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ARTIFICIAL MODEL FOR PREDICTION OF FLEXURAL STRENGTH OF A PLA PROTOTYPE PRINTED

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Abstract- The research of mechanical properties of 3D printed parts is a primary objective for most researchers since experimental studies still test samples to characterize these mechanical properties and deformations on printed prototypes. The process control of additive manufacturing, especially the mechanical properties of the printed parts is so difficult because of a large number of parameters that influence these properties. As such, the combination of these parameters makes the process expensive. That is why previous investigations that deal with the same subject are limited in their study to some parameters. The objective of this study is to take advantage of the performance of artificial intelligence tools and build artificial models that can take advantage of some experimental results in order to predict the desired property (flexural strength).

Keywords: Artificial Intelligence, Neural Network, Additive Manufacturing, 3D printing, Flexural Strength.

1. INTRODUCTION

The process of additive manufacturing, otherwise known as 3D printing, is still a new sector that has undergone a rapid evolution due to an accelerated development of computer means, including information analysis techniques. The sector of additive manufacturing, which offers a number of possibilities, advantages, and complexity of products, has attracted the attention of more researchers especially in the industrial fields. Also, the quality of the printed parts, namely the mechanical properties and its deformations under various requests, depends on a lot of process parameters.

Artificial intelligence tools, thanks to their flexibility and performance, have been found in several sectors [1], [2, 3], and their qualities can be an effective means to develop artificial models that take into consideration the maximum number of process parameters and that give an optimum relationship between many parameters and the desired property.

Collection research has been carried out on a set of experimental studies. The collection of reliable information is mandatory to create a data base that can be used in the training of artificial models. The results of the different studies have been elaborated with different parameters, such as: Temperature and Infill density [4]; Printing temperature, Orientation and Layer thickness [5]; Layer Thickness, Feed rate, Build orientation [14]; Printing temperature, Layer thickness, Printing speed [15], Layer Thickness, Infill speed, Nozzle temperature [16]; Layer Thickness and Infill Pattern [17]; Raster direction, Layer Thickness, Build Orientation [18]; infill density and infill speed [19].

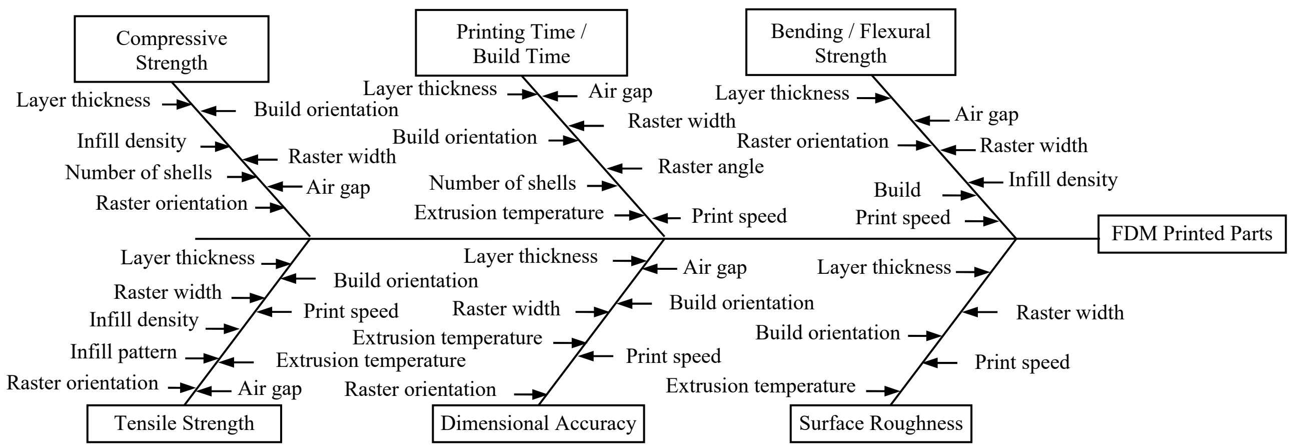


Figure 1. Cause and effect diagram [6]

2. FDM PROCESS PARAMETERS

The set of causes affecting in general the properties of the printed prototypes [6] are shown in Figure 1. Table 1 indicates a set of studies that were interested in the study of the materials and that have carried out experiments on the PLA, used in the process FDM.

