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Optimising Parameters of Fused Filament Fabrication Process to Achieve Optimum Tensile Strength Using Artificial Neural Network

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Abstract: Currently, the Additive Manufacturing (AM) process has become the most researched area, leading to a revolution in the manufacturing industries. Among all additive manufacturing techniques, fused filament fabrication (FFF) is famous because simple to use and economical. However, in the FFF process, the final quality of parts depends upon the rigorous selection of process parameters, as it is necessary to understand the physical phenomena of process variables and their impact on the mechanical properties. This study involves the independent analysis of three process variables like layer thickness, orientation, and printing temperature. Taguchi L9 orthogonal array opted to investigate the tensile strength of Acrylonitrile butadiene styrene (ABS). By using this, the number of experimental reduced from L27 to L9 experiments. The specimens are fabricated based on ASTM D-638 tensile standard design. For training and testing purposes, the Artificial Neural Network tool has opted by using MATLAB software 2015.

Keywords: Additive manufacturing; Fused filament fabrication; 3-D printer; Artificial neural network.

1. Introduction

In the era of digital manufacturing, various business organizations have become more competitive to fulfill their end-user demand and want to be more comfortable with the current innovation in the manufacturing industries. As we know, Additive manufacturing expanding its market in different sectors, and it seems to be a competitive technique over conventional manufacturing processes. It involves cutting tools, preparation of mold/die, and material removing process but AM techniques opposite to this method. In the AM process, components are fabricated through by the material addition one layer over another layer with the help of embedded M code and G code within a 3-D printer machine. 3-D printing and AM both terms are interchangeable to each and used in different industries. AM process begins with the conceptualization of design and making it into the CAD (Computer-aided design) modeling software. Then convert this 3D model into the STL (Standard tessellation language) file format which is a necessary step for the understanding of the 3D printer machine^{1), 3)}. The complex design takes too much time in the conventional process compared to the same

can be done simply through a single source of the machine in 3-D printing technology with less time. In the current scenario, Additive Manufacturing has been finding popularization in various industries such as the aircraft industry for lightweight modules, automobiles industries for spare parts, biomedical field for implants and dental applications, building and construction industries, and food packaging industries. AM enabled shortening the lead time of development due to their ability to quickly manufactured the prototypes and specific intricate modules. At present various self-replicating systems like Rep Rap, Formlabs FAb@home, Makerbot, and HP fusion Jet 3-D printer^{4), 5)} capable of its components.

Although, AM comprises different processes based on the starting phase of the material liquid, solid and powder form, the pattern of energy and support procedure. Fused filament fabrication (FFF), Laminated object manufacturing (LOM), Direct ink writing (DWI) are the techniques in which the input material in the solid-state. In liquid-based, stereolithography (SLA), multi-jet modeling (MJM) and digital light processing

(DLP) is the most common technique. Three-dimensional printing (3-DP), selective laser sintering (SLS), selective laser melting (SLM), electron beam melting (EBM), direct energy deposition (DED), and laser engineered net shaping (LENS) are the techniques in which input material used as powder form⁽⁶⁻⁸⁾. Fused filament fabrication (FFF) is one of the most often used consumer-focused technology among all of the AM processes. The FFF is comparatively simpler to set up and easier to use for prototype applications, and it is commercially available. FFF technology is primarily focused on 3-D desktop printers so that a person can imagine the concept practically and efficiently, validate the functionality, and prepare a prototype of any conceptual design. This process uses the material in the form of filament/wire and fitted into the extruder head, where it is heated above the melting temperature coverted into the semi-molten liquid state and deposited into the build platform through the nozzle. Common materials like Acrylonitrile butadiene styrene, polylactic acid, and Nylon are used in this process⁹⁻¹¹⁾. The extrusion head is usually attached to a displacement table XY, so each layer is formed by adjoining fibers. A z level is for vertical displacement of the extrusion head, which makes each layer is to be bonded on the former one. In the FFF setting¹²⁾, the materials used to create 3-D prints have a considerably low mechanical strength, which restricts their use for high scale modules. FFF has many goals, but the quality evaluation of the manufactured parts still one of the biggest challenges.

