Manufacturing and Machining Performance Analysis of Al/SiC$_5$ MMC using Soft Computing Techniques

Amol A. Chavan*[1], Dr. D.N. Raut[2], Dr. D. K. Shinde[3]

1*Research Scholar, Department of Production Engineering, VJTI, Mumbai, Maharashtra, INDIA.

2,3. Department of Production Engineering, VJTI, Mumbai, Maharashtra, INDIA.

***Corresponding author Email address**: chavan.amol85@gmail.com

Abstract

Now a day's, metal matrix composites (MMCs) are taking a superior position among the available material. The presented work aims to investigate the ease of machining for Aluminium based MMC (AlSiC5- with 5% Silicate). These MMCs are extensively used in space, defence, automobile, etc. To analyze the process, an effective two techniques ie. Response surface method (RSM) & artificial neural networks (ANN) have been selected to analyze the process. Taguchi's L_{27} plan was used for data collection. The parameters like current (AMP) and pulse on time (TON) are the basically dominant parameters, followed by voltage (VOLT) and pulse off time (TOFF). The ease of machining performance measured in terms of surface roughness (Ra). From obtained result, it is seen that the ANN & RSM presents an exemplary commitment. An adequate contract was observed with the high correlation coefficient value (R2 = 0 9863) in RSM and (R2 = 0 9764).

Keywords: Machining, Composite Material EDM, AlSiC$_5$, Soft Computing, ANN, RSM, Surface roughness.

Introduction:

Now a day's, MMCs take more attraction due to their enormous properties. Most of the industries are trying to replace most of the conventional materials with MMCs for various industrial applications. The properties which attract the industries are comparative like low density, low coefficient of thermal expansion, higher strength and so on. It takes a vital role in the field such as structural engineering, manufacturing, aerospace, automotive industries and so on. Kumar et.al [1] has investigated the dry turning operation. Speed, feed and depth with three test points were considered to investigate their impact on rate of material removal (MRR) and quality of machining surface (Ra). From the investigation, it is observed that the feed rate and cutting speed is the most influencing process parameter which affects MRR and Ra. Chia-Chi et al [2] has investigated to optimize the machining process. A fuzzy based approach was used during the investigation. Huu-Phan et.al. [3] has examined the EDM of alloy using Taguchi-TOPSIS method. There were three responses MRR, Ra and hardness of finished surface. Copper and electrode were used for the machining.

Jenarthanani et al [4] has optimized the glass-fibre reinforced plastic (GFRP) composites using desirability function analysis (DFA). An orthogonal array (L_{27}) was used for the investigation. Mevada et. al. [5] examined machining performance and surface quality after machining. This investigation was done to optimize the responses. The independent parameters are pulse on time, pulse off time and peak current. Some of the latest article related t the presented work as tabulated in table 1.

Table 1 : Summarised representation of process parameters used by the researchers .

Rf. No	List of Inputs (I/P) and Outputs (O/P)	Material used for machining
[6]	Input Current, service factor , pulse on time , gap voltage & surface roughness	Al (6351) eSiC& Al (6351)eSiCeB4C composites.
[7]	maximum current, pulse on time, voltage and material contains	EN-19 alloy structural steel.
[8]	Profile of Tool pin, Material of Tool speed, force & ultimate tensile strength	aluminum alloys with 5 mm thick

[9]	TC/GC hybrid fillers ratio, temperature of Nozzle, speed of injecting, temperature of mold &flexural strength	The PP raw material, (PETOPLEN EH 102
[10]	Tribological properties pre and post machining	Ti6Al4V (Ti64)
[11]	Pulse ON, Pulse OFF, Pressure, Feed of and Voltage, MRR & Ra	Aluminium based Hybrid Metal Matrix Composite
[12]	Speed, feed and depth of cut, SiC % **&** Ra	Al–SiCp metal–matrix composites
[13]	speed, feed ,depth of cut and Ra	Aluminium alloy with silicate
[14]	Input Current, service factor , pulse on time , gap voltage & surface roughness	mild steel work surface
[15]	pulse-on time, pulse-off time, peak current and spark voltage. MRR, Ra, gap current	ballistic grade aluminium alloy AleMgeSi-based alloy (6063),
[16]	Speed, feed and depth of cut & tool tip temperatures and surface roughness	AISI 1040 Steel
[17]	Pulse current (I),Ton, Toff , vibration frequency (F), MRR and Ra	aluminium alloy
[18]	Ton, Toff, current, weight fraction MRR, rate, electrode wear rate, Ra	Al-4.5Cu-SiC Composite
[19]	Ton, Toff , current, voltage, wire feed rate, wire tension, SiC contain, thermal expansion coefficient, thermal conductivity.	Al 2124 SiCp Metal Matrix Composite (MMC)
[20]	Ton, Toff , peak current, Servo voltage, **Ra and MRR**	Nimonic-263 alloy

2.Materials and methods

2.1 Preparation of MMC

In the presented work, aluminum-based matrix composite (MMC) with Aluminum is used as an alloying element and 5 % Silicate with dimensions 35mm x 35 mm x 10 mm was used. The experiments were carried out on Sprconix 25 ampere machine work bed size 1000x500x500 mm machine (Figure 1). The EDM performance was measured in the form of machined product roughness of the surface (Ra) which was measured using portable digital surface roughness tester (Mitutoyo SJ-201).

2.2 Experimental plan :

In the initial stage of the experimentation various process parameters were identified. After fixing input parameters and the target response, the experimentation were carried out with three replicates using Taguchi's L_{27} plan of experimentation. Finally the experimental was used to carry out the analysis using ANN and RSM techniques. In this research, MATLAB E2015 has been used to carry out the experimental data analysis and getting technical result. The lists of parameters associated with the experimentation are as tabulated in Table 2. The experimental result is tabulated in Table 3.

Table2: Process parameters associated with the presented work.

Sr. No	Parameters	Dimensions	Levels		
			Low [1]	Medium [2]	High [3]
1	Pulse_on_ time [PON]	Micro-sec	5	6	7
2	Pulse_off_time [POFF]	Micro-sec	5	6	7
3	Current [AMP]	Amp	7	8	9

4	Voltage [VOLT]	Volts	50	60	65

Table3: Experimental plan and data.

Exp No	TON	TOFF	AMP	VOLT	Ra
1	5	5	7	50	2.25
2	5	5	7	50	2.27
3	5	5	7	50	2.29
4	5	6	8	60	3.01
5	5	6	8	60	2.96
6	5	6	8	60	2.98
7	5	7	9	65	3.37
8	5	7	9	65	3.42
9	5	7	9	65	3.51
10	6	5	8	65	3.29
11	6	5	8	65	3.5
12	6	5	8	65	3.69
13	6	6	9	50	3.94
14	6	6	9	50	4.01
15	6	6	9	50	4.09
16	6	7	7	60	2.43
17	6	7	7	60	2.36
18	6	7	7	60	2.68
19	7	5	9	60	3.62
20	7	5	9	60	3.75
21	7	5	9	60	3.78
22	7	6	7	65	2.91
23	7	6	7	65	2.89
24	7	6	7	65	2.96
25	7	7	8	50	3.49
26	7	7	8	50	3.61
27	7	7	8	50	3.69

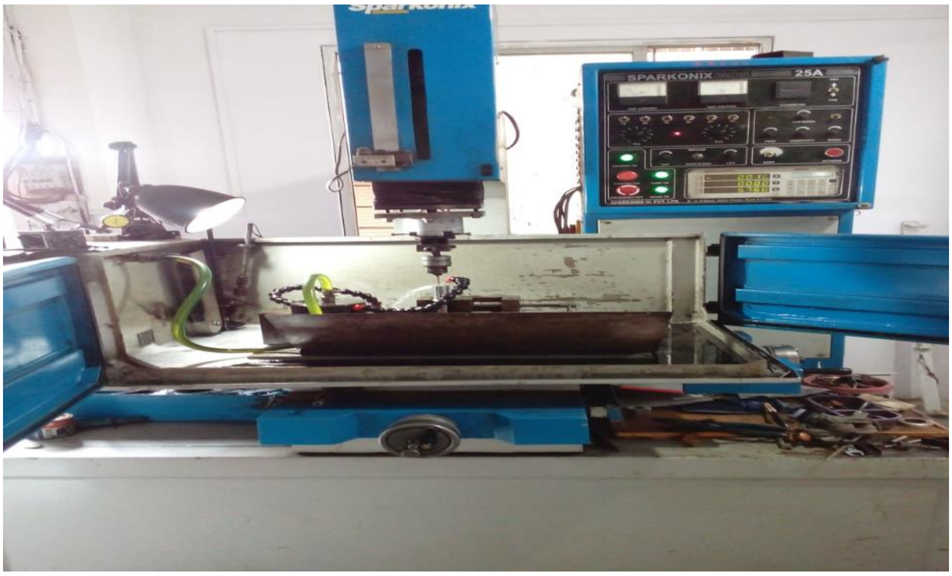


Figure 1: Experimental set up

2.3. Response Surface Method (RSM):

RSM link dependent process parameters with the number of independent parameters. In the present work 3 dimensional response surface is used during the investigation. Two independent process parameters were considered at a time and third independent process keep constant throughout the analysis. MINITAB 18 software was used to develop the RSM model. RSM model as given by the Eqn. (1).

$$Y = A_0 + A_1Y_1 + A_2Y_2 + A_3Y_3 + A_{11}{Y_1}^2 + A_{22}{Y_2}^2 + A_{33}{Y_3}^2 + A_{12}Y_1Y_2 + A_{13}Y_1Y_3 + A_{23}Y_2Y_3 \quad (1)$$

Where, 'Y' is the output variable and 'X' is the value of input variables and A_0,A_1,A_2.................A_{23} are the regression coefficient.

