Optimization of Processing Parameters for 3D Printed Product Using Taguchi Method

Farhana Yasmin [1], Mustafa Khan [2] and Qingjin Peng [3]

[1] University of Manitoba yasminf@myumanitoba.ca
[2] University of Manitoba, khanm5@myumanitoba.ca
[3] University of Manitoba, Qingjin.Peng@umanitoba.ca

Corresponding author: Qingjin Peng, Qingjin.Peng@umanitoba.ca

Abstract. Additive Manufacturing (AM) or 3D printing techniques use fused layers of the material to build cross sectional geometry of product. As variable processing parameters have an impact on the product quality, it is crucial to ascertain relationships of AM process parameters, productivity, sustainability, and structure performance. This study investigates the effect of the fused deposition modelling (FDM) process parameters on the response variables including mechanical attributes, energy consumption, material consumption and manufacturing time of the 3D printed product. Experiments are conducted for the FDM variable parameters of the infill pattern, infill density, layer height, printing speed, printing temperature and wall thickness. The design of the experiment approach is used to determine the best combination of the chosen parameters. A L18 orthogonal design method is employed to collect the testing data. Taguchi and analysis of variance methods are applied in the data analysis of variable FDM parameter settings. The research finds different effects on the response variable by the layer height. The wall thickness has the least impact on all the response variables.

Keywords: 3D printing, Additive manufacturing (AM), Design of experiment (DOE), Fused deposition modeling (FDM), Optimization, Taguchi method, Analysis of variance (ANOVA), Mechanical attributes, Sustainability.
DOI: https://doi.org/10.14733/cadaps.2024.281-300

1 INTRODUCTION

3D printing or additive manufacturing (AM) technologies provide flexible and efficient solutions in processing complex geometric structures of product [24]. AM in rapid product prototyping grows because of the digitization of production processes [26]. Extensive activities have been conducted to enhance the quality of 3D printed products, particularly in product mechanical characteristics and precision [32]. Researchers have looked at the effect of 3D printing parameters to enhance the part quality, shorten the building cycle, and ensure reliable structural performance [27]. Although different solutions have been proposed to select printing parameters for the process efficiency and product quality [21], there is a lack of research on the method to increase the mechanical strength of printed products using FDM. The optimal setting of printing parameters is necessary to build high-quality and durable parts with the least time and materials.

This research investigates the effects of 3D printing parameters on tensile and compression attributes of the product built by FDM. The characteristics of polylactic acid (PLA) specimens are studied using the Taguchi design of experiments approach. The Taguchi L18 Orthogonal array is formed based on 2 and 3 mixed levels of factors. Processing factor effects on response variables of the ultimate strength and modulus are studied to find the optimal set of printing parameters.

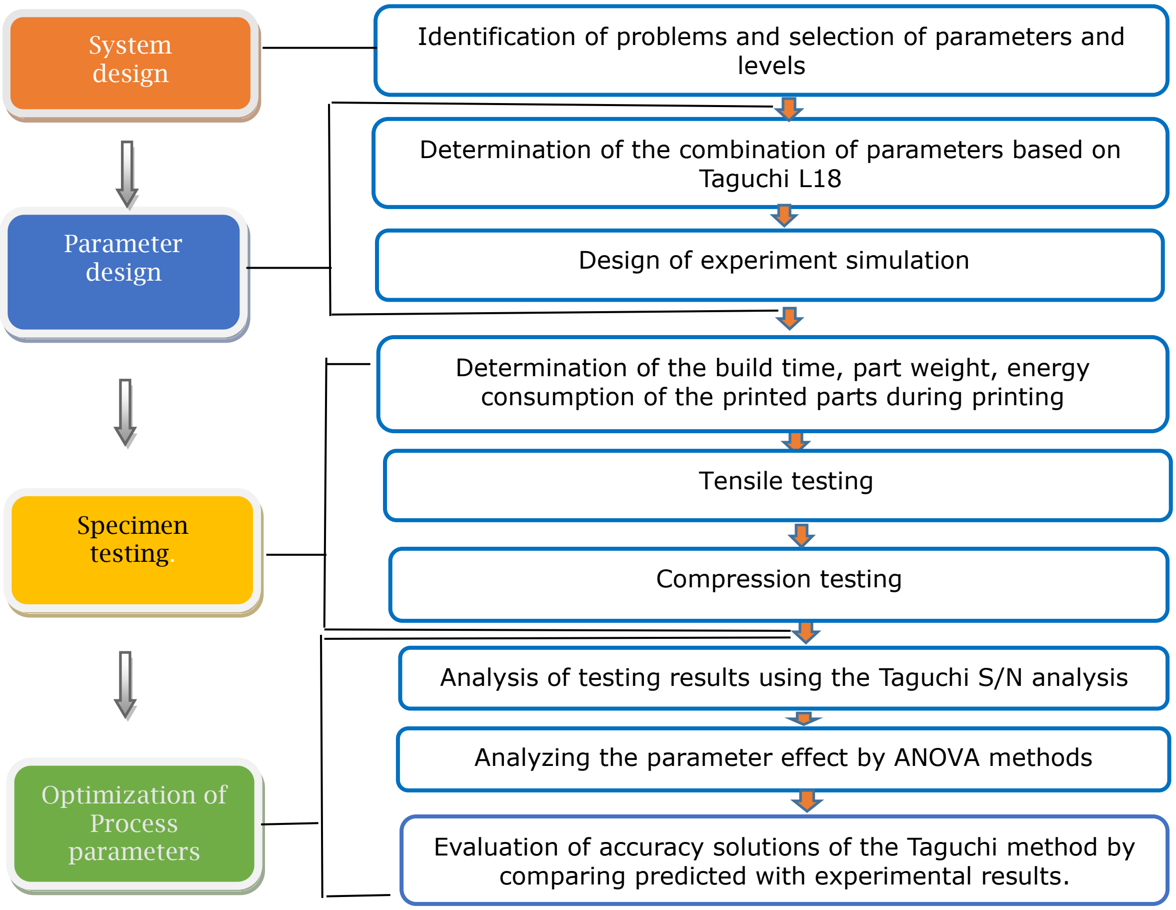


Figure 1: Flowchart of the method.

A framework of the proposed method is shown in Figure 1. The system design phase begins with the identification of research problems and choice of parameters and levels to find the optimum solutions for AM sustainability. The focus of this study is to analyze how the selected parameters in AM impact the usage of energy and material consumption, printing time along with the tensile and compressive attributes during the process. The second stage of the process involves selecting the combination of parameters using the Taguchi L18 orthogonal array. The third stage designs the experimental simulation to gather data from tests. The combination of these two stages is the parameter designing phase in the process. Specimen testing, the following phase, is a combination of stages four, five, and six. The final phase is the optimization of the process parameters developed through stages seven, eight, and nine. Throughout these study stages, data are examined using the Taguchi S/N analysis to determine optimal parameter settings and interactions. ANOVA analysis is performed to find out the parameter effects on response and determine the best parameter settings. To verify the outcome of the simulation, an experiment is conducted to compare the predicted values with the experimental results.

In general, the research is conducted through material and parameter selection, experimental design, sample design and printing, sample testing and experiment result analysis as shown in the method flowchart. The following parts of this paper are organized as follows. Section 2 reviews the existing research. In Section 3, the research method is proposed to examine the effects of AM parameters on response variables. Experiments in the case study are discussed in Section 4. Section 5 discusses findings, solutions and evaluations of the proposed method, followed by conclusions of this paper in Section 6.

2 LITERATURE REVIEW

2.1 Effect of 3D Printing Parameters

3D printing parameters affect the product quality, building cycle, and structural performance [3]. Research efforts have been made to improve the quality of printed products, mechanical characteristics, and dimensional accuracy. It was found that mechanical qualities like the tensile strength are significantly impacted by 3D printing parameters, including the build direction, layer thickness, and set nozzle temperature, stability, stiffness, and Young's modulus [1]. For example, Wang et al. [29] conducted experiments and micromechanical simulations to examine the minute pores effect on material mechanical properties in the FDM process. Popescu et al. [19] examined mechanical characteristics of printed products for the printing settings that affect the tensile, compression, fracture, or impact strengths of the products.

