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Mathematical modeling and parametric optimization of surface roughness for evaluating the effects of fused deposition modeling process parameters on ABS material

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Abstract*— Fused deposition modeling (FDM) technology is production devices that use plastic material in the semi-molten state to harvest the products directly from the CAD model. This study describes the development of mathematical models to predict the effects of significant process parameters of the FDM on the surface roughness of ABS material. Experiments were planned as per Taguchi L_9 orthogonal array. Experiments were conducted under different printing input parameters of layer thickness, orientation angle, and infill angle. Response surface methods (RSM) have been employed to develop a predictive mathematical model in terms of controllable input parameters. Analysis of Variance (ANOVA), main effect and interaction plot, 3D surface, and contour plot were used to investigate the influence of various printing parameters on surface roughness. Finally, Taguchi methodology and RSM approaches have been applied successfully for the optimization of surface roughness (Ra) in FDM printing parts. It was observed that the models can adequately describe the responses within the ranges considered as the maximum error percent in the prediction of mean Ra and S/N ratio of Ra are 14.61% and 18.83% respectively, which is in good agreement. The optimal combination of printing process parameters obtained indicates that optimum surface quality is layer thickness at 0.1mm, orientation angle at 0º, and infill angle at 0º.

I. INTRODUCTION

Additive manufacturing (AM) is a technology that uses digital three-dimensional model data to manufacture physical objects. In the AM process components are built gradually layer by layer. Nevertheless, in the traditional manufacturing process material have to machine to fabricate parts. Additive manufacturing processes use multiple 3D printing methods, but the most used is the process known as Fused Deposition Modeling (FDM) [1]–[4].

FDM printers use thermoplastic filaments that are heated to melting point and then through extrusion nozzle layer by layer to create 3D objects according to CAD design. The system is made up of a control system, a production platform, and an extrusion nozzle. FDM can create conceptual models, production parts, and working prototypes with exceptional thermal and chemical resistance and excellent strength-to-weight ratios. FDM uses technical grade solid materials such as ABS, polycarbonate, and ULTEM ™ 9085 resin [5]–[7].

FDM technology offers considerable advantages such as simpler and easy demodulation frequency, not need synchronization between its transmitter and receiver, the slow narrowband fading only one channel gets affected, It is used for analog signals, and simultaneously many signals can be transmitted [8]–[12].

When setting the printing options of the machine, several process parameters have to be taken into account, such as temperature, build speed, infill densities, etc., which directly influence the quality (surface roughness) of the fabricated parts. Selecting these parameters also a great challenge for the users and is generally solved by experience without considering their influence on the product[13]–[18].

Several authors have experimentally studied the problems related to the surface roughness of plastic parts produced by FDM and developed theoretical and empirical models. P. Wang et al.[19] studied the effects of the printing parameters of molten deposit modeling on the mechanical properties, surface quality, and microstructure of polyetheretherketone (PEEK). The FDM method was applied to obtain the 3D printing of PEEK. Finite Element Analysis (FEA) was used to simulate the melting conditions and fluidity of PEEK in a flow channel, to determine the parameters necessary to print PEEK parts in 3D with sufficient surface quality and improved mechanical properties.

P. Wang et al.[20] Studied influence of FDM printing parameters such as; nozzle temperature, printing speed, layer thickness, deposition road width as well temperature of printing platform on the surface morphology of printed parts. The experiments were performed on FDM 3D printing several times and the surface roughness result was used to develop a predictive model. The experimental results were in good agreement with the predicted model.

D. Yadav et al.[21] Studied the influence of 3D printing parameters such as material density, infill density, and extrusion temperature on tensile strength of printed parts using FDM. Acrylonitrile Butadiene Styrene (ABS), Polyethylene Terephthalate Glycol (PETG), and Multi-material were used for printing materials. 30 parts were printed having different parameters as per the ASTM D638-(IV) standard. For training and optimization, purpose the artificial neural network (ANN) and genetic algorithm-artificial neural network (GA-ANN) hybrid tool were used. It was observed that the tensile strength is improved by 4.54% and it has been proved experimentally.

C. Abeykoon et al. [22] Examined three FDM parameters like infill pattern, infill density, and infill speed, at two variable settings for building test parts on the properties of FDM 3D, printed specimens (i.e., mechanical, thermal, and morphological). Comprehensive analyses were performed to test printing parts and the result showed increasing infill density will increase the strength of the printed parts.

V. Wankhede et al. [23] Studied the effect of 3D FDM process parameters on printed part quality by using Acrylonitrile Butadiene Styrene (ABS) polymer material. Inputs factors are infill density, layer thickness, and support style, and the output factors were Surface roughness and build time of part. Analysis of Variance (ANOVA) is established to understand the significant characteristics of the process variables. The set of input variables has been determined for the individual output response variable. From the study of research papers on FDM, it is found that different process parameters for improving quality of printed part like, DA, Ra, and UTS, etc., different optimization techniques were used in single or hybrid with other technique. Since this technology is resent insufficient work has been done for modeling and optimization of flash forge creator process parameters for certain materials.