2.4. Artificial Neural network (ANN)

ANN is well known technique. It is used by so many researchers. The approach of ANN is synonymous to the mechanism human brain system. It consists of three layers network consists of input, hidden and output layer. The nodes are distributed in various layers. The fundamentals of ANN approach is as shown in fig. 2. An input layer is receiving data through various nodes and forwards it to the next layer where different weights are assigned and the data will get normalised for the further processing. The data will be forwarded to output layer for getting the best one. The selection of network is based on the accuracy required. Feed forward back propagation neural network (FFBPNN) was selected for getting the best response during training.

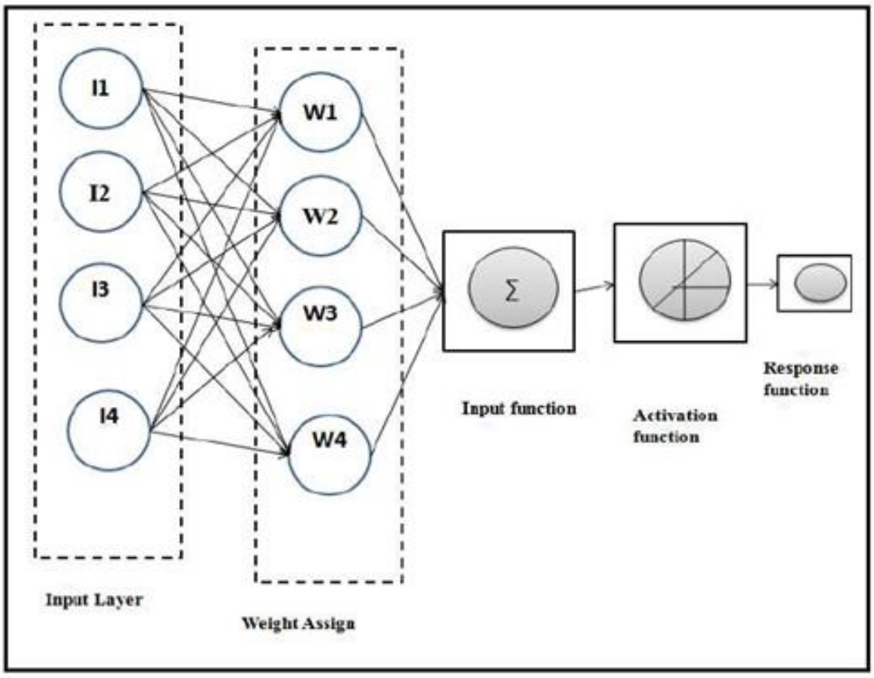


Figure 2: ANN basic methodology

3. RESULTS & DISCUSSION :

3.1 RSM Based Model

Pareto chart obtained during the data analysis is as shown in figure 3 (a). Pareto chart is used to find out the effect of the various process parameters and their interactions. The normal probability plot and the residual plot are as shown in figure 3(a) and 3(b) respectively. These plots are used to know the accuracy of the model. The horizontal line in the Pareto chart (figure3) represents the significance of the associated parameters. The bars C(AMP), A(TON), and D (VOLT) are showing significant impact on the quality of surface as compare to B (TOFF).

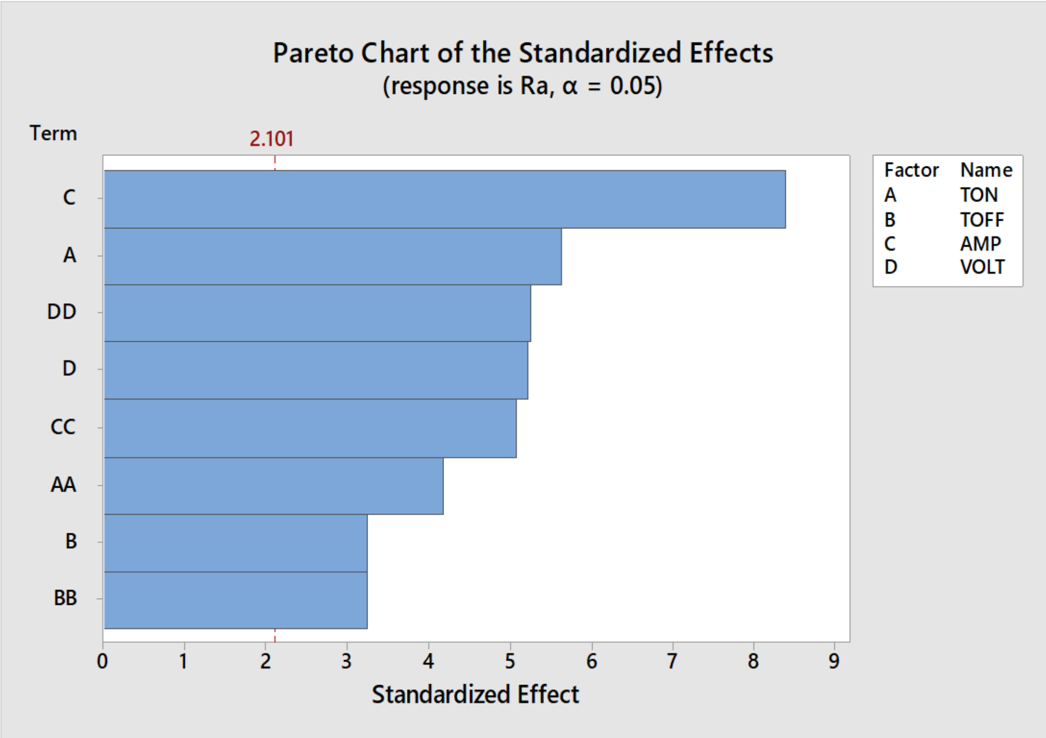


Figure 3(a) : Pareto chart.

