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A Novel FDM Based Additive Manufacturing of PLA Components Using Optimized Deep Learning Strategy

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Abstract: Fused Deposit modeling (FDM) is an additive manufacturing (AM) process that's frequently used to fabricate geometrically complex shaped prototypes and complex parts. It's gaining market as it reduces cycle time for product development without the need for high priced tools. Still, the commercialization of FDM technology in other artificial operations is presently limited due to several failings, alike as inadequate mechanical properties, poor surface quality, and low dimensional accuracy. The rates of FDM- produced products are affected by other process parameters, for illustration, layer thickness, build angle, raster width, or print speed. The process parameters and their range depends on the section of FDM machines. Filament materials, nozzle dimensions, and the type of machine determine the range of other parameters. The optimum setting of parameters is supposed to ameliorate the rates of three-dimensional (3D) printed specimens and may reduce post-production work. This paper intensely reviews state-of-the- art literature on the influence of parameters on part qualities and the being work on process parameter optimization. Also, the failings of being workshop are linked, challenges and openings to work in this field are estimated, and directions for future research and development in this field are suggested

Keywords: Fused deposition modelling; process parameters; part characteristics; optimization.

I. INTRODUCTION

The commercialization of FDM technology in various industrial applications is currently limited due to several shortcomings, like insufficient mechanical properties, poor surface quality, and low dimensional accuracy. The qualities of FDM-produced products are stricken by various process parameters, for example, layer thickness, build orientation, raster width, or print speed. The process parameters and their range depends on the section of FDM machines [4]. Filament materials, nozzle dimensions, and so the factors of the machine determine the range of varied parameters. The optimum setting of parameters is deemed to reinforce the qualities of three-dimensional (3D) printed parts and will reduce post-production work. Due to the unique advancement, the AM framework has grown widely in many real-time applications. So, the function of the AM process FDM was often used, considering the other approaches FDM has a low price and is straightforward to use. But in several strategies, this method suffered a lot because of its complex design and fewer prediction measure [2]. So, to bolster the AM mechanism an optimized deep neural model is planned to implement to maximize the defeat detection rate and designed object behaviour.

II. EXPERIMENTAL PROCEDURE

.Polylactic acid also known as (PLA) is a thermoplastic monomer derived from renewable, organic sources such as starch and sugarcane Formula : (C₃H₄O₂)_nThe basic properties of PLA are given below in comparison with ABS material

PLA is used shrink-wrap material as it constricts under heat. It is green material, uses 65% less energy than ABS and it is in toxic. PLA is popular for 3D printing as it can easily be sanded, painted, post-processed. A user-friendly material, this plastic works with low extrusion temperatures and there is no need for a heated bed, printer chamber, or a reinforced nozzle.

Reason for selecting PLA over ABS is mentioned below in the form of comparison. [Fig1. \[1\]](#)

| Property | PLA | ABS |
|---------------------------------|----------|---------------------|
| Printing temperature (°C) | 180–230 | 210–250 |
| Build platform temperature (°C) | 20–60 | 80–110 |
| Raft | Optional | Mandatory |
| Strength | High | Medium |
| Flexibility | Brittle | Moderately flexible |
| Heat resistance | Low | Moderate |
| Biodegradability | Yes | No |
| Moisture absorption | Yes | Yes |

Fig1. Comparison of PLA and ABS material

A. Methodology

The Taguchi approach is used for experimental design. Solidworks 2020 is used for developing CAD model and conversion to .STL format. After that Cura ultimaker 2020 is used as a stimulator of sample fabrication process [3-9]. The extrusion based additive manufacturing technology utilizes and produces test specimens. The compressive and tensile tests are performed on universal testing machine (UTM). The acquired data is further used for statistical analysis and model development. Based on Taguchi approach array has been created. The parameters used are print speed (mm/sec), distance from each point (mm), layer thickness (mm), and nozzle diameter (mm). Some authors studied the effect of layer thickness on elastic properties of PLA material.

