Indian Journal of Pure & Applied Physics
Vol. 59, March 2021, pp. 244-251

Parametric Influence of Process Parameters on the Wear Rate of 3D Printed Polylactic Acid Specimens

Manohar Singh [a,b *] & Pushpendra S Bharti [a]

[a] U S I C T, Guru Gobind Singh Indraprastha University, Delhi -110 078, India
[b] Galgotias College of Engineering & Technology, UP-201 310, India

Received 27 January 2021; accepted 17 February 2021

Fused deposition modeling (FDM) is a 3D printing technique that prints thermoplastic layer by layer. Various parameters affect the properties of the final printed object. The exact identification of variation in the properties of the printed object is still a very popular issue among the researchers. In the present work, an effort has been made to identify the parametric influence of layer thickness, infill density, print speed and extruder temperature on the wear behavior of the printed specimens. The specimens of polylactic acid (PLA) have been printed using Fused Deposition Modeling (FDM). The combinations of input parameters during the fabrication have been considered as per the Taguchi L16 Orthogonal Array. Moreover, to identify the parametric influence on wear, mathematical modeling has been done using regression and artificial neural networks. The results show that the average percentage variation in predicted experimental values for regression and ANN models are, 5.04% and 1.94%, respectively. Moreover, for minimum wear layer thickness should be kept between 0.28- 0.34mm. Similarly, infill density, print speed, and extruder temperature should be between 70-72, 125-175mm/s and 195-202 degree, respectively.

Keywords: Additive manufacturing (AM), Fused deposition modeling (FDM), Artificial neural network (ANN)

1 Introduction

Traditional manufacturing processes are subtractive manufacturing *i.e*. the final object is formed by material removal. This wastage of material lead to birth of Additive manufacturing wherein final object is prepared by addition of material. One of the popular forms of additive manufacturing is 3D printing where material is printed in 2D and then such successive layers are printed over previous one to obtain the desired dimension or design. This wonderful technique of producing 3D objects by stereo lithography, with minimum wastage, was filed for patent in 1986 by Charles W.Hull[1]. Since then, various methods and printable materials have been developed in the field of 3D printing.

FDM based 3D printer was selected for preparing the specimen owing to its low cost, high speed, good strength and its ability to be used with both acrylonitrile butadienestyrene (ABS) and polylactic acid (PLA). The process was filed for patent in 1989 by S. Scott Crump[2]. In FDM, heated filament is extruded through the nozzle towards the platform layer by layer.

Polymers used in FDM exhibit thermo plasticity due to which layers join together while printing and then solidify as a single object. Various researchers have studied the effect of process parameters on mechanical properties. The parameter studied were layer thickness, air gap, Raster angle, build orientation, road width, number of contours[3,4] and fibre orientation[5] for wear behavior of ABS specimens[3,6], printed using FDM. The study suggested that wear rate increases with increase in layer thickness and orientation while it decreased with increase in raster angle and air gap. The coefficient of friction was observed to be more for fibres oriented[6] at 90°. Definitive screening design[4] was applied to study the effect of six parameters on specific wear rate on specimens printed with PCABS (Polycarbonate-Acrylonitrile Butadiene Styrene).

Norani *et al*.[6] found that the impact of layer height is the most significant factor followed by Nozzle temperature and pattern on wear behavior of specimens printed with ABS. Further efforts were made to compare the effect of process parameters on wear behavior of 3D printed specimen with composite fibres and ABS. Composite fibres studied include Nylon 6-Al-Al_2O_3[7], CFPLA[8], Nylon6 with Si C and Al_2O_3[9]. Samples with the lowest layer thickness and highest infill density provided better results for wear resistance[9] and wear resistance of composite material was more[7,8,9].

*Corresponding Author (Email: manoharmnr@gmail.com)

Singh *et al.*[10] developed wear resistant hybrid filament consisting of Nylon matrix and Al_2O_3 powder for grinding purpose. Hanon *et al.*[11] studied the effect of orientation on mechanical properties and found highest friction in vertically oriented specimens but wear depth was lowest. Amiruddin *et al.*[12] studied the tribological behavior of ABS specimen printed using FDM. The wear rate increased with increase in load but decreased at higher load.

