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Wear assessment of 3–D printed parts of PLA (polylactic acid) using Taguchi design and Artificial Neural Network (ANN) technique

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Abstract

Additive manufacturing (AM) is a rapidly growing technology with promising results and challenges. The aim of this study is to optimize the process parameters of fused deposition modeling (FDM) by exploring the wear performance of Polylactic acid (PLA). In this work, variation of process parameters like layer thickness, orientation and extruder temperature has been investigated. Based on these parameters wear specimen (accordance to ASTM G99) was printed by using FDM. The wear behavior of polymer pin under low sliding speed was investigated. Taguchi Design of experiments by using L9 orthogonal array is applied to optimize the process parameters at which minimum wear rate is obtained and the same has also been investigated by using analysis of variance (ANNOVA) and artificial neural network (ANN) technique for rigorous validation/optimization. Results show that build orientation have major influence on the wear performance of polymer pin. The paper is presented with the display of results, discussion, and conclusions drawn.

1. Introduction

Conventional manufacturing methodologies are enveloped with an idea of removing material from a preformed raw shape or raw material and generate a desired shape. Though, it is widely accepted and used idea to manufacture any product, it has some serious challenges when it comes to manufacturing of the complex geometric shapes. Additive Manufacturing (AM), on the other hand works on the opposite idea i.e.; adding material in a predefined manner to generate a final shape layer by layer. The technology is also popular among its users as 3D printing, Direct digital manufacturing, Solid ground curing, and Layer manufacturing [1]. The early concept of 3D printing evolved around 1980s using photo resin polymers that turned into solid state interaction with UV light [2]. With successive interaction with the UV light a layer of the workpiece is deposited over another, thus coining the term ‘Additive’ into the manufacturing scenario [3]. Nearly after four decades of its inception, the additive technology is one of the most emerging manufacturing technologies in the current time frame as it presents a great amount of possibilities, with a lot of areas for further development and challenges [4]. Currently, AM technology is developed for a wide variety of material ranging from low grade polymers to precious metals, composite alloys and ceramics [5]. According AM F-42 technologies are classified into seven categories, these are extrusion based (fused deposition modeling), powder bed fusion, binder jetting, multi material jetting, direct energy deposition based, photo polymerization based and laminated object manufacturing [6]. Among all AM processes, the Fused deposition modeling (FDM) is most widely used process because of its simple setup and cost effective. It uses polymers as its raw material into the form of wire/filament. FDM uses the polymers such as Acrylonitrile Butadiene Styrene (ABS), Poly Lactic Acid (PLA) and Nylon [7]. Figure 1 shows the processing steps of making a prototype starts from Computer Aided Design (CAD) software like CATIA, Solid Works, and Fusion 360 so on. The CAD data is then converted into Standard Tessellation
Language (.STL) file format and this file format represent the surface geometry of the CAD model with a mesh of triangles composed vertices edges and faces transferred to the 3D printer to start the printing process.

The conversion of CAD model into STL file format and then its slicing is a preprocessing step. This preprocessing step involve several important steps such as selection of process parameters, build volume, orientation and display the amount of material required and fabrication time for printing. For each sliced layer, the preprocessing software generates tool path or creates instructions for extruder head which is develop for each layer. Model is sent to the FDM machine for printing. Material is in the form of wire/filament is drawn from a spool into liqueﬁer head by driving wheels, in which material heated into a melting state and then extruded from the nozzle tip into the build platform. Support material is required to avoid the hanging or warping of the part from build surface. If it is needed, it can be drawn from another spool into the liqueﬁer head to deposit the support material till the final fabrication (figure 2). Currently, FDM process finds application in prototyping [8], biomedical field [9, 10], bone implant [11], aerospace industry [12], as well as recommended for future manufacturing to develop a conceptual models and products.

There are plenty of literatures has been done on the different optimization techniques to find a suitable best combination of parameters, such as Taguchi design methodology, response surface methodology, factorial design, central composite design, etc, but Taguchi’s approach has been found the most effective approach for selection of process parameters. Since the development of high-quality parts at lower cost and timely to fulfill the market demand is the need of the current scenario [13]. The materials used to make a 3D prints in the FDM environment, has considerably low mechanical strength which limits its usage to desktop printers. Moreover, the purpose of this study is to evaluate the effect of FDM parameters on the performance of constructed parts by using Taguchi design of experiments and further its evaluation is done by artificial neural network (ANN) method. A limited study has been done the PLA polymer. The main objective of this study is to understand the tribological phenomena of PLA. It might be beneﬁcial to analyze the behavior of PLA material sample for implant application. It is biodegradable in nature and degradation of this material is less harmful compared with other materials. In section 2 there is review on the available literature about the optimization of FDM process parameters. Section 3 displays the methodology along with experimental setup and discusses about the procedure for selection of parameters. Section 4 displays the results and discusses about the optimal parameters settings. Section 5 discusses about the ANN method for predicting the optimum value of parameters, and comparison is also done between the experimental results and ANN predicted results, then ﬁnally conclusion of the study is done.
2. Literature review