Table 1. Summary of research that addresses experiments with 3D printed parts

Ref	Author/s (year)	Material/s	Testing Technique/s
[8]	A. Kaptan, F. Kartal (2020)	PLA	Tensile- flexural
[9]	Tian, et al. (2016)	PLA and Carbon fibre	Flexural and SEM
[10]	H. Gonabadi, A. Yadav, S.J. Bull (2020)	PLA	Tensile
[11]	Li, et al. (2016)	PLA and Carbon Fibre	Tensile, Flexural, DMA, SEM
[12]	G. Cwikla, C. Grabowik, K. Kalinowski, I. Paprocka, P. Ociepka	PLA	Tensile
[14]	J.M. Chacon, M.A. Caminero, E. Garcia-Plaza, P.J. Nunez (2017)	PLA	Tensile and Flexural
[20]	Harpool (2016)	PLA	Tensile
[21]	Alafaghani, et al. (2017)	PLA	Tensile
[22]	Behzadnasab and Yousefi (2016)	PLA	Tensile and Rheological
[23]	M.R. Ayatollahi, A. Nabavi-Kivi, B. Bahrami, M. Yazid Yahya, M.R. Khosravani (2020)	PLA	Tensile

The marketing of PLA materials, respect the values of the mechanical properties represented in Table 2. The process parameters in addition to the feed rate, directly influence the properties of the print prototype Figure 2.

The data shown in Table 3 are the results of a series of experiments conducted with the aim of measuring the flexural strength of PLA prototypes. The experiments follow the methods ASTM D638.The variables of experience are the speed of advance (F_r), the layer thickness (L_t), and the temperature of the printing nozzle maintained at T = 210 °C. The study of these results in ref. [14] has given regression models shown in Table 4.

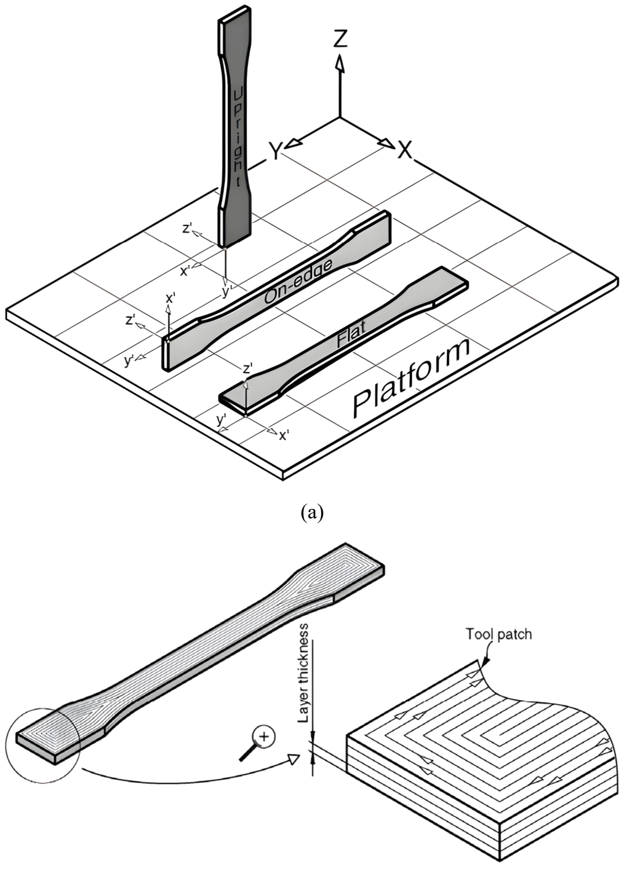
3. ARTIFICIAL NEURAL NETWORK MODELLING

The artificial neural network model is applied to predict the flexural strength in an ideal way. The training is carried out on the basis of the collected experimental data. The parameters that are taken into account are the feed rate and layer thickness. Figure 3 represents the artificial neural network diagram.

For the Upright orientation, the choice of neural network parameters is shown in Table 5, a series of iterations showed the impact of each parameter on the MSE (Mean Squared Error) network performance.