2. Background

Most of the literature has focused on the optimization process parameters, and evaluating the effect of parameters on the performance of output responses such as surface quality, surface morphology, wear resistance capacity, tensile strength, so on. In the FFF method, the part formed by the layer by layer formation, there are chances of voids presented between the adjacent layers. Jianlei Wang et al.¹³⁾ conducted an approach by combining the thermally expandable microsphere's matrix with the FFF process to avoid the formation of voids between the layers. Aladdin Alafaghani et al.¹⁴⁾ experimented to find the effect of extrusion temperatures, infill patterns, and percentage, build direction, print speed, and layer height individually on study established a new method formed for modeling FFF parts using Finite element analysis. The results show that layer height, build direction, and extrusion temperature is the most affecting parameters. Anhua Peng et al.¹⁵⁾ focuses on input variables like layer height, line width compensation, filling velocity, and extrusion velocity to find its response on dimensional error, warp deformation, and built time. The fuzzy interference method has opted for data analysis and also the results validated by an artificial neural network (ANN). Jun Yin et al.

¹⁶⁾explored the interfacial bonding strength dependencies on the process parameters. The process parameters under consideration were the nozzle temperature, bed build temperature, and printing speed. The measured nozzle temperature effect only contributed about 15 percent of the bond strength at the interface. Antonio Armillotta et al.¹⁷⁾ investigated the warpage defect effect on the print geometry or deviation from the dimensional accuracies. As the nozzle moves from one point to another Fused filament fabrication process has thermal cycles throughout the layers. It generates thermal stress in the layers. Layer deposited above a layer tends to shrink and bend the layer beneath it. The study was analyzed statistically, and it observed that when the build is at half of its height, the thermal stress overcomes the yield point of bending stress; the part starts to warp and deviate from its original dimensions. This phenomenon is dominant when the dimensions of the ABS component are longer in the horizontal plane. Omar Ahmed Mohamed et al.¹⁸⁾ showed a method to tackle the problem of minimizing build time and material consumption without compromising the mechanical performance of the component fabricated through FFF. An experimental plan based on Q-optimal response surface methodology used to understand the effects of layer thickness, air gap, raster angle, build orientation, road width, and the number of contours on build time, material consumption, and flexural modulus. The mathematical model of varying parameters used to predict the outcomes Deswal et al.¹⁹⁾ investigated the influence of layer thickness, orientation, a number of contour, and infill density on the 3-D printed parts. The author attempted to increase the dimensional accuracy of components using the artificial neural network-genetic algorithm. Saroj kumar Padhi et al.²⁰⁾ studied the process parameters of FFF process using ABS material. Fuzzy fuzzy inference system coupled with Taguchi's philosophy was used for optimization. They conclude that more number of process parameters using the ANN model is better to predict the overall performance.

Despite this, there are lots of research paper has been published on the optimization of process parameters of FFF, so few references discuss the effect of the extrusion temperature on the mechanical properties. In the AM process, the quality of the product most importantly depends upon the rigorous selection of process parameters. There are several process parameters such as layer thickness, orientation, platform temperature, printing temperature, infill pattern, density, raster width, printing speed, raster angle, and air gap, and each parameter has an impact on the final quality. Understanding the phenomena of parameters of AM technology should be advantageous for industries. The industry must attain this knowledge as early as possible. This paper discussed the tensile strength of Acrylonitrile butadiene styrene (ABS) material. Samples are designed based on the ASTM standard. The artificial neural

network model is applied to predict the optimum value of printing parameters and validate the results.

3. Methodology

3.1. Specimen design

ASTM D-638 test standard used as a reference document ^{21), 22)} for ascertaining the dimensions of the specimen to manufacture a tensile test specimen made up of plastic. The geometry is designed using Autodesk Fusion 360 modeling software. The specification of the model illustrated in Fig. 1. All specimens were made of using ABS filaments, and a Cubepro duo 3-D printer. Fig. 2 shows the CAD model of the specimen.