Research shows raster layup effects on the final material characteristics of PLA-based FDM printed products [3] through the analysis of the toughness, strength, and stiffness of the product. An experiment was performed to look at effects of processing parameters on the mechanical characteristics and dimensional accuracy repeatability of FDM parts [20]. Impacts of different FDM parameters were examined including the layer thickness and raster angle. FDM parameters that affect mechanical properties were analyzed using ANOVA [8]. An investigation was performed to find the optimal factor level for the best product quality by using the Taguchi method and Gray relational analysis to improve the fast-prototyping process [28]. For the dimensional variation of printed objects, four printing parameters were used to find the optimal combination of printing parameters. The Taguchi method for optimization was paired with a fuzzy thorough evaluation [30]. A study was conducted to find the impact of the infill rate, infill pattern, and layer thickness on the dimensional accuracy of FDM. An orthogonal array L27 and a fuzzy technique were used in conjunction with the CAD model of the object to improve the printing settings [33].

However, there is a lack of research on AM processing settings that affect energy, time and material used to maintain the mechanical strength. Most of the existing research simply considers two levels of parameters or assumes linear relationships between the parameters. The relationship of the product characteristics, processing energy and material consumption requires a thorough investigation of AM processing at multiple levels to find each parameter contribution for response variables.

2.2 Taguchi Method

Taguchi Method is known as a robust design approach to reduce variations in a process by exploring parameters effect on the mean and variance of process performance characteristics. An orthogonal array is used in the Taguchi method to develop the experiment design [6]. Experimental factors and associated levels are chosen to form the orthogonal array. Taguchi loss functions assess performance features for measures of robustness by limiting effects of noise components for control factors to reduce variability in the process [14]. The signal to noise (S/N) ratio decides the impact of the response to the target value in various noise environments. The S/N ratio includes three categories: nominal is the best, greater is better, and smaller is better.

Which one is best depends on the goal of the study [4]. The Taguchi approach employs a two-step process for optimization. The first step identifies control elements to reduce variability using a S/N ratio, and the second decides control factors that move the mean towards the target with little or no impact on the S/N ratio [16].

The Taguchi approach is applicable to a broad range of engineering disciplines. It is useful for 'tuning' a given process for the optimal result [12]. Taguchi orthogonal arrays can be used to confirm the impact of printing settings on the object surface roughness for the best printing parameters [22].

However, the Taguchi approach presents orthogonal arrays in a different way from those often presented in statistical literature [2]. Taguchi orthogonal array design is a variant of the standard fractional factorial design approach for a set of combinations of various factors in different levels. All levels of each factor are equally considered by using balanced Taguchi orthogonal arrays. The full factorial, central composite, Box-Behnken, Plackett-Burman, Taguchi, and response surface method are just a few of the numerous DOE methods [5]. The sensitivity of each component and effects of two or more factors can be investigated using a DOE technique. Design of experiment and Genetic Algorithms methods were applied in case studies for searching the single and multi-objective optimization with the low cost, robustness, and high effectiveness [18]. Different statistical and data science techniques, such as the analysis of variance (ANOVA) and Taguchi method, have been investigated to find the best FDM parameters that enhance the characteristics and quality of product [25]. The Taguchi method provides an effective approach to find appropriate process parameters for sustainable solutions with the low energy and material cost.

2.3 Analysis of Variance (ANOVA)

The analysis of variance (ANOVA) technique is typically used to examine impacts of process factors on quality attributes. The importance of the predictor on responses is assessed using the F-statistic and p values of the ANOVA result [8]. ANOVA is used in this study to identify the key process variables influencing the overall objective, which evaluates experiment data and draws conclusions based on the Analysis of variance.

ANOVA is employed to evaluate comparison experiments for the single difference in significant. A ratio of the two variances determines the experimental statistical significance. This ratio is unaffected by a few potential changes to experiment findings. The importance is unaffected by the addition of a constant to all observations. There is no change in importance when all observations are multiplied by a constant [3]. ANOVA employs the conventional standardized terminology. The equation for a sample variance is as follows.

$$S^2 = \frac{1}{N}\sum_i ((y_i - \bar{y})^2 \tag{2.1}$$

where the squared terms represent deviations from the sample mean, the divisor is referred to degrees of freedom (DF), the sum is referred to as the sum of squares (SS), and the result is referred to as the mean square (MS). There are three sample variances: a total variance based on all observational departures from the mean, an error variance based on all observational deviations from the means of the applicable treatments, and a treatment variance [23]. To consider the discrepancy between the variance of observations and variance of means, the treatment variance is based on departures of treatment means from the overall mean. The primary procedure includes dividing the entire sum of squares (SS) into parts that are connected to the model effects as shown in Equation (2.2).

$$SS_{Total} = SS_{Error} + SS_{Treatments} \tag{2.2}$$

where similar splitting can be used to determine the number of DF, the component for error provides a Chi-squared distribution that defines the sum of squares associated with it, but the component for "treatments" specifies the same thing if there is no treatment effect. A general equation for degree of freedom (DF) is represented by Equation (2.3).

$$DF_{Total}=DF_{Error}+ DF_{Treatments} \tag{2.3}$$

P-values are used in the regression analysis and analysis of variance to assess the significance of the parameter or parameter interactions that influence the response variables. Because these analytical techniques are based on their hypothesis testing on probability or P-value, the lower the P-value, the greater the likelihood that the null hypothesis will be rejected. As a result, the parameter or interaction will be regarded as significant [32]. For comparing components of the overall deviation, F-test is employed. The F-value in an ANOVA is determined by dividing the variation in sample means by the variation in the samples, shown in Equation (2.4). For instance, in one-way or single-factor ANOVA, the F-test statistic is used to compare statistical significance [9].

$$F= \textit{variance between treatments/Variance within treatments} \tag{2.4}$$
$$F = MS_{Treatments}/MS_{Error}$$

In terms of minimizing false negative errors for a fixed rate of false positive errors, the ANOVA F-test is used. ANOVA is applicable to the investigation of combined effects of several variables. Factorial experiments are those that include observations across all possible values of each factor. Factorial experiments are more effective than a series of experiments with a single factor. The effectiveness increases with the number of factors [17]. The term "adjusted R-squared" refers to a version of R-squared that is changed to account for the number of predictors in the model. A corrected model accuracy indicator for linear models is called adjusted R-square. When the additional term enhances the model more than that anticipated by chance, the adjusted R-squared rises. It falls off when a predictor makes a smaller contribution to model improvement than anticipated value. A normal adjusted R-squared value is one that is positive. It is always less than the R-squared value. [15].

3 PROPOSED METHOD

Four key FDM process responses are investigated, including the printing time, energy consumption, material used and mechanical properties of specimens through tensile and compressive tests. Six parameters are examined for their effects on the printed product. An optimal AM process should use less energy, material, and time. Effects of these parameters at various levels are evaluated using the smaller-better Taguchi S/N ratio formula. The larger-better S/N ratio is used for the tensile modulus, ultimate tensile strength and compressive stress. The experimental trials are conducted using an L18 orthogonal array. The best value for each of the parameters is chosen based on the analysis of variance.

3.1 Material and Parameter Selection

Acrylonitrile Butadiene Styrene (ABS) and PLA are two thermoplastic polymers utilized in FDM [7]. Since PLA has excellent mechanical strength and affordability, we chose PLA material in this study. The material filament is 1.75 mm in diameter with an accuracy of +/- 0.01 mm. Parameter settings are combined to produce high-quality components in FDM with the least amount of time. The product CAD model can be used to extract functional specifications and identify input process parameters. There are many parameters in a 3D printing system, but not all the parameters have an impact on the strength and printing time. The selection of input parameters and ranges of each parameter in the FDM machine are examined in accordance with the process knowledge, literature review and experience to determine levels for each process parameter.

