Optimization of Fused Deposition Modelling process parameters using Teaching Learning Based Optimization (TLBO) algorithm

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Abstract. Fused Deposition Modelling (FDM) is one of the most commonly used Additive Manufacturing (AM) techniques with a wide range of applications in various modern manufacturing industries. It is widely employed to fabricate prototypes where immense surface finish is required. Furthermore, the literature suggests that process parameters such as nozzle temperature (NT), nozzle diameter (ND), and feed rate (FR) have a significant influence on the surface finish achieved in an FDM process. Hence, this work intends to examine the effect of process parameters viz. NT, ND, and FR on the side and top surface roughness of poly-lactic acid (PLA) sample fabricated through FDM process. Experiments are designed as per Taguchi’s L18 orthogonal array and a population-based algorithm identified as Teaching Learning Based Optimization (TLBO) algorithm is used to determine the optimal process parameter settings for optimum side and top surface roughness simultaneously. The results of the study reveal that NT of 493 K, ND of 0.4 mm and FR of 60 mm/s results in optimum side and top surface roughness simultaneously.

1. Introduction

Additive Manufacturing (AM) processes are the commonly used modern manufacturing method adopted to fabricate intricate components with increased complexity. Industrial demands of the products with flexible and complex geometries are driving manufacturers to study and improve the specifications of AM process that has potential applications in numerous modern manufacturing industries such as automotive, aerospace, art, jewelry, etc.[1]. One of the most commonly used AM processes is the Fused Deposition Modeling (FDM) technique, which has several driving factors such as availability of a vast variety of materials, low maintenance cost, easy material handling, compact size, low operating temperature, lower tolerance, and rapid production of thin components. However, the surface roughness (Ra) of the product manufactured using FDM is an essential factor that affects the functionality of the product, lower Ra enhances the component accuracy, and reduces the post-processing investment [2,3]. Therefore, investigating the Ra of the products manufactured using FDM process is an area of interest among researchers. Plethora of research work has been done to investigate the influence of various control parameters such as layer thickness, infill percentage, infill pattern, and extrusion temperature on Ra, dimensional accuracy (DA) and mechanical properties of FDM components. But, very few work has been performed to investigate the influence of nozzle temperature (NT), nozzle diameter (ND), and feed rate (FR) on Ra of various faces of FDM components.
components. Deng et al. [4] investigated the influence of NT and FR on the emission of particles during FDM of acrylonitrile butadiene styrene (ABS) and polyactic acid (PLA) material and concluded the followings (i) for PLA material low values of NT ranging between 180°C to 200°C were preferable for high particle count, as the decomposition temperature of PLA material is around 220°C, (ii) in case of ABS material the preferable temperature range is found to be 200°C to 240°C, as its decomposition temperature is about 270°C, and (iii) for both the materials, increasing the FR from 30 mm/s to 60 mm/s improve the particle count thereby decreases the Ra of the product but further rise of feed rate to 90 mm/s significantly increase the Ra because the elevated FR increases the material fraction, which facilitates the high printing speed and heat dissipation that margins the thermal decomposition and increases Ra. According to Alsoufi and Elsayed [5] decrease in the layer height and nozzle diameter from 0.3 mm to 0.1 mm, and 0.5 mm to 0.2 mm respectively, significantly reduces the Ra of the component whereas increases the fabrication time. Mahapatra and Sood [6] proposed a Back Propagation Algorithm based Artificial Neural Network (ANN) model to explore the relationship between process parameters including layer thickness, raster angle, orientation, raster width, and air gap with top surface roughness (\(R_T\)), back surface roughness (\(R_B\)) and side surface roughness (\(R_S\)) of the FDM component, and concluded that among the various factors, the raster width and the raster angle has the most significant influence on \(R_T\), whereas the orientation of the part and layer thickness has the most significant influence on \(R_B\) and \(R_S\) respectively. From above literatures, it has been witnessed that apart from top surface roughness (\(R_T\)), back surface roughness (\(R_B\)) and side surface roughness (\(R_S\)) have a significant effect on overall product quality.