Proposed Methodology

The proposed methodology has been divided into four phases. In the first phase, the selection of process parameters, machine, and material has been done. Thereafter, the design of the experiment has been developed in the second phase. The third phase is dedicated to the fabrication of specimens, followed by the post-processing and measurement of wear. In the last phase, the analysis of the data has been done. In this phase mathematical models have been generated using regression and artificial neural network techniques. The experimental data has been used for developing these mathematical models. The developed mathematical models have been verified by measuring the average percentage deviation between the experimental and predicted values. The most suitable model among the two models has been further analyzed in order to identify the range of process parameters at which the wear is minimum.

2 Material & Methods

In order to fabricate 3D printed wear specimens, dimensions were taken as per ASTM G99 standards[13]. First of all the specimen has been modelled in Solid works software which has been converted to .stl (Stereolithography) file format, there after transferred to the 3D printer for slicing and triangulation. The printing of specimens has been done on Flash forge Dreamer NX printer. The input parameters selected are layer thickness, infill density, print speed, and extruder temperature. The levels of input parameters have been mentioned in Table 1.

The design of experiment based on L16 Orthogonal array has been used for the fabrication of the specimens as shown in Table 2. Total 16 different samples have been fabricated considering the repetition rate as 3 per sample.

Fabrication and Testing

The fabrication of the specimens has been done as per the design of experiments shown in Table 2. Each specimen has been fabricated thrice in order to avoid any chance of error and variation in the properties of the material while testing. The testing of the

Table 1 — Printer Parameters with Various Levels

Printer Parameters	Symbol	Level 1	Level 2	Level 3	Level 4
Layer Thickness (mm)	A	0.20	0.25	0.30	0.35
Print Speed (mm/sec)	B	50	100	150	200
Infill Density (%)	C	70	80	90	100
Extruder Temperature (degree)	D	190	200	210	220

Table 2 — L16 Orthogonal array based on Taguchi Design of Experiment

Specimen No.	LayerThickness (mm) 'A'	Print Speed (mm/sec) 'B'	Infill Density (%) 'C'	Extruder Temperature (degree) 'D'
1	0.20	50	70	190
2	0.20	100	80	200
3	0.20	150	90	210
4	0.20	200	100	220
5	0.25	50	80	210
6	0.25	100	70	220
7	0.25	150	100	190
8	0.25	200	90	200
9	0.30	50	90	220
10	0.30	100	100	210
11	0.30	150	70	200
12	0.30	200	80	190
13	0.35	50	100	200
14	0.35	100	90	190
15	0.35	150	80	220
16	0.35	200	70	210

specimens has been done using a pin on disk machine, generally used for measuring the wear. A pin on disc machine is used to conduct wear test of the specimens by loading a pin (specimen) against a rotating disc (Disc material EN-31 steel) as per ASTM G99 standard. Initially the track diameter was set as 70 mm and a load of 5Kg has been applied on the pin. The timer was set for 50 minutes and RPM as 150. All the data like wear, time, friction *etc*. has been recorded.

Each specimen has been weighed before and after the test on a digital weighing machine with accuracy up to four decimal places. Thereafter the wear rate and specific wear rate of the specimens have been calculated using the following relations;

$$\Delta w = w_1 - w_2 \quad \ldots (1)$$

where,
Δw = Total weight loss,
w_1 = Weight of the specimen before Testing,
w_2 = Weight of the specimen after Testing

$$\Delta V = \frac{\Delta w \times 1000}{\rho} \quad \ldots (2)$$

Where, ΔV= Volume loss, ρ = Density of the specimen

$$\Delta w = \Delta V / s \quad \ldots (3)$$

where, w is the wear rate, s is the sliding distance

$$SWR = w / f \quad \ldots (4)$$

where, $SWR =$ Specific Wear Rate, f is the applied load

The obtained values of the wear rate for all the 48 tests have been noted and the average value of repeated test has been calculated. Table 3 shows the average value of wear rate for 16 different samples.

Mathematical Modelling

In order to visualize the variation in response with the change in input parameters and to predict the variation, mathematical models have been generated using regression analysis as well as artificial neural network. The models generated by the two methods are then compared in order to identify the best model. For the comparison between the models, the efficiency of the model in predicting the output has been evaluated as mentioned in the ensuing sections.