Taguchi Orthogonal Array (OA), a highly fractional design method, is employed to estimate main effects with a limited number of experimental runs. It can study main effects when factors have more than two levels of complexity and are not just limited to two level factorial trials. There are various methods available to explore primary impacts for unique mixed-level studies where all the components do not have the same number of levels [34]. According to Taguchi principles, the choice of OA depends on the overall degrees of freedom (DOF) of the processing parameters and levels. In this study, six processing parameters are identified. Five of these parameters have three levels with two DOF, while one parameter has two levels with a single DOF, resulting in a total of 11 DOF. The DOF is defined as the number of levels subtracted by one (DOF = number of levels - 1). To achieve the best parameter configuration, the choice of OA must be equal to or greater than the total number of DOF, as recommended by Taguchi. After evaluating several OA designs, the L18 OA is identified as the optimal choice for the layout experiment. The L18 OA has the smallest array with 17 DOF, allowing all six processing parameters to be set. This design ensures that effects of the processing parameters on the manufacturing execution (ME) system's performance are adequately captured. Table. 1 lists factors and levels of the experimental design in this research. The AM process parameters or control factors are explained as follows.

3.1.1 Wall thickness

The distance between one surface of a 3D model and its opposing counterpart is referred as the wall thickness. It is the minimum thickness of a 3D model. The structure and design of the 3D model have a significant impact on the minimum wall thickness. There is a minimum wall thickness for each material that have advised to avoid issues. Two different levels of wall thickness, 0.8 and 1mm, are considered for PLA material to find out the effect on the printing product.

3.1.2 *Layer height*

The layer height describes the precise height of each layer of material that a 3D printer extrudes or sinters. Layer height is a user-controlled parameter that can be changed using 3D printer software, although the minimum and maximum layer heights are constrained by the printer's physical features, such as the nozzle diameter and other considered features. For the layer height, 0.1,0.2 and 0.3mm are three levels considered in this research.

3.1.3 Infill density

The amount of material needed to fill the printing interior depends on its infill density. Printing can be completed quickly if the low infill percentage is used. In this study, three unique infill percentage values 25 %, 50% and 75 % are used.

3.1.4 Infill pattern

The inside framework of a 3D printed component is referred to as infill pattern. Many different shapes can be used to create this internal structure. Optimization of the component weight, strength, printing time are the various goals of choosing the infill pattern. Infill patterns in Figure 2 are chosen because they provide the required structural integrity.

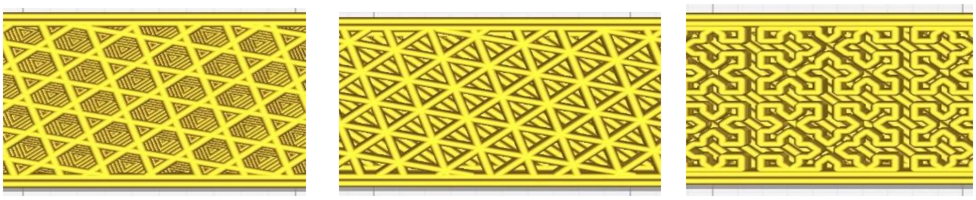


Figure 2: a) Cubic, b) Triangular, c) Cross.

3.1.5 Printing speed

It is the movement rate along X and Y axes by the printhead as it deposits layers of material. In the test runs, printing speeds of 50, 75 and 100 mm/s are employed.

3.1.6 Printing temperature

Printing temperature is the extrusion temperature of the 3D printer. The temperature affects the consistency and quantity of extruded filament in printing. Three different temperatures are considered in this research as shown in Table 1.

Factor	Level 1	Level 2	Level 3
Wall thickness (mm)	0.8	1.0	—
Layer height (mm)	0.1	0.2	0.3
Infill density (%)	25	50	75
Infill pattern	Cubic	Triangular	Cross
Print speed (mm/s)	50	75	100
Printing temperature (℃)	200	210	220

Table 1: Experimental parameters and levels.

3.2 Experimental Design Using the Taguchi Method

The experiment searches for effects of control factors for the part characteristics. Ultimate tensile stress, tensile modulus, compressive stress, energy use, material consumption and printing time are response variables of the parameters effect. Ranges of process parameters are used in determining levels for each parameter to find the optimal parameter combination. Results for printing time, material consumption, energy used and compression and tensile attributes are shown in the following section.

A mixed-element OA is a matrix with $m + n$ columns and N rows, where initial m columns contain s items and subsequent n columns contain t elements. This matrix is denoted by $OA_N\ (S^m \times t^n)$. A typical mixed-element array is $OA_N\ (2^1 \times s^m)$, where s is a prime integer (like 3 or 5) or a power of a prime number and $N = 2s^2$. $OA_N\ (2^1 \times s^m)$ represents a $N/(2^1 \times s^m) = (1/s)^{m-2}$ factorial plan. Therefore, $OA_{18}(2^1 x 3^5)$ is a part of a complete ($2^1 x 3^5$) factorial design, that is $(1/3)^{5-2} = (1/3)^3$ [13].

There are two levels (1, 2) of the wall thickness and three levels (1, 2, 3) of other five factors, where levels 1, 2 and 3 represent low, medium and high levels of related factors. Therefore, L18 orthogonal array $OA_N\ (S^m \times t^n)$ is formed based on factors and levels. The orthogonal design is written as $OA_{18}\ (2^1 \times 3^5)$, where t=2, n=1, s=3 and m=5. Number of columns for matrix = $m + n$ = 5+1 =6. The number of rows for matrix $N = 2s^2$ =18.

Effects of processing factors on the response variables are assessed using the Taguchi L18 OA. For each combination of control factors and levels, experiments are conducted. Table 2 displays the L18 OA design with combinations of parameters used in the study.

Sample	Wall thickness (mm)	Layer height (mm)	Infill density (%)	Infill pattern	Print speed (mm/s)	Printin g temp (℃)
1	0.8	0.1	25	Cubic	50	200
2	0.8	0.1	50	Triangular	75	210
3	0.8	0.1	75	Cross	100	220
4	0.8	0.2	25	Cubic	75	210
5	0.8	0.2	50	Triangular	100	220
6	0.8	0.2	75	Cross	50	200
7	0.8	0.3	25	Triangular	50	220
8	0.8	0.3	50	Cross	75	200

9	0.8	0.3	75	Cubic	100	210
10	1	0.1	25	Cross	100	210
11	1	0.1	50	Cubic	50	220
12	1	0.1	75	Triangular	75	200
13	1	0.2	25	Triangular	100	200
14	1	0.2	50	Cross	50	210
15	1	0.2	75	Cubic	75	220
16	1	0.3	25	Cross	75	220
17	1	0.3	50	Cubic	100	200
18	1	0.3	75	Triangular	50	210

Table 2: L18 orthogonal array design.

The data are statistically analyzed based on the Taguchi S/N ratio response. The S/N ratio formula is shown in Table 3, where n represents the number of experiments performed, Y refers to the measured value and σ represents the standard deviation. The larger-better S/N ratio is employed for the ultimate tensile strength, tensile modulus, and compressive strength. The smaller-better S/N ratio is used for examining the printing time, energy use and material use.

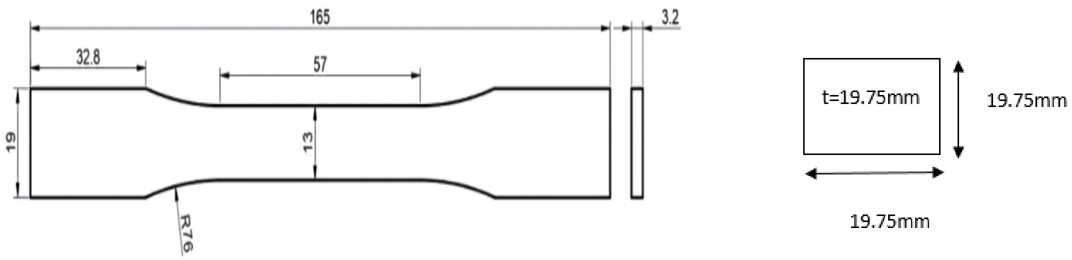
S/N ratio	**Experimental objective**	**Equation for S/N ratio**
The bigger, the better	Maximize the response	$S/N = -10 * \log(\Sigma (1/Y^2)/n)$
The smaller, the better.	Minimize the response	$S/N = -10 * \log(\Sigma (Y^2)/n)$
Closer to the nominal value, the better.	Nominal is the target	$S/N = -10 * \log(\sigma^2)$

Table 3: Signal to noise (S/N) ratio [10].