II. EXPERİMENTAL DETAİL

2.1 Experimentation setup: Selection of parameter

Printing parameters have a dominating impact on the quality of build part characteristics and their production efficiencies. To ensure the quality of printed parts, it is necessary to study the influence of inputs printed parameters and out factors. In this paper, layer thickness (mm), orientation angle (°), and infill angle (°) were considered as controllable input parameters. Table 1 shows three input variables of the experiment, coded value, and actual values of their level.

Table.1: Controllable input parameters and their levels

Input parameters	Symbol	Unit	Levels		
			1	2	3
Layer thickness	A	mm	0.1	0.2	0.3
Orientation angle	B	°	0	15	30
Infill angle	C	°	0	30	30

2.2 Design of experiment

The design of the experiment using Taguchi's provides an efficient plan to study the experiments, with a minimum amount of experimentation. Based on selected process parameters and their levels an experimental design matrix was constructed (Table 2) using Taguchi L9 orthogonal array (three levels-three factors) were selected depends on the number of input parameters and their levels. Each experimental trial in the design consists of different FDM printing parameters with different levels.

Table.2: L_9 orthogonal array design of experiments (DOE)

EXP. Trials	Input parameters		
	A	B	C
	mm	°	°
1	0.1	0	0
2	0.1	15	30
3	0.1	30	60
4	0.2	0	30
5	0.2	15	60
6	0.2	30	0
7	0.3	0	60
8	0.3	15	0
9	0.3	30	30

2.3 Specimen fabrication

The 3D models of specimens are generated using SOLID WORK 2016 solid modeling software and exported as STL (stereolithography) file to FDM software (Insight). Figure 1 is showing the specimen model on solid work. The specimen was placed flat on the building plate virtually in the slicing software. X, Y, and Z-axis directions are shown. After this process, the data is sent to the FDM hardware for modeling. Figure 2 shows the FDM machine while printing parts. Figure 3 shows parts fabricated by using FDM.

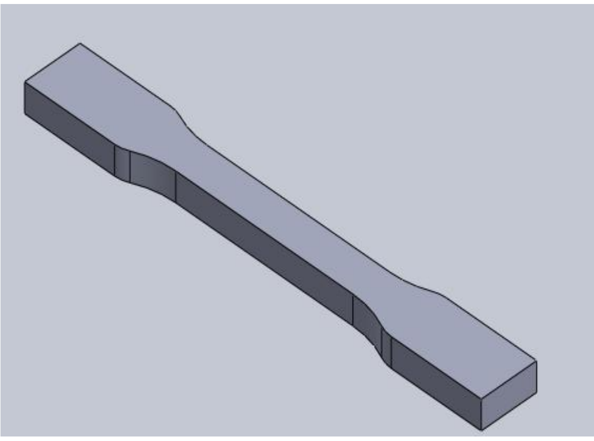

Fig. 1: Specimen model on Solid work

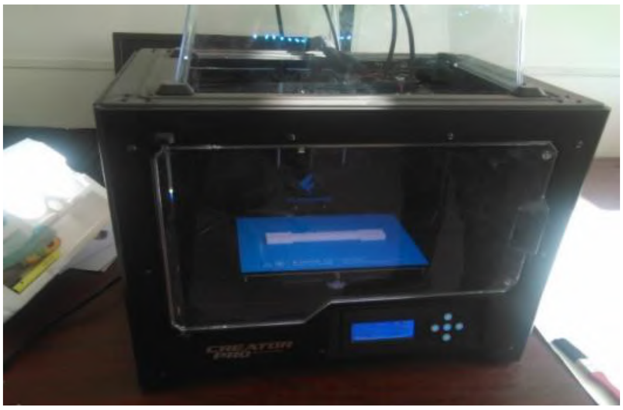

Fig. 2: FDM machine

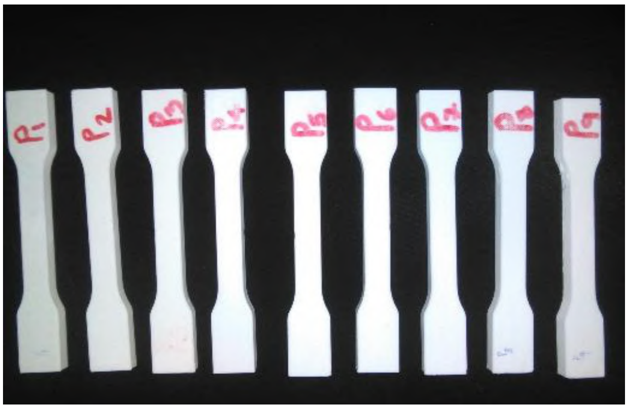

Fig.3: Parts fabricated by FDM machine

2.3 Experimentation setup: Selection of parameter

The surface roughness of each fabricated part was measured at five different places on the top and bottom surfaces and the average values used for analysis, the unit of measure is µm. The laser scanning microscopy (VK- X 200 K, Keyence, Japan) equipment is used to measure the surface roughness of the fabricated part. Table 3 shows the experimental data set and experimental results.