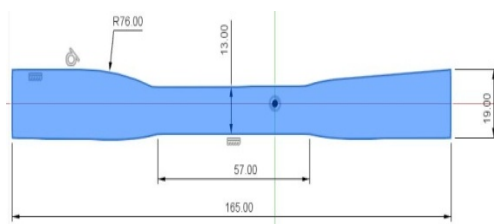


Fig.1: Schematic of tensile specimen

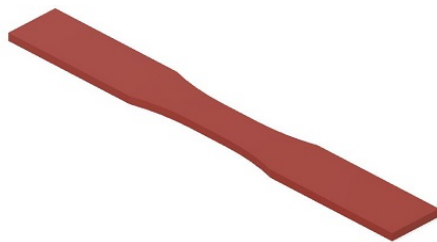


Fig.2: CAD model of Tensile Test Specimen

Three processing parameters layer thickness, printing orientation, and printing temperature has selected for the study based on the printer configuration. The Cubepro Duo printer is capable of producing high-resolution layers with thicknesses 70µm, 200 µm, and 300 µm for each layer. High-resolution printer settings lay down very nearby a fiber considerably reduces the size of voids, but it takes a decent time to produce a print. Different orientations developed different areas of contact between the layers and also display variations in a similar section of void density. The third parameter is the printing temperature of ABS ^{23), 24)} material ranging from 260° C to 290° C. The grade of plastic used in the 3-D printing process depends on printing temperature. High-temperature component printing allows more welding time at the interface and better bonding development at the interface. However, rising temperature far too high above its recrystallization

temperature can lead to imperfect workpiece printing. Cubify offers a decent range of parameters compatible with 3-D systems Cubepro Duo printer. The following parameters are available at user disposal to design a part (Fig.3).

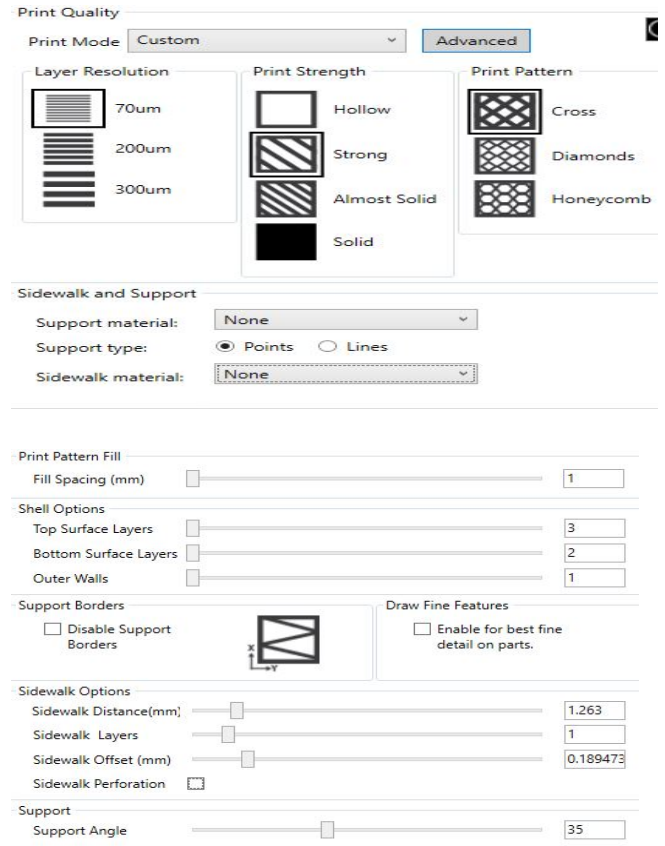


Fig. 3: Cube Pro Duo printer configuration

Based on analysis regarding the functioning of Cubepro Duo and literature survey in the AM field, L_9 orthogonal array is created by MINITAB V18 with the assumption that there is no interaction between the selected factors. The values of parameters are listed in the Table 1.

