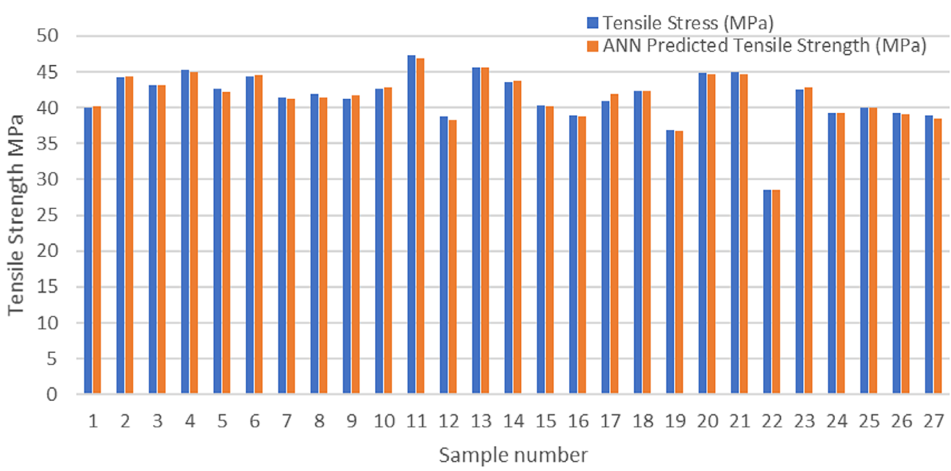


Figure 8. Comparison between experimental vs. ANN predicted values for tensile strength

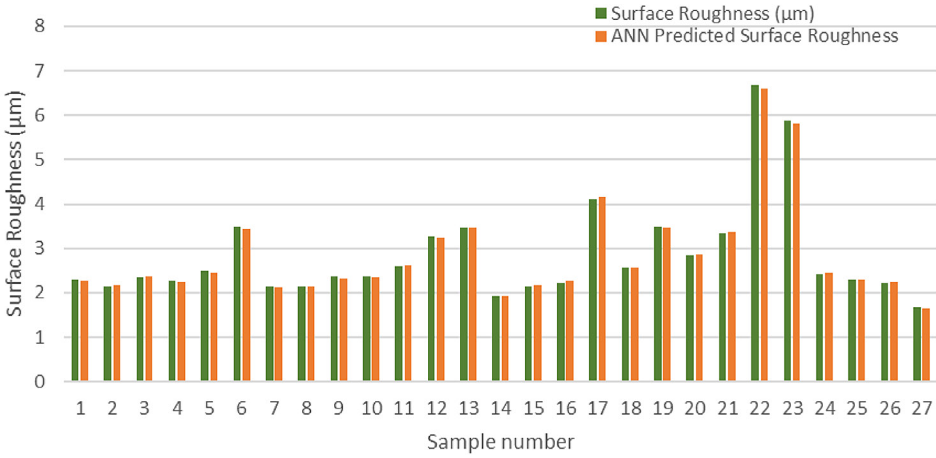


Figure 9. Comparison between experimental vs. ANN predicted values for surface roughness

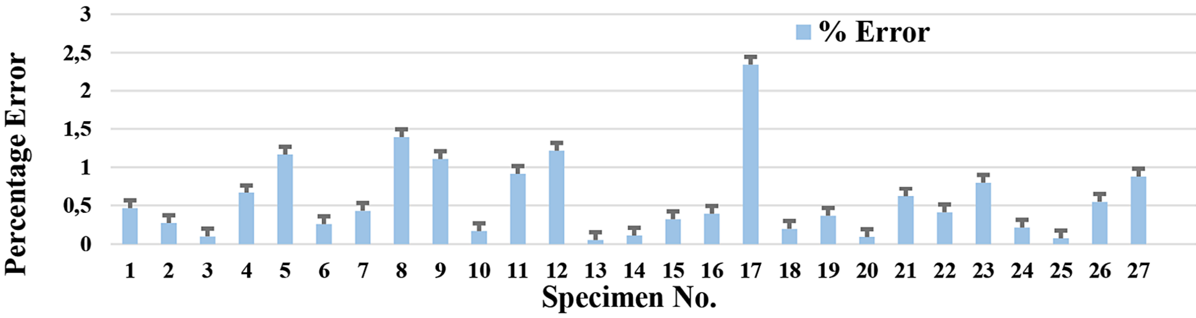


Figure 10. The percentage error in tension strength between the experimental and the predicted

