Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Optimization of Manufacturing Parameters of PLA Components Using Taguchi and Neural Network (NN) Technique

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The present paper is based upon the study of 3d printer material Polylactic acid used in fused deposition modeling method. The sustainable and building of a biodegradable filament called polylactic acid are vastly functioning and operative in the industry. The study inspects the effect of various printing process parameters on the impact strength on printed components using PLA filament. As per ASTM standards for impact specimen D 256 is used. For evaluation of strength purpose, selected printing parameters are layer height, print speed, infill pattern and shell thickness and ANOVA technique and L27 orthogonal array is used to find the best combination of parameters yield highest impact strength. Results expose that layer thickness is one of the most significant factors, as layer thickness increases impact strength also increases.

From this study possibly will be beneficial for enhancing printing parameters to yield. The predictions of impact strength by these models are evaluated against the data generated in experimental study. Results conclude that the model generated by Neural Network to get better parameters to fit for optimizing the FDM process.
Keywords: Fused Deposition modelling, Impact Strength, Manufacturing Parameters, PLA, Neural Network.

1. Introduction

The AM process prints material by adding layer by layer, in this AM there are solid based, powder based and liquid based. In this project one of the most used solid based technique called Fused Deposition Modelling (FDM) and used biodegradable material called polylactic acid (PLA) (1). Printing parameters, which affect the part quality, mechanical properties, build time and dimensional accuracy (2). Escalating this technique to industrial applications to print the components without defects (3) and maximum mechanical properties with minimum weight and printing time (4). Most of the researchers worked on process parameters to attain good strength of printed parts, most of the cases identical parameters are selected but combination of multi parameters are differ. Here some of the researchers opted the multiple parameters like parameter air gap disturbs the tensile properties of the material based on the thick build of overlapping together. (5). Another parameter volume printed in the given component called infill percentage and it is directly influencing the properties of printed components mostly higher strength will get full volume of material deposited inside the components whereas less strength will occur at lower filling of material and also it will reflect on build time also compare to lesser volume, higher volume will take more to print part. (6) Another parameter infill pattern, deposition of layer in internal structure, in that honey comb got good mechanical properties (7). Print speed pointedly disturbs the build time and quality of the part (8). Shell thickness affects the mechanical properties of the printed part (9) and as it increases flexural strength for PLA printed parts (5) and researchers used different optimization techniques(16-17) are used like artificial neural network (10), RSM, Full factorial, genetic algorithm (11- 13) and mostly commonly used it taguchi (14-15) to optimize the number of printing parameters for improving impact strength. It is also important to be able to know the performance of parts after testing to evaluate their strength of the printed component.

Most of the researchers done on the parameters of infill, layer thickness, orientation and speed but the parameter shell thickness were not done, the most important here in this is he thickness of the outer layer thickness / perimeter of the part and it is called shell thickness by varying thickness with different ranges and also induced with infill and layer thickness simultaneously. Presently in this research finding out the impact strength of the components printed with different combination of printing process parameters and evaluate whether it is withstood or not and also print quality.

2. OBJECTIVES

- Identification of process parameters working ranges and their levels in FDM.
- Optimization of FDM process parameters for each performance measure individually using Taguchi method.
- Experimental investigation of process parameter effects on output responses like Impact strength.
- Prediction of optimal process parameters setting for performance measures simultaneously.

3. DESIGN & EXPERIMENTATION

The Taguchi method is used to improve the quality of products and processes. Improved quality results when a higher level of performance is consistently obtained. The highest possible performance is obtained by determining the optimum combination of design factors. In this project, there is a total of 4 parameters. They are shell thickness, Infill %, layer thickness and infill pattern. And for layer thickness and shell thickness consider of 3 values. They are one low value, intermediate value and high value. So, there are 2 factors and 3 level and other parameters are constant. as shown in table 1.

Table:1 Manufacturing Parameters

Printing Parameters	Levels		
	1	2	3
Layer Thickness	0.1mm	0.2mm	0.3mm
Shell Thickness	4	6	8
Infill Percentage	100%		
Infill Pattern	Line		
Print Speed	60 mm/sec		

As per ASTM standards impact Specimens are modelled by using Creo 7.0 software then by using slicing software Ultimaker Cura 5.5.0, mainly the software is used to select printing parameters later to get G-Code file which is used to direct the 3d printer machine, later stored in external disk, by fixing disk to transfer to 3d printer machine Pratham 5.0 to print specimens according to the sequence of direction in the G-Code.

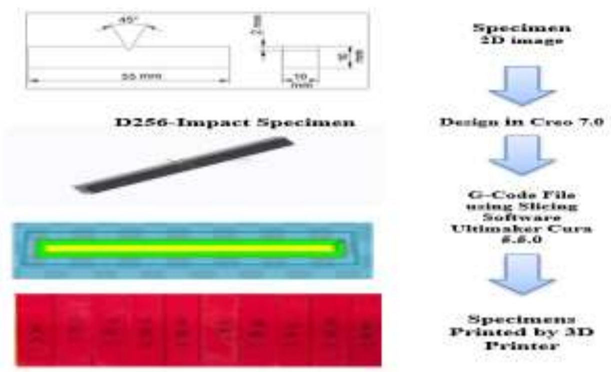

Figure :1 Process of Printing

4. RESULTS

After fabricating all components then tested on impact machine to find the impact strength and the results are given below.