Table 1. L_9 Orthogonal array

Layer thickness (µm)	Orientation (°)	Temperature (°C)
70	0	280
200	90	280
300	45	280
70	90	285
200	45	285
300	0	285
70	45	290
200	0	290
300	90	290

3.2. Fabrication

Fig. 4 shows the nine samples, fabricated according to Table 1. A Cubepro duo printer was used to fabricate the samples. The output from Cubify software is a “.cubepro” extension file. This file contains the necessary G & M Codes for printing layers. The output file is transferred to the printer for executing the print.

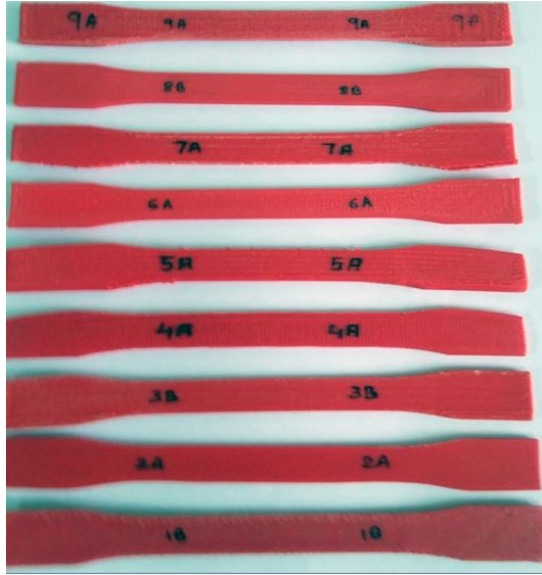


Fig. 4: Fabricated test samples

3.3. Experimental set up

The electromechanical universal testing machine is utilized to test the tensile strength of ABS material. The fabricated components were tested using electronic tensometer, KIPL - PC 2000. The PC 2000 is a computer controlled mini UTM. It has a servo drive mechanism to pull grips and apply strain, with a range of 0.2 - 500 mm/min. For the purpose of testing, strain rate of 3 mm/min used to apply loads. The machine has a maximum load cell value of 20KN. Displacement of the specimen is measured via an optical encoder and recorded with applied load to plot the displacement-load graph.

3.4. Artificial Neural Network (ANN)

Fascinated with the working of the human brain as a computational tool, the artificial neural network began its development in the 1940s. Today it is one of the most widely used computational tools. The human brain has an excellent capacity to learn, adapt, and evolve. ANN works in an almost similar way. ANN is made up of artificial neurons configured with a complex interconnection that maps the inputs and outputs. The first step in creating a neural network is the creation of

layers with neurons. The neurons in a layer are inter-connected with neurons from another layer. Each of these connections and neurons is assigned weights and biases to process inputs. Further, in the ANN model 70 % data is used for training purpose^{25), 26)} and the remaining 30 % data used for testing purposes. In this analysis, the same has been done by using the tangent sigmoid activation function, and the feed-forward back propagation network has been created for each layer.

4. Results and Discussions

The specimens were prepared using the FFF 3-D printing using different process parameters and tested for tensile strength on the electromechanical universal testing machine (UTM). The process parameters are optimized using an artificial neural network tool.

4.1. Tensile strength and analysis

Table 2 shows the tensile strength of nine 3-D printed test specimens that were tested on the UTM. It was analyzed through MINITAB 18 software. It is assumed that the factors under observation do not influence one another. This software is helpful in the reduction of a L_{27} orthogonal array to a L_9 orthogonal array. A clear trend was seen in the obtained stress data. By decreasing the layer thickness, specimen tends to achieve the strength of a molded specimen. It is observed that increasing the temperature as well as the angle of orientation also increases the Engineering stress. To validate these observations, data sets are validated statistically using the concept of artificial neural networks.