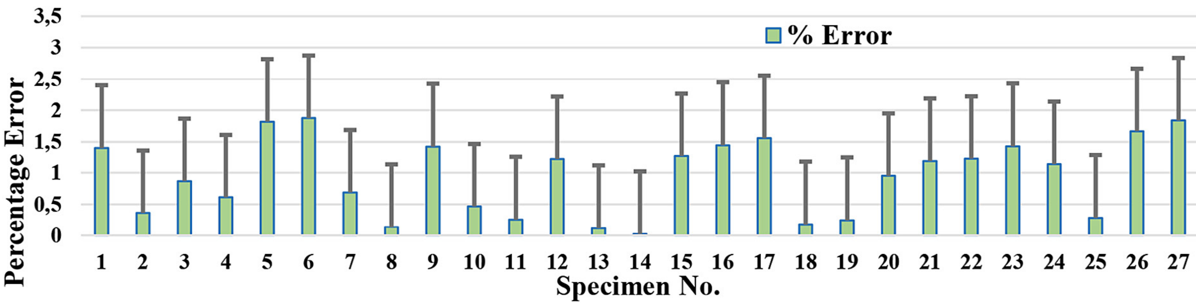


Figure 11. The percentage error in surface roughness between the experimental and the predicted

Figures 10 and 11 depict that the percentage error falls within an acceptable range, which means that the ANN model has been able to predict the tensile strength and the surface roughness of the specimens.

$$Error\,\% = |((measured\ value - Predictedvalue)/measured\ value) \cdot 100| \tag{4}$$

A desirability analysis was also used in the current study to optimize printing parameters. In Figure 12, Minitab 20 is utilized in the evaluation of the optimal printing parameters that will give the maximum tensile and minimum surface roughness. It is also important to optimize all responses at once since the best parameters of responses usually become conflicting. A unique composite desirability value of 0.9006 was arrived at after multi-optimizing all the parameters together under desirability analysis (DA). The best parameters were a layer thickness of 0.2mm, 0^0 orientation, and 236.2625 °C. The best results demonstrated the maximum tensile strength and the minimum value of surface roughness,44.5427 MPa and 1.9173 μm, respectively.

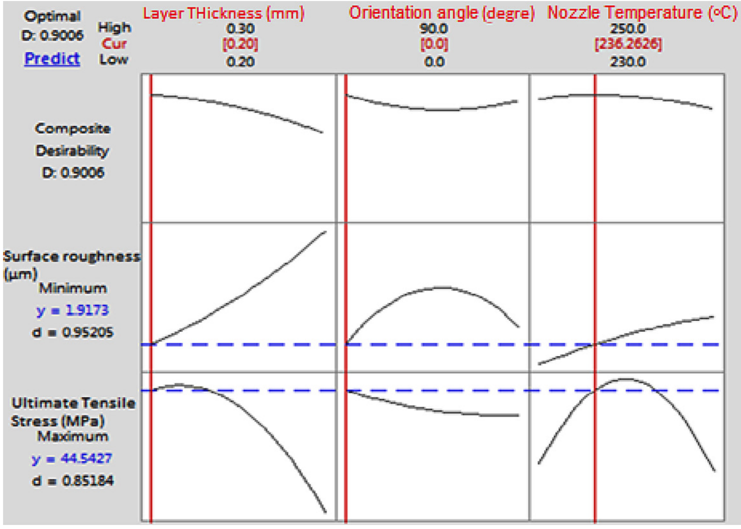


Figure 12. Optimization of multi-responses using desirability analysis

CONCLUSIONS

This paper aimed to design an ANN model for quantitatively predicting the mechanical strength and surface quality of FDM-manufactured parts, using process key parameters. The findings and the key objectives are summarized in the following way:

1. The experiment aimed at maximizing tensile strength and surface roughness through the investigation of the influence of layer thickness, orientation angle, and nozzle temperature on FDM-printed specimens.
2. The experimental results indicated that tensile strength maximized at 0.25 mm layer thickness, 0° as orientation angle, and 240 °C as nozzle temperature.
3. The best surface roughness was observed as 1.67778 µm, which was acquired at a layer thickness of 0.30 mm, nozzle temperature of 250 °C, and an orientation angle of 90°.
4. The ANN model being trained using 17 experimental patterns was able to predict tensile strength and surface roughness with the greatest percentage error of 2.346% and 1.876% respectively, a verdict of high accuracy.
5. The best combined results were determined using the desirability analysis of tensile strength and surface roughness levels of 44.5427 MPa and 1.9173 µm, respectively, at the given process parameters.
6. The thickness of the layer was verified to be the most relevant parameter affecting tensile strength (43.67% variance explained) and surface roughness (46.38% variance explained).
7. Further advantages of prediction may be attained by more training patterns, which would advance the generalization and dependability of the models in optimization of the FDM processes.

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