From the MSE values of these iterations, we notice that reduced MSE of 6.36×10^{-14} is obtained at iteration number 9 with the following parameters:

- Learning algorithm LM: Levenberg-Marquardt
- Hidden layer activation function: Logsig
- Number of neurons: 10
- Output layer activation function: Purelin



(a)

(b)

Figure 2. Process parameters, (a) Build orientation, (b) Layer thickness [14]

Table 2. Typical ranges of mechanical properties for PLA materials [13]

Properties	PLA
Tensile Strength (MPa)	15.5-72.2
Tensile Modulus (GPa)	2.020-3.550
Elongation at Break (%)	0.5-9.2
Flexural Strength (MPa)	52-115.1
Flexural Modulus (GPa)	2.392-4.930

Table 3. Flexural test results of the samples and process parameter ranges [14]

Build Orientation		Flexural strength F_r=20 mm/s σ_t (MPa)	Flexural strength F_r=50 mm/s σ_t (MPa)	Flexural strength F_r=80 mm/s σ_t (MPa)
L_t=0.06 mm	Upright	25.1	15.4	14.3
	On-edge	53.0	52.8	65.0
	Flat	53.0	55.3	56.0
L_t=0.12 mm	Upright	34.5	32.2	23.8
	On-edge	64.8	64.2	61.3
	Flat	51.4	47.0	49.0
L_t=0.18 mm	Upright	29.8	29.9	19.4
	On-edge	62.9	62.0	61.0
	Flat	51.4	53.4	51.4
L_t=0.24 mm	Upright	32.4	31.0	28.4
	On-edge	61.1	61.7	64.2
	Flat	46.3	46.0	46.2

Table 4. Regression models for construction orientations in bending strength tests [14]

Orientation		Optimum Model
Flexural Strength	Upright	$F_s = 394.365L_t - 1084.36L_t \times L_t - 0.00129941F_r \times F_r$
	On Edge	$F_s = 622.043L_t + 0.538345F_r - 2.85053L_t \times F_r - 1429.2L_t \times L_t$
	Flat	$F_s = 548.51L_t + 0.516918F_r - 1365.74L_t \times L_t - 2.88973L_t \times F_r$