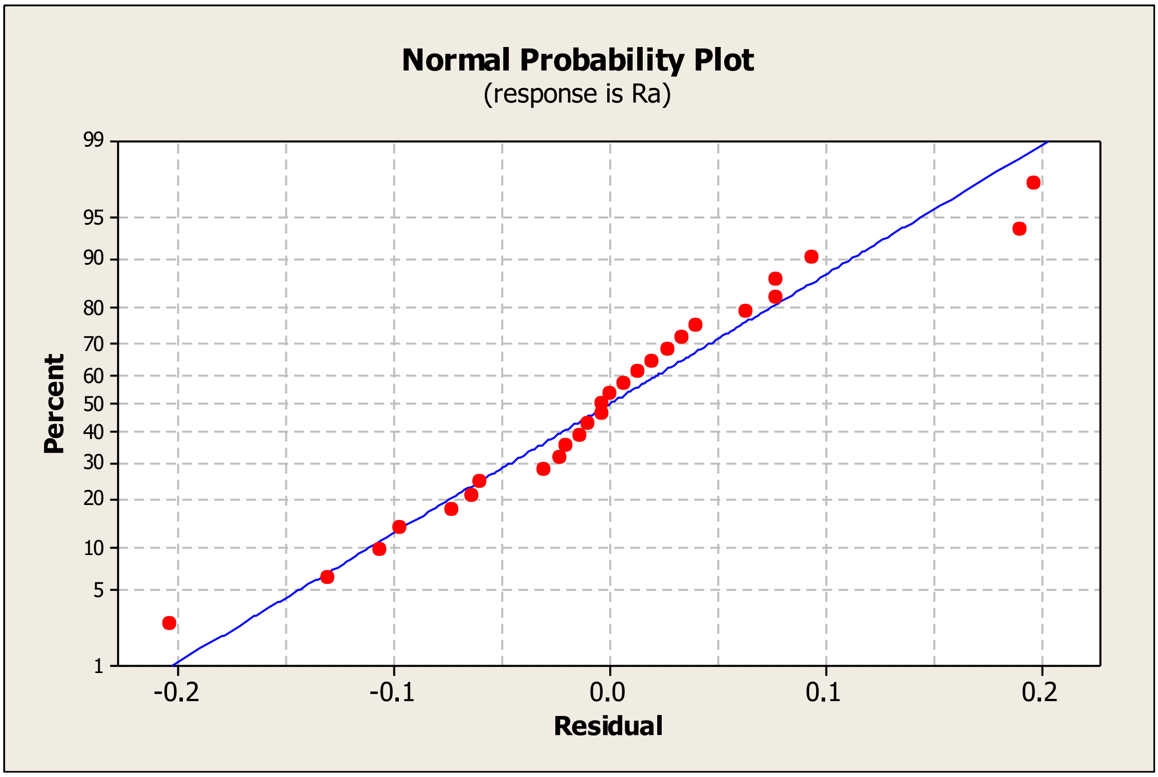


Figure 3(b): Plot representing (normal) probability.

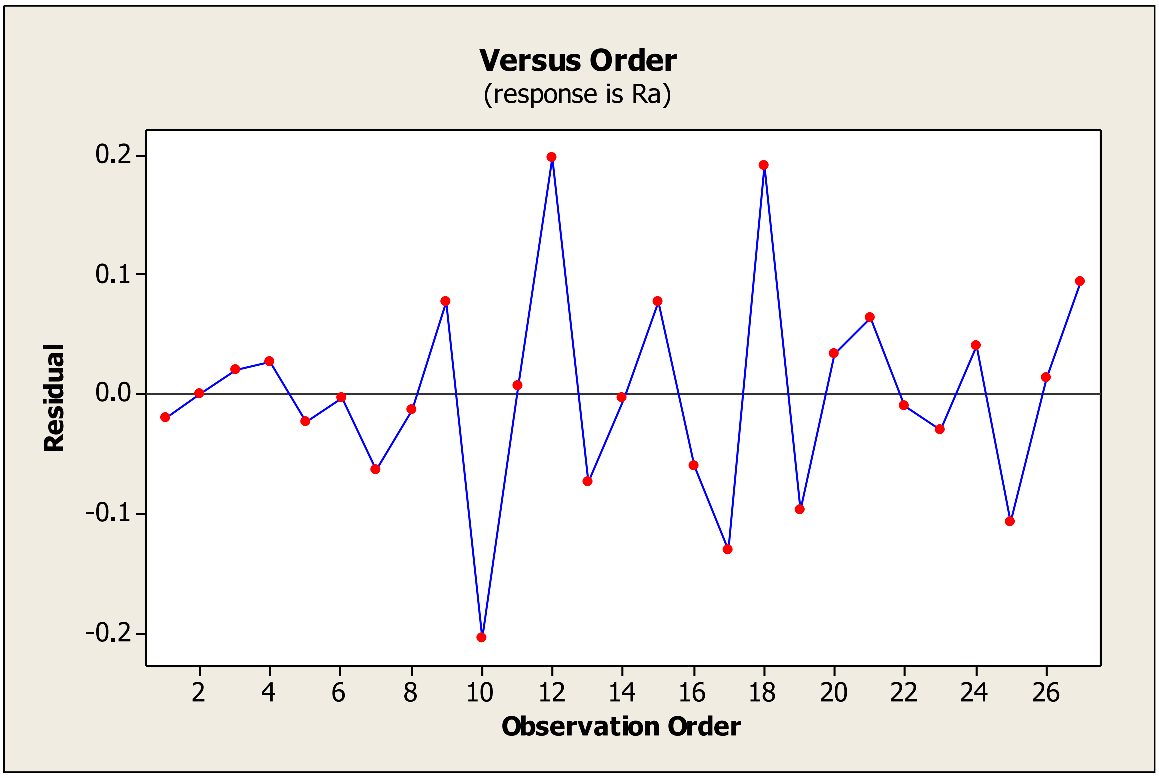


Figure 3(c) : Residual plot.

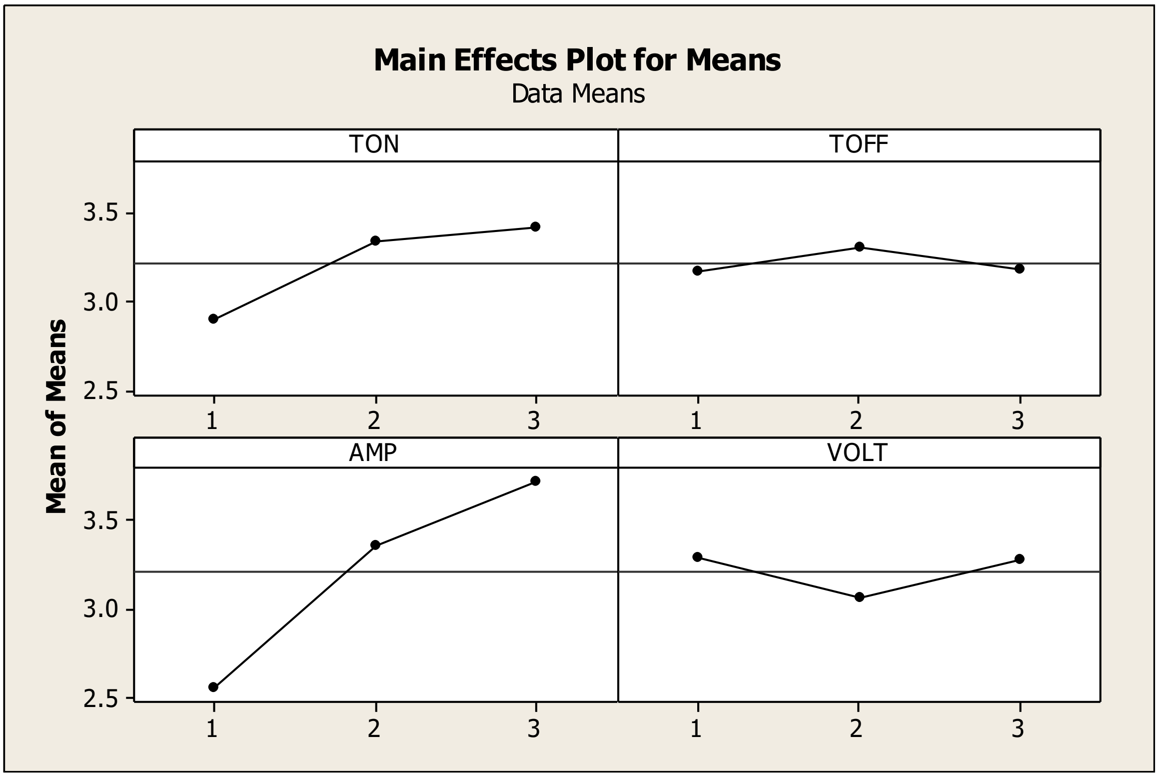


Figure 4: Plot representing impact of process parameters.

The impact of various process parameters is as tabulated in table 4. It was noted that current (AMP) has shown the significant impact followed by the TON and voltage. The parameters TOFF has shown a least impact on the roughness.

Table 4: Response table for means (Smaller the better criterion)

Level	TON	TOFF	AMP	VOLT
1	2.896	3.160	2.560	3.293
2	3.332	3.306	3.358	3.063
3	3.411	3.173	3.721	3.282
Delta	0.516	0.146	1.161	0.230
Rank	2	4	1	3

Analysis of variance (ANOVA) is done to know the impact of process parameters on the response. ANOVA results are as shown in the table 5. It is noted that all four process parameter has a notable impact on the surface roughness. But current and pulse on time has a dominant impact on response as compare to the remaining process parameters.