4 CASE STUDY

4.1 Specimens Design

Tensile and compression tests are mechanical experiments to evaluate product quality. By extrapolating between the stress/strain curves, the strength and modulus of the tested part can be decided. Two types of specimens for tensile and compression tests are designed based on the ASTM standard dimensions as shown in Figure 3.



(a) Tensile specimen (b) compression specimen

Figure 3: Specimens (in mm).

4.2 3D Printer Specifications

The specimens are produced using a Creality Ender 3 3D printer. Specifications of the 3D printer are shown in Table 4. Figure 4 depicts simulation of the printing procedure. The Creality software tool is used to set up printing parameters and collect data during the printing process. For each specimen, the part weight, scrap weight, consumption of energy and printing duration are collected. Printing parameters include Wall thickness, Layer height, Infill density, Infill pattern, Printing speed and Printing temperature.

Printer properties	Value
Build Volume	220 x 220 x 250 mm.
Layer Resolution Low	0.4 mm
Layer Resolution High	0.1 mm
Nozzle Diameter	0.4 mm
Filament Diameter	1.75 mm

Table 4: Creality 3D printer specifications.

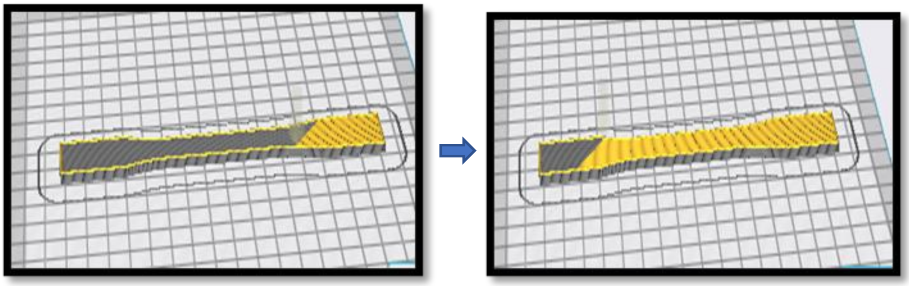


Figure 4: Tensile Specimen printing simulation.

4.3 Mechanical Testing of Specimens

For examining mechanical attributes of printed samples, tensile and compression tests are conducted. Testing procedures of the specimens are shown in Figure 5.

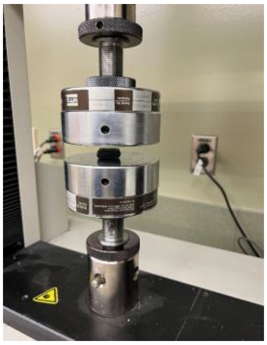
4.3.1 Tensile test

The specimen's two grips are used to secure it in the tensile testing equipment. The crosshead speed applied is 1 mm/min. Tensile stress is tested using stretching or tensile forces. It causes the material to elongate along the axis of the applied load as shown in Figure 5 (a). Megapascals (MPa) is the unit of measurement, and all stress values are determined using the specimen's original cross-sectional area. Figure 5 (b) is the fractured samples after tensile test elongation.

4.3.2 Compression test

A universal Instron testing machine is used for compression testing. The specimens are compressed by 9.88 mm along with 50% strain as shown in Figure 5 (c). During the test, a preload of 100 KN and a speed of 5 mm/min are applied. The compressive stress is computed based on the experimental results. Figure 5 (d) shows the compressed sample after conducting the compression test.

(a) Tensile testing (b) Tensile samples after the test

(c) Sample before compression, (d) Sample after compression

Figure 5: Testing the specimens.

4.4 Experimental Study

According to the orthogonal design, 18 specimens for tensile and compression tests are printed by FDM. A stopwatch is used to record the duration of printing the object. A digital laboratory scale is used to measure the part and scrap weights for the material use. A power quality analyzer is used to gauge the printing-related power consumption. The total energy used is then calculated (in kWh) by multiplying the power used by the duration to build the samples (in hours). The test data are collected in Table 5.

Specimen	Power consumption (KWH)	Scrap Weight (g)	Part Weight (g)	Printing time (min)	Compressive stress (Mpa)	Ultimate tensile strength (MPa)	Tensile modulus (MPa)
L1R	0.11	0.10	5.22	77	28.4	16.50	501.53
L2R	0.10	0.15	6.67	70	43.0	18.50	615.63
L3R	0.20	0.15	7.40	130	65.8	15.90	555.83
L4R	0.05	0.17	6.49	39	13.3	22.15	670.56
L5R	0.06	0.08	7.48	38	29.6	24.43	719.33
L6R	0.11	0.17	7.80	80	65.7	18.90	628.62
L7R	0.06	0.20	7.90	45	15.9	27.40	512.74
L8R	0.06	0.11	8.07	41	29.7	25.52	782.53
L9R	0.05	0.13	8.84	33	62.6	30.20	829.93
L10R	0.09	0.14	5.24	65	30.1	14.90	438.39
L11R	0.13	0.12	6.70	89	42.1	21.60	633.09
L12R	0.11	0.11	7.70	81	58.9	20.55	661.57
L13R	0.05	0.11	6.36	34	14.9	21.13	585.52
L14R	0.09	0.07	7.13	66	40.1	19.70	612.63
L15R	0.07	0.12	8.40	47	75.8	31.12	830.65
L16R	0.05	0.14	7.84	37	15.2	29.60	787.32
L17R	0.04	0.11	8.10	32	27.7	25.40	710.39
L18R	0.07	0.07	8.87	49	61.1	32.90	920.67

Table 5: Experimental data collected.

5 DATA ANALYSIS AND DISCUSSION

The collected experimental data are analyzed to find the significant difference in results by using Minitab-19 statistical software. Means and S/N ratio are used to determine the ideal combination of parameters. To find contributions of control factors and parameters to response variables, the

ANOVA analysis is used to evaluate experimental data and search conclusions based on the results.

5.1 Tensile Test Analysis

5.1.1 Ultimate tensile strength and tensile modulus

Main effects plots of the ultimate tensile strength (UTS) and tensile modulus for specimens are shown in Figures 6 (a) and (b) to determine the optimal set of parameters for the greatest tensile strength. The graph shows that if we increase the wall thickness, layer height, infill density and printing temperature, and reduce printing speed using a cubic infill pattern, the UTS can be improved.

The ideal parameter combination determined by the S/N ratio analysis is shown in Tables 6 and 7 for UTS and tensile modulus respectively. The findings demonstrate that the layer height has the biggest impact for both tensile strength and tensile modulus. It can be concluded that the combination of parameters with wall thickness (A) at 1 mm, layer height (B) of 0.3 mm, infill density (C) of 50%, infill pattern (D) of triangular, printing speed (E) at 75 mm/s and printing temperature (F) at 220, or A2B3C3D1E2F3, gives the maximum tensile strength.

