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# Experimental and Investigation of ABS Filament Process Variables on Tensile Strength Using an Artificial Neural Network and Regression Model

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**Abstract**

Fused deposition modeling (FDM) is a commonly used 3D printing technique that involves heating, extruding, and depositing thermoplastic polymer filaments. The chosen processing settings greatly influence the quality of FDM components. In this study, the Taguchi technique and artificial neural network were employed to predict the ultimate tensile strength of FDM components and establish a mathematical model. The mechanical properties of ABS (Acrylonitrile Butadiene Styrene) were analyzed by varying parameters such as layer thickness, printing speed, direction angle, number of parameters, and nozzle temperature at five different levels. FDM 3D printers were used to fabricate samples for testing, following the ASTM-D638 standards. The results indicated that the printing process factors had a significant impact on tensile strength, with test values ranging from 31 to 38 MPa. The neural network achieved an average percentage error of 1.42% when predicting the tensile strength values of FDM components. While the analytical model exhibited an average percentage error of 7.297%. The Shell number of (28.73%) which is the largest effect on tensile strength and layer thickness has a small effect at (9.94%).

**Keywords:** FDM, ABS, 3D Print Parameters, Tensile Strength, Artificial Neural Network.

# البحث التجريبي ودراسة متغيرات عملية خيوط ABS على مقاومة الشد باستخدام الشبكة العصبية الاصطناعية ونموذج الانحدار

مصطفى عادل عبد الله حامد

**الخلاصة:**

نمذجة الترسيب المنصهر (FDM) هي تقنية طباعة ثلاثية الأبعاد شائعة الاستخدام تتضمن التسخين والبثق وترسيب خيوط البوليمر البلاستيكية الحرارية. تتأثر جودة مكونات FDM إلى حد كبير بإعدادات المعالجة المختارة. في هذه الدراسة، تم استخدام تقنية تاكوشي والشبكة العصبية الاصطناعية للتنبؤ بقوة الشد لمكونات FDM وإنشاء نموذج رياضي. تم تحليل الخواص الميكانيكية لـ ABS من خلال عوامل مختلفة مثل سماكة الطبقة وسرعة الطباعة وزاوية الاتجاه وعدد اطبقات القشرة ودرجة حرارة الفوهة على خمسة مستويات مختلفة. تم استخدام طابعات FDM ثلاثية الأبعاد لتصنيع عينات للاختبار، باتباع معايير ASTM-D638، باستخدام طريقة التصميم التجريبي للصفوف المتعامد Taguchi لتعيين محددات العملية. أشارت النتائج إلى أن عوامل عملية الطباعة كان لها تأثير كبير على قوة الشد، حيث تراوحت قيم الاختبار من ٣١ إلى ٣٨ ميكاباسكال. حققت الشبكة العصبية معدل معدل خطا مقداره1.42% عند التنبؤ بقيم قوة الشد، بينما أظهر النموذج الرياضي خطأ قدره 7.297%. • عدد طبقات القشرة اكبر عامل مؤثر على قوة الشد بنسبة(٢٨,٧٣٪) وسمك الطبقة له تأثير بسيط بنسبة (٩,٩٤٪).

**الكلمات المفتاحية:** نمذجة الترسيب بالمنصهر,خيوط ABS البلاستيكية, متغيرات الطابعة الثلاثيةالابعاد ,قوة الشد ,الشبكة العصبية الاصطناعية.

# 1. Introduction

Additive manufacturing (AM), often known as 3D printing, uses 3D models to produce items layer by layer. This technology speeds up and reduces design and production costs. For complex shapes, traditional manufacturing takes time and money, so many companies use 3D printing equipment to build the parts during design. FFF(Fused Filament Fabrication), SLA(Standard Tessellation Language). One of many 3D AM devices is fused deposition modeling (FDM), which uses layers of thermoplastic filaments.

Additive manufacturing is a promising emerging industrial technology. Despite its widespread use, this approach requires additional research [1]. Fused Deposition Modeling (FDM) printers utilize programmable extrusion machines to transform CAD models into physical components. An individualized software program utilizes a stable 3D model in STL format to produce the G code necessary for printing. The solid model is first divided into layers before generating the G-code. The layers are sequentially generated using thermoplastic materials extruded through a nozzle positioned on the printing platform. The extruder traverses the X-Y plane. In FDM, semi-molten thermoplastic filaments are expelled via a hardening nozzle at room temperature [3].