Regression Modelling

A lot of researchers have used regression modeling in order to develop relation between the input and output[14-16]. In the present work the regression analysis has been done using the MINITAB17 software. During the analysis the correction factor has been kept at 95. The generated model and the associated ANOVA have been shown in Eq. 5 and Table 4. Moreover, the R-sq value obtained is 78.01%. From the ANOVA table, it is very clear that the regression model is significant as the P value of the model is less than 0.05. Also, the P values of input parameter layer thickness (A) and infill density (C) are lower than 0.05, which means that both layer thickness and infill density are more significant than that of other input parameters. Figure 1 represents the normal probability plot for the regression analysis. From the figure it has

Table 3 — Test results of all specimens

Specimen No.	Layer Thickness (mm)	Print Speed (mm/sec)	Infill Density (%)	Extruder Temperature (degree)	Wear Rate($\times 10^{-2}$) mm^3/m
1	0.20	50	70	190	1.7211
2	0.20	100	80	200	1.8340
3	0.20	150	90	210	1.8370
4	0.20	200	100	220	2.3380
5	0.25	50	80	210	1.5750
6	0.25	100	70	220	1.6380
7	0.25	150	100	190	1.8830
8	0.25	200	90	200	1.7410
9	0.30	50	90	220	1.8680
10	0.30	100	100	210	1.8780
11	0.30	150	70	200	1.3870
12	0.30	200	80	190	1.5990
13	0.35	50	100	200	1.8190
14	0.35	100	90	190	1.4820
15	0.35	150	80	220	1.5800
16	0.35	200	70	210	1.6240

Table 4 — Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	0.566349	0.141587	9.76	0.001
A	1	0.178633	0.178633	12.31	0.005
B	1	0.008236	0.008236	0.57	0.467
C	1	0.310466	0.310466	21.39	0.001
D	1	0.069014	0.069014	4.76	0.052
Error	11	0.159635	0.014512		
Total	15	0.725984			

Table 5 — Predicted values and percentage deviation

S. no.	A	B	C	D	Experimental values	Predicted values	% Deviation
1	0.20	50	70	190	1.7211	1.5738	8.558
2	0.20	100	80	200	1.8340	1.7774	3.086
3	0.20	150	90	210	1.8370	1.9810	7.839
4	0.20	200	100	220	2.3380	2.1846	6.561
5	0.25	50	80	210	1.5750	1.7213	9.289
6	0.25	100	70	220	1.6380	1.6757	2.302
7	0.25	150	100	190	1.8830	1.8937	0.568
8	0.25	200	90	200	1.7410	1.8481	6.152
9	0.30	50	90	220	1.8680	1.8101	3.100
10	0.30	100	100	210	1.8780	1.8963	0.974
11	0.30	150	70	200	1.3870	1.4841	7.001
12	0.30	200	80	190	1.5990	1.5703	1.795
13	0.35	50	100	200	1.8190	1.7228	5.289
14	0.35	100	90	190	1.4820	1.5598	5.250
15	0.35	150	80	220	1.5800	1.6316	3.266
16	0.35	200	70	210	1.6240	1.4686	9.569
Average percentage deviation							5.04%