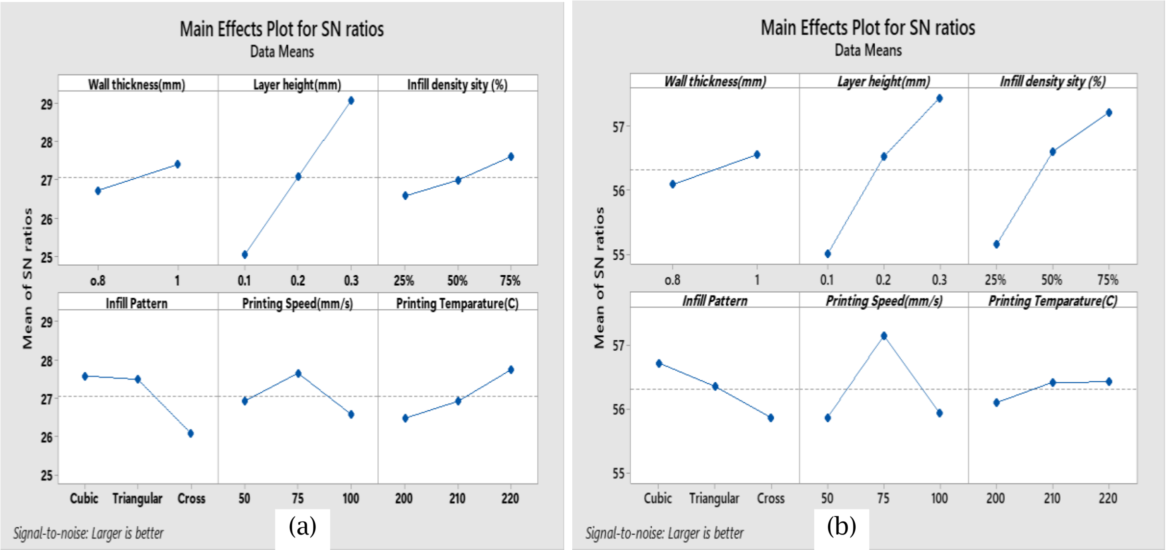


Figure 6: S/N ratio effect plots. (a) ultimate tensile strength (UTS), (b) tensile modulus.

Similarly, based on the S/N ratio in Figure 5(b), it can be concluded that the combination of A2B3C3D1E2F2, i.e., wall thickness (A) of 1 mm, layer height (B) at 0.3, infill density(C) of 75%, infill pattern (D) for cubic, printing speed (E) of 75mm/s and printing temperature (F) of 210℃, gives the optimal tensile modulus.

Level	**Wall thickness(mm) [A]**	**Layer height(mm) [B]**	**Infill density sity (%) [C]**	**Infill Pattern [D]**	**Printing Speed(mm/s) [E]**	**Printing Temperature (℃) [F]**
1	26.71	25.02	26.57	27.58	26.93	26.48
2	27.39	27.07	26.99	27.49	27.65	26.92
3		29.06	27.60	26.08	26.57	27.75
Delta	0.68	4.04	1.04	1.50	1.08	1.27

Rank	6	1	5	2	4	3

Table 6: S/N response table for the UTS.

Level	wall thickness(mm)	Layer height(mm)	Infill density(%)	Infill pattern	Print speed(mm/s)	Printing temperature (℃)
1	56.09	54.99	55.14	56.73	55.87	56.11
2	56.56	56.52	56.60	56.36	57.15	56.44
3		57.45	57.22	55.87	55.94	56.43
Delta	0.47	2.45	2.08	0.85	1.28	0.32
Rank	5	1	2	4	3	6

Table 7: S/N responses for the tensile modulus.

5.2 Printing Time

According to the main effects plot for printing time in Figure 7 (a). The specimen shows the least printing time when using the 25% infill density, 100 mm/s printing speed, maximum layer height and cubic filling pattern. Based on Table 8, when the layer height increases, fewer layers are required to construct the item, the number of layers is reduced to reduce the processing time. The combination of A2B3C1D1E3F2 gives in the least printing time.

5.3 Energy Consumption

The energy used shows a similar pattern as the printing time in Figure 7 (b). The layer height and printing speed have significant effects on energy usage. The best combination of parameters is shown in Table 9. is A2B3C1D1E3F1. Energy consumption is reduced along with the reduction of processing time.

Level	Wall thickness(mm)	Layer height(mm)	Infill density(%)	Infill Pattern	Printing Speed(mm/s)	Printing temperature (℃)
1	-34.90	-38.39	-33.48	-33.74	-36.34	-34.49
2	-34.35	-33.66	-34.37	-34.03	-33.99	-34.26
3		-31.83	-36.02	-36.10	-33.54	-35.12
Delta	0.55	6.56	2.54	2.36	2.80	0.86
Rank	6	1	3	4	2	5

Table 8: S/N response for printing time.

5.4 Material Consumption

The material consumption includes the part weight and scrap weight. The weight of the part indicates the material used to create the part itself, whereas the weight of the scrap represents the support material used during printing. Effect plots for the part weight and scrap weight are displayed in Figures 8 (a) and (b), respectively. The least layer height value, triangular pattern, and least infill density can reduce the material use. In comparison to other factors, the wall thickness has the least impact on the part weight. Table 10 shows the S/N response for the part weight. The best parameter combination is A1B1C1D3E3F2.

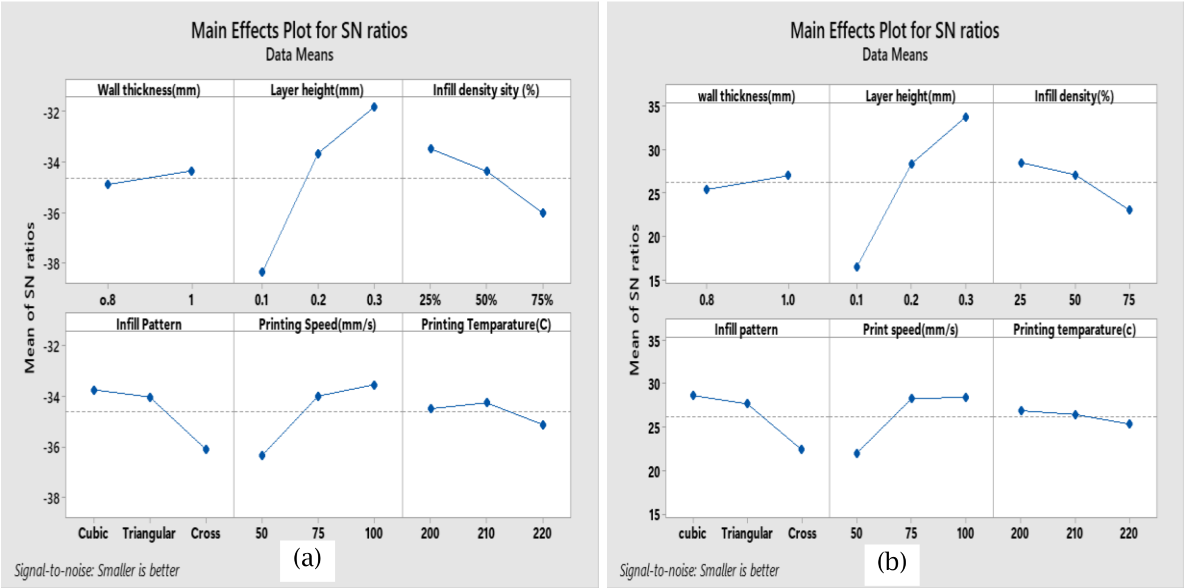


Figure 7: S/N ratio effect plots. (a) printing time, (b) Energy consumption.

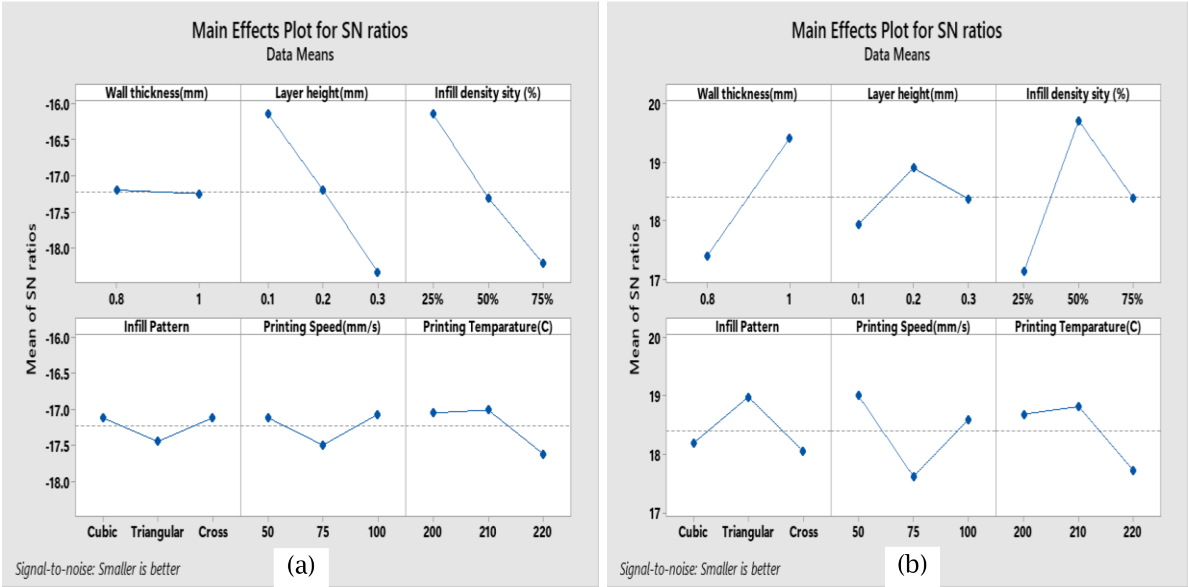


Figure 8: Main effect plot for S/N ratio. (a) Part weight, (b) scrap weight.