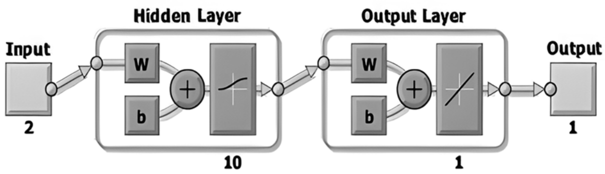


Figure 3. The neural network diagrams

Table 5. The choice of neural network parameters

No.	Algorithm	Hidden layer activation function	Number of neurons	Output layer activation function	MSE
1	LM	logsig	20	logsig	4.23
2	LM	logsig	20	tansig	1.16×10^{-11}
3	LM	logsig	20	purelin	3.39×10^{-6}
4	LM	logsig	15	logsig	0.6
5	LM	logsig	15	tansig	9.09×10^{-12}
6	LM	logsig	15	purelin	1.71×10^{-11}
7	LM	logsig	10	logsig	0.6
8	LM	logsig	10	tansig	5.44×10^{-13}
9	LM	logsig	10	purelin	6.36×10^{-14}
10	LM	tansig	20	logsig	9.14×10^{-2}
11	LM	tansig	20	tansig	0.49
12	LM	tansig	20	purelin	6.55×10^{-2}
13	LM	tansig	15	logsig	7.05×10^{-2}
14	LM	tansig	15	tansig	0.36
15	LM	tansig	15	purelin	3.3×10^{-2}
16	LM	tansig	10	logsig	6.81×10^{-2}
17	LM	tansig	10	tansig	0.21
18	LM	tansig	10	purelin	1.07×10^{-3}
19	LM	purelin	20	logsig	41.2
20	LM	purelin	20	tansig	31.9
21	LM	purelin	20	purelin	26.2
22	LM	purelin	15	logsig	29.9
23	LM	purelin	15	tansig	23.6
24	LM	purelin	15	purelin	18.3
25	LM	purelin	10	logsig	20.8
26	LM	purelin	10	tansig	13.7
27	LM	purelin	10	Purelin	10.5
28	BR	logsig	20	logsig	5.66×10^{-3}
29	BR	logsig	20	tansig	5.87×10^{-2}
30	BR	logsig	20	purelin	7.21×10^{-3}
31	BR	logsig	15	logsig	5.04×10^{-3}
32	BR	logsig	15	tansig	5.54×10^{-2}
33	BR	logsig	15	purelin	7.45×10^{-3}
34	BR	logsig	10	logsig	4.57×10^{-3}
35	BR	logsig	10	tansig	5.13×10^{-2}
36	BR	logsig	10	purelin	8.61×10^{-3}
37	BR	tansig	20	logsig	0.1
38	BR	tansig	20	tansig	0.11
39	BR	tansig	20	purelin	0.023
40	BR	tansig	15	logsig	0.12
41	BR	tansig	15	tansig	0.18
42	BR	tansig	15	purelin	0.037
43	BR	tansig	10	logsig	0.14
44	BR	tansig	10	tansig	0.19
45	BR	tansig	10	purelin	0.056
46	BR	Purelin	20	logsig	40.3
47	BR	Purelin	20	tansig	33.9
48	BR	Purelin	20	purelin	21.7
49	BR	Purelin	15	logsig	45.1
50	BR	Purelin	15	tansig	39.8
51	BR	Purelin	15	purelin	25.6
52	BR	Purelin	10	logsig	53.4
53	BR	Purelin	10	tansig	42.8
54	BR	purelin	10	purelin	28.3
55	GD	logsig	20	logsig	5.9×10^{-2}
56	GD	logsig	20	tansig	6.26×10^{-1}
57	GD	logsig	20	purelin	3.01×10^{-3}
58	GD	logsig	15	logsig	5.66×10^{-2}
59	GD	logsig	15	tansig	5.88×10^{-1}
60	GD	logsig	15	purelin	2.59×10^{-3}
61	GD	logsig	10	logsig	5.41×10^{-2}
62	GD	logsig	10	tansig	5.1×10^{-1}
63	GD	logsig	10	purelin	2.33×10^{-3}
64	GD	tansig	20	logsig	0.0077
65	GD	tansig	20	tansig	0.092
66	GD	tansig	20	purelin	0.035
67	GD	tansig	15	logsig	0.0038
68	GD	tansig	15	tansig	0.079
69	GD	tansig	15	purelin	0.029
70	GD	tansig	10	logsig	0.0023
71	GD	tansig	10	tansig	0.056
72	GD	tansig	10	purelin	0.02
73	GD	Purelin	20	logsig	82.3
74	GD	Purelin	20	tansig	73.4
75	GD	Purelin	20	purelin	33.9
76	GD	Purelin	15	logsig	74.3
77	GD	Purelin	15	tansig	52.9
78	GD	Purelin	15	purelin	29.4
79	GD	Purelin	10	logsig	58.2
80	GD	Purelin	10	tansig	45.7
81	GD	purelin	10	purelin	23.5

The constructed model is trained from the results of experiments with 70% of the data while the validation is done with 30% of the data. Finally, the test is carried out with also 30% of the data. The best regressions of training and validation with the best correlation coefficient are represented in Figure 5, Figure 7, Figure 9 for each orientation. The artificial model with neural network succeeded in predicting an improved way the resistance to flexural. The output of network reduced the error between the predicted values and the values of experiments compared with the experimental model.

4. RESULTS AND DISCUSSION

The results calculated by the network are shown. The artificial neural network models show a very high power to predict the flexural from the test results. As depicted output predicted by the network is well consistent with the experimental results, but the deviation from the experimental model is very small. As shown in Figure 4, for upright orientation the output predicted by the network is well consistent with the experimental results.