Table 5 : ANOVA Table for response Ra

Parameters (Source)	**DF**	**Adjusted SS**	**Adjusted MS**	**F ratio**	**P-Value**
Model	8	8.1574	1.01967	92.98	0.000
Linear	4	1.5356	0.38391	35.01	0.000
TON	1	0.3480	0.34802	31.73	0.000
TOFF	1	0.1161	0.11612	10.59	0.004
AMP	1	0.7718	0.77176	70.37	0.000
VOLT	1	0.2998	0.29976	27.33	0.000
Square	4	0.8931	0.22328	20.36	0.000
TON*TON	1	0.1920	0.19201	17.51	0.001
TOFF*TOFF	1	0.1157	0.11574	10.55	0.004
AMP*AMP	1	0.2831	0.28311	25.82	0.000
VOLT*VOLT	1	0.3023	0.30225	27.56	0.000
Error	18	0.1974	0.01097		
Total	26	8.3548			
S		Correlation coefficient	Correlation coefficient (adj)	Correlation coefficient (pred)	
0.104722		97.64%	96.59%	94.68%	

Regression Equation for response surface roughness:

Ra = -4.91 + 1.689 TON + 1.118 TOFF + 2.318 AMP - 1.801 VOLT - 0.1789 TON*TON - 0.1389 TOFF*TOFF - 0.2172 AMP*AMP + 0.2244 VOLT*VOLT

(2)

The input process parameters are correlated with response variable by using regression analysis in MINTAB software. The regression model for the response surface roughness is given by equation 2.

Table 6: Coefficient of the RSM model

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.499	0.302	1.65	0.116	
TON	0.973	0.173	5.63	0.000	49.00
TOFF	0.562	0.173	3.25	0.004	49.00
AMP	1.449	0.173	8.39	0.000	49.00
VOLT	-0.903	0.173	-5.23	0.000	49.00
TON*TON	-0.1789	0.0428	-4.18	0.001	49.00
TOFF*TOFF	-0.1389	0.0428	-3.25	0.004	49.00
AMP*AMP	-0.2172	0.0428	-5.08	0.000	49.00
VOLT*VOLT	0.2244	0.0428	5.25	0.000	49.00

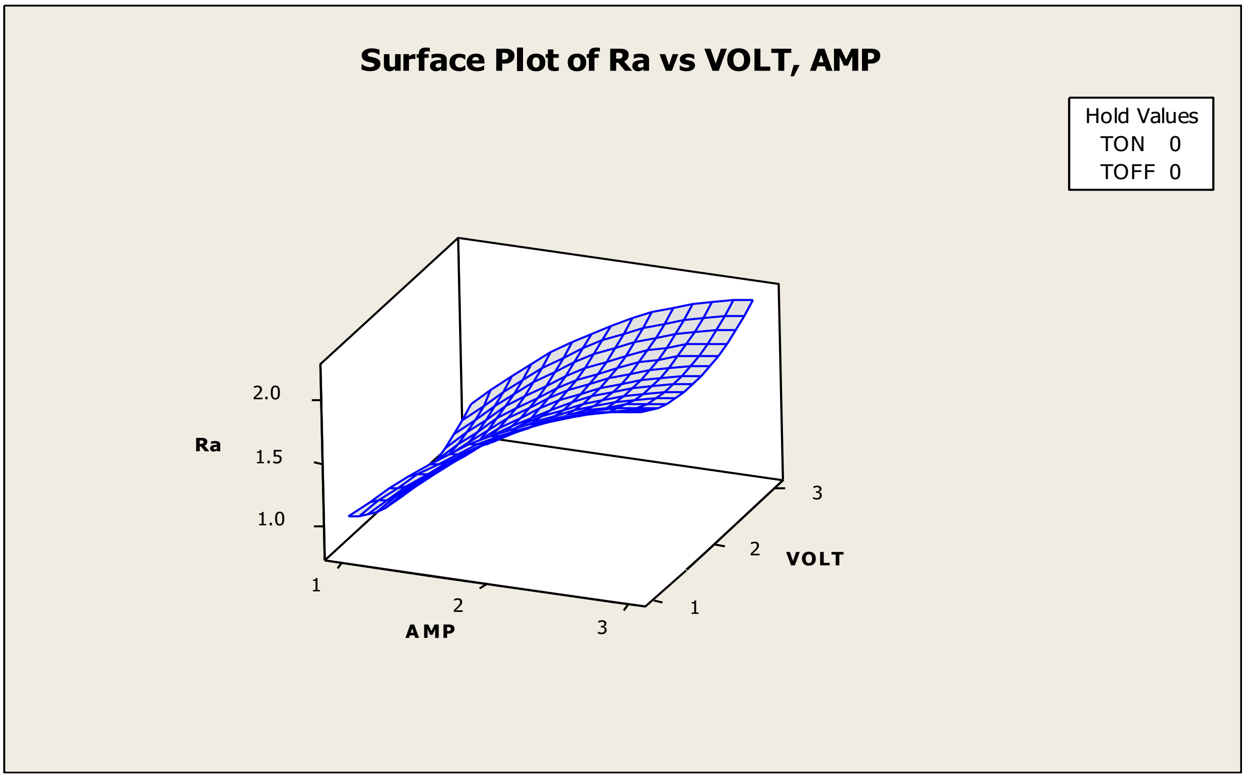


Figure 5(a): RSM plot for surface roughness considering variable ‘AMP’ & ‘VOLT’.

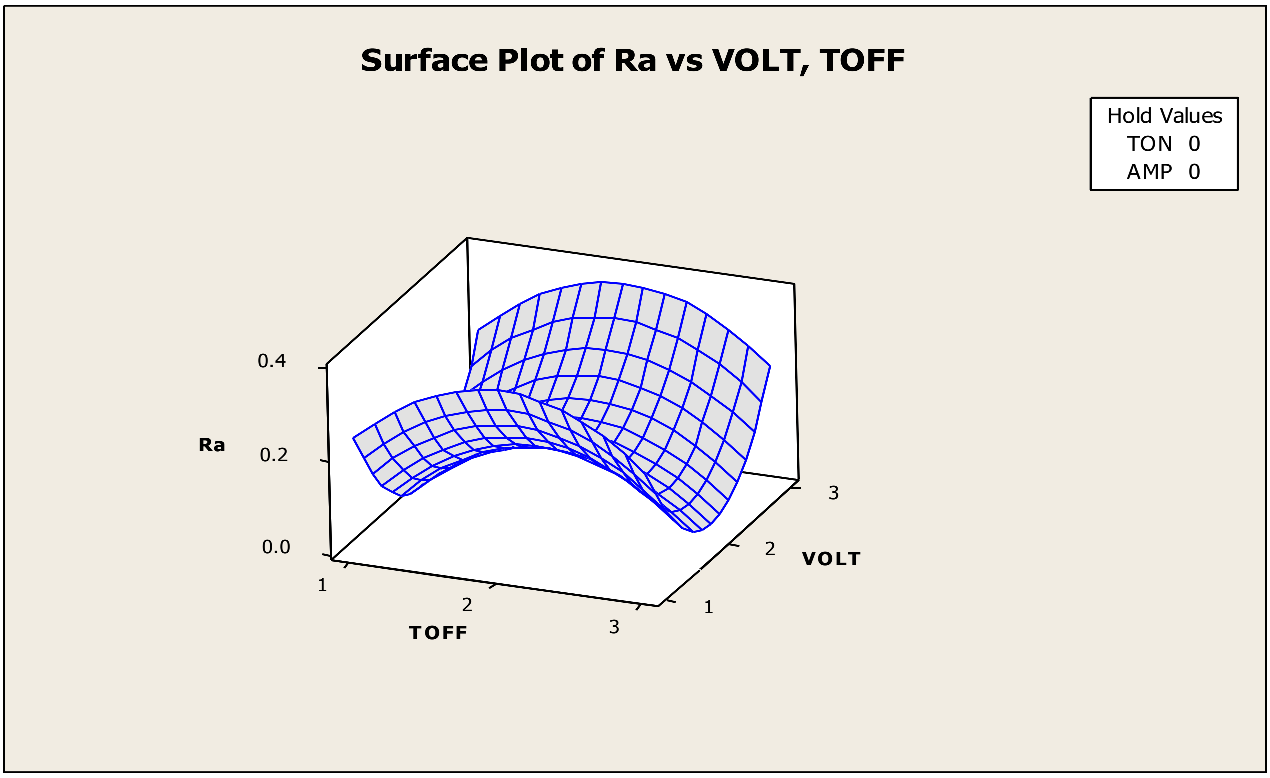


Figure 5(b): RSM plot for surface roughness considering variable 'TOFF' & 'VOLT'.