There have been done Literature reviews on various aspect of additive manufacturing especially in the field of FDM process. The study carried out over the fabrication part to investigate the effect of various processing parameters of FDM process. Mathematical studies have also been undertaken to arrive at strength contributed by filaments in FDM process. Mohamed et al [14] examined the behavior of 3D printer processing parameters on the tribological characteristics and surface properties. Definitive screening design (DSD) was adapt to study the FDM parameters namely air gap, raster angle, build orientation, road width, layer thickness and number of contours. It was concluded that number of contours, raster angle, build orientation and layer thickness are the most affecting parameters on wear performance. Byun et al [15] studied the optimal part orientation that improves the surface roughness, it is the most critical factor in rapid prototyping process, because it affects the build time, product quality and product cost. The main objective of this study to determine the optimum part orientation, when part is build with different layer resolution for different rapid prototyping (RP) systems. They used the genetic algorithm with considering fuzzy weight for surface roughness and build time. The algorithm can help to predict best build up direction of part and create well planned process planning for RP users. Ertan et al [16] discussed the bio-carbon reinforced poly lactic acid filaments are available for 3D printing and they are successfully integrated into PLA. They investigated that friction is more constant for 30% reinforced PLA in comparison to virgin PLA. Gurrula et al [17] explained the effect of FDM process parameters on tribological properties such as wear rate and frictional force. They considered two Pin-on-Disc (POD) parameters like load, sliding speed and varying orientation. In this work, Analysis of Variance (ANOVA) is applied on the test results. They found orientation has a significant effect on tribological properties as compared with other two parameters. Hussein et al [18] performed Pin-on-disc (POD) wear testing of biomaterials which is used for total hip replacement. They found that every year millions of people are implanted with total hip replacement (THR) to restore function and reduce the pain. They conducted the POD test on ultra high molecular weight polyethylene bio polymer which is used for THR process. Sood et al [19] studied the process parameters of FDM process on the compressive stress test specimen. The optimal parameter setting is obtained by Quantum-behaved particle swarm optimization (QPSO) and compressive stress is predicted using artificial neural network (ANN) compared with QPSO predicted equation. Darbar et al [20] studied three process parameters of FDM method such as layer thickness, raster width and parts build orientation. The ANN technique is used to predict compressive and impact strength of test. They figured out that experimental data and ANN is closely correlated which validated the models. Camposeco-Negrete [21] conducted an experimental study to understand effect of processing variables (processing time, the energy consumption of the 3D printer, and dimensional accuracy) manufactured through the FDM machine. Taguchi design is applied on the five parameters (layer thickness, filling pattern, printing plane, orientation and state of part on the build platform) to optimize the variables, the
result concludes that printing plane is most effective parameter for reducing the energy consumption and processing time. Uz Zaman et al [22] studied the effect of FDM process variables on the strength of printed parts by performing Taguchi methodology. The parameters are chosen for these studies are shells, layer thickness, infill pattern and infill percentage on an industrial case study from the aerospace industry. FDM process involves complex phenomenon for parts building, so it is difficult to anticipate the output responses accurately by traditional methods. Out of all non traditional method Artificial neural network (ANN) and Genetic Algorithm have gained popularity in most of engineering application and in specific manufacturing process. At present FDM has limited scope towards the industries because the compatibility issue between the machine and material [23], apart from this the most studies focused by researchers on ABS material. However, less study is done on other materials such as PLA, Nylon and polyether ether ketone (PEEK), and these materials printed parts have poor mechanical properties, dimensional accuracy, surface finishing etc. Research is going on the improvement of the processing parameters of FDM process with the help of creating new design of material, understating the effect of process parameters, enhancing the printer hardware setup. The appropriate selection of parameters plays an important role to get manufactured part accurately in first attempt. It requires a deep, clear understanding of the parameters. The process parameters which can be optimized and considered in an FDM process are inclusively sketched in figure 3.

### 3. Methodology

**3.1. Material, machine, sample**

The material used for this study is PLA (purchased by 3D systems incorporation). The specimens are fabricated through the FDM process using the raw material in the form of filaments with a diameter of 1.75 mm. The main properties of PLA material specification are shown in table 1.

Different parameters combination set is available in FDM process such as layer thickness, orientation, raster angle, air gap, infill pattern, infill density, bed temperature, extruder temperature and so on. To obtain a profound set of results Taguchi's Design philosophy was used to create statistical set of experiments. Different orientations would generate different contact areas among the layers and also show variations in void density in particular section. The orientations are varied in such a way that the raster angles are kept at the constant magnitude. To do so, the object is rotated along any of the one axis fixed on the build plate i.e.; x-axis or y-axis. Every 3D printer has their own slicing software like CURA, Meshmixer and Blender. For this analysis, Cube-pro duo slicing software is used which has the capability to make high resolution layers with thickness of 0.07 mm, 0.2 mm and 0.3 mm [25]. The bonding process, whether it is within the layer or in between the layers, it is due to thermal fusion. Bonding by thermal fusion is dependent on temperature and time allowed to freely develop a weld zone at the interfaces of filaments. For this study specimens are design according to ASTM G99 test.