The FDM process is influenced by various elements that impact the specifications of the model. These factors have an impact on standard samples [4]. Optimizing the beneficial effects of process variables (FDM) might be challenging to achieve through their combination. Effect [5]. At present, the aerospace and dental sectors utilize FDM technology for the production of prototypes and functional components [6]. Fused Deposition Modeling (FDM) is a technique that uses extruded filamentous materials to build a final object. The materials are printed in 2D layers on a platform [7].

A multitude of researchers are currently engaged in the development of novel materials for various applications in aviation, medicine, and communications. Certain disadvantages are associated with utilizing FDM to produce work parts [8]. Garg et al. [9] investigated the impact of the build direction (X, Y, Z) and point angle on the tensile strength and surface roughness in three-dimensional space. The ABS created has undergone evaluation by FDM. Pico et al. [10] conducted ABS research to investigate the upper and lower surface layers, grout spacing, and layer accuracy. Mathematical modeling included optimization and ANOVA techniques. The process parameters that exhibited the greatest tensile strength and the lowest cost were identified. Alvarez et al. [11] The researchers investigated the mechanical characteristics of 3D-printed objects made from ABS. Experimental samples were printed with varying fill ratios to assess this impact while keeping all other printing parameters constant and showing the effect of no of shell in the process. Lee et al. examined a rapid prototyping machine that is compatible with ABS material using the FDM method [12]. Figure 1 shows the Print designs. The FDM printer heads move in the X and Y axes, and The Z axis moves the filament. CAD software is used to produce a 3D FDM design. After saving in STL format, the slicer software segments the 3D model.

FDM technology is environmentally friendly, flexible, and low maintenance compared to other AM technologies. Additionally, 3D printing reduces the consumption of wasted materials, labor, and manufacturing delays. Some disadvantages of FDM include:

Structure requirements, long construction times, and temperature-induced delamination. Aviation, civil engineering, automotive, medicine, etc. use 3D printing [15-19].

Tianyun et al. [20] ultimate tensile strength of 3D ABS materials made with FDM. Variable layer thicknesses were applied at angles. Multipurpose plastic test specimens were generated by ISO 527-2-2012. The theoretical model accurately predicted the tensile strength of FDM at all angles and thicknesses. When printing angle, the layer thickness is maximum, and the ultimate tensile strength minimum. Using polylactic acid (PLA), Abbas et al. [21] examined how process factors affect the dimensional deviation of 3D-printed FDM. Layer height, contours, filler density, angle, print speed, nozzle temperature, bed temperature, and print direction are selected for the printing process. The pilot trials used a three-level critical screening design (DSD). The filler density mainly influenced the length and width deviation.

Dezaki et al. [22] investigated how filler density affects surface roughness and tensile strength. Concentric, zigzag, triangular, grid, and pattern tool paths with FDM machine-specific densities were used. FEA compares printing and simulation processes. Grid paths and concentric tools have the best surface quality. In contrast, ultimate tensile strength testing found that the zigzag pattern had insufficient design, adhesion, and mechanical properties. Daddonna et al. [23] focused on improving FDM. Parameters using ABS. The layer thickness, printing speed, and filler ratio were selected. The L16 Taguchi matrix, consisting of three components with four levels, was used to generate the experiment. Desire has also been used to optimize the FDM process parameters. The results indicated that the optimal variables were layer thickness of 0.3 mm, print speed of 81 mm/s, fill life of 55%, filament length of 2.10 m, component weight of 5.68 g, and printing time of 20.01 minutes. Pang et al. [24] examined how printing temperature affects the bonding and tensile properties. PLA test samples were printed at 180-240°C, increments of 10°C at a time. Uniaxial tensile testing for each variant was repeated five times under ASTM D638-14 at a 1 mm/min rate. Based on the results, specifications printed at a higher temperature perform better.

The study examines ABS filament for FDM components and the effect of the 3d printing factor on tensile strength. The ANN (Artificial Neural Network) and regression model predict the ultimate tensile strength and the largest expected working error.