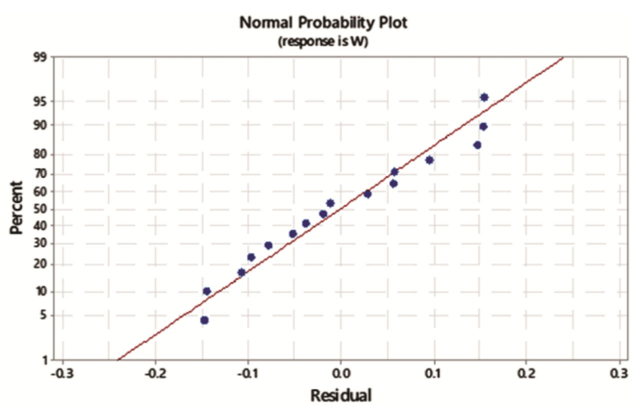

Fig. 1 — Normal Probability Plot

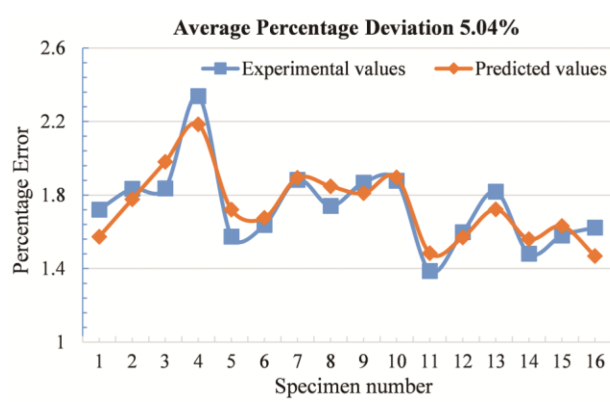

Fig. 2 — Experimental versus Predicted values for regression Model

been perceived that the data is normally distributed over the range. However, the R-sq value is a bit low *i.e.* 78.01%, which suggest that the model might not predict the variation accurately. In order to verify the same, the percentage deviation between the predicted and experimental values have been calculated. Table 5 represents the predicted versus experimental data.

$$W = -0.056 - 1.890\times A + 0.000406\times B + 0.01246\times C + 0.00587\times D \quad \ldots (5)$$

For calculating the deviation between the experimental and predicted values following relation has been used:

$$percent\ deviation = \frac{experimental\text{-}predicted}{experimental}\times 100 \quad \ldots (6)$$

From Table 5, it has been found that the average percent deviation between the predicted and experimental values is 5.04 %. For visualizing the variation more precisely a plot has been drawn between the experimental and predicted values as shown in Fig. 2.

Artificial Neural Network (ANN) modelling

ANN is based on functioning of human brain consisting of layers of interconnected neurons that map input and output. A lot of researchers have adopted ANN for generating relation between input and output parameters[17-19]. First of all, a neural network consisting of interconnected layers of neurons has been constructed[15]. The input is processed by assigning weights and biases to the neurons and the connections. The architecture of the ANN has been shown in Fig. 3. The architecture consists of input layer with 4 input neurons viz. A, B, C and D. One hidden layer having 3 neurons viz. X, Y and Z. Output layer with one neuron *i.e.* W. After defining the architecture, the feed-forward back proportion technique has been used for training and testing the data. The activation function selected is TANSIG. The training and testing of data has been done in ratio of 80:20, respectively.

The weights and biases obtained between input layer and hidden layer have been shown in Table 6. The weights and biases between hidden layer are X_w = -0.47992, Y_w = -1.5481, Z_w = -0.8947 and $(BIAS)_w$ = 1.8238. Moreover, the value of R-sq is 0.98.

Mathematical Expression for ANN

In order to develop the mathematical model, the obtained weights have been analyzed using the procedure given by Shrivastava *et al.*[18]. The intermediate variable 'm' has been calculated using the expressions shown below and the weights obtained between input layer and hidden layer.

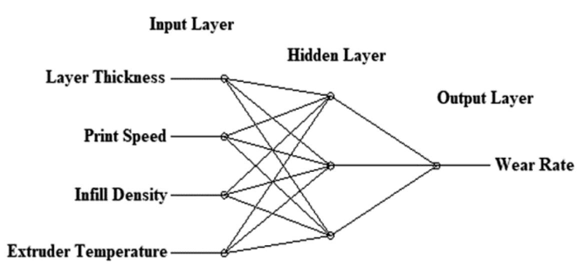

Fig. 3 — ANN Architecture

$$m_X = A_X \times A + B_X \times B + C_X \times C + D_X \times D + BIAS_X$$
$$m_Y = A_Y \times A + B_Y \times B + C_Y \times C + D_Y \times D + BIAS_Y$$
$$m_Z = A_Z \times A + B_Z \times B + C_Z \times C + D_Z \times D + BIAS_Z \quad \ldots (7)$$

Moreover, the value of neurons in the first hidden layer has been calculated using the expressions;

$$X = \frac{2}{[1+exp(-2\times m_X)]} - 1$$
$$Y = \frac{2}{[1+exp(-2\times m_Y)]} - 1 \quad \ldots (8)$$
$$Z = \frac{2}{[1+exp(-2\times m_Z)]} - 1$$