Table.3: Experimental layout and results

Exp. Trials	A	B	C	Experimental results	
				Ra (µm)	S/N ratio
1	0.1	0	0	0.3265	9.72234
2	0.1	15	30	0.5925	4.54623
3	0.1	30	60	0.5988	4.45436
4	0.2	0	30	1.0545	-0.46093
5	0.2	15	60	1.2165	-1.70224
6	0.2	30	0	1.2095	-1.65212
7	0.3	0	60	1.3375	-2.52588

8	0.3	15	0	1.3425	-2.55829
9	0.3	30	30	1.6542	-4.37176

III. RESULT AND DISCUSSION

3.1 Surface roughness (Ra) analysis

Analysis of variance (ANOVA) was used for analyzing experimental results of surface roughness to identify the significant factors affecting the performance measures. In table 4 result of the ANOVA for the mean surface roughness at a 95% confidence interval is given. For significance check, F – value, and P-value are given in the ANOVA table are used. The principle of the F-test and P-test is that the larger the F value and a smaller value for a particular parameter, the greater the effect on the performance characteristic due to the change in that process parameter. ANOVA table shows that layer thickness (F – value 193.88), Infill rate (F – value 4.28) has the most significant factor that affects the Ra and has an insignificant effect on Ra respectively. Table 5 shows the ranks of various factors in terms of their relative significance.

Table 4: ANOVA table for Surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
A	2	1.39034	0.695172	193.88	0.005
B	2	0.09308	0.046541	12.98	0.072
C	2	0.03066	0.015330	4.28	0.190
Error	2	0.00717	0.003586		
Total	8	1.52126			

Table 5: Response Table for Means surface roughness

Level	A	B	C
1	0.5059	0.9062	0.9595
2	1.1602	1.0505	1.1004
3	1.4447	1.1542	1.0509
Delta	0.9388	0.2480	0.1409
Rank	1	2	3

The main effects plot for the Ra is shown in Figure 4, which shows the variation of surface roughness with the input parameters. The interaction plot for the Ra is shown in Figure 5, which shows the interaction between process parameters on the surface roughness. From the main effect plot for mean surface roughness, it is indicated that the orientation angle and infill angle have less influence on surface roughness. The percentage contribution pie chart plot for the Ra is shown in figure 6, which shows the influence of each process parameters in percentage. The percentage contribution of layer thickness is 91.827 %, the contribution of the orientation angle is 6.148 % and the contribution of infill angle is 2.025 %. This shows that layer thickness has a significant contribution to surface roughness followed by orientation angle.

Fig. 4: Main effects plot for means Ra with all process parameters

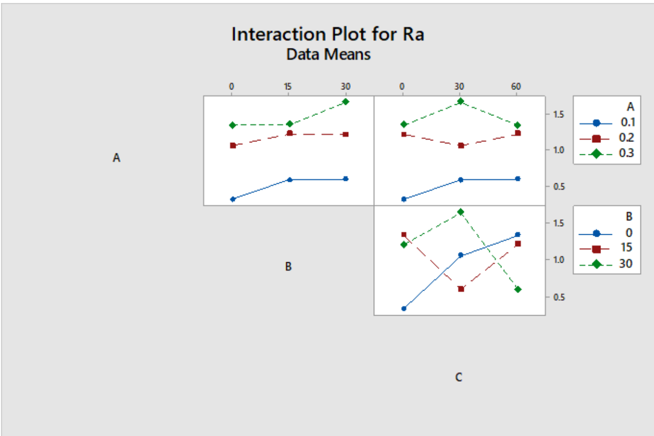

Fig. 5: Interaction plot of Ra for means with all process parameters

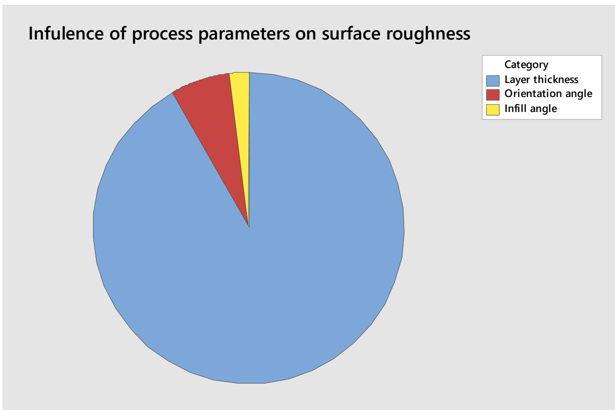

Fig. 6: Pie chart for percentage contributions

3.2 Response surface method (RSM) modeling

3.2.1 Regression analysis

The experimental data obtained from the L_9 orthogonal array was analyzed for surface roughness using regression analysis. The analysis was done using coded units. Once the Ra values were entered into Minitab V18 (trial version 18.1), a whole analysis can be performed using regression analysis. The results shown in Table 7 are the estimated regression coefficients for surface roughness to all the terms in the model.