Table:2 Results of Impact Strength

S. No	Layer Thickness (mm)	Shell Thickness (count)	Impact Strength	Impact Prediction	Error	Tag	Strength/ Weak
1	0.1	4	14.69	19.24	-4.5	Train	
2	0.1	4	19.25	19.24	0.0	Validation	
3	0.1	4	23.79	19.24	4.6	Train	
4	0.1	6	14.57	23.85	-9.3	Validation	
5	0.1	6	20.41	23.85	-3.4	Test	Good
6	0.1	6	23.85	23.85	0.0	Train	
7	0.1	8	20.2	21.73	-1.5	Train	
8	0.1	8	20.14	21.73	-1.6	Train	
9	0.1	8	24.85	21.73	3.1	Train	
10	0.2	4	14.74	19.59	-4.9	Train	
11	0.2	4	20.39	19.59	0.8	Validation	
12	0.2	4	24.44	19.59	4.8	Train	
13	0.2	6	20.12	22.12	-2.0	Train	
14	0.2	6	20.27	22.12	-1.9	Test	Good
15	0.2	6	24.13	22.12	2.0	Train	
16	0.2	8	20.16	22.65	-2.5	Test	Good
17	0.2	8	20.39	22.65	-2.3	Train	
18	0.2	8	24.9	22.65	2.3	Train	
19	0.3	4	20.66	23.11	-2.5	Train	
20	0.3	4	19.63	23.11	-3.5	Train	
21	0.3	4	29.05	23.11	5.9	Train	
22	0.3	6	24.93	24.93	0.0	Train	
23	0.3	6	24.7	24.93	-0.2	Test	Good
24	0.3	6	29.15	24.93	4.2	Validation	
25	0.3	8	20.85	24.90	-4.1	Train	
26	0.3	8	24.25	24.90	-0.7	Train	
27	0.3	8	29.61	24.90	4.7	Train	

From table 2 impact strength results got high for high Shell thickness 8- and lower-layer thickness and shell thickness of 0.3mm and 4count. Similarly got low strength for Shell thickness 4, low layer thickness and shell thickness of 0.1 microns and 4.

Comparing results, Shell thickness 8, 0.3mm layer thickness and 100% infill got is prominent parameter impact strength.

Table:3 ANOVA for Impact Strength (I)

Source	DF	SS	MS	F-Val	P-Val	
Model	2	64.29	32.143	3.81	0.036	Significant
LH	1	49.63	49.634	5.89	0.023	Significant
ST	1	14.65	14.652	1.74	0.200	Not Significant
residual	24	202.36	8.432			
Total	26	266.64				

In day-to-day problems most of the complicated problems are involving intelligence recognition is used to find out solution here in this to automate opted neural network. Some important specifications of parameters that are frequently required throughout the modeling process. Form the above ANOVA Table3. it can be observed that the Model F-value of 3.81

implies the model is significant. P-values less than 0.05 indicate model terms are significant. In this case layer height is significant model terms. The predicted model is given as:

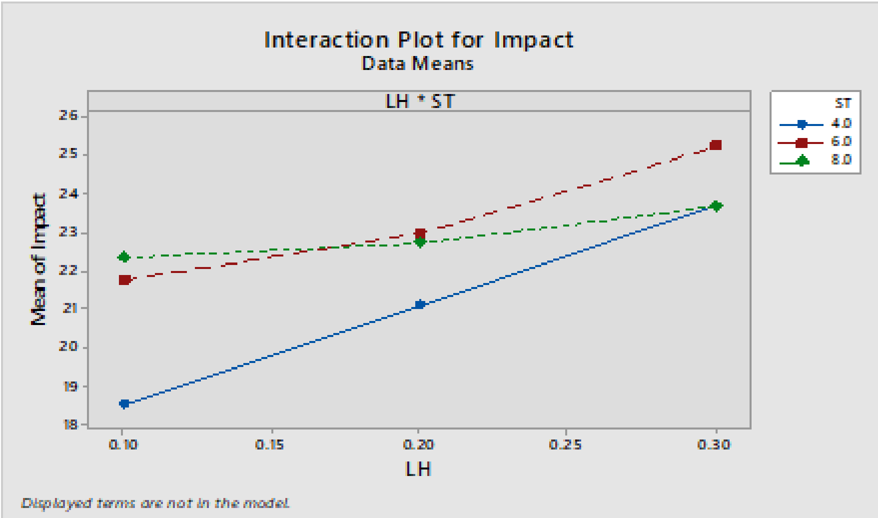

Figure: 2 Interaction plots for Impact

Impact = 16.42 + 16.61 LH + 0.451 ST

In this interaction plot, the lines are not parallel. This interaction effect indicates that the relationship between Layer height and strength depends on the value of shell thickness. from the graph layer thickness 0.3mm & shell thickness 6 is associated with the highest mean strength. However, if you use layer thickness 0.1, shell thickness 8 is associated with the highest mean strength.