To achieve the optimum possible Ra through FDM process, the selection of optimum control factors is very important. Literature demonstrates that numerous work has been performed to explore the influence of several control factors on different performance characteristics of FDM process by using single and multi-optimization techniques [7]. However, very less work has been reported to investigate the influence of nozzle temperature (NT), nozzle diameter (ND), and feed rate (FR) on the Ra of different faces of the FDM components. Further, there are very few researches that have used evolutionary algorithms to optimize the multiple output responses simultaneously. With this inspiration, a population based evolutionary algorithm identified as Teaching-Learning Based Optimization (TLBO) algorithm is used in this work to optimize the \(R_S\) and \(R_T\) simultaneously of the FDM product. TLBO algorithm is a very efficient optimization algorithm for multiple constrained engineering problems that does not require any parameters related to a specific algorithm [8]. Hence, the objective of this work is to analyze the effect of NT, ND, and FR and thereby employing TLBO algorithm for the multi-response optimization of \(R_S\) and \(R_T\). The remaining of the paper is structured as follows: section 2 of the paper discusses the materials and methods used in this work. Section 3 of the paper demonstrate the results of the study and finally, section 4 presents the conclusion of the work.

2. Materials and Methods
This study aims to investigate the influence of three process parameters on the surface quality of the products fabricated using FDM process. To achieve the research objectives the research methodology adopted in this work begins from experiment setup and selection of process parameters and their levels. Subsequently, Taguchi’s Design of Experiment (DOE) is used to define a well-defined set of experiments based on which experiments are carried out and output performances are measured. Finally, the results were analyzed and TLBO algorithm is used to obtain the optimum combination of process parameters for optimum results of \(R_S\) and \(R_T\) simultaneously.

2.1. Material Selection
Figure 1 (a) shows a desktop type RxP-2000 FDM 3D printing machine which is used to fabricate the samples. Samples of dimension 16 mm×12 mm×10 mm were fabricated using PLA filament of diameter 3 mm. PLA is one of the most commonly used plastic materials in FDM process due to its lower melting point, low cost, less toxic, good biocompatibility, good biodegradability, and less
energy requirement [9]. The experiments have been performed in a fabrication chamber as shown in Figure 1 (b).

Figure 1. (a) RxP-2000 3D printing machine; (b) Fabrication of component in the chamber

2.2. Process parameters and their levels
In light of the literature associated with surface quality improvements of a component in FDM process, the effect of three process parameters viz. nozzle diameter (ND), nozzle temperature (NT), and feed rate (FR) have been investigated in this study. Effect of three levels of ND viz. 0.4 mm, 0.5 mm, and 0.6 mm were examined with the feasible range of temperature from 473 K and 493 K and FR 70 mm/s to 90 mm/s. Three levels of ND and FR and two levels of NT were selected as shown in Table 1.

Table 1. Process parameters and their levels.

| Process parameter         | Symbol | Units | Level 1 | Level 2 | Level 3 |
|---------------------------|--------|-------|---------|---------|---------|
| Nozzle Diameter (ND)      | ND     | mm    | 0.4     | 0.5     | 0.6     |
| Nozzle Temperature (NT)   | NT     | K     | 473     | 493     | -       |
| Feed rate (FR)            | FR     | mm/s  | 70      | 80      | 90      |

2.3. Taguchi Experimental Design
Design of experimentation is helpful in studies involving process parameters where the analysis of the combined effect of process parameters on an output response is required [10]. Among the different methods of experimental designs, Taguchi experimental design is an efficient and widely accepted method used to investigate the combined effect of process parameters [11,12]. It has the advantage of a cutback in cost, time, and resources as it reduces the number of experiments to be performed. Taguchi proposed standard orthogonal arrays (SOAs) in which several experiments are arranged in rows and process parameters in columns [13]. The selection of orthogonal arrays (OA) for conducting experiments is based on the total degree of freedom (DOF) of the process parameters. It has been suggested that any OA having a DOF equal to or more than the total DOF of the process parameters can be used for performing experiments [14]. The DOF of a specific process parameter is calculated by subtracting one from the number of levels. In this study, three factors are considered with two factors having three levels and one factor having 2 levels. Hence, the DOF of process parameters will be 5 [(2×2) + (1×1)]. The DOF of SOAs is defined as one less than the total number of experiments in the OA. Therefore, Taguchi’s L18 orthogonal array is found suitable for the considered combinations and levels of process parameters.