5.5 Compression Test Analysis

Based on data in Table 11. the infill density has the biggest impact on the compressive stress. Layer height and printing speed also impact the compressive stress. Figure 10 shows the compressive stress vs strain curve for samples from the compression test. The samples are labelled in the graph such as Sample 1 represents L1, Sample 2 for L2. The highest peak compressive stress is achieved by sample 15 with 75.8 MPa. Sample 4 has the lowest peak compressive stress 13.3 MPa among all samples. It is evident that each run produces distinct results based on the settings for the parameter combinations used in the factorial design. At a high level of the wall thickness, a better compressive stress is produced by the 75% infill density for the samples. The values in the compression tests support this situation. The best combinations of the suggested parameters are identified by the DOE approach. Outcomes of this investigation show that the impact of layer height varies for each output. 1 mm in wall thickness, cubic and cross structures often produce the best results when the infill density is 75%. The infill density varies depending on the infill pattern.

Effects graphs for the means and S/N ratio analyses are shown in Figure 9. The combination of A2B1C3D3E1F2, i.e., 0.8mm of wall thickness (A), 0.1mm layer height (B), infill density (C) of 75%, cross infill pattern (D), 50mm/s printing speed (E) and 210℃ printing temperature (F), achieves the ideal compression performance.

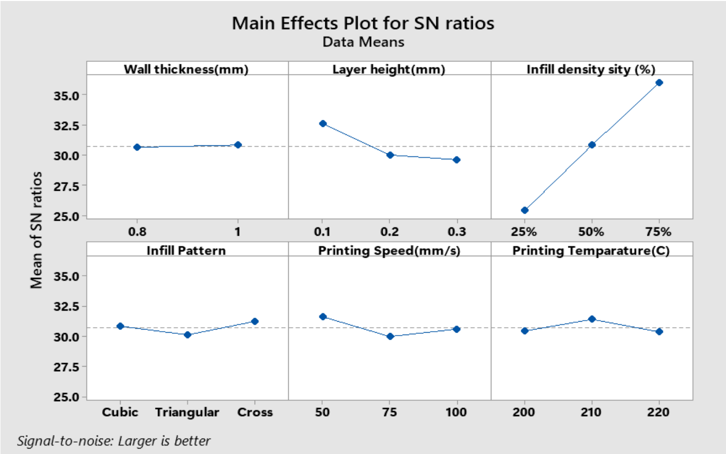
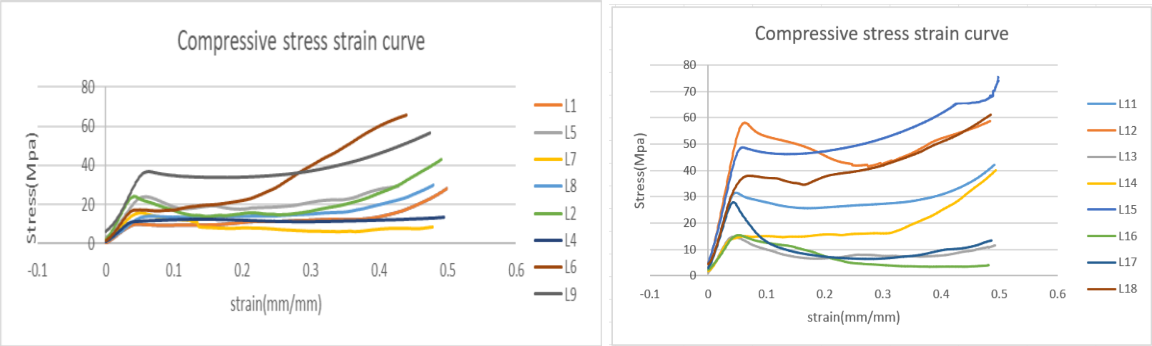


Figure 9: Effect plots S/N ratio for compressive stress.



(a) At low level wall thickness (b) At high level wall thickness

Figure 10: Stress - Strain graph for compression testing samples.

Level	wall thickness(mm)	Layer height(mm)	Infill density(%)	Infill pattern	Print speed(mm/s)	Printing temperature(c)
1	25.39	16.41	28.51	28.59	21.96	26.85
2	26.99	28.35	27.09	27.63	28.21	26.42
3		33.81	22.98	22.36	28.40	25.30
Delta	1.60	17.40	5.53	6.23	6.44	1.55

Rank	5	1	4	3	2	6

Table 9: S/N response for energy consumption.

Level	Wall thickness(mm)	Layer height(mm)	Infill density (%)	Infill pattern	Printing speed(mm/s)	Printing temperature (C)
1	-17.20	-16.14	-16.15	-17.12	-17.11	-17.05
2	-17.25	-17.20	-17.31	-17.45	-17.49	-17.01
3		-18.34	-18.22	-17.11	-17.07	-17.62
Delta	0.05	2.20	2.07	0.33	0.42	0.61
Rank	6	1	2	5	4	3

Table 10: S/N response for the part weight.

Level	Wall thickness(mm)	Layer height(mm)	Infill density (%)	Infill pattern	Printing speed(mm/s)	Printing temperature (C)
1	30.64	32.59	25.37	30.84	31.62	30.43
2	30.82	30.00	30.82	30.12	29.98	31.41
3		29.60	36.00	31.24	30.60	30.36
Delta	0.18	2.99	10.63	1.12	1.64	1.04
Rank	6	2	1	4	3	5

Table 11: S/N response for compressive stress.

5.6 ANOVA Statistical Analysis

ANOVA is used to further determine effects of control factors on the process response. An F-test and the analysis of variance are used to determine the impact of each component. These analyses use a 95% confidence level. The proportion of contributions in ANOVA is employed for the effect analysis because the Taguchi approach could not determine the impact of individual parameter on the total process. The proportion of factor contributions to the total shows the effect at reducing variation. A modest change will have a significant impact on performance when a factor makes up a high percentage of the contribution [32]. The percentage of contribution (f_i) is a function of the sum of squares for each item as follows [2].

$$f_i=(SS'_{fi} \,/\, \text{Seq } SS_{TOTAL}) \tag{5.1}$$

where f_i is the *ith* factor, SS'_{fi} is the pure sum of squares for fi, and Seq SS_{TOTAL} is the mean of the sequential sum of squares overall. After analyzing the F Value and percentage of contributions of printing parameters, the layer height shows the biggest impact on the mechanical strength (both for UTS and tensile modulus), where the infill density and layer height have the most impact on the compressive stress. The wall thickness has the least impact on all the response variables. The analysis of variance along with the contribution percentages has been conducted to find each parameter contributions on the variables shown in Tables 12 to 17.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution
Wall thickness(mm)	1	2.079	2.079	2.0794	6.08	0.049	2.82%
Layer height(mm)	2	48.925	48.925	24.4625	71.54	0.000	66.54%
Infill density (%)	2	3.264	3.264	1.6319	4.77	0.057	4.44%
Infill Pattern	2	8.540	8.540	4.2700	12.49	0.007	11.61%
Print speed(mm/s)	2	3.648	3.648	1.8238	5.33	0.047	4.96%