B. Procedure

The basic steps procedure is given below in the form of flow chart. Fig2. [7]

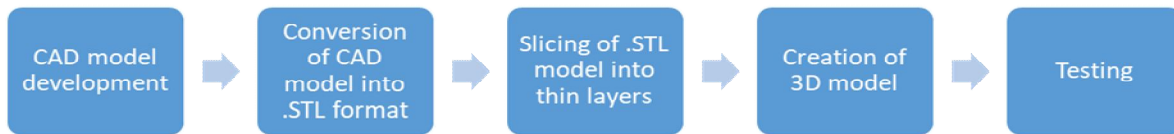


Fig2. Procedure for sample fabrication

The modelling part has been carried out by using Solidworks 2020 and then converted into .STL format. After this, .STL format is sliced in Cura ultimaker software using parameters such as speed (mm/sec), distance from each point (mm), layer thickness (mm), and nozzle diameter (mm).The dimension of testing specimen is set according to American Society for Testing and Measurements (ASTM). Four infill parameters with three levels are been selected for analysis. These parameters are selected as they produce lightweight and strong parts. In this study the four variable parameters are speed (mm/sec), distance from each point (mm), layer thickness (mm), and nozzle diameter (mm) and their variable levels are as follows. Table1. [10-15]

Table1. Parameters of fabrication.

| Factor | Level 1 | Level 2 | Level 3 |
|-----------------------------------|---------|---------|---------|
| Print speed(mm/s) | 40 | 60 | 80 |
| Distance from each print line(mm) | 0.3 | 0.5 | 0.7 |
| Layer thicknss(mm) | 0.1 | 0.2 | 0.3 |
| Nozzle diameter(mm) | 0.4 | 0.4 | 0.4 |

1) Manufacturing

There are five steps in manufacturing in Cura Ultimate 2020

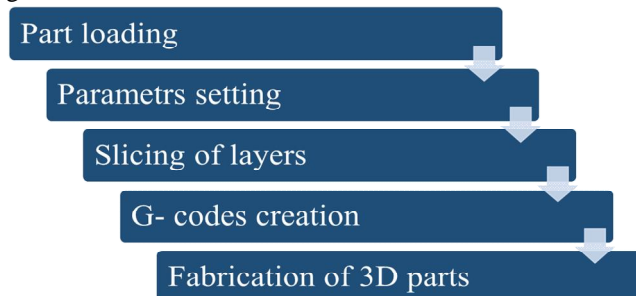


Fig3. Steps in Cura ultimaker2020



Fig4. FDM machine D 300

The specimen is fabricated using the above steps and then subjected to physical measurement and mechanical testing. The machine used for fabrication is: D 300 3DeoMetry Make: Build 300 X 300 and testing machine is UNITEK 94100, Tensile testing Machine: ASTM 638 (type IV), Universal Testing Machine: Zwick Type (1474): ASTM D695