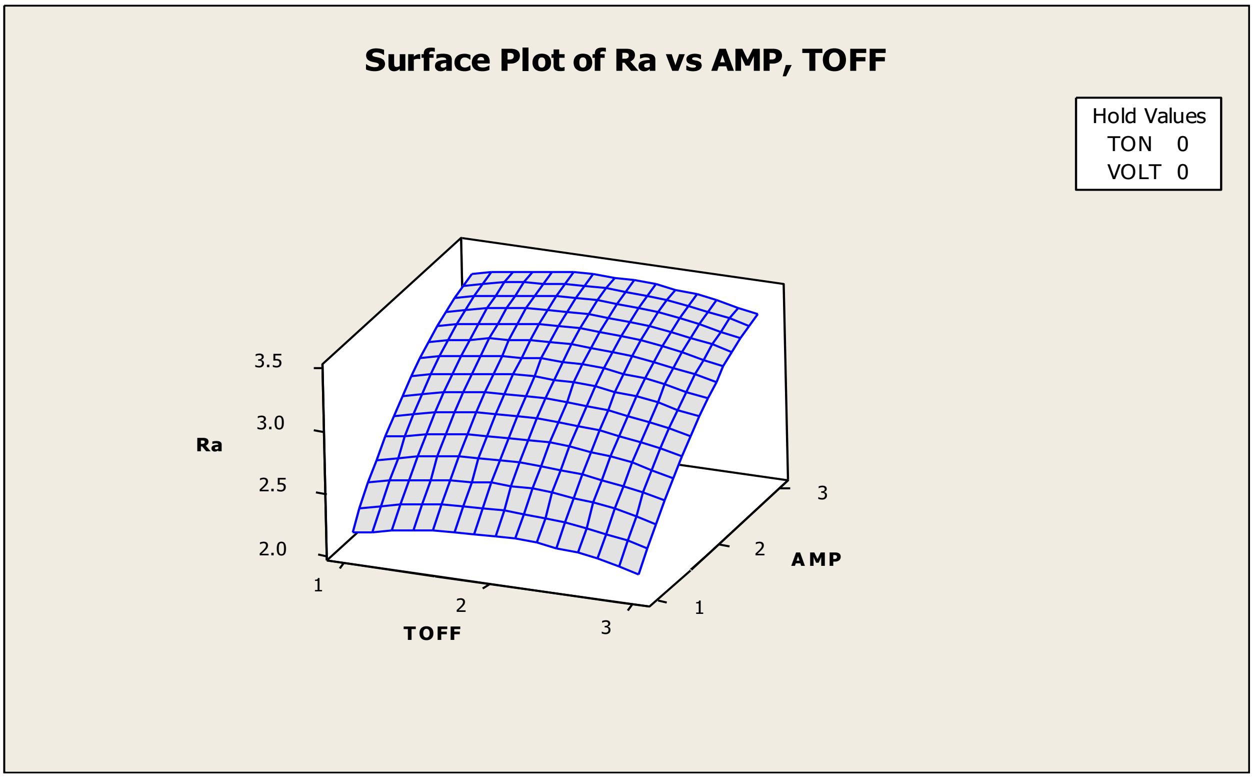


Figure 5(c): RSM plot for surface roughness considering variable 'AMP' & 'TOFF'.

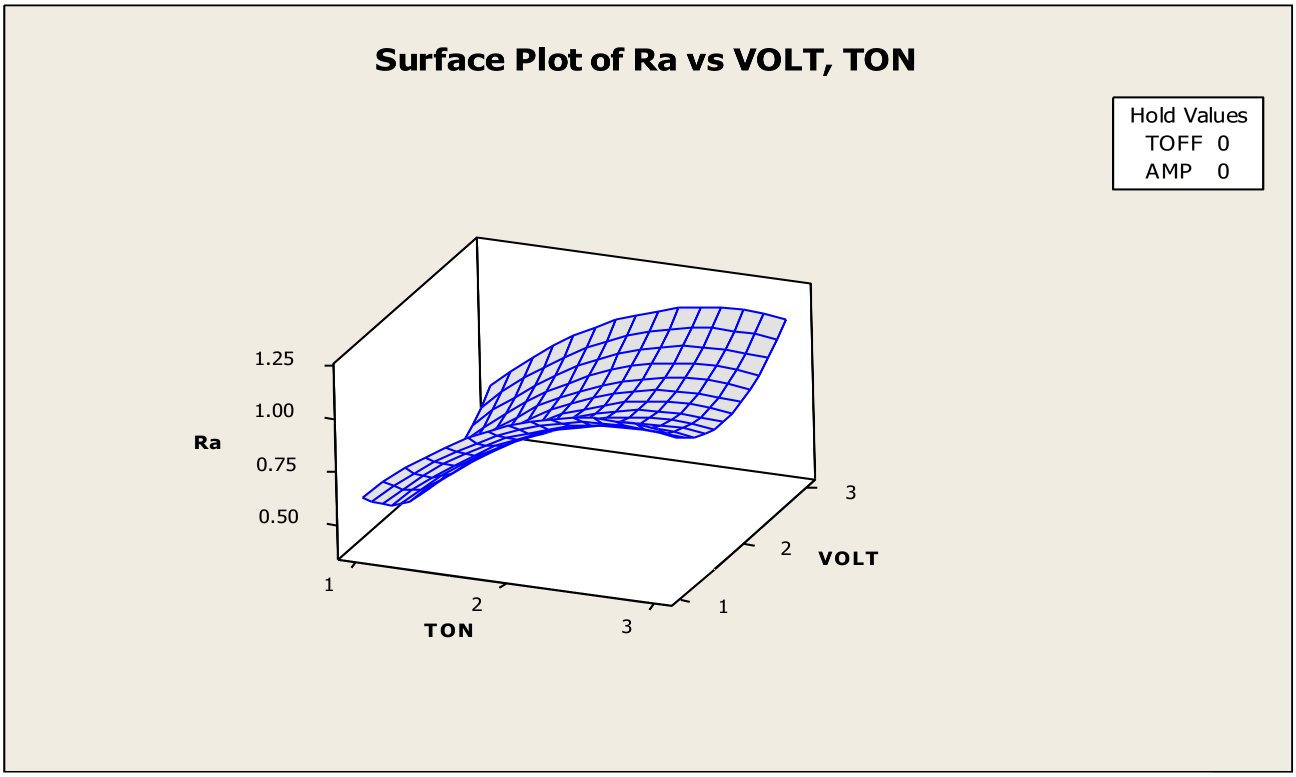


Figure 5(d): RSM plot for surface roughness considering variable ‘TON’ & ‘VOLT’.

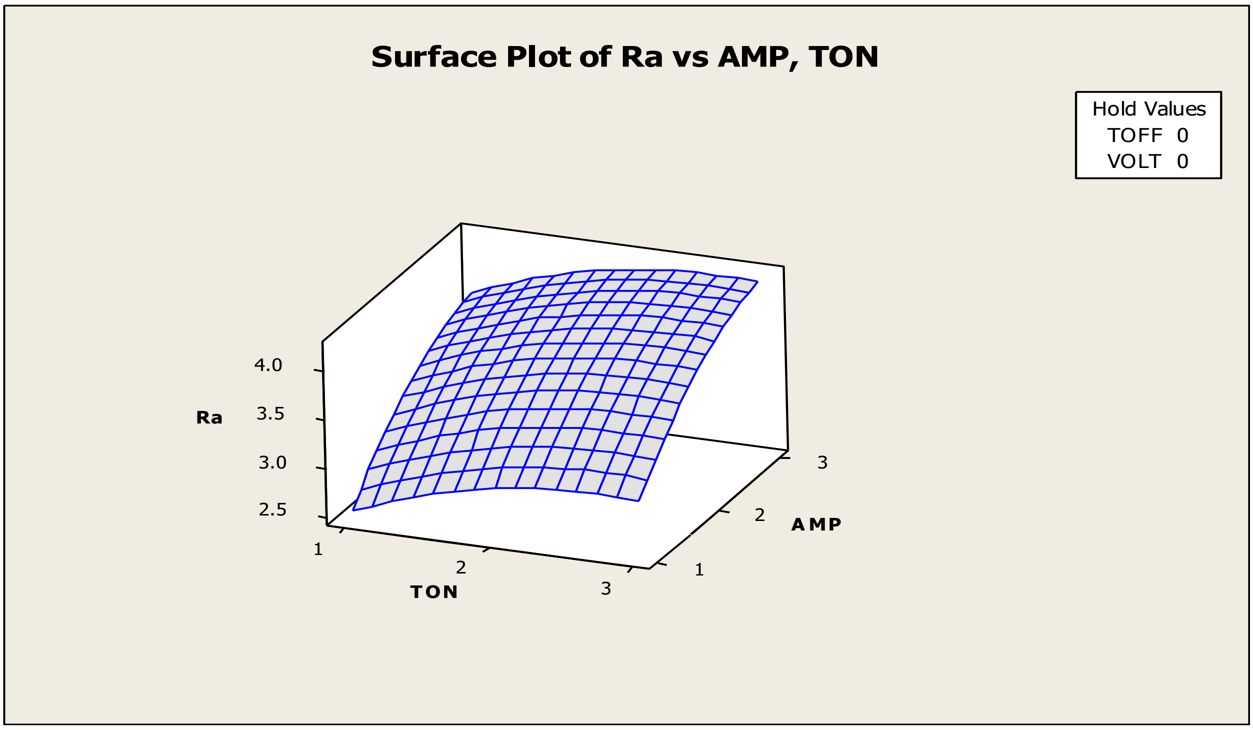


Figure 5(e): Plot for surface roughness considering variable ‘AMP’ & ‘TON’.