Printing temperature(c)	2	5.020	5.020	2.5102	7.34	0.024	6.83%
Residual Error	6	2.052	2.052	0.3419			2.79%
Total	17	73.528					100%

S=0.5847, R-Sq=97.21%, R-Sq(adj)=92.09%

Table 12: ANOVA and contribution analysis for S/N ratio for UTS vs control parameters.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution
wall thickness(mm)	1	0.9899	0.9899	0.9899	0.81	0.403	2.009%
Layer height(mm)	2	18.4006	18.4006	9.2003	7.51	0.023	37.35%
Infill density(%)	2	13.6919	13.6919	6.8459	5.59	0.043	27.78%
Infill pattern	2	2.2013	2.2013	1.1007	0.90	0.456	4.47%
Print speed(mm/s)	2	6.2251	6.2251	3.1125	2.54	0.159	12.63%
Printing temperature(c)	2	0.4145	0.4145	0.2073	0.17	0.848	0.84%
Residual Error	6	7.3467	7.3467	1.2244			14.91
Total	17	49.2700					100%

S=1.1065, R-Sq=85.09%, R-Sq(adj)=57.75%

Table 13: ANOVA and contribution analysis of S/N ratio for tensile modulus vs control parameters.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution
wall thickness(mm)	1	0.005000	0.005000	0.005000	1.06	0.343	3.04%
Layer height(mm)	2	0.078633	0.078633	0.039317	8.35	0.018	47.26%
Infill density (%)	2	0.018100	0.018100	0.009050	1.92	0.227	10.88%
Infill pattern	2	0.019733	0.019733	0.009867	2.09	0.204	11.86%
Print speed(mm/s)	2	0.007233	0.007233	0.003617	0.77	0.505	4.34%
Printing temperature(c)	2	0.009433	0.009433	0.004717	1.00	0.422	5.67%
Residual Error	6	0.028267	0.028267	0.004711			16.99%
Total	17	0.166400					100%

S=0.686, R-Sq=83.01%, R-Sq(adj)= 51.87%

Table 14: ANOVA and analysis of N/S ratio for Energy Consumption vs control parameters.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution
Wall thickness(mm)	1	1.351	1.351	1.351	1.22	0.311	0.63%
Layer height(mm)	2	137.550	137.550	68.775	62.27	0.000	64.002%
Infill density (%)	2	19.972	19.972	9.986	9.04	0.015	9.29%
Infill Pattern	2	19.898	19.898	9.949	9.01	0.016	9.25%
Printing Speed(mm/s)	2	27.116	27.116	13.558	12.28	0.008	12.61%
Printing temperature(C)	2	2.399	2.399	1.199	1.09	0.396	1.11%
Residual Error	6	6.627	6.627	1.104			3.08%
Total	17	214.912					100%

S=1.0509, R-Sq=96.92%, R-Sq(adj)= 91.26%

Table 15: ANOVA and contribution analysis for S/N ratio for printing time vs control parameters.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution
Wall thickness(mm)	1	0.0120	0.0120	0.01199	0.11	0.756	0.39%
Layer height(mm)	2	14.4730	14.4730	7.23648	63.74	0.000	47.31%
Infill density (%)	2	12.9497	12.9497	6.47486	57.03	0.000	42.33%

Infill Pattern	2	0.4308	0.4308	0.21541	1.90	0.230	1.408%
Printing Speed(mm/s)	2	0.6532	0.6532	0.32662	2.88	0.133	2.135%
Printing temperature(C)	2	1.3863	1.3863	0.69315	6.11	0.036	4.53%
Residual Error	6	0.6812	0.6812	0.11353			2.22%
Total	17	30.5862					100%

S=0.3369, R-Sq=97.77%, R-Sq(adj)=93.69%

Table 16: ANOVA and contribution analysis for S/N ratio for part weight vs control parameters.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution
Wall thickness(mm)	1	0.152	0.152	0.152	0.06	0.821	0.038%
Layer height(mm)	2	31.622	31.622	15.811	5.81	0.040	7.84%
Infill density (%)	2	338.840	338.840	169.420	62.24	0.000	84.05%
Infill Pattern	2	3.880	3.880	1.940	0.71	0.528	0.96%
Printing Speed(mm/s)	2	8.230	8.230	4.115	1.51	0.294	2.04%
Printing temperature (℃)	2	4.085	4.085	2.042	0.75	0.512	1.013%
Residual Error	6	16.331	16.331	2.722			4.05%
Total	17	403.140					100%

S=1.6498, R-Sq=95.95%, R-Sq(adj)=88.52%

Table 17: ANOVA & contribution analysis of S/N ratio for compressive stress vs control parameter.

5.7 The Method Evaluation

The proposed method is evaluated by comparing the DOE method and lab testing solution for the prediction accuracy of the mechanical and sustainable characteristics of sample parts as shown in Table 18. The most disparity between the experimental and Taguchi method solutions is 9.24%. Therefore, it is concluded that the Taguchi approach can accurately predict the mechanical and other characteristics for 3D printed parts.

Response variables	Experimental result	Predicted result	Difference (%)
Ultimate tensile strength	32.90 Mpa	35.94 Mpa	9.24
Tensile modulus	920.67 Mpa	996.07 Mpa	8.12
Compressive strength	75.8 Mpa	82.36 Mpa	8.64
Part weight	5.22 g	5.28 g	1.16
Energy consumption	0.02 KWH	0.0211KWH	5.5

Table 18: Comparison of the experiment and Taguchi method results.

6 CONCLUSIONS

The Taguchi DOE approach is used in this research to determine the optimal FDM process parameters and simultaneously examine the impact of various process variables on 3D printed parts. FDM technology is used to build 18 samples by different parameter combinations of the wall thickness, layer height, infill density, infill pattern, printing speed and printing temperature in the 3D printing process. The greater-better criterion is used to examine S/N ratio of mechanical qualities of tested samples. For analyzing the printing time, energy utilization and material quantity, a lower S/N ratio is utilized. Based on the Taguchi S/N ratio analysis, the ideal condition for the best performance of the printed parts is identified. Although the modulus of elasticity shows slight variations from the tensile strength in the parameter optimization, it discovers that the layer height is the most important parameter among all the selected six parameters on the response variables except the compressive stress. The infill density has the highest impact on the compressive stress. The layer height is the second most impact parameter. By using the Taguchi S/N ratio analysis, the best parameter level combination of parameter optimization is found for all the responses. The ANOVA and contribution analysis are used to identify percentages of parameter contributions on the responses. The Taguchi design approach and experimental results match well for the solutions.

The limitation of this research is the use of simple and small numbers of specimens. The carbon emission analysis is excluded. The method solution depends on the process of the simulation and experiment used to determine the impact of the process parameters. Different material samples, and AM processes should be considered to generate more general solutions. There are also different printing parameters to affect the result, such as the nozzle diameter, nozzle temperature, print bed temperature, and raster angle. These parameters will be considered in our further research.

ACKNOWLEDGEMENT
The authors would like to acknowledge that this research is supported by the MITACS Lab2market program.