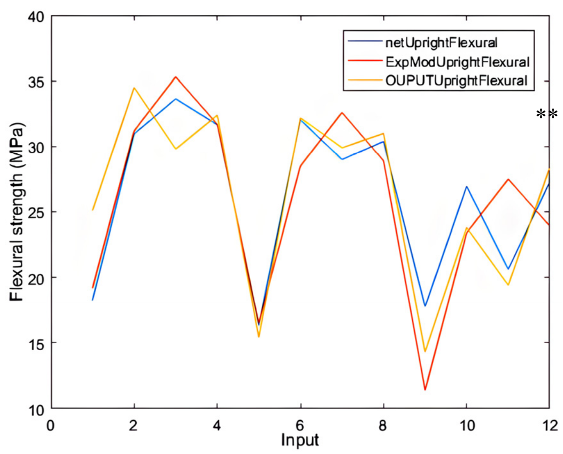


Figure 4. Comparative graphs of target and output values of bending strength for upright orientation

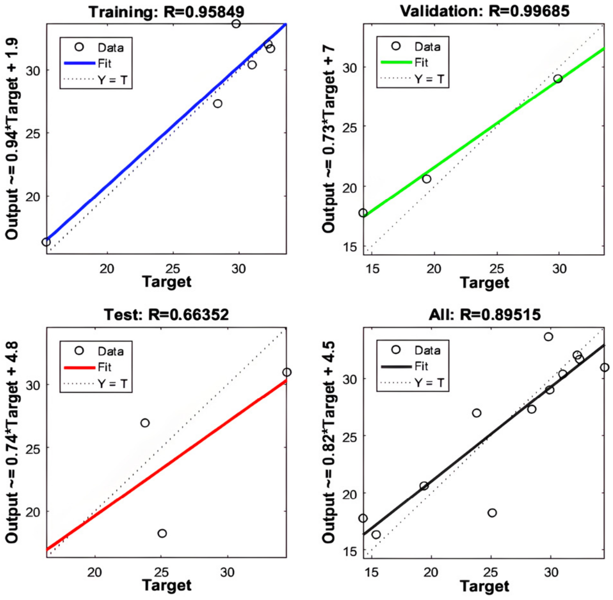


Figure 5. Plot regression for upright orientation

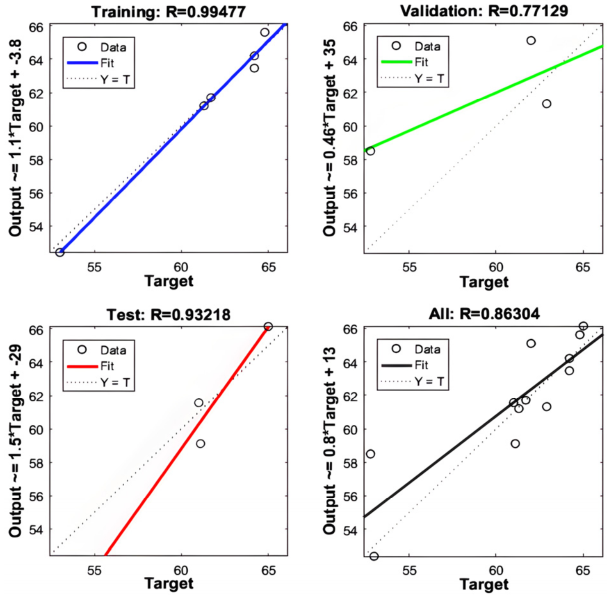


Figure 8. Plot regression for on edge orientation.

Similarly, for on edge orientation Figure 6, the predicted output is always much closer to the experimental values when compared with the results calculated by the experimental regression model.

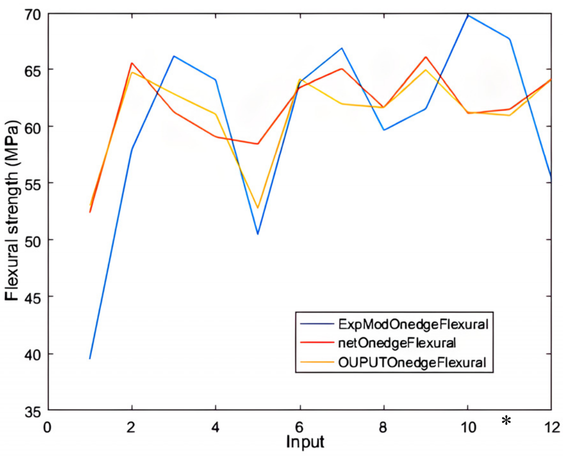


Figure 6. Comparative graphs of target and output values of bending strength for on edge orientation