**Table 1. Technical property of PLA [24, 25].**

| Parameters            | Specification | Units       |
|-----------------------|---------------|-------------|
| Tensile strength      | 60            | N mm$^{-2}$ |
| Elongation at break   | 7             | %           |
| Density               | 1.24          | g cm$^{-3}$ |
| Tensile modulus       | 3750          | N mm$^{-2}$ |
| Printing Temperature  | 180–230       | °C          |
| Diameter              | 1.75          | mm          |
| Diameter Tolerance    | ±0.05         | mm          |
Figure 5. CAD model of specimen.

Table 2. FDM parameter levels and values.

| Factor                        | Level 1 | Level 2 | Level 3 |
|-------------------------------|---------|---------|---------|
| Layer thickness (μm)          | 70      | 200     | 300     |
| Orientation (°)               | 45      | 60      | 90      |
| Extruder Temperature (°C)     | 220     | 225     | 230     |
| Top solid layers              | 20      |         |         |
| Bottom solid layers           | 20      |         |         |
| Perimeter shell               | 1       |         |         |
| Infill Pattern                | Cross   | Rectilinear |       |
| Nozzle diameters              | 0.4 mm  |         |         |
| Bed Temperature               | 60 °C   |         |         |

Figure 6. Samples after printing.

Figure 7. Pin-on-Disc (POD) machine set up.
standard suitable for wear test analysis of metals and polymer materials [26, 27]. The specimen is made of PLA material because it is biodegradable in nature. Depending upon the working environment it degrades within 6 to 12 months. The printing temperature range in Cube-pro duo is 180 °C to 230 °C range for PLA. It is dependent upon the grade of plastic which is being used in the 3D printing process [28, 29]. Table 2 shows the FDM process parameters with their levels. Autodesk Fusion 360 is used to create CAD model of specimen. The CAD geometry with dimension shown in figures 4 and 5 and fabricated samples are in figure 6.

3.2. Orthogonal array

Instead of performing all the possible combination, Taguchi design is an effective tool to select the special arrangements of combination called as orthogonal array (OA). Appropriate Taguchi OA is designed based on the control factors and selected settings [30]. The choice of a specific OA depends on the number of factors, the levels for each factor. Table 3 shows a L9 orthogonal array, which represents nine combinations of factors, varying statistically.

3.3. Experimental set up

Wear is a surface phenomenon in which deterioration of material takes place from one or both of two solid surfaces in solid state contact [31]. Wear depends upon the internal resistance of part against the external force; if the internal structure bonding is strong, it may resist wearing [32]. Figure 7 shows wear tester POD machine setup to measure the wear rate and frictional force. To study wear of PLA polymer plastic, the wear process performed in a controlled manner by keeping wear tester parameters (shown in table 4) constant for each specimen and analyzed the influence of combined parameters (layer thickness, orientation & extruder temperature) for different specimens. The parameters are chosen on the basis where the load and speed requirements are low generally for biomedical, implant and prototyping application [33]. Dry sliding wear test for different polymer specimens are being performed on POD wear tester machine [34]. The test is performed to two times for individual parameter settings. Total 18 samples are tested. Samples are weighed prior and after the wear test up to the accuracy level of 0.0001 g. The pin rubbed against the counter face of rotating disc which is generally made of steel, aluminum and brass etc. For this experimental work steel disc is selected against the thermoplastic PLA polymer pin. A constant force was applied on the pin which in turn exerted on the disc. The revolution of the disc kept low so that the sample does not heated up due to rubbing and the test performed under the room temperature. The results at the end of sliding wear test are extracted from the computer software.

The specific wear rate of the specimen is obtained by using the formula = \( \Delta m/F \times L \times \rho \), where \( W \) denotes specific wear rate in \( \text{mm}^3/\text{N} \cdot \text{m} \), \( \Delta m \) denotes mass of specimen considered in gs, \( L \) is the sliding length in meters, \( \rho \) is the density of polymer material in g mm\(^{-3}\), and \( F \) is applied force in Newton.

| Table 3. Orthogonal array L9. |
|-----------------------------|
| Layer thickness (μm) | Orientation (°) | Extruder temperature (°C) |
| 70 | 60 | 220 |
| 70 | 45 | 225 |
| 70 | 90 | 230 |
| 200 | 60 | 225 |
| 200 | 45 | 230 |
| 200 | 90 | 220 |
| 300 | 60 | 230 |
| 300 | 45 | 225 |
| 300 | 90 | 220 |

| Table 4. List of parameters of dry sliding wear test. |
|-------------|-----------------|-----------------|------------|
| Parameter | Load (counter weight kg) | Wear track diameter (mm) | Speed in rpm | Time (min) |
| 1. Disc specification | 5 | 60 | 100 | 45 |