Similarly, the intermediate variable (n) between hidden layer and output layer has been calculated using the following expression;

$$n_W = X_W \times X + Y_W \times Y + Z_W \times Z + BIAS_W \quad \ldots (9)$$

The mathematical model has been generated using the expressions in the Eq. 9 as shown below;

$$W = \frac{2}{[1+exp(-2\times n_w)]} - 1 \quad \ldots (10)$$

Equation 10 has been used to predict the values of wear. Table 7 shows the experimental and experimental values of wear. Fig. 4 shows the

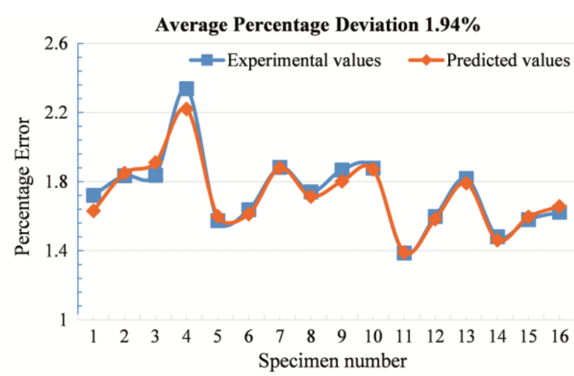

Fig. 4 — Experimental versus Predicted values for regression Model

Table 6 — Weights between input layer and hidden layer

	A_k	B_k	C_k	D_k	$(BIAS)_k$
X	2.5631	-2.588	-1.8996	-1.6552	-0.5892
Y	0.92854	-0.66715	-1.1478	-2.5899	2.4799
Z	1.1523	2.4799	-1.5661	0.64966	2.8398

k varies from X to Z

Table 7 — ANN Predicted values and percentage deviation

Specimen No.	A	B	C	D	Experimental values	Predicted values	% Deviation
1	0.20	50	70	190	1.7211	1.6310	5.235
2	0.20	100	80	200	1.8340	1.8490	0.818
3	0.20	150	90	210	1.8370	1.9110	4.028
4	0.20	200	100	220	2.3380	2.2210	5.004
5	0.25	50	80	210	1.5750	1.6000	1.587
6	0.25	100	70	220	1.6380	1.6130	1.526
7	0.25	150	100	190	1.8830	1.8792	0.202
8	0.25	200	90	200	1.7410	1.7143	1.534
9	0.30	50	90	220	1.8680	1.8021	3.528
10	0.30	100	100	210	1.8780	1.8710	0.373
11	0.30	150	70	200	1.3870	1.3900	0.216
12	0.30	200	80	190	1.5990	1.5833	0.982
13	0.35	50	100	200	1.8190	1.7910	1.539
14	0.35	100	90	190	1.4820	1.4612	1.404
15	0.35	150	80	220	1.5800	1.5960	1.013
16	0.35	200	70	210	1.6240	1.6570	2.032
Average percentage deviation							1.94 %

variation between experimental and predicted values. From the Table 7, the percentage deviation has also been calculated. It has been found that the percentage deviation in case of ANN model is comparatively less than that of Regression one. Also the R-sq value of ANN model suggests that the ANN model is more accurate than the regression model. Hence, the ANN model has been used to analyse the variation in wear with the change in input parameters.

3 Results and Discussion

The mathematical model developed using ANN has been plotted in the form of contour plots for the given range of input parameters considering two parameters at a time. These contour plots have been shown in Fig. 5(a-f). The contour plots show that the variation in wear is in the range of 1.4-2.2 approximately. In order to identify the combination or range of input parameters at which the wear is minimum, it is necessary to identify the value of wear up to which it is acceptable. For the given input parameters and machine, the wear less than 1.6 (red region) is acceptable. Considering the value of wear appropriate ranges of input parameters have been identified. For example Fig. 5(a) represents the variation in wear, with the change in the values of input parameters layer thickness (A) and print speed (B). In this plot the region in red color resembles minimum wear. If the value of A is selected between 0.28-0.35 with the value of Between 125-200, then the obtained wear will be less than 1.6. Similarly in other plots the range has been identified. Table 8 shows the range of input parameters obtained by analyzing the plots.