REFERENCES

[1] Abeykoon, C.; Sri-Amphorn, P.; & Fernando, A.: Optimization of fused deposition modeling parameters for improved PLA and ABS 3D printed structures. International Journal of Lightweight Materials and Manufacture, 3(3), 2020, 284-297. https://doi.org/10.1016/j.ijlmm.2020.03.003
[2] Alhubail, M.: Statistical-based optimization of process parameters of fused deposition modelling for improved quality, Doctoral dissertation, University of Portsmouth. 2012.
[3] Camposeco-Negrete, C.: Optimization of printing parameters in fused deposition modeling for improving part quality and process sustainability, The International Journal of Advanced Manufacturing Technology, 108, 2020, 2131-2147. https://doi.org/10.1007/s00170-020-05555-9
[4] Camposeco-Negrete, C.: Optimization of printing parameters in fused deposition modeling for improving part quality and process sustainability. The International Journal of Advanced Manufacturing Technology, 108, 2020, 2131-2147. https://doi.org/10.1007/s00170-020-05555-9
[5] Davis, R.; & John, P.: Application of Taguchi-based design of experiments for industrial chemical processes. Statistical approaches with emphasis on design of experiments applied to chemical processes, 137, 2018. https://doi.org/10.5772/intechopen.69501
[6] Design of Experiments via Taguchi Methods: https://eng.libretexts.org/Bookshelves/Industrial_and_Systems_Engineering/Chemical_Process_Dynamics_and_Controls_(Woolf)/14%3A_Design_of_Experiments/14.01%3A_Design_of_Experiments_via_Taguchi_Methods_-_Orthogonal_Arrays
[7] Fernandes, J.; Deus, A. M.; Reis, L.; Vaz, M. F.; & Leite, M.: Study of the influence of 3D printing parameters on the mechanical properties of PLA, Proceedings of the 3rd International Conference on Progress in Additive Manufacturing, 2018, 14-17.
[8] Gopalsamy, B. M.; Mondal, B.; & Ghosh, S.: Taguchi method and ANOVA: An approach for process parameters optimization of hard machining while machining hardened steel, Journal of Scientific & Industrial Research, 88, 2009, 686-695,
[9] Heidari-Rarani, M.; Ezati, N.; Sadeghi, P.; Badrossamay, M. R.: Optimization of FDM process parameters for tensile properties of polylactic acid specimens using Taguchi design of experiment method, Journal of Thermoplastic Composite Materials, 35(12), 2022, 2435-2452. https://doi.org/10.1177/0892705720964560
[10] Huynh, H. N.; Nguyen, A. T.; Ha, N. L.; & Thai, T. T. H.: Application of fuzzy Taguchi method to improve the dimensional accuracy of Fused Deposition Modeling processed product.

International Conference on System Science and Engineering (ICSSE), 2017, July, 107-112. https://doi.org/10.1109/ICSSE.2017. 8030847
[11] Hinkelmann, K.; & Kempthorne, O.: Design and analysis of experiments; Introduction to experimental design (Vol. 1). John Wiley & Sons. 2007.
[12] Introduction to Taguchi method,https://www.ee.iitb.ac.in/~apte/CV_PRA_TAGUCHI_INTRO.htm
[13] Kacker, R. N.; Lagergren, E. S.; Filliben, J. J.: Taguchi's orthogonal arrays are classical designs of experiments, Journal of research of the National Institute of Standards and Technology, 96(5), 1991, 577. https://doi.org/10.6028/jres.096.034
[14] Kellens, K.; Mertens, R.; Paraskevas, D.; Dewulf, W.; Duflou, J. R.: Environmental impact of additive manufacturing processes: does AM contribute to a more sustainable way of part manufacturing? Procedia CIRP, 61, 2017, 582-587. https://doi.org/10.1016/j.procir.2016.11.153
[15] Karch, J.: Improving on Adjusted R-squared, Collabra: Psychology, 6(1), 2020, 45. https://doi.org/10.1525/collabra.343
[16] Minitab 18 Support.: https://support.minitab.com/en-us/minitab/18/help-andhow-to/modeling-statistics/doe/supporting-topics/taguchi-designs/what-is-thesignal-to-noise-ratio/
[17] Montgomery, D. C.: Design and analysis of experiments. John wiley & sons. 2017.
[18] Nguyen, V. H.; Huynh, T. N.; Nguyen, T. P.; & Tran, T. T.: Single and multi-objective optimization of processing parameters for fused deposition modeling in 3D printing technology. International journal of automotive and mechanical engineering, 17(1), 2020, 7542-7551. https://doi.org/10.15282/ijame.17.1.2020.03.0558
[19] Popescu, D.; Zapciu, A.; Amza, C.; Baciu, F.; & Marinescu, R.: FDM process parameters influence over the mechanical properties of polymer specimens: A review, Polymer Testing, 69, 2018, 157-166. https://doi.org/10.1016/j.polymertesting.2018.05.020
[20] Qattawi, A.; Alrawi, B.; & Guzman, A.: Experimental optimization of fused deposition modelling processing parameters: a design-for-manufacturing approach. Procedia Manufacturing, 10, 2017, 791-803. https://doi.org/10.1016/j.promfg.2017.07.079
[21] Radhwan, H.; Shayfull, Z.; Nasir, S. M.; Irfan, A. R.: Optimization parameter effects on the quality surface finish of 3D-printing process using Taguchi method, IOP Conf. Series: Materials Science and Engineering, 864(1), 2020, 012143. https://doi.org/10.1063/1.5118163
[22] Radhwan, H.; Shayfull, Z.; Nasir, S. M.; & Irfan, A. R.: Optimization parameter effects on the quality surface finish of 3D-printing process using Taguchi method. In IOP Conference Series: Materials Science and Engineering, 864(1), 2020. https://doi.org/10.1088/1757-899X/864/1/012143
[23] Roy, R. K.: A primer on the Taguchi method. Society of Manufacturing Engineers. 2010.
[24] Shabani, B.; Dukovski, V.: Integration of Reverse Engineering and Topology Optimization with Additive Manufacturing, Computer-Aided Design & Applications, 19(1), 2022, 164-175. https://doi.org/10.14733/cadaps.2022.164-175
[25] Sheoran, A. J.; & Kumar, H.: Fused Deposition modeling process parameters optimization and effect on mechanical properties and part quality: Review and reflection on present research. Materials Today: Proceedings, 21, 2020, 1659-1672. https://doi.org/10.1016/j.matpr.2019.11.296
[26] Salehi, M.; Saadatmand, M.; & Mohandesi, J. A.: Optimization of process parameters for producing AA6061/SiC nanocomposites by friction stir processing. Transactions of Nonferrous Metals Society of China, 22(5), 2012, 1055-1063. https://doi.org/10.1016/S1003-6326(11)61283-1
[27] Valerga, A. P.; Batista, M., Salguero, J.; & Girot, F.: Influence of PLA filament conditions on characteristics of FDM parts. Materials, 11(8), 2018, 1322. https://doi.org/10.3390/ma11081322

[28] Wang, C.; Lin, T. W.; & Hu, S. S.: Optimizing the rapid prototyping process by integrating the Taguchi method with the Gray relational analysis. Rapid prototyping journal, 13(5), 2007, 304-315. https://doi.org/10.1108/13552540710824814
[29] Wang, X.; Zhao, L.; Fuh, J. Y. H.; & Lee, H. P.: Effect of porosity on mechanical properties of 3D printed polymers: Experiments and micromechanical modeling based on X-ray computed tomography analysis. Polymers, 11(7), 2019, 1154. https://doi.org/10.3390/polym11071154
[30] Wang, Y.; Liu, Y.; & Sun, Y.: A hybrid intelligence technique based on the Taguchi method for multi-objective process parameter optimization of the 3D additive screen printing of athletic shoes. Textile research journal, 90(9-10), 2020, 1067-1083. https://doi.org/10.1177/0040517519886073
[31] Wang, T.; Wang, L.; Ma, Z.; & Hulbert, G. M.: Elastic analysis of auxetic cellular structure consisting of re-entrant hexagonal cells using a strain-based expansion homogenization method. Materials & Design, 160, 2018, 284-293. https://doi.org/10.1016/j.matdes.2018.09.013
[32] Yang, C. J.: Accelerated quality improvement of 3D printed objects based on a case-based reasoning system, The International Journal of Advanced Manufacturing Technology, 119 (7), 2022, 4599-4612. https://doi.org/10.1007/s00170-022-08672-9
[33] Yao, T.; Ye, J.; Deng, Z.; Zhang, K., Ma, Y.; & Ouyang, H.: Tensile failure strength and separation angle of FDM 3D printing PLA material: Experimental and theoretical analyses. Composites Part B: Engineering, 188, 2020, 107894. https://doi.org/10.1016/j.compositesb.2020.107894
[34] Zaman, U. K. U.; Boesch, E.; Siadat, A.; Rivette, M.; & Baqai, A. A.: Impact of fused deposition modeling (FDM) process parameters on strength of built parts using Taguchi's design of experiments, The international journal of Advanced Manufacturing technology, 101, 2019, 1215-1226. https://doi.org/10.1007/s00170-018-3014-6