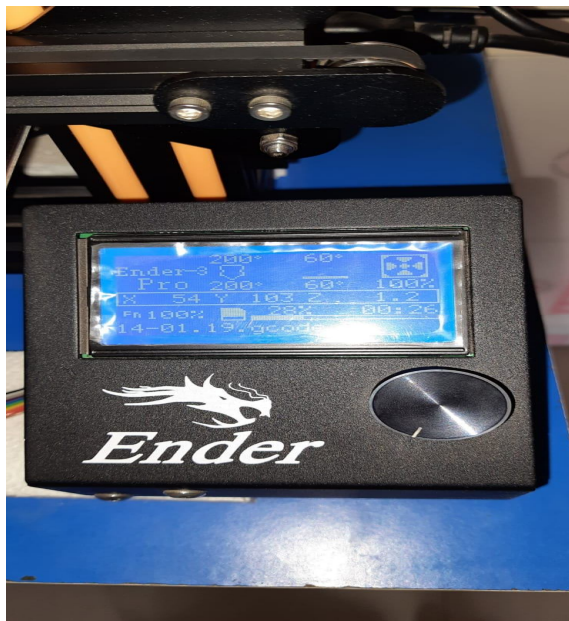


Fig5. FDM G codes



Fig6. FDM G codes

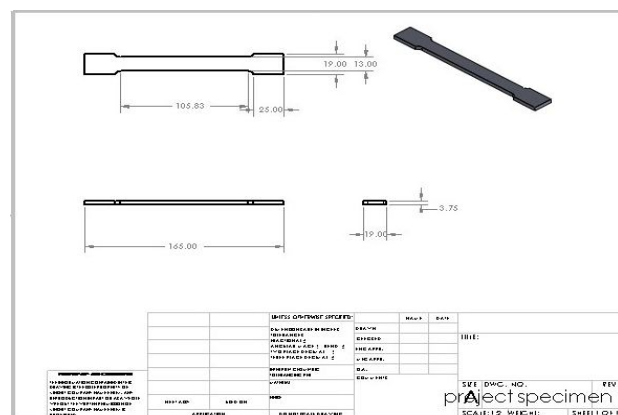
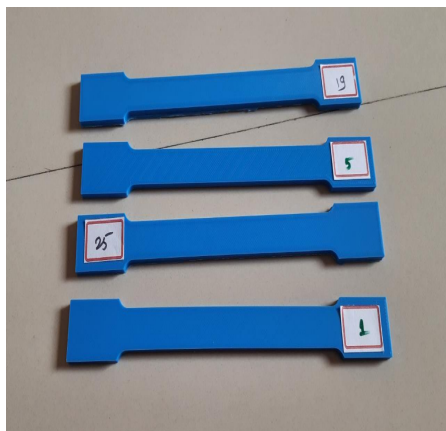


Fig7. Fabricated parts and CAD Model

2) Experimental Results

Table2. Experiment results

| Sr No | Print speed(mm/s) | Distance from each print line (mm) | Layer thickness (mm) | Nozzle diameter (mm) | Tensile strength (MPa) | Compressive strength (MPa) |
|-------|-------------------|------------------------------------|----------------------|----------------------|------------------------|----------------------------|
| 1 | 40 | 0.3 | 0.1 | 0.4 | 34.871 | 29.980 |
| 2 | 40 | 0.3 | 0.2 | 0.4 | 34.871 | 29.700 |
| 3 | 40 | 0.3 | 0.3 | 0.4 | 38.153 | 31.000 |
| 4 | 40 | 0.5 | 0.1 | 0.4 | 34.051 | 28.578 |
| 5 | 40 | 0.5 | 0.2 | 0.4 | 34.871 | 29.652 |
| 6 | 40 | 0.5 | 0.3 | 0.4 | 34.871 | 29.789 |
| 7 | 40 | 0.7 | 0.1 | 0.4 | 33.641 | 28.231 |
| 8 | 40 | 0.7 | 0.2 | 0.4 | 32.821 | 27.976 |
| 9 | 40 | 0.7 | 0.3 | 0.4 | 37.333 | 30.855 |
| 10 | 60 | 0.3 | 0.1 | 0.4 | 33.230 | 28.000 |
| 11 | 60 | 0.3 | 0.2 | 0.4 | 32.820 | 27.435 |
| 12 | 60 | 0.3 | 0.3 | 0.4 | 32.820 | 26.899 |
| 13 | 60 | 0.5 | 0.1 | 0.4 | 33.641 | 27.200 |
| 14 | 60 | 0.5 | 0.2 | 0.4 | 34.051 | 28.999 |
| 15 | 60 | 0.5 | 0.3 | 0.4 | 30.769 | 23.800 |
| 16 | 60 | 0.7 | 0.1 | 0.4 | 34.871 | 28.999 |
| 17 | 60 | 0.7 | 0.2 | 0.4 | 35.692 | 30.528 |
| 18 | 60 | 0.7 | 0.3 | 0.4 | 30.769 | 23.750 |
| 19 | 80 | 0.3 | 0.1 | 0.4 | 35.282 | 29.989 |
| 20 | 80 | 0.3 | 0.2 | 0.4 | 34.461 | 29.654 |
| 21 | 80 | 0.3 | 0.3 | 0.4 | 30.769 | 23.981 |
| 22 | 80 | 0.5 | 0.1 | 0.4 | 34.051 | 28.888 |
| 23 | 80 | 0.5 | 0.2 | 0.4 | 32.000 | 26.333 |
| 24 | 80 | 0.5 | 0.3 | 0.4 | 33.230 | 26.752 |
| 25 | 80 | 0.7 | 0.1 | 0.4 | 31.589 | 25.632 |
| 26 | 80 | 0.7 | 0.2 | 0.4 | 30.769 | 24.000 |
| 27 | 80 | 0.7 | 0.3 | 0.4 | 30.358 | 23.600 |