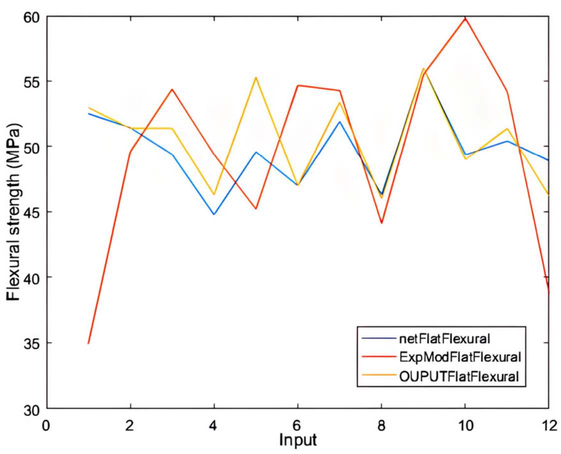


Figure 7. Comparative graphs of target and output values of bending strength for Flat orientation

Finally, for Flat orientation Figure 7, always the bending strength predicted by the network is even more improved and closer to the experimental results. The correlation coefficient plot in Figures 5, 8 and 9 for each orientation, represents the best coefficients found after a series of iterations.

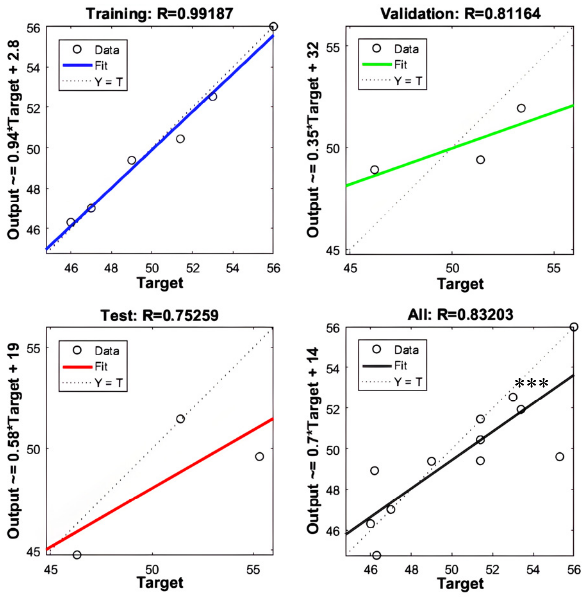


Figure 9. Plot regression for Flat orientation

5. CONCLUSIONS

This contribution is first a preliminary study with the aim of collecting maximum experimental results by working on the same materials with the same standard of test. One knows well that the applications of artificial intelligence are based on the availability of the data which are costly; hence the importance of this first step. Second, given that the large number of experiments are expensive, it is essential to take advantage of artificial intelligence tools (ANN) and exploit these limited data.

The goal is to build a model ANN performance by choosing its parameters, the subject of this study, so we made 81 iterations to choose the optimal parameters of our model ANN.

The difficulty in general in the applications of artificial intelligence is the collection of training data. To have efficient ANN models, it is necessary to have a large number of data, which is not always possible. The second difficulty is to have correct data or normative data. The third difficulty is when we have applications with a large number of parameters. In this case, the combination between these parameters becomes so difficult.

NOMENCLATURES

1. Acronyms

FDM Fused Deposition Modeling
Learning algorithm:
LM Levenberg-Marquardt
BR Bayesian Regularization
GD Gradient Descent
Activation function:
Log logsig
Tan tansig
Pure purelin

2. Parameters

* Upright Orientation
ExpModUprightFlexural: Regression model of flexural
NetUprightFlexural: The values calculated by the neural network model of flexural
OUPUTUprightFlexural: Actual values measured by flexural experiment
**Onedge Orientation
ExpModOnedgeFlexural: Regression model of flexural
NetOnedgeFlexural: The values calculated by the neural network model of flexural
OUPUTOnedgeFlexural: Actual values measured by flexural experiment
***Flat Orientation
ExpModFlatFlexural: Regression model of flexural
NetFlatFlexural: The values calculated by the neural network model of flexural
OUPUTFlatFlexural: Actual values measured by flexural experiment

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BIOGRAPHIES

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