Table 2. Customized Taguchi Design and experimental results

Layer Thickness (μm)	Orientation ($^\circ$)	Temperature ($^\circ\text{C}$)	Engineering Stress (MPa)
70	0	280	29.5
200	90	280	26.6
300	45	280	16.5
70	90	285	36.5
200	45	285	24.5
300	0	285	11.4
70	45	290	31.9
200	0	290	16.0
300	90	290	19.1

The tensile strength of ABS printed part was recorded for nine specimen and the stress versus strain graph generated which is shown in Fig. 5.

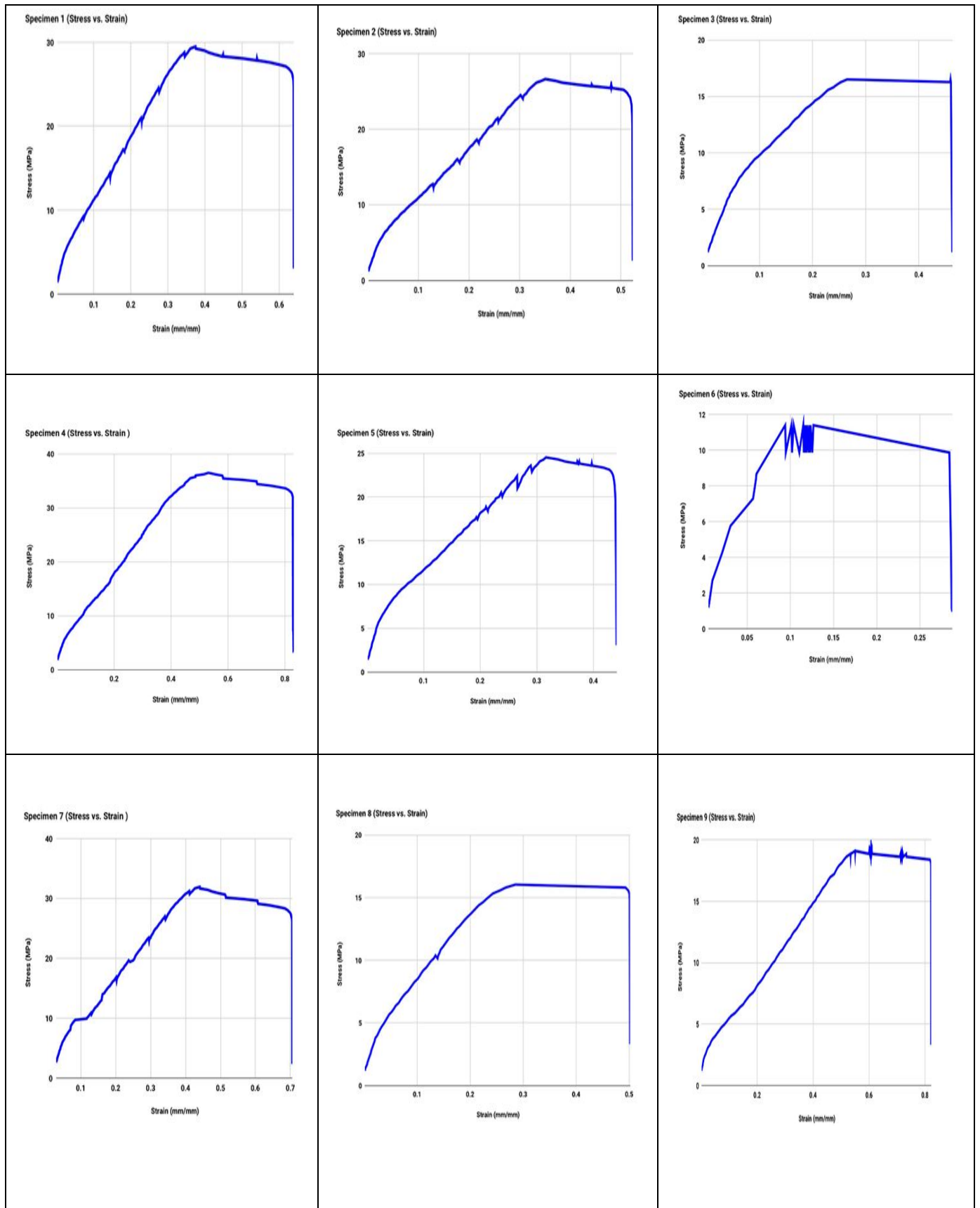


Fig. 5: Calculated stress - strain graph for all nine specimen

The preliminary analysis shows that increasing the extruder temperature harms the tensile strength. It seems contrary to logic that higher temperatures will enable better fusion at various bonding interfaces and improve the strength of the component. Fig. 6 shows a neural network with inputs, one hidden layer with fifty neurons to process information, and one output layer to represent the computed values.

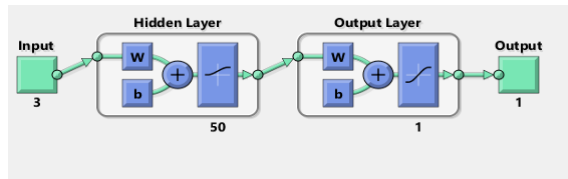


Fig. 6: Structure of ANN

Working with ANN is an iterative process. With the given inputs, ANN tries to achieve a target value. The connection used in this work is a simple arithmetic function with weights and biases chosen randomly by the computer program. The weights and biases are adjusted by ANN to achieve the target values. The process of achieving target values is