C. Statistical Model and Multi Objective Optimization

The experimental results developed are further considered for optimization of process parameters. The generated model of material strength and material consumption helps to decide the process parameters.

The algorithm is obtained from Matlab software 2019. This study focuses on simultaneous maximization of mechanical strength and minimization of material consumption. The outline of the basic algorithm for optimization used in Matlab is given below

```

Algorithm.1 proposed SMbDBNS

Input: Nozzle design parameters

Start

Initialization
{
    Int  $P_s, P_l, L_t, L_d, \pi^* \Rightarrow I_v$ 
    // here,  $I_v$  is the input variable
}

Neural layers training
 $T' = I_v$ 

Layer thickness
 $\pi^* = nL$ 
    // here,  $nL$  is the number of layers

Lateral displacement
 $q(a, b) = \text{each layers of the nozzle}$ 

Evaluate start and end point printing line
    Find starting point printing line
         $SM_{starting\_line} \Rightarrow \text{Nozzle layers}$  // local leader fitness

    Find ending pint printing line
         $SM_{ending\_line} \Rightarrow \text{Nozzle layers}$  // global leader fitness

3D printing process
        Fault detection based on  $SM_{starting\_line}, SM_{ending\_line}$ 
        Continuously monitor the connection status

Stop

Output: finest solution

```

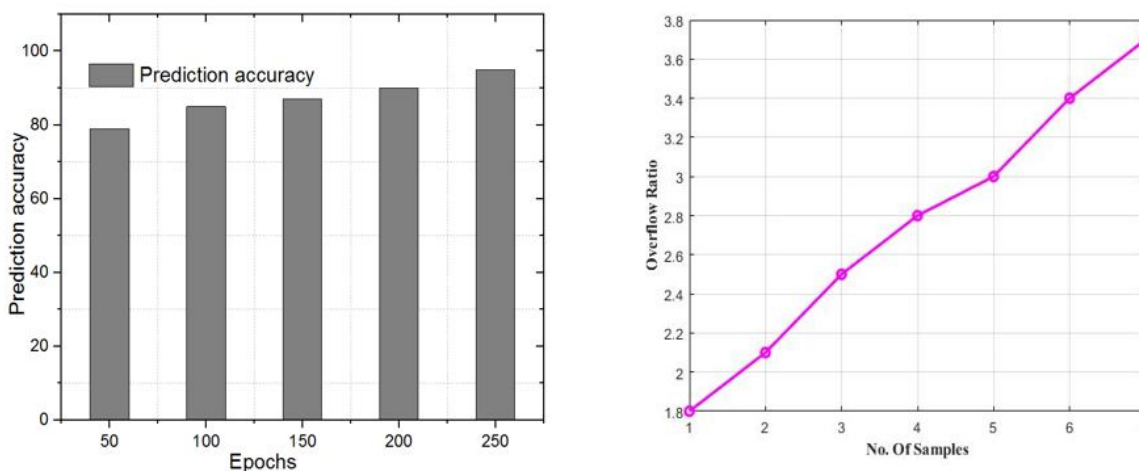
Fig8. Proposed Algorithm

III. RESULT AND DISCUSSION

The results have been represented in [Table2](#), which shows tensile and compressive strengths for different parameters.