Disc specification Diameter 165, 8 mm thick, ground to surface roughness 1.6 Ra, EN 8 steel, hardened to 64 HRC.
start

Data selection and pre-processing. 
Defining inputs and output parameters for the process

Input parameters: L9 orthogonal array 
Number of input variables = 3 
1. Layer thickness (LT) 
2. Orientation 
3. Temperature 

Output variable: simulated/predicted Wear rate 
Number of output variables = 1 
1. Wear rate

L0 Array of input parameters = Input Data
Experimental wear Rate = Target Data
Getting these input and target data for training and validation

Selecting ANN Architecture:
Feed-forward back propagation (FFNN)
Number of Neurons = 10

Training the Network
Training method: Gradient Descent with Momentum & Adaptive LR 
Performance Technique: Mean Squared Error

Iterating and modifying:
1. Learning / Training technique 
2. Performance technique 
3. Number of layers and neurons 
4. Number of iterations

Validating the network
Are results satisfactory?

End

Simulating results for all the 27 combinations and checking for error percentage

Figure 8. Proposed methodology for FDM parameters using ANN.

\[
W = \frac{\Delta m}{F^*L*\rho}
\]

\[F(\text{load}) = 5 \times 9.81 \, \text{N}, \, L(\text{sliding distance}) = (\pi \, D \, N/60) \times t = 0.84823 \, \text{mm}, \, \rho \text{ density of polymer material (PLA)} = 1240 \, \text{g mm}^{-3}.
\]
3.4. S/N calculation and ANOVA
Signal-to-Noise (S/N) ratio is used to decide the robustness of the design, where signal shows the controllable value, while noise represents the uncontrollable values. The data points are calculated by using ‘smaller is better’ approach because this study concerned with minimum wear rate. The objective function chosen for analysis is to reduce the wear rate so that S/N ratio categorized as
\[
\frac{S}{N} = -10\log_{10}\left(\frac{1}{n}\sum Y_i^2\right)
\]
Where \( n \) is the sample size, \( Y_i \) = wear rate of the material.

The analysis of variance (ANOVA) is a general linear model used to fit the regression curve and to obtain a relationship between input variables and output responses. ANOVA is being performed to analyze that results obtained from Taguchi design whether those are consistent or not. It uses the p value that can determine the significant parameters which influence the response as well as the percentage contribution of the error.

3.5. Artificial neural network
Ann is a family of models inspired by biological neural networks. Ann is presented as systems of interconnected neurons which exchange information between each other. The connections have weights that can be tuned in making neural network adjustable for input and capable of learning. In ANN optimization process the main objective is to find optimized values of weights of neural network so that the objective function errors can be minimized [36–38]. Figure 8 shows the flow diagram using ANN methodology.

4. Results and discussion
Experiments are conducted to configure that the wear rate of samples should be minimum. For each experiment the control factors setting (see table 4) of wear tester machine were kept the same. After testing the worn surface of samples are shown figure 9. The results for experiments are displayed (see table 5) along with the discussion. The experimental data are generated from Du-com software (POD) shown in table 5 and these data were

![Figure 9. Samples after testing.](image)

**Table 5. Experimental results of test.**

| Sr No. | Wear rate (μm) | Initial mass (g) | Final mass (g) | Mass loss (g) | Frictional force (N) | Specific wear rate (mm³/Nm) | Coefficient of friction |
|--------|----------------|-----------------|----------------|--------------|---------------------|-----------------------------|------------------------|
| 1      | 1373.49        | 1.6934          | 1.5814         | 0.1120       | 13.64               | 2.17*10⁻³                   | 0.278                  |
| 2      | 650.48         | 1.7336          | 1.6232         | 0.1104       | 20.75               | 2.14*10⁻³                   | 0.423                  |
| 3      | 812.43         | 1.7707          | 1.7499         | 0.0208       | 20.19               | 4.03*10⁻⁴                   | 0.411                  |
| 4      | 1155.80        | 1.7061          | 1.6905         | 0.0156       | 15.88               | 3.02*10⁻⁴                   | 0.323                  |
| 5      | 817.43         | 1.9027          | 1.8707         | 0.0320       | 18.12               | 6.20*10⁻⁴                   | 0.369                  |
| 6      | 992.87         | 1.7280          | 1.6890         | 0.0390       | 17.10               | 7.56*10⁻⁴                   | 0.348                  |
| 7      | 861.23         | 1.1771          | 1.1596         | 0.0175       | 14.95               | 3.39*10⁻⁴                   | 0.304                  |
| 8      | 561.68         | 1.3860          | 1.3729         | 0.0134       | 23.55               | 2.60*10⁻⁴                   | 0.480                  |
| 9      | 446.55         | 1.1530          | 1.1411         | 0.0121       | 19.41               | 2.35*10⁻⁴                   | 0.395                  |
analyzed using Minitab-18 software. ANOVA and S/N ratio analysis are conducted to recognize the optimum combination of process parameters. The response table for data mean and S/N ratio is shown in table 6. In this the result orientation rank is 1(delta = 4.40) followed by layer thickness (delta = 4.25) and extruder temperature (delta = 2.39). The rank is used to identify which factor has greatest influence over the responses. The reason for dominance of orientation over the other parameters might be variation in surface texture by varying the orientation into three dimensions[39–42]. In several literatures it is also found that orientation has major influence of 3D printed part. It indicates that, build orientation affect the mechanical properties of AM components but also depict the influence of wear resistance in dynamic system [43].
The effect of control factor ascertained by response graph in figures 10 and 11. In figure 10 main effects for S/N ratio predicts the optimal parameters, in which points of highest value are selected. A layer thickness parameter 0.3 mm level has highest average than 0.07 mm and 0.2 mm. Similarly orientation parameter 45° has higher value than 60° and 90°. Extruder temperature parameter 225°C levels have higher value than 220°C and 230°C.