2.4. Measurement of output response
In the present study $R_s$ and $R_T$ are evaluated to analyze the overall quality of the fabricated surface. The measurement of surface roughness of 18 samples was performed on one of the side surface and top surface for each sample using a contact system type Mitutoyo SJ210 Perthometer, model surface roughness tester. It employs the stylus retractable drive unit method of measurement with a stylus tip.
radius of 2 μm and tip angle of 60°. A tracing length of 4 mm was used for analysis. The surface roughness of each sample was measured at the center position of the fabricated surface.

2.5. Teaching Learning Based Optimization (TLBO) algorithm

TLBO algorithm was proposed by [8] which is popular among researchers due to its simple concept, no requirement of the algorithm-specific parameter, fast convergence, and easy and effective execution process. It has been widely accepted and positively employed to solve the optimization problem on different knowledge domains [8]. The iterative method of TLBO algorithm is separated into two parts. First part is named as teacher phase which is inspired from learning of students from the teacher. While in the second part regarded as learner’s phase, the knowledge is gained by interacting with each other. For an optimization problem with decision variables X = [x1, x2, .........., xn] and an objective function f(X), TLBO algorithm considers desired objective function value as the knowledge level of a learner and the search points in the decision variable space as learners. The computational steps involved in the teacher and learners phase is discussed as follows:

2.5.1. Teaching Phase.

As the name suggests, teaching phase of TLBO algorithm involves knowledge enhancement through teacher. Considering N number of learners (population size = N) with knowledge x1, x2, .........., xn (decision variables) in n subjects. The aim is to maximize the overall knowledge (objective function) of the learners which depends upon the knowledge in each subject. It noteworthy that for a maximising problem highest value and for minimizing problem least value of the objective function shows high overall knowledge. The first step is to identify the teacher which will improve the knowledge in each subjects resulting in overall knowledge enhancement of the learners. In this algorithm, the teacher is identified as the learner with highest overall knowledge. Further the knowledge alteration in each subject by interaction with teacher is computed using Eqn. (1).

\[
x_{i,j}^{new} = x_{i,j} + r_{i}(x_{T,j} - T_{r} M_{j})
\]

where, \(x_{i,j}^{new}\) and \(x_{i,j}\) are the updated and original knowledge of learner i in subject j respectively. \(x_{T,j}\) depicts the knowledge of the teacher in subject j. \(M_{j}\) denotes the mean knowledge of the all the learners in subject j. \(r_{i}\) is a random number between 0 and 1. \(T_{r}\) is defined as the teaching factor whose value is determined using Eqn. (2).

\[
T_{r} = round[1 + rand(0,1)]
\]

2.5.2. Learning Phase.

In learning phase, each learner enhances his/her knowledge by interacting with each other. This interaction may be partial or complete. In partial interaction, learners interact with each other randomly while in complete interaction each learner interacts with other learner to modify his/her knowledge level. In this work complete interaction has been considered. The modified knowledge in subject “j” of learner “P” when interacts with learner “Q” is computed using Eqn. (3) and Eqn. (4) according to the required objective function value as maximum or minimum respectively.