called training of the neural network. In this work, ANN is employed as a prediction tool to check the tensile strength value at the optimum parameter setting. Fig. 7 shows the training and testing plot in which R values close to 1 mean that minimum error is obtained. But the data available for this analysis is less so that R-value for validation and testing does not fulfill the criteria. Fig. 8 show the performance plot at which testing, training and validation curves meet to give the best performance.

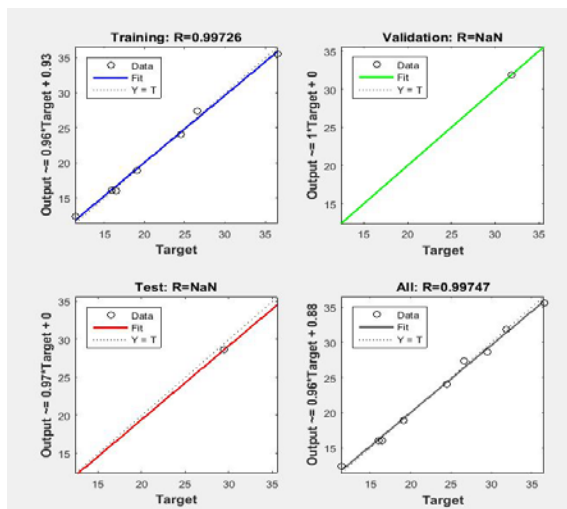


Fig. 7: Regression plot of ANN

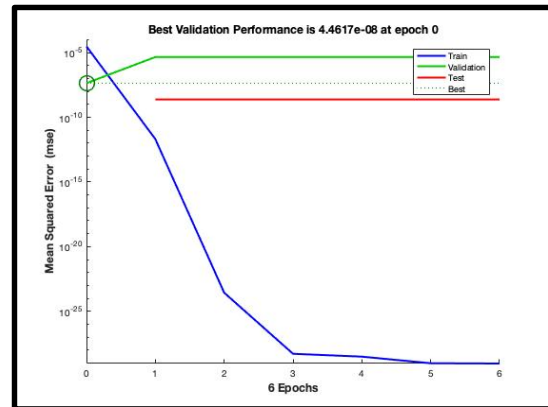


Fig. 8: Performance plot

Table 3 shows the various combinations of process parameters at which the ultimate tensile strength of samples is maximum. The performed experiments are highlighted shown in above table 3. From the table, it may be concluded that the decrease in layer thickness higher the tensile strength of the part this is due to that at minimum thickness the voids between the adjacent layers is minimum. It is observed from the table 3 that the maximum tensile strength predicated by ANN tool as following parameters:

Temperature:	290 °C
Layer Thickness:	70 μ m
Orientation:	90°
Predicted Value:	36.4696 MPa

Fig. 9 shows the training plot of ANN model. It indicates the numbers of training vectors are used once the weights are update.