Figure 11 shows the main effect plot for means. These plots differentiate the effect of parameters on wear rate which is verified by each parameter level. If the mean line is parallel to x axis then it means parameters have no influence on wear rate.

The S/N ratio graph clearly concludes the value of optimum process parameters which would result in minimum wear rate of samples. The S/N and means graph show that with the increase in layer thickness and decrease in build orientation minimizes the surface property. The Taguchi analysis is a simple yet efficient way to easily optimize a machine to achieve target values. Table 7 describes the comparison of experimental and optimized results as per Taguchi method. Though layer thickness is same yet there is change in orientation and extruder temperature.

4.1. Regression equation in terms of actual factor

The regression equations for wear rate in coded units are obtained by using MINITAB software.

\[
\text{Wear rate} = 845.8 + 99.7 \text{Lr}_0.7 + 142.9 \text{Lr}_0.200 \\
-242.6 \text{Lr}_0.300 - 189.2 \text{orient}_0.45 + 284.4 \text{orient}_0.60 \\
- 95.2 \text{orient}_0.90 + 110.2 \text{Temp}_0.220 - 94.8 \text{Temp}_0.225 \\
- 15.4 \text{Temp}_0.230 
\]  

Equation (3) is expressed in terms of process parameters which affect the output responses. These expressions are helpful in defining the nature of response variable for selected input variables.

The analysis is performed with a confidence level of 95% that shows variables for study are statistically significant. Table 8 describes briefly the ANOVA table for wear rate of specimens.

| Table 7. Comparison between experimental and optimized results. |
|---------------------------------|-----------------|-----------------|-----------------|
| Parameters                      | Layer thickness (μm) | Orientation (°) | Extruder temperature (°C) |
| Optimized results               | 300              | 45              | 225              |
| Experimental results            | 300              | 90              | 220              |

| Table 8. ANOVA table for wear rate analysis. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| Source                          | Degree of freedom | Adj. sum of squares | Adj. mean squares | F value | P value |
| Layer thickness                 | 2               | 239379           | 119690           | 72.13   | 0.014  |
| Orientation                     | 2               | 355344           | 177672           | 107.07  | 0.009  |
| Extruder Temperature            | 2               | 78178            | 39089            | 23.56   | 0.041  |
| Error                           | 2               | 3319             | 1659             |         |        |
| Total                           | 8               | 676221           |                 |         |        |

Figure 12. Neural network connections.
The p value in table 8 is an indicator in which the assumption holds firmly. The p values less 0.005 are statistically significant and it validates the results obtained from the Taguchi design.

R square describes the range to which input variables interpret the modification of output response and predicted variable. The higher value of R square is directly proportional to a good model. In the above table 9 R-square is 0.9927, it means that 99.27% of the deviation in the output response is given by input variables. R-square has predicted 85.22% model results satisfactorily. Deviation in the experimentally measured wear rate and using Taguchi method has been discussed in table 10 along with ANN predicted values where deviation up to 6% has been observed. Specimen for the wear assessment of PLA using optimized parameters in accordance to Taguchi method has been prepared and the deviation of 3.98% is observed in the wear rate computed through