The general linear model results indicate that the interaction between layer thickness and shell thickness is significant.

Table 3 Parameters used in NN Modelling

S. No.	Parameter	Data	Technique
1	No. of Inputs	2	
2	No. of Outputs	1	
3	Proportion of training, validation & testing data (%)	70:15:15	
4	Data normalization	0.05 - 0.95	Min-max data normalization technique
5	Transfer function	0 &1	Levenberg-Marquardt backpropagation function (for both hidden & output layer)
6	Mode of training		Batch mode

Experimental results were used to develop an NN model for predicting Impact strength. In this, two inputs and one output are considered as the data of NN model with two numeric input variables shell thickness, layer thickness and the output variables Tensile and Impact. A total of 27 experimental data is taken for neural network modeling, out of which 70% is trained for the, 15% has been validated and remaining network 15% has been tested. The summary of the network table 3.

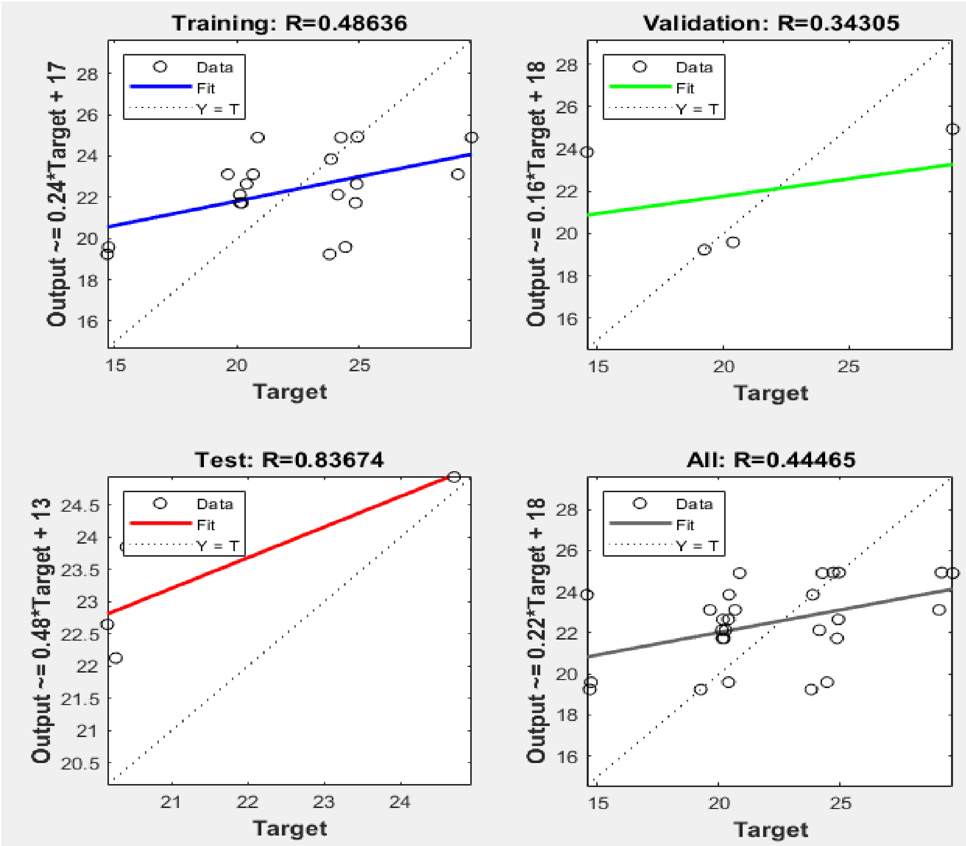

Figure 3. Correlation factors for the network

Table 4 Training and Testing Information

Name	Trained on Impact
Configuration	NN Numeric Predictor
Category variable	1 PT
Numeric variable	2 (ST, LH)
Response Variable	I
Training	
No. of Cases	19
Training Time	0.000
Number of Trials	96
Validation	
No. of Cases	4
Testing	
No. of Cases	4
Data Set	
Name	Impact
No. of Rows	27
Manual Case	No
R-Square Training	0.486
R-Square Validation	0.343
R-Square Testing	0.836

From Table 4 among all 27 cases only seven experiments in the design matrix were first tested at random for prediction using the network model and confirmation tests were performed for testing the significance of the model. Regression plots for the mean square error for trained, validated, test values and overall regression plot is shown in the figure 6. The R values of >0.1 for all trained, validated, test and overall experimental runs prove the model validity as shown in fig 3.

5. CONCLUSION

- PLA printed specimen mechanical properties were tested. For impact testing, it was experimentally determined that layer thickness and shell thickness specimen were observed to be strongest.
- From the response surface analysis, maximum impact strengths can be obtained when the component or specimen is printed at layer thickness is significant as $P<0.05$.
- It is also evident that layer thickness and shell thickness are feasible for 3D printing with satisfactory output.
- By neural network NN Model have been validated with R2 >0.1 and errors in all responses were found that <= 10% from this it concludes that models that are settled much effective and can predict the experimental responses with in the production range.

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