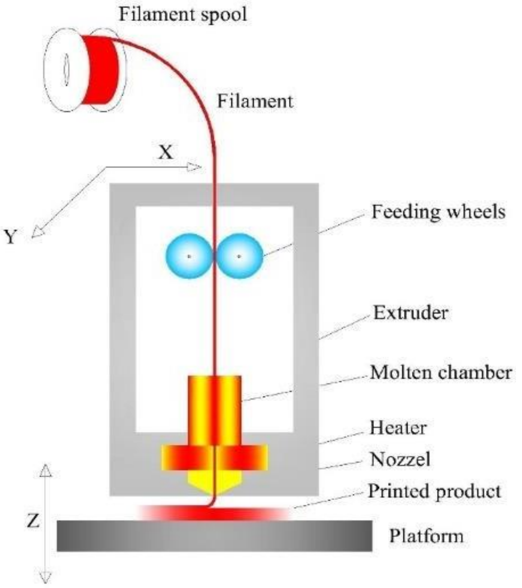


**Figure (1):** Shown the principal part for FDM-3D-printing.

## 2. Materials and Process

Material selection is crucial for 3D printing. Application type and mechanical properties can influence material selection. This section discusses material and printing factors that affect manufacturing.

### 2.1. Material

ABS, or Acrylonitrile Butadiene Styrene, is a popular 3D printing material. This biodegradable thermoplastic is manufactured from sugarcane, tapioca, corn, and potato starch. ABS is easy to print and does not release harmful fumes. ABS may degrade and produce lactic acid, making it suitable for surgical implants and suturing.

FDM can print items with varied fill densities, its biggest advantage. We save material, money, and time and reduce product weight. ABS Creality filament was with 1.75mm filament wire Used in Creality Ender-5 3D-printing. The tensile specimen was tested since it was easy to prepare and suitable for FDM.

### 2.2. Process parameters

Layer thickness greatly affects printing time, accuracy, and mechanical qualities. Thick layers reduce the modulus of elasticity, tensile strength, and elongation at break. The surface roughness increases with the number of layers [25].

The ideal FDM printing speed depends on the material, extrusion temperature, and resolution The print speed refers to the rate at which the nozzle tip covers a distance of 1 millimeter per second.

Bonding and mechanical strength. Faster printing results in more voids and worse layer bonding [20]. Lower printing speeds increase manufacturing time, so the appropriate speed must be chosen to achieve the desired result. The raster angle represents the printing path on the platform, along with the interior of the completed product, concerning the x-axis [26][27].

## 3. Experiment Design

The study investigated how several factors affect tensile strength. Few parameters were maintained, such as a filling density of 80%, a Gyroid pattern, and a bed temperature of 55°C. Five levels of layer thickness, print speed, print temperature, direction angle, and shell number were used in this investigation. The levels and values of specific process parameters are in Table 1. And shown in Figure (2).

Design of experiments (DOE) solves the problems. The DOE subfield of statistics improves trial outcomes by improving planning, organization, and execution. Taguchi's analysis reduces experimentation in most investigations. This research used the L25 Taguchi orthogonal matrix to examine the effect of selected parameters; Table 2 displays the ABS samples produced.

## 4. Specimens Fabrication

Design is the most important part of production; SolidWorks was used to design the sample. The CAD files are then converted to STL files. Ultimate CURA software configures the printing parameters to print the component. The features and size required may affect time, but the complexity of the design does not. The Reality Ender-5 3D printer made the tensile samples. Figure 3 shows that the samples were manufactured according to ASTM D638 standard.

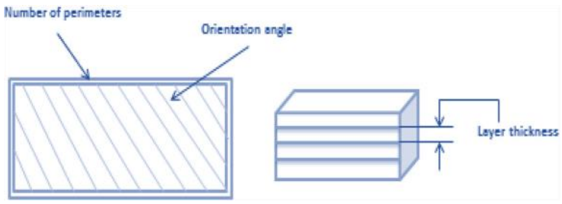


**Figure (2):** 3D printer's process parameters.

**Table (1):** shows the parameter levels used.

| Factor | Level | | | | |
|---|---|---|---|---|---|
| Layer thickness (mm) | 0.1 | 0.15 | 0.2 | 0.25 | 0.3 |
| Printing speed (mm/s) | 40 | 45 | 50 | 55 | 60 |
| Print temp C | 230 | 235 | 240 | 245 | 250 |
| Orientation angle | 0 | 20 | 45 | 70 | 90 |
| Shell Number | 1 | 2 | 3 | 4 | 5 |