Table 6: Estimated regression coefficient for mean surface roughness

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-0.688	0.209	-3.30	0.030	
A	12.09	2.31	5.23	0.006	49.00
B	0.00827	0.00220	3.76	0.020	1.00
C	0.00152	0.00110	1.39	0.238	1.00
A*A	-18.48	5.71	-3.23	0.032	49.00

Applying the ANOVA on the experimental data, we obtained the influence of each parameter and the adequacy of the data. Table 7 shows ANOVA for Ra and a summary of the model. Values of "Prob > F" less than 0.0500 (i.e., α = 0.05, or 95% confidence level) indicate model terms are significant. P - Values greater than 0.1000 indicate the model terms are not significant, which implies the Lack of Fit is significant, this large could occur due to noise. R- sq. shows the agreement between actual and fitted value, in this case, R-sq. is given as 98.28%, which showed that the model is fit.

Table 7: ANOVA for surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	1.49514	0.373785	57.25	0.001
A	1	0.17890	0.178902	27.40	0.006
B	1	0.09226	0.092256	14.13	0.020
C	1	0.01254	0.012540	1.92	0.238
A*A	1	0.06833	0.068327	10.46	0.032
Error	4	0.02612	0.006529		
Total	8	1.52126			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0808051	98.28%	96.57%	91.47%

Based on the developed surface roughness regression equation, 3D surface and contour graphs are plotted for surface roughness against layer thickness, orientation angle, and infill angle. Figure 7 (a-b) shows a 3D surface and contour plot of the interaction analysis between layer thickness and orientation angle. The infill angle for this analysis was set at a constant 30 degrees. From this plot, it is clearly shown that the lower surface roughness is obtained at a layer thickness between 0.10 mm to 0.15 mm, and the orientation angle between 0 to 5 degrees. We can be also observed that the surface roughness was high at higher layer thickness and orientation angle.

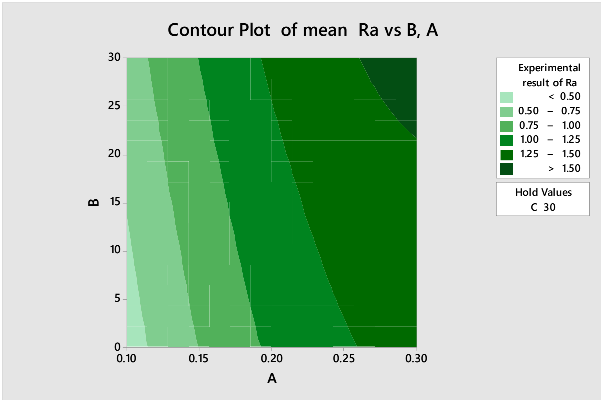

Fig. 7(a): Contour plots of Ra against layer thickness and orientation angle

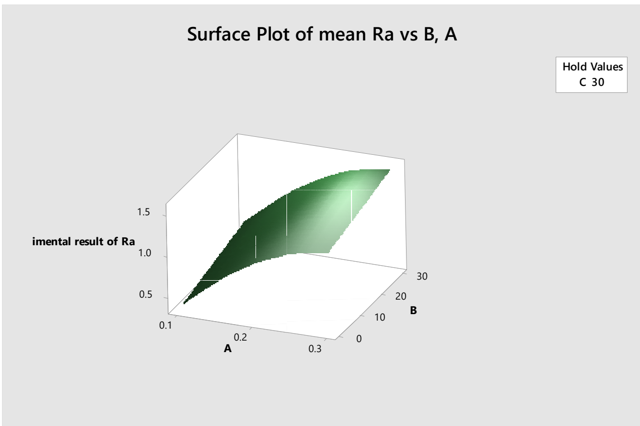

Fig. 7(b): 3D Surface plots of Ra against layer thickness and orientation angle

Figure 8(a-b) shows a 3D surface and contour plot of the interaction analysis between layer thickness and infill angle. The orientation angle for this analysis was set at a constant 15 degrees. From this plot, it is shown that the lower surface roughness is obtained at a layer thickness between 0.10 mm to 0.15 mm, and the orientation angle between 0 to 30 degrees. We can be also observed that the infill angle has an insignificant effect on kerf width.