\[
x_{P,j}^{new} = \begin{cases} 
    x_{P,j} + r_{i}(x_{P,j} - x_{Q,j}) & ; \text{if } f(X_{P}) < f(X_{Q}) \\
    x_{P,j} + r_{i}(x_{Q,j} - x_{P,j}) & ; \text{if } f(X_{Q}) < f(X_{P})
\end{cases}
\]

\[
x_{Q,j}^{new} = \begin{cases} 
    x_{P,j} + r_{i}(x_{P,j} - x_{Q,j}) & ; \text{if } f(X_{Q}) < f(X_{P}) \\
    x_{P,j} + r_{i}(x_{Q,j} - x_{P,j}) & ; \text{if } f(X_{P}) < f(X_{Q})
\end{cases}
\]

where, \(x_{P,j}^{new}\) and \(x_{P,j}\) are the updated and original knowledge of learner P in subject j after teaching phase respectively. \(x_{Q,j}\) is the knowledge of learner Q after teaching phase.
The knowledge level of learners after teacher phase and learner phase together completes the one iteration of the TLBO algorithm. This process is iterated again and again till the knowledge level i.e., objective function value for each learner become equal or reaches a desired level.

3. Result and Discussion

To investigate the influence of various process parameters on the surface quality of PLA test samples fabricated using FDM process experimentations were performed as per design shown in Table 2. While performing the experiments, the experimental sequence was not followed rather they are conducted in randomized manner to reduce the biasness in the results. Further, $R_S$ and $R_T$ of the samples are computed using a contact system type Mitutoyo SJ210 perthometer, model surface roughness tester and the results are shown in Table 2.

| Exp No. | ND | NT  | FR  | $R_S$ | $R_T$ |
|---------|----|-----|-----|-------|-------|
| 1       | 0.4| 473 | 70  | 15.956| 6.956 |
| 2       | 0.4| 473 | 80  | 18.548| 7.545 |
| 3       | 0.4| 473 | 90  | 20.941| 7.842 |
| 4       | 0.5| 473 | 70  | 25.944| 8.245 |
| 5       | 0.5| 473 | 80  | 26.542| 9.445 |
| 6       | 0.5| 473 | 90  | 28.605| 10.509|
| 7       | 0.6| 473 | 70  | 31.841| 13.245|
| 8       | 0.6| 473 | 80  | 33.405| 14.455|
| 9       | 0.6| 473 | 90  | 35.605| 15.509|
| 10      | 0.4| 493 | 70  | 12.256| 5.85  |
| 11      | 0.4| 493 | 80  | 16.962| 6.21  |
| 12      | 0.4| 493 | 90  | 18.524| 6.695 |
| 13      | 0.5| 493 | 70  | 23.997| 7.192 |
| 14      | 0.5| 493 | 80  | 24.696| 7.506 |
| 15      | 0.5| 493 | 90  | 24.645| 7.905 |
| 16      | 0.6| 493 | 70  | 30.986| 11.592|
| 17      | 0.6| 493 | 80  | 31.235| 13.141|
| 18      | 0.6| 493 | 90  | 33.436| 14.305|

Figure 2 (a) Main effect plot for $R_S$; (b) Main effect plot for $R_T$
Figure 2(a) and 2(b) shows that $R_S$ and $R_T$ value rises with increase in ND and FR, however increase in NT reduces the $R_S$ and $R_T$ respectively. Further, to optimize the parameters using TLBO algorithm, it is needed to represent the output response as a function of process parameters. For this purpose, regression analysis was performed. A quadratic regression equation with highest R² value of 99.22% and 99.38% is obtained for of $R_S$ and $R_T$ which is shown in Eqn. (5) and Eqn. (6) respectively.

$$R_S = -32 - 0.1025 * NT + 241.2 * ND + 0.506 * FR - 113 * ND^2 - 0.630 * ND * FR$$ (5)

$$R_T = 82.22 - 0.07419 * NT - 179.3 * ND - 0.1222 * FR + 181.2 * ND^2 + 0.406 * ND * FR$$ (6)

where, NT = Nozzle Temperature, ND = Nozzle Diameter, FR = Feed rate

Further, the optimization problem for $R_S$ and $R_T$ so formulated is shown in Eqn. (7) and Eqn. (8) respectively.