**Table (2):** shows the parameters used in the experiment.

| No | Layer thickness (mm) | Printing speed (mm/s) | Printing temp (C) | Shell number | Angle (degree) |
|---|---|---|---|---|---|
| 1 | 0.10 | 40 | 230 | 1 | 0 |
| 2 | 0.10 | 45 | 235 | 2 | 20 |
| 3 | 0.10 | 50 | 240 | 3 | 45 |
| 4 | 0.10 | 55 | 245 | 4 | 70 |
| 5 | 0.10 | 60 | 250 | 5 | 90 |
| 6 | 0.15 | 40 | 235 | 3 | 70 |
| 7 | 0.15 | 45 | 240 | 4 | 90 |
| 8 | 0.15 | 50 | 245 | 5 | 0 |
| 9 | 0.15 | 55 | 250 | 1 | 20 |
| 10 | 0.15 | 60 | 230 | 2 | 45 |
| 11 | 0.20 | 40 | 240 | 5 | 20 |
| 12 | 0.20 | 45 | 245 | 1 | 45 |
| 13 | 0.20 | 50 | 250 | 2 | 70 |

| | | | | | |
|---|---|---|---|---|---|
| 14 | 0.20 | 55 | 230 | 3 | 90 |
| 15 | 0.20 | 60 | 235 | 4 | 0 |
| 16 | 0.25 | 40 | 245 | 2 | 90 |
| 17 | 0.25 | 45 | 250 | 3 | 0 |
| 18 | 0.25 | 50 | 230 | 4 | 20 |
| 19 | 0.25 | 55 | 235 | 5 | 45 |
| 20 | 0.25 | 60 | 240 | 1 | 70 |
| 21 | 0.30 | 40 | 250 | 4 | 45 |
| 22 | 0.30 | 45 | 230 | 5 | 70 |
| 23 | 0.30 | 50 | 235 | 1 | 90 |
| 24 | 0.30 | 55 | 240 | 2 | 0 |
| 25 | 0.30 | 60 | 245 | 3 | 20 |