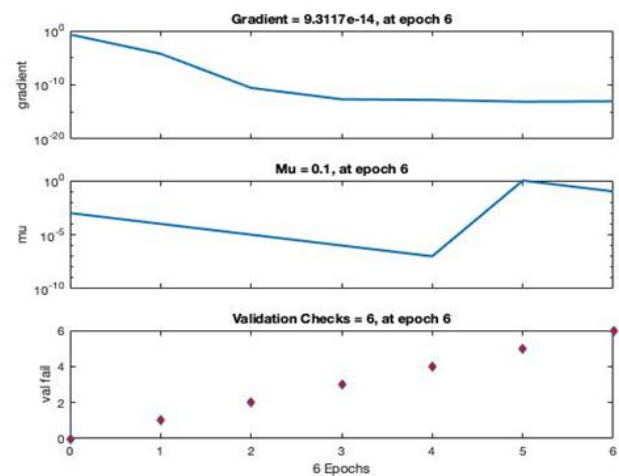


Fig. 9: Training Plot

Table 3. ANN simulated ultimate tensile strength

Layer thickness (μm)	Orientation ($^{\circ}$)	Temperature ($^{\circ}\text{C}$)	Simulated UTS (MPa)
70	0	280	29.4762
70	45	280	36.1453
70	90	280	35.9215
200	0	280	14.0384
200	45	280	30.2990
200	90	280	26.5753
300	0	280	11.7749
300	45	280	16.4854
300	90	280	14.3533
70	0	285	33.7821
70	45	285	36.2695
70	90	285	36.3478
200	0	285	13.6802
200	45	285	24.4546
200	90	285	34.6503
300	0	285	11.6627
300	45	285	14.0370
300	90	285	21.3862
70	0	290	36.2713
70	45	290	36.4527
70	90	290	36.4696
200	0	290	15.9715
200	45	290	34.0409
200	90	290	35.2295
300	0	290	12.5224
300	45	290	14.9957
300	90	290	19.0743

5. Conclusions

Additive Manufacturing is gradually revolutionizing the production scenario. It needs to understand the process parameters and their effect on the final build part to produce a component of consistent quality. This paper reported the influence of process parameters on the tensile strength of the ABS material used part. Based on the experimental studies carried out for optimization of process parameters, some important findings as follows:

1. For the least change in layer thickness, build

orientation, and printing temperature, the optimum level of setting of FDM parameters are as follows: layer thickness 70 μm , orientation 90 $^{\circ}$ and printing temperature 290 $^{\circ}\text{C}$.

2. High temperatures not show much favorable response to the tensile strength. A thorough study is analyzed to learn the temperature dependence of the bonding process.
3. Understanding the influence of temperature on the thermal stress produced and the wrapping of parts is required to create reasonable quality parts.
4. Reducing layer thickness decreases the size of voids, and increases the tensile properties, but building a part with less layer thickness consumes much larger time as compared to building with larger layer thickness.
5. Increasing print speed to reduce build time impacts the surface finish and poor bonding, thus resulting in failed prints.
6. Altering the spatial orientation increasing the number of layers carrying the load it is also impacting the dimensions of a single layer considerably.
7. For higher degree of accuracy ANN tool required a rigorous collection of data so that it can predict well the optimized parameters.

The future direction to build in this work is to use an artificial neural network model with more number of data and considering the study with larger number of process parameters for achieving better quality product. If more data available for ANN model it simulate equivalent results to experimental values, so that there is less error in the optimized results. Also Finite element analysis simulation can be done with other processing parameters like infill pattern, environmental condition and the combined effect of processing parameters at multiple levels.

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