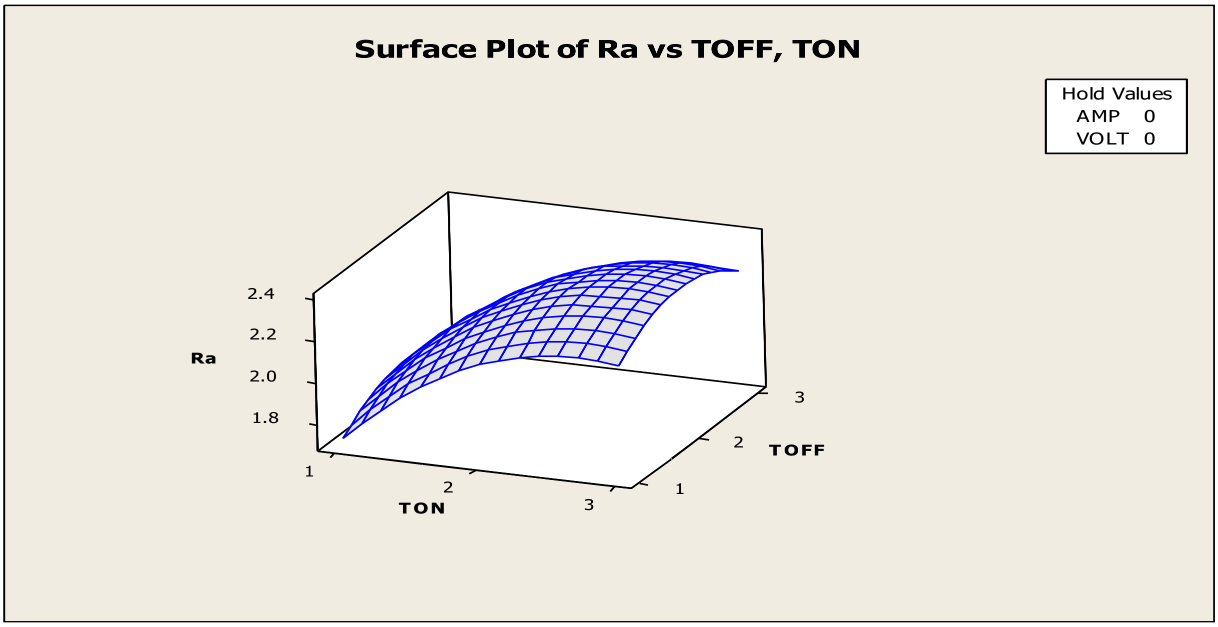


Figure 5(f): RSM plot for surface roughness considering variable 'TON' & 'TOFF'.

Surface plots for the response (Ra) are revealed in Fig. 5 (a)-5(f). This are the 3D plots which represents the variables on X and Y axis. The Z axis represents the output. Two variables are considered at a time while third variable is keeping constant throughout the analysis. From fig. 5, it can seen that the surface roughness goes on increasing w.r.t. the raise in the 'TON'. Hence it is directly propositional to the 'Ra'. The other variable 'TOFF' has insignificant impact on the 'Ra'. AMP is directly affects the response. Increasing from level 1 to 2 as shown

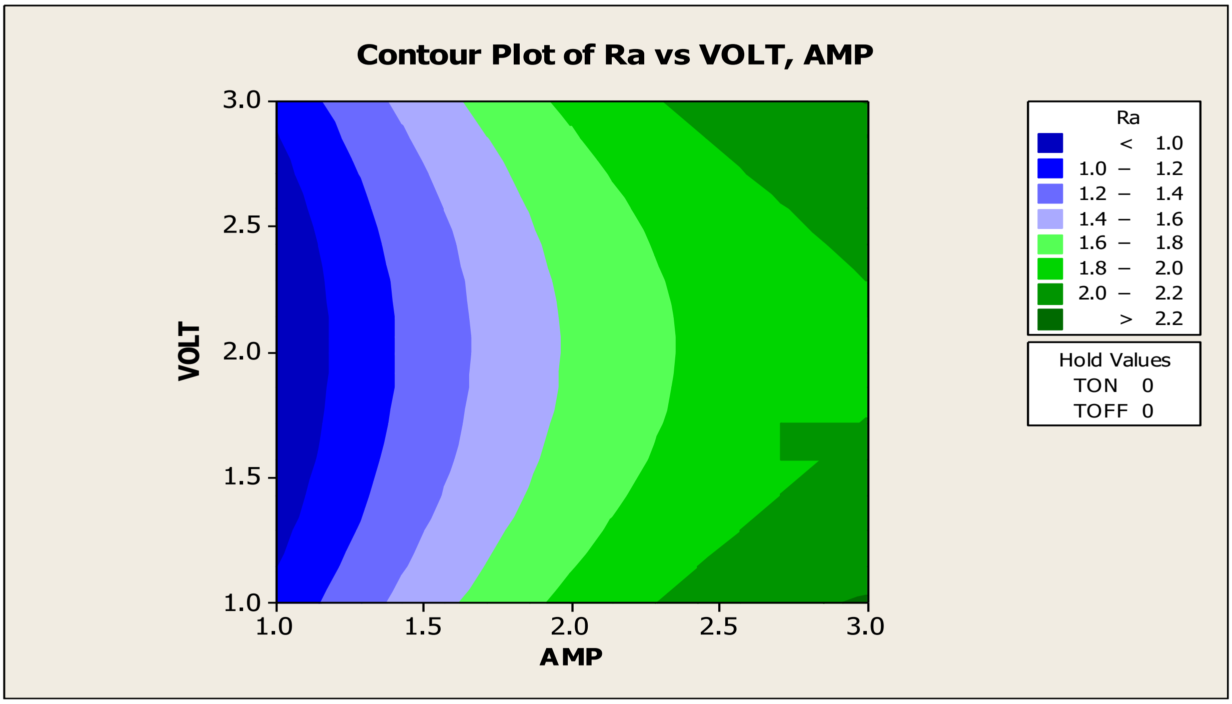


Figure 6(a): Contour plot for "Ra" considering variable 'AMP' & 'VOLT'.