Minimize $R_S = -32 - 0.1025 * NT + 241.2 * ND + 0.506 * FR - 113 * ND^2 - 0.630 * ND * FR$

Subject to: $473 \leq NT \leq 493$ ; $0.4 \leq ND \leq 0.6$ ; $70 \leq FR \leq 90$ (7)

Minimize $R_T = 82.22 - 0.07419 * NT - 179.3 * ND - 0.1222 * FR + 181.2 * ND^2 + 0.406 * ND * FR$

Subject to: $473 \leq NT \leq 493$ ; $0.4 \leq ND \leq 0.6$ ; $70 \leq FR \leq 90$ (8)

TLBO algorithm was run with a population size of 10 and is iterated 20 times. It was found that using TLBO algorithm the minimum $R_S$ i.e. 13.648 µm is obtained with ND of 0.4 mm, NT of 493K and FR of 70 mm/s. Whereas, minimum $R_T$ i.e. 5.682 µm is obtained with ND of 0.416 mm, NT of 493K and FR of 70 mm/s. Further, to optimize both the parameters simultaneously, the non-dominated sorting TLBO algorithm is employed. According to this approach, the weighted sum of the objective functions are used to formulate a single a single fitness function. It is likely that the different objective functions may be defined over different range of values. Therefore, normalized objective functions are considered to convert them into same range. For this study, the $R_S$ and $R_T$ are normalized and combined according to Eqn. (9)

$$CSR = \frac{R_T}{R_T^*} + \frac{R_S}{R_S^*}$$ (9)

where, $R_T^*$ and $R_S^*$ are the minimum values of top and side surface roughness obtained when they are optimized independently.

Thus, the optimization problem for combined optimization of both $R_S$ and $R_T$ so formulates is shown in Eqn. (10).

Minimize $Z = \frac{R_T}{5.682} + \frac{R_S}{13.648}$

Subject to: $473 \leq NT \leq 493$ ; $0.4 \leq ND \leq 0.6$ ; $70 \leq FR \leq 90$ (10)

Considering a similar population size and number of generation as in individual optimization, the results obtained by TLBO algorithm for combined optimization of $R_S$ and $R_T$ and comparison with the experimental results is shown in Tables 3.

| Parameters          | Experimental Results | TLBO results |
|---------------------|----------------------|--------------|
| Diameter            | 0.4 mm               | 0.416 mm     |
| Temperature         | 493 K                | 493 K        |
| Feed rate           | 70 mm/s              | 70 mm/s      |
| Top surface roughness| 5.85 µm              | 5.682 µm     |
| Side surface roughness| 12.256 µm           | 13.648 µm    |
4. Conclusion

FDM process helps to fabricate products from the elementary design of the components. It allows low cost, lightweight, and rapid prototyping in comparison to other conventional manufacturing process. This work aims to investigate the influence of three process parameters viz. NT, ND, and FR on the surface quality of polylactic acid (PLA) test samples fabricated by FDM process. To achieve the desired objectives of the study, test samples of dimension 16 mm x 12 mm x 10 mm were fabricated using PLA filament of diameter 3 mm on a desktop type RxP-2000 FDM 3D printing machine. Experiments are designed as per L18 Taguchi’s orthogonal array which was found suitable for the considered levels of process parameters. Further, output responses viz. side and top surface roughness are measured using a contact system type Mitutoyo SJ210 perthometer, model surface roughness tester. Subsequently, TLBO was employed to determine the optimal combination of process parameters. The major conclusions of the conducted study are presented as follows:

- For low side and top surface roughness, lower values of ND and FR, and higher value of NT are desired.
- The optimal combination of process parameters i.e. NT, ND and FR for small top surface roughness are found to be 493 K, 0.4 mm and 70 mm/s respectively.
- A process parameter setting of NT = 493 K, ND = 0.416 mm and FR = 70 mm/s results in lower top surface roughness.
- The multiple optimization of top and side surface roughness using TLBO suggests that optimal combination of process parameter NT, ND and FR is 493 K, 0.4 mm and 70 mm/s respectively.

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