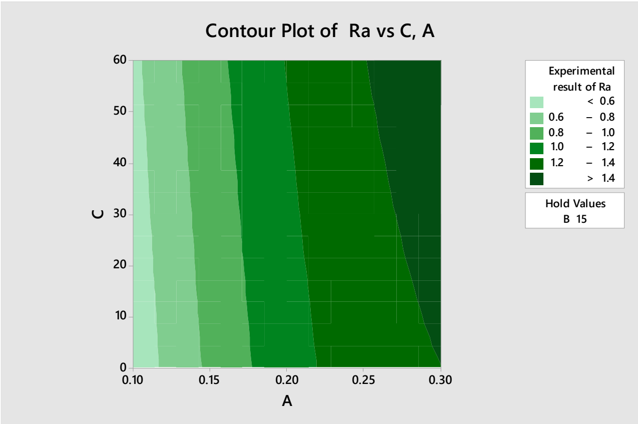

Fig. 8(a): Contour plots of Ra against layer thickness and infill angle

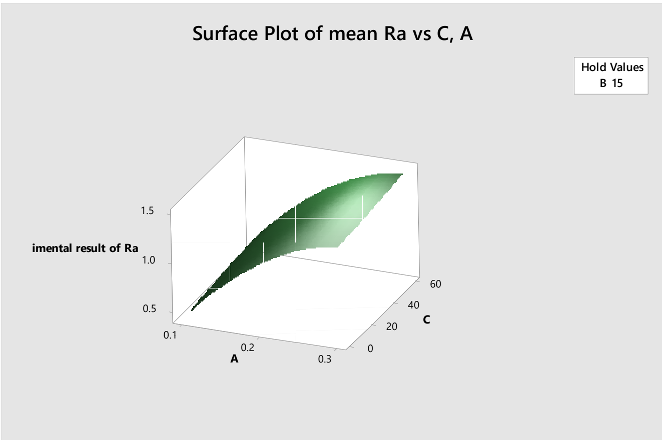

Fig. 8(b): 3D Surface plots of Ra against layer thickness and infill angle

Figure 9(a-b) shows the 3D surface and contour plot of the interaction analysis between orientation angle and infill angle. The layer thickness for this analysis was set at a constant of 0.2 mm. From this plot, it is shown that the lower surface roughness is obtained at an orientation angle between 0 to 5 degrees, and an infill angle between 0 to 10 degrees. At high orientation angle and infill angle, the surface roughness was higher.

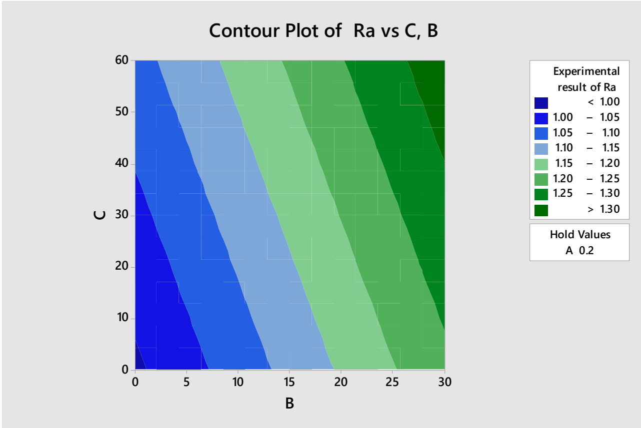

Fig. 9(a): Contour plots of Ra against orientation angle and infill angle

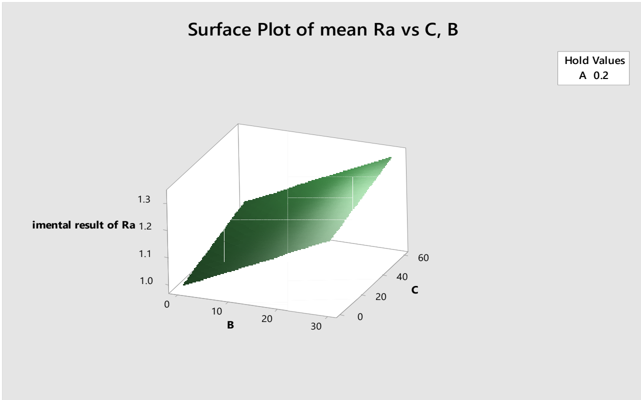

Fig.9(b): 3D Surface plots of Ra against orientation angle and infill angle

3.2.2 Mathematical modeling: mean surface roughness and S/N ratio

The mathematical models for the printed part using Fused deposition modeling (FDM) were developed to evaluate the relationship between process parameters to the fabricated part quality. To model the experimental data, response surface models were used with the help of Minitab statistical software. Through these models, experimental results of Ra by any combination of printing parameters can be estimated. The output response and the input printing parameters are related through the mathematical model given in Equations (2) and (3).

$Equation - 2$

$$Ra = 0.688 + 12.09\,A + 0.00827\,B + 0.00152\,C - 18.48\,A * A$$

$Equation - 3$

$$\frac{S}{N} ratio = 21.81 + 160.3\,A + 0.0947\,B + 0.0302\,C - 282.7\,A * A$$

The mathematical model developed in Equations (2) and (3) above was used for the prediction of Ra and the S/N ratio of Ra. Table 9 summarizes the predicted result of the mean and S/N ratio of Ra. The time series plot for the Ra is shown in Figures 10(a) and (b), shows the comparison between the experimental results and predicted results for the mean and S/N ratio of Ra. It can be realized from the results that the predicted values are close to experimental values. Therefore, the developed regression equation can be used as the objective function for the optimization.