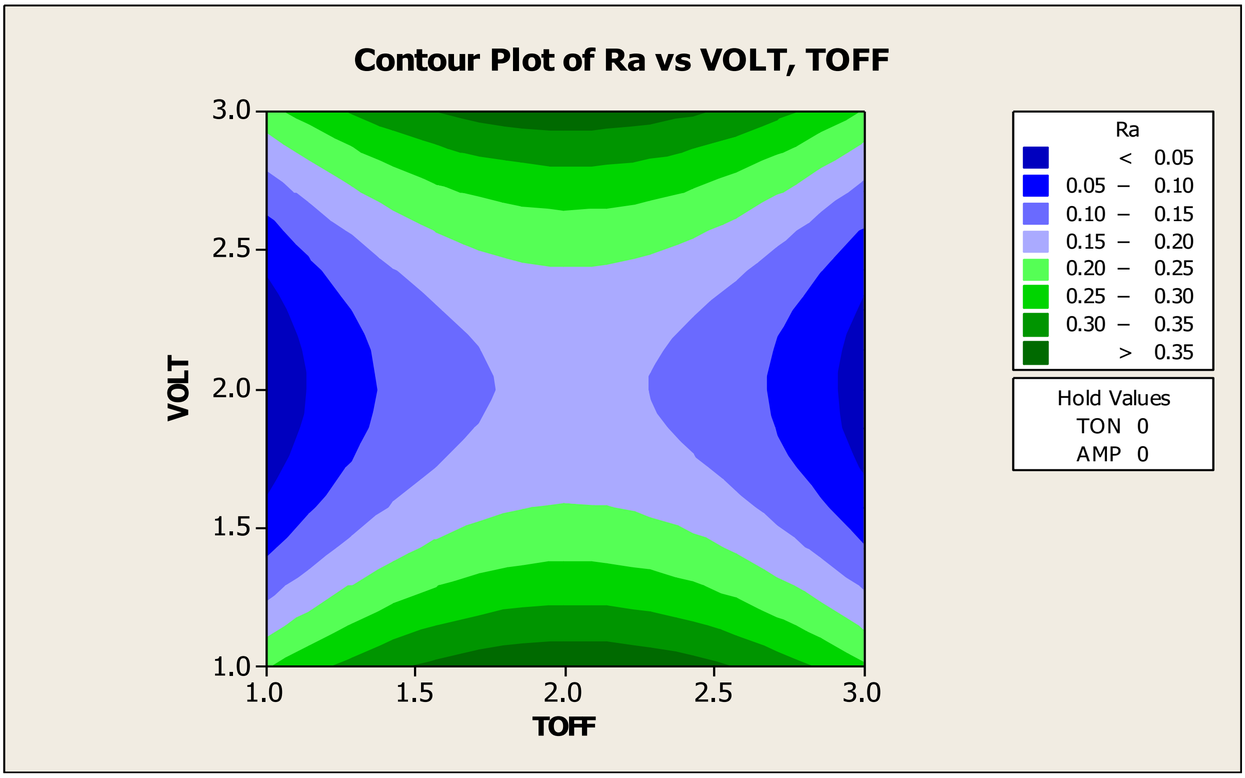


Figure 6(b): Contour plot for “Ra” considering variable ‘TOFF’ & ‘VOLT’.

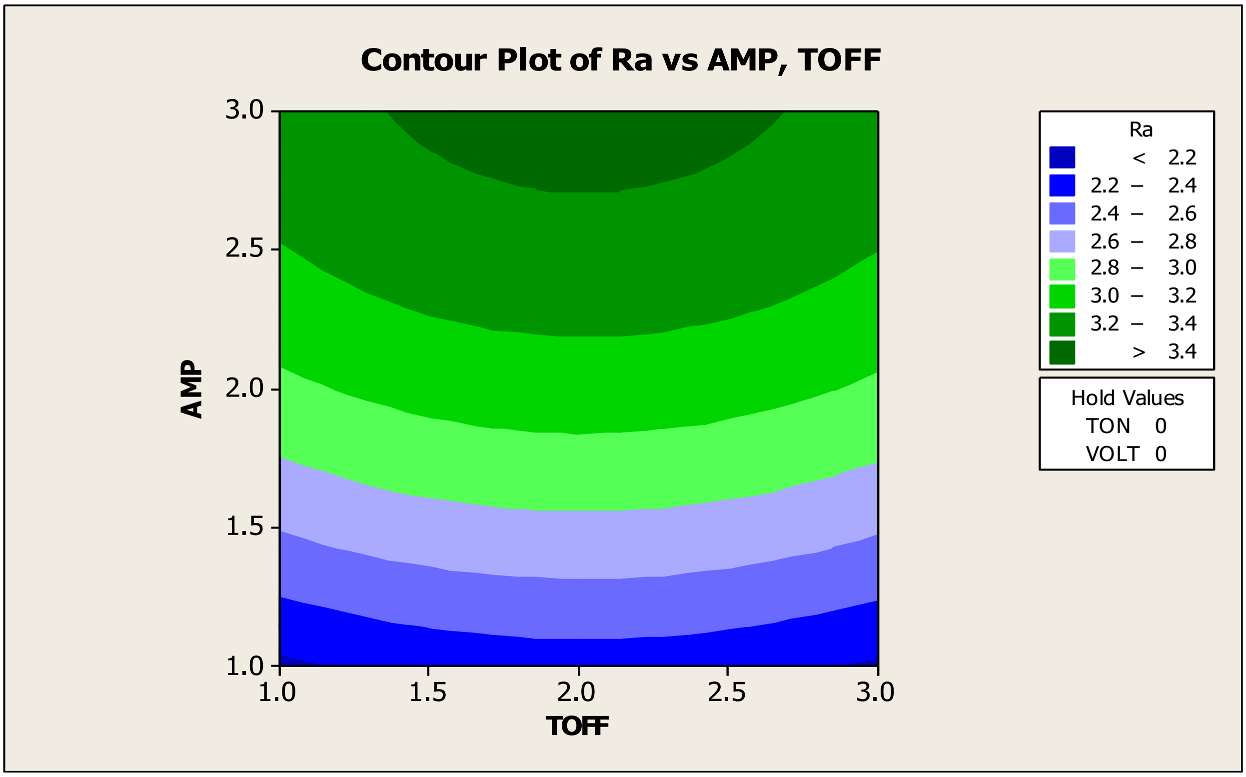


Figure 6(c): Contour plot for “Ra” considering variable ‘AMP’ & ‘TOFF’.

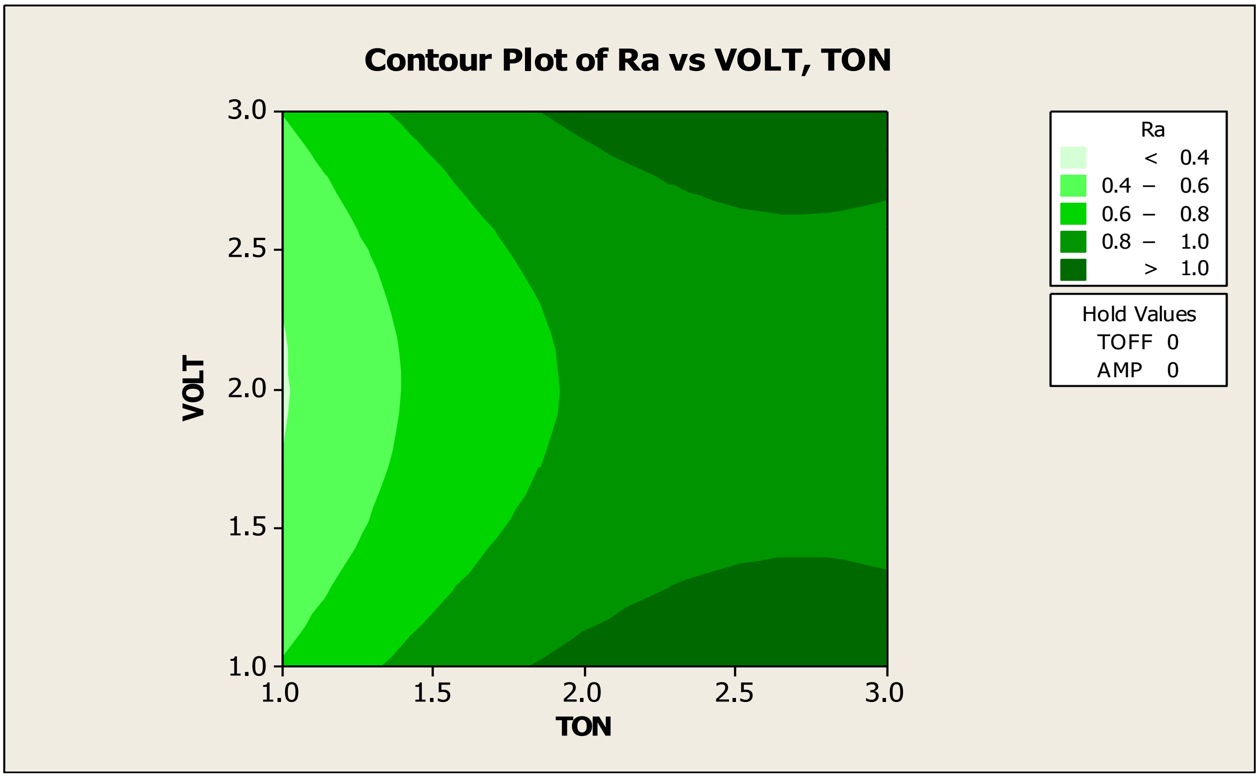


Figure 6(d): Contour plot for "Ra" considering variable 'TON' & 'VOLT'.