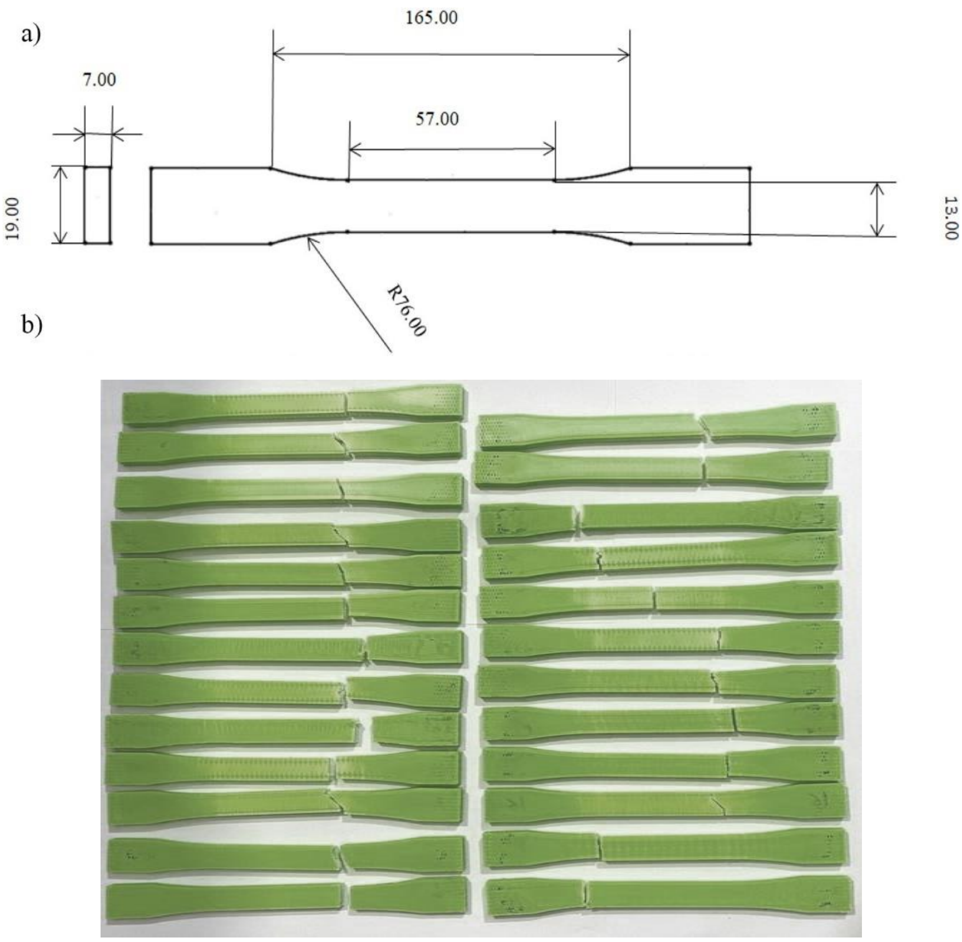


**Figure (3):** (a) shown tension sample used ASTM D638 standard (b) 25 ABS specimen.

## 4. Results and discussions:

ANN are information processing paradigms modeled after biological nerve systems like the brain. Neurons form an ANN's layers. Neurons receive and output signals. Neural network predictive modeling implicitly recognizes complicated nonlinear correlations and independent variable interactions. A black box prediction model using multi-layered. ANN may adapt the system model since they are da-driven and self-adaptive. Fit is seen without describing the model's functional form [16, 17]. The output is predicted using an artificial neural network. Neural networks have three layers: input, output, and hidden. Between input and output parameters, the ANN model was trained. See Figure 4 for the neural fitting tool import of the 5x25 input matrix and 1x25 output data.

The ANN was trained. Different regression values are evaluated to relate the outputs to the objectives. To discover relationships between outputs and objectives, several regression values are examined. A regression R-value close to 1 indicates the best fit and strong association between variables, while 0 indicates random association. Figure 6 contains 4 graphs. Training data is used to train the model, while validation data is used to evaluate the model's performance during training. After training, test data is used to evaluate the model, and all-in plots

Provide a final, unbiased measure of the model's performance

In terms of accuracy, indicating the future usefulness of the product. The dashed line in each plot reflects the optimal target output ratios, while the solid line refers to the regression model.

A higher signal-to-noise ratio (S/N) is indicative of superior performance across the board. Therefore, the highest value setting for the machining parameters is the best option. The (tensile strength) was maximized based on the projected ideal parameter value, which is noted in Figure 5. The x-axis in the graphs represents the value of each machining parameter, while the y-axis represents the response value (tensile strength).

The analysis of variance analysis (ANOVA) method was used to analyze the results of experiments to determine the impact of 3D printing factors on tensile strength that is dependent on cutting variables Table 3 exhibits the findings of the analysis of variance for tensile strength, Consequently, the most effective variable is the Shell number of (28.73%) which is second the angle of (25.75%), while nozzle temperature, print speed, and layer thickness have a small effect at (15.34%)(15.15%) and (9.94%) respectively.