Table 8: Experimental results and predicted result for surface roughness

Exp. trials	**A**	**B**	**C**	**Experimental results**		**predicted results**	
				Ra (µm)	S/N ratio	Ra (µm)	S/N ratio
1	0.1	0	0	0.3265	9.72234	0.33622	8.50610
2	0.1	15	30	0.5925	4.54623	0.50593	6.24098
3	0.1	30	60	0.5988	4.45436	0.67565	3.97585
4	0.2	0	30	1.0545	-0.46093	1.03617	0.11241
5	0.2	15	60	1.2165	-1.70224	1.20588	-2.15271
6	0.2	30	0	1.2095	-1.65212	1.23845	-1.77499
7	0.3	0	60	1.3375	-2.52588	1.36645	-2.64875
8	0.3	15	0	1.3425	-2.55829	1.39902	-2.27103
9	0.3	30	30	1.6542	-4.37176	1.56873	-4.53615

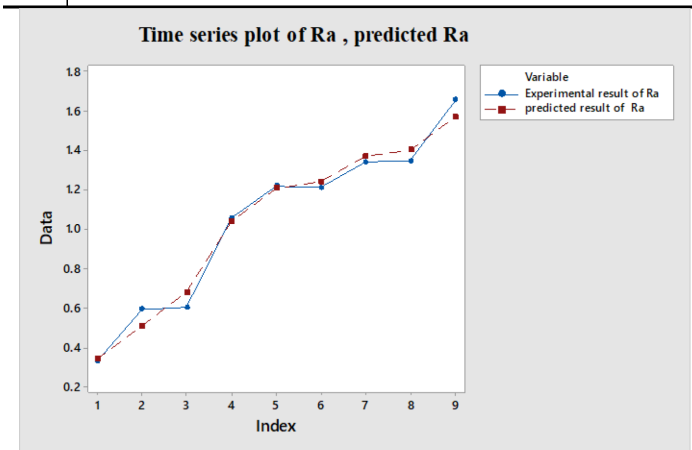

Fig. 10(a): A time series plot: experimental result and predicted result for mean Ra

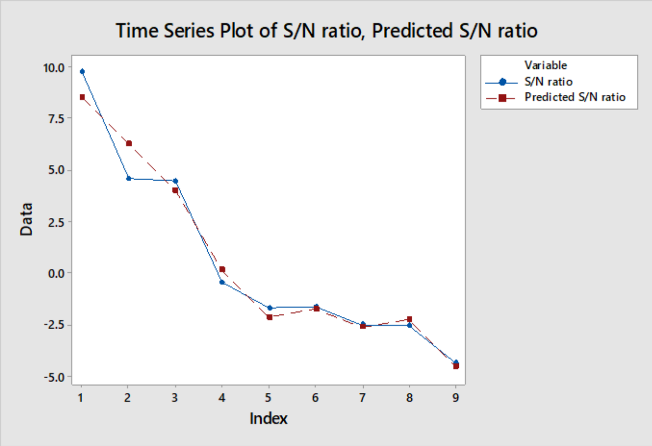

Fig. 10(b): A time series plot: experimental result and predicted result for S/N ratio

3.2.3 validation of the model

Validation of the mathematical models with the experimental results is shown in Figures 10 (a) and (b). The percentage of prediction error is calculated as:

Equation 4

$$Prediction\ error\ \% = \frac{Eperimental\ result - predicted\ result}{Experimental\ result} \times 100$$

It is observed that the models can sufficiently describe the responses within the ranges considered as the maximum error percent in the prediction of mean and S/N ratio of Ra are 14.61% and 18.83% respectively, which is in good agreement. This indicates that the average percentage accuracy in the mean and S/N ratio of Ra values is 85.39 % and 81.17 % respectively.

3.3 Multi-objective optimization

3.3.1 Taguchi method optimization

Optimization using Taguchi methods have three conditions; smaller is better, nominal is better, and large is better. In this condition of the printed part using FDM, the smaller the surface roughness is the optimal condition. Process parameters settings with the highest S/N ratio always yield the optimum quality with minimum variance. Based on the S/N analysis, the optimal printing parameters for Ra are at layer thickness 0.1mm, the orientation angle of 0 degrees, and 0 degrees infill angle.

3.3.2 RSM optimization

From the optimization plot Figure 11, it is observed that mean surface roughness and S/N ratio shows individual desirability as 0.99268 and 0.91371respectively. The optimum response values of mean Ra and S/N ratio obtained are 0.3362 µm and 8.5061 respectively. Tables 8 summarize optimum values using Taguchi methodology and predicted optimum values using the RSM approach for mean Ra and S/N ratio Ra.