| Sr No | Experimental wear rate (μm) | ANOVA predicted wear rate | ANN simulated wear rate (μm) | Deviation between experimental and ANOVA predicted wear rate (%) | Deviation between experimental and ANN predicted wear rate (%) | Which (ANOVA/ANN) is closer to experimental observations |
|-------|-----------------------------|---------------------------|-------------------------------|--------------------------------------------------------------|-------------------------------------------------------------|----------------------------------------------------------|
| 1     | 1373.49                     | 1346.78                   | 1352.94                       | 1.94                                                         | 1.49                                                         | ANN                                                      |
| 2     | 650.48                      | 668.76                    | 651.18                        | −2.7                                                        | −0.108                                                      | ANN                                                      |
| 3     | 812.43                      | 821.57                    | 813.24                        | −1.12                                                       | −0.1                                                        | ANN                                                      |
| 4     | 1155.80                     | 1164.94                   | 1156.57                       | −0.79                                                       | −0.06                                                       | ANN                                                      |
| 5     | 817.43                      | 790.17                    | 818.34                        | 3.26                                                        | −0.11                                                       | ANN                                                      |
| 6     | 992.88                      | 1010.46                   | 993.43                        | −1.77                                                       | −0.05                                                       | ANN                                                      |
| 7     | 861.23                      | 878.80                    | 797.03                        | −1.1                                                        | −0.07                                                       | ANN                                                      |
| 8     | 561.68                      | 570.82                    | 562.02                        | −1.62                                                       | −0.06                                                       | ANN                                                      |
| 9     | 446.55                      | 419.83                    | 456.43                        | 5.98                                                        | −2.21                                                       | ANN                                                      |

Figure 13. Regression plot.
Table 11. ANN predicted wear rate.

| Sr. No. | Layer Thickness (µm) | Orientation (°) | Temperature (°C) | Wear rate (µm) |
|---------|----------------------|----------------|-----------------|----------------|
| 1       | 70                   | 45             | 220             | 1348.31        |
| 2       | 70                   | 45             | 225             | 651.18         |
| 3       | 70                   | 45             | 230             | 778.20         |
| 4       | 70                   | 60             | 220             | 1352.94        |
| 5       | 70                   | 60             | 225             | 1168.13        |
| 6       | 70                   | 60             | 230             | 1044.37        |
| 7       | 70                   | 90             | 220             | 1326.82        |
| 8       | 70                   | 90             | 225             | 1330.01        |
| 9       | 70                   | 90             | 230             | 813.24         |
| 10      | 200                  | 45             | 220             | 1260.27        |
| 11      | 200                  | 45             | 225             | 591.04         |
| 12      | 200                  | 45             | 230             | 818.34         |
| 13      | 200                  | 60             | 220             | 1345.46        |
| 14      | 200                  | 60             | 225             | 1156.57        |
| 15      | 200                  | 60             | 230             | 967.65         |
| 16      | 200                  | 90             | 220             | 993.43         |
| 17      | 200                  | 90             | 225             | 1196.64        |
| 18      | 200                  | 90             | 230             | 958.16         |
| 19      | 300                  | 45             | 220             | 870.92         |
| 20      | 300                  | 45             | 225             | 562.02         |
| 21      | 300                  | 45             | 230             | 952.73         |
| 22      | 300                  | 60             | 220             | 1117.84        |
| 23      | 300                  | 60             | 225             | 541.45         |
| 24      | 300                  | 60             | 230             | 797.03         |
| 25      | 300                  | 90             | 220             | 456.43         |
| 26      | 300                  | 90             | 225             | 654.57         |
| 27      | 300                  | 90             | 230             | 875.09         |
findings of experimental and Taguchi method. As Taguchi method suffers from some limitations in presenting optimized results e. g;

a. Difficulties in accounting interactions between parameters.

b. Inappropriate for a dynamically changing process.

Hence for the rigorous validation, ANN technique has been implemented in upcoming section. In this study our objective function is to minimize the wear rate. ANN with back propagation algorithm has been used to predict the optimum value of process parameters.

In figure 12 there are three input variables for one output response (wear rate), the connection uses 10 hidden layers. In the present analysis layer thickness, orientation and temperature factors are taken as three inputs. Each of these factors are identified by one neuron. Figure 13 indicates the training and testing plot for the data points generated by MATLAB 2017 software. The data points separated into two categories first is a training category which is used to regulate the network weights and second is testing category which is analogous to the data set which confirms the results of the training protocol. In this analysis 70% of data randomly used for training category and remaining the 30% used for testing category to analyze the data.

The training of neural network comprehends the weight of the connection in such a manner that the error between the output of the neural network and actual output is minimized. The training category uses the dataset in order to fit the parameters of the model. The training category of the input variable with respect to the output response performs its resulting output against the desired result. The value of weights is calculated by performing the number of iteration by training the data set of the neural network in order to minimize the error between the prediction and actual response. The most common method which is updating the weights is called back propagation method. The mean square error criterion is used to test error in dataset by the following equation;

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (Y_i - Y_{Bi})^2
\]

where N is the number of pattern, \(Y_i\) is the actual output and \(Y_{Bi}\) is the desired output

In figure 13, the testing and validation curves show R value none, it may due to the insufficient data for testing category. If this approach is implemented for rigorous data set, it may give well performance.