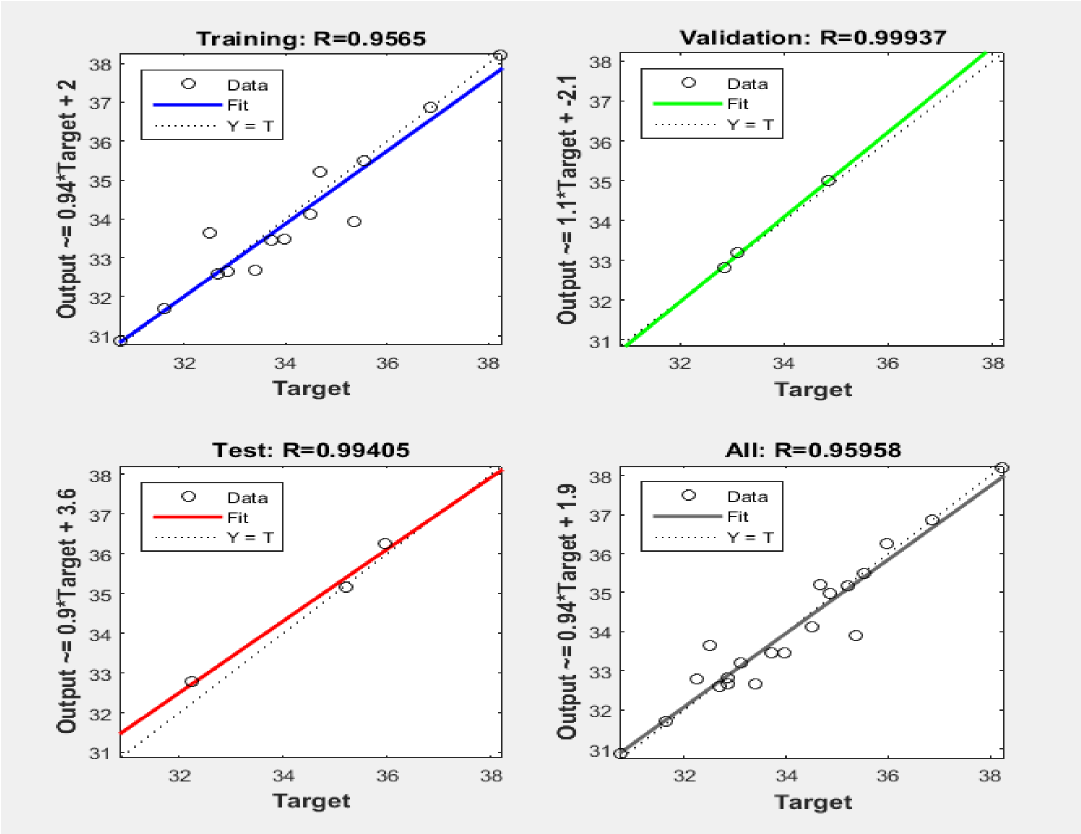


**Figure (4):** Shown the ultimate tensile strength obtained using ANN.

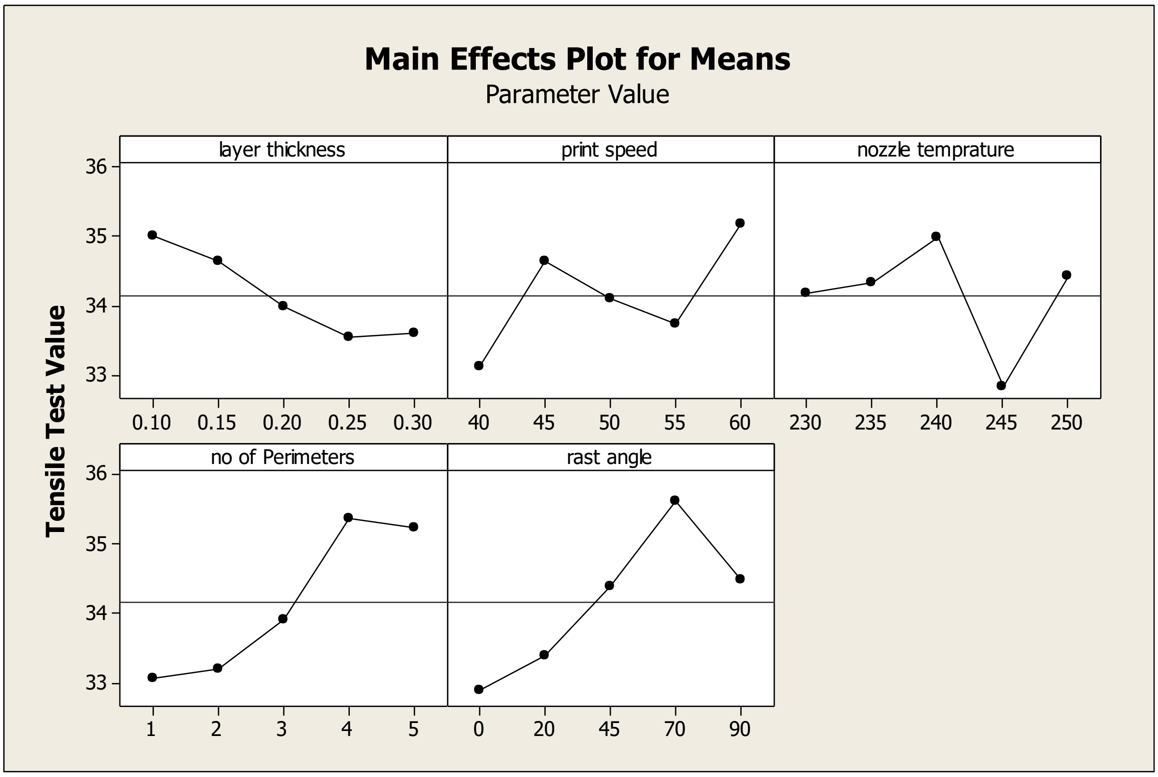


**Figure (5):** Schematic of analysis findings.

**Table (3):** ANOVA analysis findings.

| Source | DOF | SS | MS | P% |
|---|---|---|---|---|
| layer thickness | 4 | 8.28 | 2.07 | 9.94% |
| print speed | 4 | 12.62 | 3.16 | 15.15% |
| nozzle temperature | 4 | 12.78 | 3.19 | 15.34% |
| Shell number | 4 | 23.94 | 5.99 | 28.73% |
| angle | 4 | 22.28 | 5.57 | 26.75% |
| error | | 3.33 | | 4% |
| Total | 21 | 83.32 | | 100% |