Table 8 — Range of input parameters considering two parameters at a time

	A	B	C	D
A	-	0.28-0.35	0.26-0.35	0.28-0.34
B	125-200	-	125-200	125-175
C	70-81	70-81	-	70-72
D	190-202	195-204	195-208	-

Table 9 — Predicted range of input parameter with minimum wear

Parameter	Range
A	0.28-0.34
B	125-175
C	70-72
D	195-202

Table 10 — Experimental value of wear for parameters obtained by ANN

A	B	C	D	Wear
0.28	125	70	195	1.5938
0.30	145	71	198	1.4927
0.32	165	72	202	1.5292

The obtained ranges of parameters have been merged together in order to identify a signal range of single parameter. For this, the intersection of the ranges has been taken. For an example the ranges of parameters A are 0.28-0.35, 0.26-0.35 and 0.28-0.34, so the intersection range will be 0.28-0.34. Similarly the intersection range of other parameters has been identified as listed in Table 9.

Moreover, in order to verify the accuracy of the obtained range, more experiments have been performed. Table 10 shows the validation experiments performed to verify the obtained range. The table consists of combination of input parameters and the

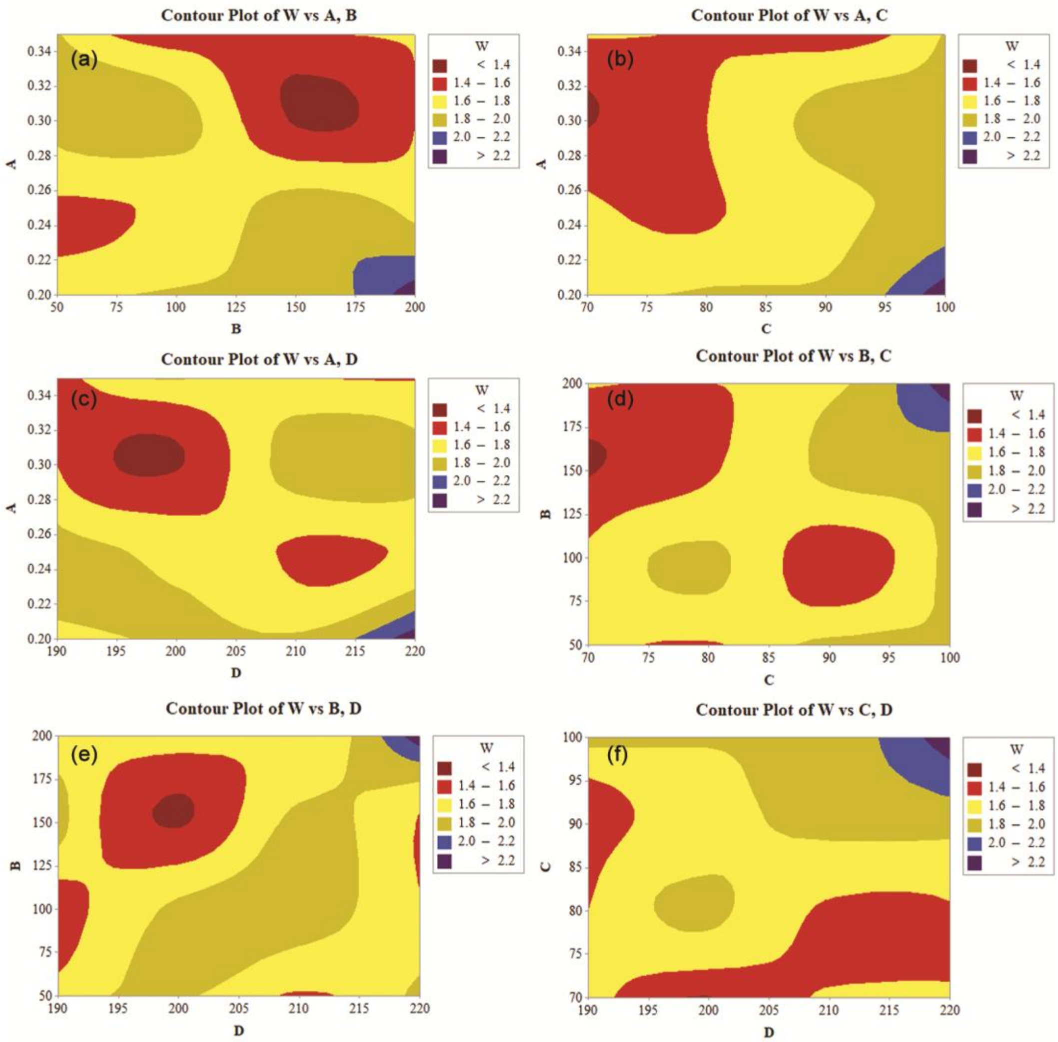

Fig. 5 — Contour Plots

measured value of wear. From the result it has been perceived that the obtained range is significant in controlling the wear property. If the fabrication is done considering the range of parameters within the obtained range, the tendency to wear will be minimum.

4 Conclusions

In the present work, an effort has been made to identify the range of input parameters pertaining to minimum wear, while fabricating the specimen using FDM. The fabrication of the specimens has been done considering the L16 orthogonal design. The measured values of wear have been further used to develop the regression and ANN models. The key findings of the work are;

1. The regression analysis reveals that the input parameters, layer thickness and infill density are more significant than that of other input parameters.
2. The R-sq values of the regression and ANN model are 5.04 and 1.94, respectively. This shows that the ANN model can predict the variation more precisely.