In table 10 we can easily observe that all the ANN predicted wear rate values are found closely correlated to experimental results in comparison to ANOVA predicted values. From the above analysis it might be concluded that multi objective optimization like ANN provides more accurate and precise results. So it is good consideration to prefer the multi objective optimization technique for better performance. We can figure out that for operating conditions, layer thickness 0.3 mm, orientation 90° and temperature 220 °C at which the minimum wear rate is 456.43 obtained. Highlighted rows in table 11 show the performed experiments and the same have been compared in table 10. It also shows the various combination of process parameters at which the wear rate of samples is minimum. It may be analyzed that the increment in the layer thickness results in better surface properties and with increase in build orientation decreases the wear rate due to the staircase effect in printing process.

5. Conclusions

Additive Manufacturing is gradually transforming the manufacturing scenario globally to manufacture products of consistent quality for which understanding of process parameters and their influence on final build quality is necessary. The paper is assessing the effect of selected FDM process parameters (layer thickness, orientation and extruder temperature) to find the wear rate of PLA material. The wear analysis of PLA part can be helpful in bio medical, prosthetic implant and tissue engineering etc. As a result a generic methodology was proposed. It is found that orientation has the most dominating factor for the design of experiments of p value 0.009. The conclusions drawn from the experiments which relate to process parameters and their influence on wear rate are summarized below.

- A realistic assessment of process variables of FDM process using Taguchi method and ANN has been presented to estimate wear rate for PLA material.

- A comparison among the experimental findings, outcome of Taguchi method and ANN has been made for rigorous evolution of process/output parameter under investigation, which points out that ANN is more appropriate in comparison to Taguchi method.
• The work can be extended to other FDM materials and PLA variants such as PLA carbon fibre, PLA wood by increasing the number of process parameters.

• Limitation of this study for ANN model is that due to lack of data, ANN model doesn’t predict the performance curve values appropriately. For future direction, this study can be analysed by using L27 OA by considering various process parameters so the ANN model can be analysed more rigorously.

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**References**

[1] Calignano F, Manfredi D, Ambrosio E P, Biamino S, Lombardi M, Atzeni E and Fino P 2017 Overview on additive manufacturing technologies Proc. IEEE 105 593–612

[2] Gao W and Yungbozhang D 2015 The status, challenges, and future of additive manufacturing Comput. Aided Des. 69 65–89

[3] Mellor S, Hao L and Zhang D 2014 Additive manufacturing: a framework for implementation Int. J. Prod. Econ. 149 194–201

[4] Negi S, Dhiman S and Sharma R K 2014 Basics and application of rapid prototyping medical models Rapid Prototyping Journal 20 256–67

[5] Srivastava M and Rathee S 2018 Optimization of FDM process parameters by taguchi method for imparting for imparting customised properties to component Virtual and Physical Prototyping 13 203–10

[6] Gibson I, Rosen D W and Stucker B 2014 Additive Manufacturing Technologies. (New York: Springer) 1

[7] Tiwary V, Arunkumar P, Deshpande A S and Khorate V 2013 Studying the effect of chemical treatment and fused deposition (FDM) modelling process parameters on surface roughness to make acrylonitrile butadiene styrene patterns for investment casting process International Journal Rapid Manufacturing 5 276–88

[8] Novakova-Marcincinova L 2012 Application of fused deposition modeling technology in 3D printing rapid prototyping area Manufacturing and Industrial Engineering 11 35–7

[9] Chohan J S, Singh R, Boparai K S, Penna R and Fraternali F 2017 Dimensional accuracy analysis of coupled fused deposition modeling and vapour smoothing operations for biomedical applications Composites Part B: Engineering 117 138–49

[10] Flocher J and Panasea A 2019 Review on design and structural optimization in additive manufacturing: towards next-generation lightweight structures Materials & Design 183 108164

[11] Sahmani S, Khandan A, Esmaeili S, Saber-Samandari S, Nejad M G and Aghdam M M 2020 Calcium phosphate-PLA scaffolds fabricated by fused deposition modeling technique for bone tissue applications: fabrication, characterization and simulation Ceram. Int. 46 2447–56

[12] Kumar L J and Nair C K 2017 Current trends of additive manufacturing in the aerospace industry Advances in 3d printing & additive Manufacturing Technologies (Singapore) pp. 39–54

[13] Patel J P, Patel C P and Patel U J 2012 A review on various approach for process parameter optimization of fused deposition molding (FDM) process and Taguchi approach for optimization International Journal of Applied Engineering Research 2 361–5

[14] Mohamed O A, Masood S H and Bhowmik J L 2018 Analysis of wear behavior of additively manufactured PC-ABS parts Mater. Lett. 230 261–5

[15] Byun H S and Lee K H 2006 Determination of optimal build direction in rapid prototyping with variable slicing The International Journal of Advanced Manufacturing Technology 28 307

[16] Ertane E G, Dorner-Resiel A, Baran O, Welzel T, Matner V and Svoboda S 2018 Processing and wear behaviour of 3D printed PLA reinforced with biogenic carbon Advances in Tribology 2018 1763182

[17] Gurrala P K and Regalla S P 2017 Friction and wear rate characteristics of parts manufactured by fused deposition modelling process International Journal of Rapid Manufacturing 6 45–61