Table 9: Optimum value using Taguchi methods and RSM approaches

	Response		Factors		
	Mean Ra	S/N ratio	Layer thickness	Orientation Angle	Infill angle
Optimized Value using Taguchi methodology	0.3265μm	9.7223	0.1 mm	0 º	0º
Predicted optimum value using RSM	0.3362μm	8.5061	0.1 mm	0 º	0º

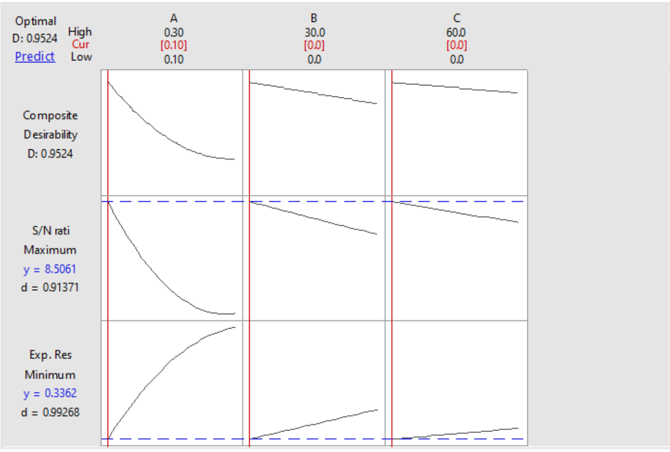

Fig. 11: Optimization of response parameters using RSM

IV. CONCLUSION

In the present work, Fused deposition modeling (FDM) has been used to print ABS parts. The experiment has been carried out using Taguchi's L_9 orthogonal array technique to relate printing parameters such as layer thickness, orientation angle, and infill angle to surface quality responses in terms of surface roughness. The surface roughness of each fabricated part was measured at five different places on the top and bottom surfaces and the average values used for analysis. To analyze the effect of each process parameters on response analysis of variance (ANOVA), main effect and interaction plot, 3D surface, and contour plot has been used. A mathematical model is developed using RSM through regression analysis for further prediction. Finally, Taguchi methodology and RSM approaches have been applied successfully for the optimization of surface roughness (Ra) in FDM printing parts.

From the result obtained, the following conclusions are drawn:

- The ANOVA result shows that surface roughness (Ra) has most significantly affected by layer thickness. On the other hand, Ra is found to be insignificantly affected by orientation angle and infill angle.
- The percentage contribution of layer thickness is 91.827 %, orientation angle is 6.148 % and infill angle is 2.025 %. This shows that layer thickness has a significant contribution to surface roughness followed by orientation angle.
- The lower surface roughness is obtained at a layer thickness between 0.10 mm to 0.15 mm, the orientation angle between 0 to 5 degrees, and infill angle between 0 to 10 degrees. At high layer thickness, orientation angle, and infill angle, the surface roughness was higher.
- The models can adequately describe the responses within the ranges considered as the maximum error percent in the prediction of mean Ra and S/N ratio of Ra are 14.61% and 18.83% respectively, which is in good agreement.
- The optimum mean Ra value through the Taguchi method is Ra = 0.3265 μm at a maximum value of S/N ratio 9.72234.
- The optimum response values of mean Ra and S/N ratio obtained using the RSM approach are 0.3362 μm and 8.5061 respectively. It was observed that surface roughness and S/N ratio show individual desirability as 0.99268 and 0.91371respectively.
- The optimal combination of printing process parameters obtained from the Taguchi method and RSM optimization indicates that optimum surface quality is layer thickness at 0.1mm, orientation angle at 0º, and infill angle at 0º.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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REFERENCES

[1] N. A. Fountas and N. M. Vaxevanidis, "Optimization of fused deposition modeling process using a virus-evolutionary genetic algorithm," *Comput. Ind.*, vol. 125, p. 103371, 2021.

[2] O. A. Mohamed, S. H. Masood, and J. L. Bhowmik, "Modeling, analysis, and optimization of dimensional accuracy of FDM-fabricated parts using definitive screening design and deep learning feedforward artificial neural network," *Adv. Manuf.*, vol. 9, no. 1, pp. 115–129, 2021.

[3] N. A. Fountas, J. D. Kechagias, D. E. Manolakos, and N. M. Vaxevanidis, "Single and multi-objective optimization of FDM-based additive manufacturing using metaheuristic algorithms manufacturing using metaheuristic algorithms," *Procedia Manuf.*, vol. 51, pp. 740–747, 2021.

[4] S. Vyavahare and S. Teraiya, "Fused deposition modeling : a review," vol. 1, no. June 2019, pp. 176–201, 2020.

[5] N. Naveed, "Investigate the effects of process parameters on material properties and microstructural changes of 3D-printed specimens using fused deposition modeling (FDM)," *Mater. Technol.*, vol. 00, no. 00, pp. 1–14, 2020.