**Table (4):** The Comparative assessment of predictive models.

| No | Tensile strength (MPa) | ANN Predicted (MPa) | Error % of ANN | Regression Model | Error % of Regression model |
|---|---|---|---|---|---|
| 1 | 31.625 | 31.701 | 1.340 | 31.114 | 1.616 |
| 2 | 33.365 | 32.669 | 3.582 | 31.705 | 4.976 |
| 3 | 35.975 | 36.262 | 0.592 | 32.174 | 10.565 |
| 4 | 35.805 | 35.804 | 1.397 | 32.204 | 10.057 |
| 5 | 38.245 | 38.197 | 1.433 | 32.620 | 14.708 |
| 6 | 35.535 | 35.501 | 1.500 | 31.981 | 10.000 |
| 7 | 37.455 | 37.568 | 1.033 | 32.583 | 13.007 |
| 8 | 32.495 | 33.647 | -2.008 | 31.475 | 3.138 |
| 9 | 32.845 | 32.824 | 1.583 | 31.384 | 4.449 |
| 10 | 34.845 | 34.987 | 1.027 | 31.968 | 8.257 |
| 11 | 33.975 | 33.470 | 2.957 | 31.748 | 6.554 |
| 12 | 37.455 | 37.455 | 1.335 | 31.298 | 16.439 |
| 13 | 34.665 | 35.194 | -0.084 | 31.911 | 7.945 |
| 14 | 33.115 | 33.193 | 1.272 | 31.640 | 4.456 |
| 15 | 35.365 | 33.913 | 5.518 | 32.026 | 9.442 |
| 16 | 30.765 | 30.873 | 1.273 | 30.816 | -0.164 |
| 17 | 32.675 | 32.583 | 1.811 | 31.409 | 3.873 |
| 18 | 34.495 | 34.128 | 2.513 | 31.723 | 8.035 |
| 19 | 34.595 | 34.594 | 1.446 | 31.893 | 7.809 |
| 20 | 35.195 | 35.176 | 1.473 | 32.169 | 8.599 |
| 21 | 33.715 | 33.462 | 2.231 | 31.796 | 5.693 |
| 22 | 36.855 | 36.871 | 1.313 | 32.384 | 12.131 |
| 23 | 32.845 | 32.662 | 2.077 | 31.455 | 4.234 |
| 24 | 32.335 | 33.163 | -1.016 | 31.162 | 3.629 |
| 25 | 32.245 | 32.771 | -0.082 | 31.282 | 2.985 |

The relationship between the output and the target is shown by the value of R. R = 1 indicates a linear relationship between the outputs and, If R values are close to zero, the output and target are not linearly related. Training, validation, testing.

ANN uses system sample data to generate fast predictions, saving time and money. Based on the ANN sample data, the mathematical model was established in Equation 1.

The experimental tensile test values ranged from (30.765-38.241) MPa, in samples (16) and (5) with stress-strain curves as shown in figure (6) which were determined by the testing instruments. The LM algorithm of ANN technology can predict the tensile test values, which are close to the real values between (30.873-32.620) MPa. The first-order mathematical model predicts tensile values between (30.873-30.873) MPa. The ANN error values ranged from (-2.008-3.582) %, while the mathematical model error values ranged from (-0.164-16.439) %.

Tensile strength = 22.5 − 0.12 (layer thickness) + 0.043 (printing speed) + 1.199 (shell number) + 0.1258 (orientation angle) + 0.055 (print temperature) …………(1)

Figure (7) illustrates the comparison of tensile strength values obtained from three distinct sources: tensile test values (in MPa), anticipated ANN values (in MPa), and mathematical model values. The graph indicates a distinction among the three sets of values. The Artificial Neural Network (ANN) predictions tend to exhibit larger values compared to the actual tensile test results, but the values obtained from the mathematical model seem to be lower. The aforementioned statement suggests that the Artificial Neural Network (ANN) approach tends to provide higher estimations for the tensile strength, whilst the mathematical model tends to provide lower estimations. It is crucial to acknowledge that these disparities may arise from the constraints and presumptions inherent in each approach. Nevertheless, the graph offers useful insights into the variations and disparities among the three approaches in estimating tensile strength.