3. On comparing the average percentage deviation of the predicted values form the models of regression and ANN, it has been found that the ANN model is more significant.
4. The obtained range of input parameters suitable for fabrication are; 0.28-0.34, 125-175, 70-72, 195-202 for A, B, C and D, respectively.
5. The validation results shows that the obtained range is significant.

In near future, the proposed methodology can be used to identify the range of input parameters in other machines also.

References

1 Hull C W, US Pat.4,575,330, to 3D Systems Inc, 1986.
2 Crump Scott S, U S Pat. 5,121,329A (to Stratasys Inc.) June 9, 1992.
3 Mohamed O A, Masood S H, Bhowmik J L & Somers A E, *J Manuf Process*, 29 (2017) 149.
4 Mohamed O A, Masood S H & Bhowmik J L, *Mater Lett*, 230 (2018) 261.
5 Kamonrattanapisud M & Tuchinda K, *Solid State Phenom*, 304 (2020) 25.
6 Norani M N M, Abdollah M F B, Abdullah M I H C, Amiruddin H, Ramli F R, Tamaldin N, *Proc Inst Mech Eng Part J J Eng Tribol*, (2020).
7 Boparai K, Singh R & Singh H, *Virtual Phys Prototyp*, 10 (2) (2015) 59.
8 Srinivasan R, Suresh Babu B, Udhaya Rani V, Suganthi M, Dheenasagar R, *Mater Today Proc*, (2020) (in press).
9 Singh R, Singh S & Fraternali F, *Compos Part B Eng*, 98 (2016) 244.
10 Singh R, Singh N, Amendola A & Fraternali F, *Compos Part B Eng*, 119 (2017) 125.
11 Hanon M M, Alshammas Y & Zsidai L, *Int J Adv Manuf Technol*, (2020).
12 Amiruddin H, Abdollah M F B & Norashid NA, *Mater Res Express*, 6 (2019) 085328.
13 ASTM G99-17, ASTM International, *Wear*, 5 (2011) 1.
14 Shrivastava P K & Pandey A K., *Infrared Phys Technol*, 89 (2018) 369.
15 Satyanarayana G, Swami Naidu G & Babu NH, *Bol la Soc Esp Ceram y Vidr*, 57 (2018) 91.
16 Rawlings J O, Pantula S G & Dickey D A, *Applied Regression Analysis: A Research Tool*, (Springer Science), 2nd Edn, 2001.
17 Shrivastava Y, Singh B, *Trans Inst Meas Control*, 41 (2019) 193.
18 Shrivastava Y, Singh B, *Eur J Mech A/Solids*, 70 (2018) 238.
19 Jeff T, *Introduction to Neural Networks with Java*, (Heaton Research Inc) 2005.