[18] Hussein M A, Mohammed A S and Al-Aqeili N 2015 Wear characteristics of metallic biomaterials: a review Materials 8 2749–68

[19] Sood A K, Ohdar R K and Mahapatra S S 2012 Experimental investigation and empirical modelling of FDM process for compressive strength improvement J. Adv. Res. 3 81–90

[20] Darbar R and Patel P M 2017 Optimization of fused deposition modeling process parameter for better mechanical strength and surface roughness International Journal of Mechanical Engineering 6 7–18

[21] Campoense-Negete C 2020 Optimization of FDM parameters for improving part quality, productivity and sustainability of the process using Taguchi methodology and desirability approach Progress in Additive Manufacturing 5 59–65

[22] uz Zaman U K, Boesch E, Siadat A, Rivette M and Baqui A A 2019 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 1215–26

[23] Filipovic A, Raos P and Sercer M 2009 Experimental analysis of properties of materials for rapid prototyping Int. J. Adv. Manuf. Technol. 40 105–15

[24] Dounkontj P and Jamnirjoch K 2019 Analysis of printing pattern and infiltration percent over the tensile properties of PLA printed parts by a fuse deposition modelling printer IOP Conf. Series: Materials Science and Engineering 501 012028(IOP Publishing)

[25] 3D Systems Inc 2015 CubePro prosumer 3D printer - user guide - original instructions 3D Syst Inc. 2015 1–86 (September)

[26] Wright K M J, Dobbs H S and Scales J T 1982 Wear studies on prosthetic materials using the pin-on-disc machine (American Society for Testing and Materials) G99.3 41–8 Standard test method for wear testing with a pin-on-disk apparatus

[27] ASTM G99-17 2017 Standard Test Method for Wear Testing with a Pin-on-Disk Apparatus (West Conshohocken, PA: ASTM International)

[28] Castro-Aguirre E, Iniguez-Franco F, Samsudin H, Fang X and Auras R 2016 Poly (lactic acid)—mass production, processing, industrial applications, and end of life Adv. Drug Delivery Rev. 107 533–66
[29] Chacón M, Caminero M A, García-P E and Nuñez P J 2017 Additive manufacturing of PLA structures using fused deposition modelling: effect of process parameters on mechanical properties and their optimal selection Mater. Des. 124 143–57
[30] Srivastava M and Rathee S 2018 Optimization of FDM process parameters by Taguchi method for imparting customized properties to components Virtual and Physical Prototyping 13 203–10
[31] Ramesh C S and Srinivas C K 2009 Friction and wear behaviour of laser sintered iron–silicon carbide composites J. Mater. Process. Technol. 209 429–5436
[32] Kennedy D M and Hashmi M S J 1998 Methods of wear testing for advanced surface coatings and bulk materials Material Processing Technology 77 246–53
[33] Kovalenko P, Perepelkina S and Korakhanov T 2017 Investigation of tribological properties of friction pairs duralumin—fluoropolymer used for design and manufacturing of biomechatronic devices Tribology in Industry 39 192–7
[34] Salguero J and Irene D S 2018 Application Pin-on-Disc techniques for the study of tribological interference in the dry machining of A92024-T3 (Al-Cu) alloys Materials 11 1236
[35] Montgomery D C 2007 Introduction to Statistical Quality Control. (New York: Wiley)
[36] Kumar V and Kumar A 2018 Improved bio bleaching of mixed hardwood pulp and process optimization using novel GA-ANN and GA-ANFIS hybrid statistical tools Bioresour. Technol. 271 274–82
[37] Patel J P, Patel C P and Patel U J 2012 A review on various approach for process parameters optimization of fused deposition modeling (FDM) process and Taguchi approach for optimization International Journal of Engineering Research and Application 2 361–5
[38] Colmenero J M M, Paramio M A R and Garcia R 2019 A numerical and experimental study of the compression uniaxial properties of PLA manufactured with FDM technology based on product specification International Journal of Advanced Manufacturing 103 1893–909
[39] Stephen O A 2015 Dimensional accuracy and surface finish optimization of fused deposition modeling parts using desirability function analysis International Journal of Engineering Research and Technology 4 197–202
[40] Alafaghani A, Qattawi A and Alrawi B 2017 Design consideration for additive manufacturing; fused deposition modeling Procedia Manufacturing 7 291–318
[41] Sood A K, Ohdar R K and Mahapatra S S 2010 Parametric appraisal of mechanical property of fused deposition modeling processed parts Material & Design 31 287–95
[42] Llanier O, Mourin D and Lancak P 2014 Effect of layer thickness deposition angle and infill on maximum flexural force in FDM–built specimen Journal for Technology of Plasticity 39 49–58
[43] Raut S, Kheddar V S and Singh N K 2014 Investigation of effect of build orientation on mechanical properties and total cost of FDM parts Procedia Manufacturing 6 1625–30