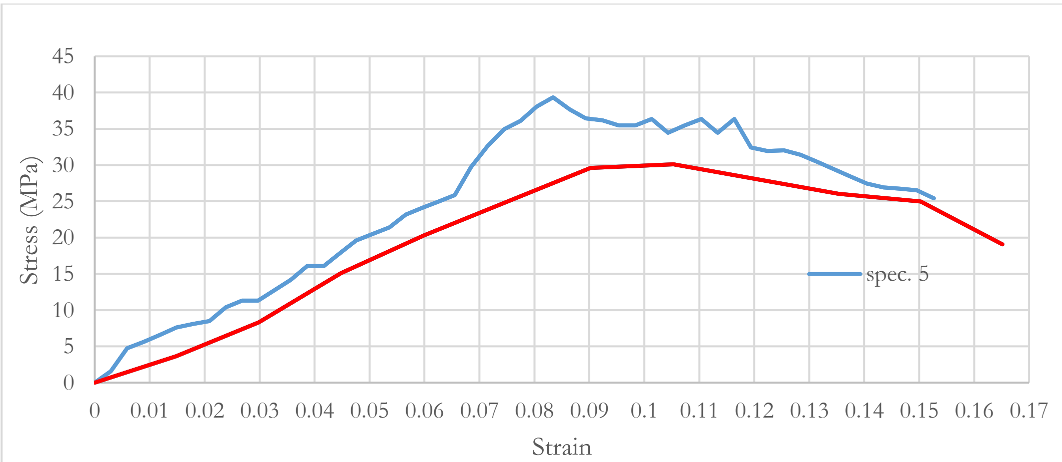


**Figure (6):** The sample (5) maximum tensile strength and sample (16) minimum tensile strength.

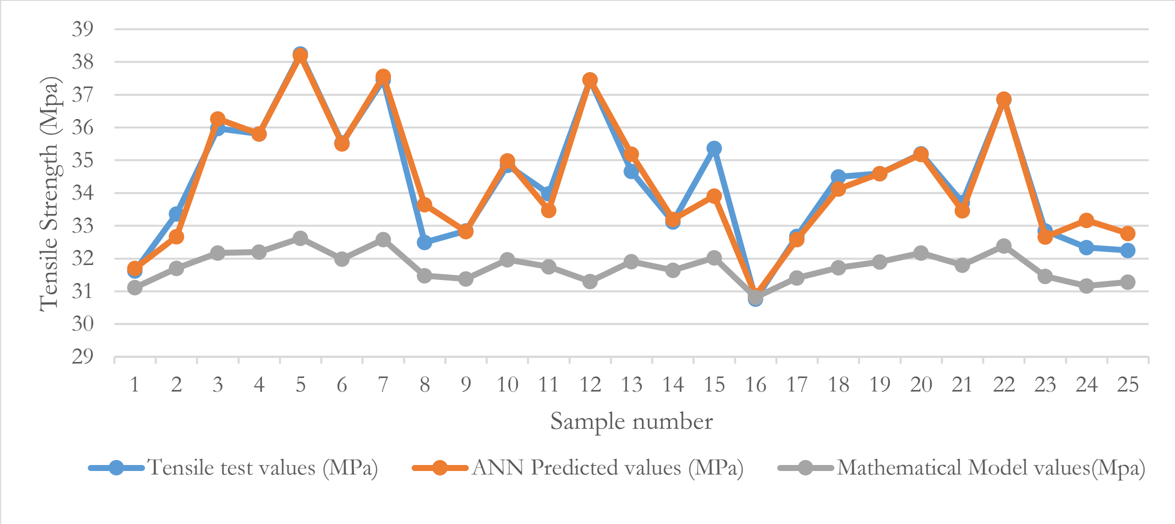


**Figure (7):** Correlation between tensile test values and anticipated values.

## 5. Conclusions

The researchers examined the impact of various factors, including layer thickness, printing speed, printing temperature, shell number, and orientation angle, on the tensile strength of the ABS sample. They employed artificial neural network (ANN) and mathematical regression models to analyze the data and identify the optimal printing parameters that would result in the highest tensile strength.

- The range of tensile strength measurements obtained was between 30.765 and 38.241 MPa, demonstrating the substantial impact of the printing process parameters on tensile strength. The ideal variables for achieving maximum tensile strength were determined to be a layer thickness of 0.10 mm, a printing speed of 60 mm/s, a print temperature of 250 °C, a direction angle of 90°, and a total of 5 circumferential numbers.
- The predictions made by both the artificial neural network (ANN) and mathematical model were compared to the results obtained from the tensile tests with an average percentage error of 1.42% when predicting the tensile strength values of FDM components. While the analytical model exhibited an average percentage error of 7.297%.
- The Shell number of (28.73%) which is the largest effect on tensile strength and layer thickness has a small effect at (9.94%).

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