A. Prediction Accuracy and Overflow Rate

A correctly predicted printing line is defined as prediction accuracy. Moreover, accuracy is calculated in the ratio of accurate prediction printing lines to the overall printing lines. In the nozzle design primarily find the starting and ending point of the printing line then only easily predict the mismatch printing line.



a) Prediction accuracy of proposed SMbDBNS b) Overflow rate of proposed SMbDBNS

Fig9. Prediction Accuracy and Overflow Ratio

The accuracy of the proposed method is represented in [Fig9](#). The representation demonstrates that the projected method has attained 95% accuracy for 250 epochs. The flow rate of nozzle is defined as the measure of nozzle diameter and differential pressure at the closed pipe. Moreover, the calculation of overflow rate is mentioned.

Moreover, the overflow rate of proposed SMBDBNS is demonstrated in [Fig9](#). During the printing process, the overflow rate is increased based on the samples.

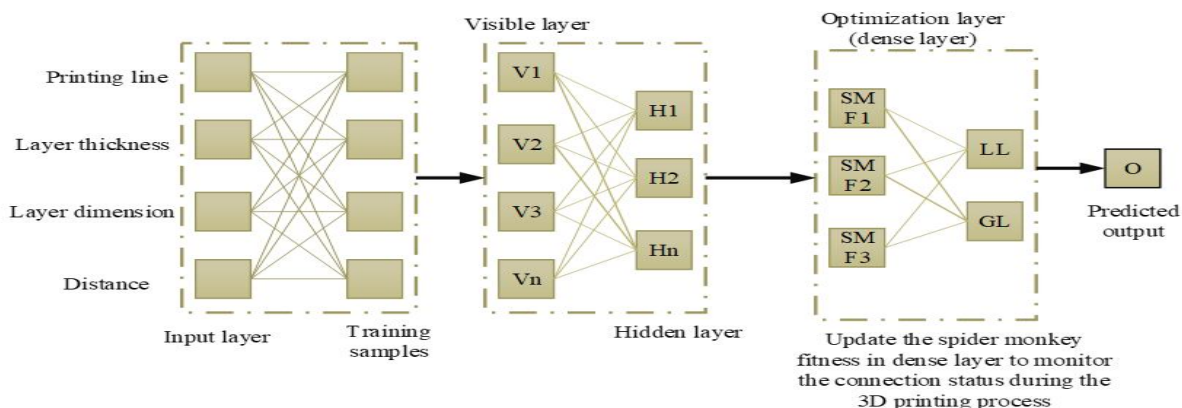


Fig10. Internal Structure of SMBDBNS

B. Tensile and Compressive strength

Tensile strength is the capacity of a material, for example, pressure to oppose disappointment under bowing pressure which can be assessed by coordinating to three- or four-points twisting elasticity test. We have found out the Tensile strength of various parameters and plotted the graph against strain value.

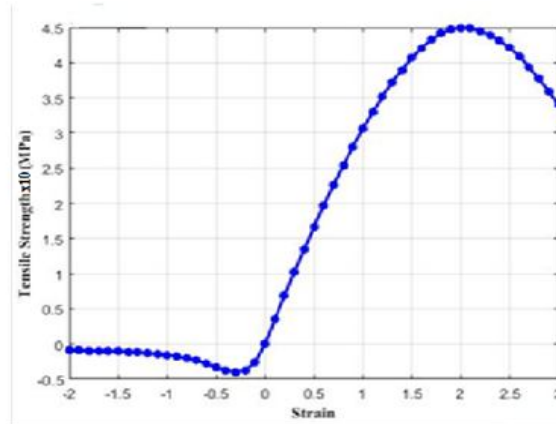


Fig11. Graph of tensile strength v/s strain.

IV. CONCLUSIONS

- A. The present study depicts the potentials of optimum process conditions inspired by natural configuration. The experiment and multi-objective optimization approach implemented to investigate the influence of process parameters.
- B. Print speed of 40mm/s and layer thickness of 0.3mm provides highest tensile and compressive strength among all selected combinations of parameters.
- C. The relationship between two selected objectives with respect to their parameters also established through SMBDBNS. The SMBDBNS can help to get maximum mechanical strength with optimized parameters. The present work can be extended to analyze mechanical properties other than analyzed with similar process conditions

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