[6] D. Pramanik, A. Mandal, and A. S. Kumar, "Materials Today : Proceedings An experimental investigation on improvement of surface roughness of ABS on the fused deposition modeling process," *Mater. Today Proc.*, no. XXXX, pp. 1–4, 2020.

[7] H. Kumar, "Optimising Parameters of Fused Filament Fabrication Process to Achieve Optimum Tensile Strength Using Artificial Neural Network Optimising Parameters of Fused Filament Fabrication Process to Achieve Optimum Tensile Strength Using Artificial Neural Network," vol. 7, no. 3, pp. 373–381, 2020.

[8] S. M. R and S. Vinodh, "Parametric optimization of fused deposition modeling process using Grey based Taguchi and TOPSIS methods for an automotive component," *Rapid Prototyp. J.*, no. October 2020.

[9] J. Singh, C. Nitin, and M. Raman, "Parametric optimization of fused deposition modeling using learning enthusiasm enabled teaching learning-based algorithm," *SN Appl. Sci.*, no. October 2020.

[10] T. Sai, V. Kumar, P. Ashish, and K. Srivastava, "Modeling and optimization of fused deposition modeling (FDM) process through printing PLA implants using adaptive neuro-fuzzy inference system (ANFIS) model and whale optimization algorithm," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 3, 2020.

[11] D. Banerjee, S. B. Mishra, M. S. Khan, and M. A. Kumar, "Mathematical approach for the geometrical deformation of fused deposition modeling build parts," *Mater. Today Proc.*, no. XXXX, 2020.

[12] N. A. Fountas, J. Kechagias, A. Tsiolikas, N. M. Vaxevanidis, and T. Education, "Multi-objective optimization of printing time and shape accuracy for FDM-fabricated ABS parts," *Metaheuristic Comput. Appl.*, no. January 2021, 2020.

[13] S. Deshwal, A. Kumar, and D. Chhabra, "Exercising hybrid statistical tools GA-RSM, GA-ANN, and GA-ANFIS to optimize FDM process parameters for tensile strength improvement," *CIRP J. Manuf. Sci. Technol.*, no. 2019, 2020.

[14] K. Depalma, M. R. Walluk, A. Murtaugh, J. Hilton, S. Mcconky, and B. Hilton, "Assessment of 3D printing using fused deposition modeling and selective laser sintering for a circular economy," *J. Clean. Prod.*, vol. 264, p. 121567, 2020.

[15] M. Subramaniyan, S. Karuppan, P. Eswaran, A. Appusamy, and A. N. Shankar, "Proceedings State of art on fusion deposition modeling machines process parameter optimization on composite materials," *Mater. Today Proc.*, no. XXXX, 2020.

[16] N. A. Fountas, P. Kostazos, H. Pavlidis, V. Antoniou, D. E. Manolakos, and N. M. Vaxevanidis, "Experimental investigation and statistical modeling for assessing the tensile properties of FDM fabricated parts," *Procedia Struct. Integr.*, vol. 26, no. 2019, pp. 139–146, 2020.

[17] A. Elmushyakhi, "Freeze-thaw stabilization of fused deposition modeling 3D-printed SABIC structures," *J. King Saud Univ. - Eng. Sci.*, no. XXXX, 2020.

[18] D. Yadav, D. Chhabra, R. Kumar, A. Ahlawat, and A. Phogat, "Materials Today : Proceedings Optimization of FDM 3D printing process parameters for multi-material using artificial neural network," *Mater. Today Proc.*, no. XXXX, 2019.

[19] P. Wang, B. Zou, H. Xiao, S. Ding, and C. Huang, "Effects of printing parameters of fused deposition modeling on mechanical properties, surface quality, and microstructure of PEEK," *J. Mater. Process. Tech.*, vol. 271, no. February, pp. 62–74, 2019.

[20] P. Wang, B. Zou, and S. Ding, "Modeling of surface roughness based on heat transfer considering diffusion among deposition filaments for FDM 3D printing heat-resistant resin," *Appl. Therm. Eng.*, vol. 161, no. April, p. 114064, 2019.

[21] D. Yadav, D. Chhabra, R. Kumar Garg, A. Ahlawat, and A. Phogat, "Optimization of FDM 3D printing process parameters for multi-material using artificial neural network," *Mater. Today Proc.*, vol. 21, pp. 1583–1591, 2020.

[22] C. Abeykoon, P. Sri-Amphora, and A. Fernando, "Optimization of fused deposition modeling parameters for improved PLA and ABS 3D printed structures," *Int. J. Light. Mater. Manuf.*, vol. 3, no. 3, pp. 284–297, 2020.

[23] V. Wankhede, D. Jagetiya, A. Joshi, and R. Chaudhari, "Experimental investigation of FDM process parameters using Taguchi analysis," *Mater. Today Proc.*, vol. 27, pp. 2117–2120, 2019.