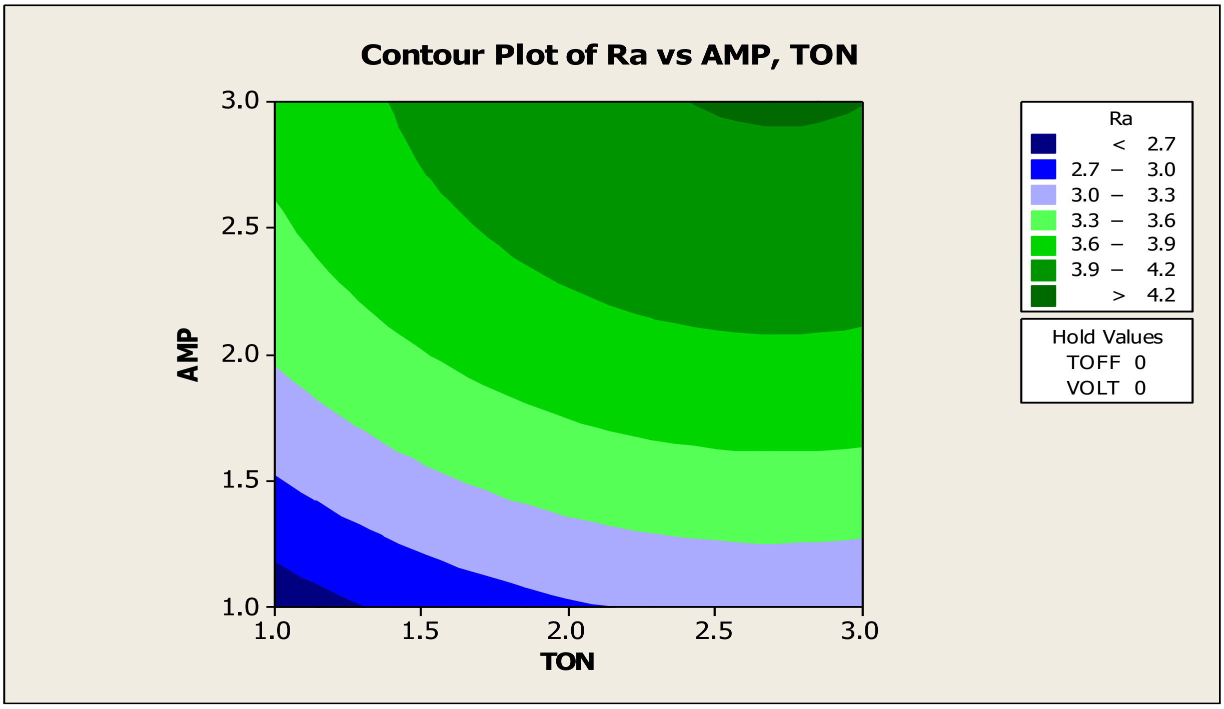


Figure 6(e): Contour plot for surface roughness considering variable 'AMP' & 'TON'.

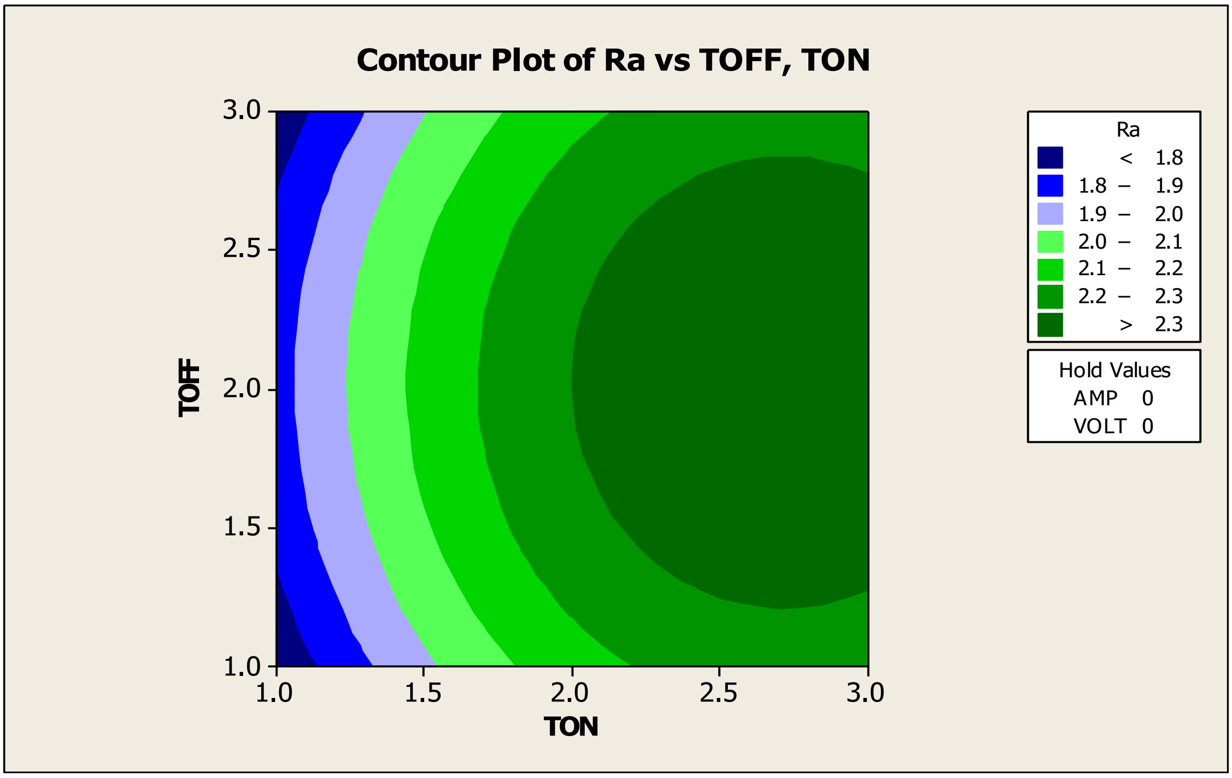
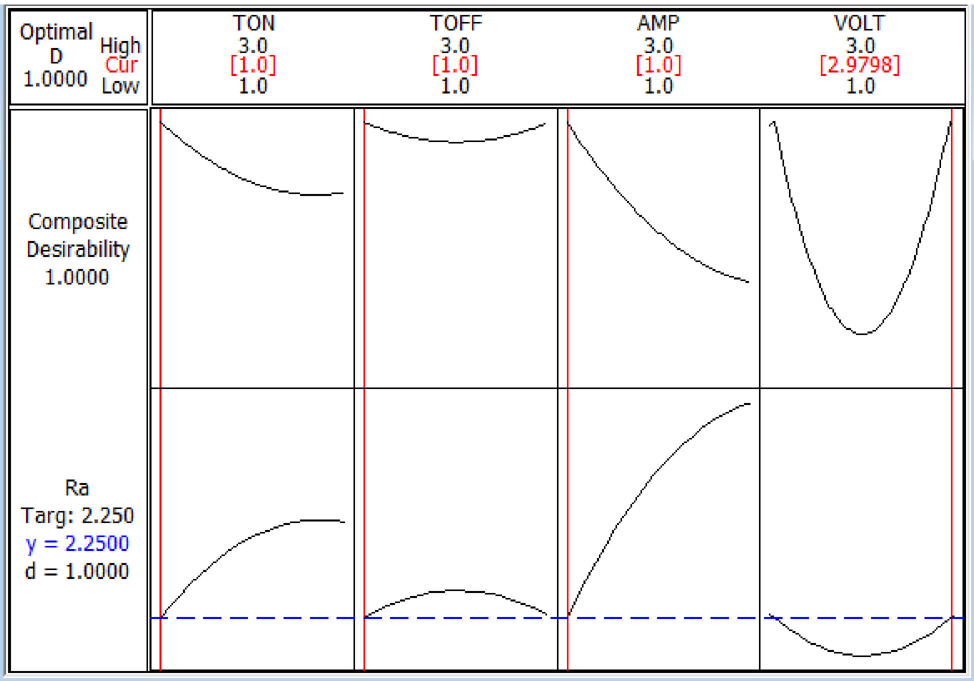


Figure 6(f): Contour plot for "Ra" considering variable 'TON' & 'TOFF'.

The effect of the process parameters on output is also express by surface contours as shown in the figures 6-(a) to 6-(f). The contour is a slice of the response surface. The elliptical slices showed the most influencing process parameters.



s

Figure 7: Optimization of surface roughness using desirability function.

The best set of process parameters to minimize the surface roughness is found out using optimization techniques. An optimal solution is obtained by using desirability function approach in MINIAB16 software. The following results are obtained from the optimization using desirability function.

TON = 1 Level
TOFF = 1 Level
AMP = 1 Level
VOLT = 2.97980 (3 Level)

Predicted Responses Ra = 2.25002, desirability = 0.999987

Composite Desirability = 0.999987

3.2 ANN based Simulation

ANN is a technique use for various engineering research. It is node based network of various layers. The working approach of ANN simulation is as shown in the following figure 2. ANN process the data in three phases i.e. training, testing and validation. 70% data is considered for the training, 15% data is considered for the testing and remaining is taken for the validation of the output.ANN response is correlated with actual experimental response to find out the degree of closeness. The correlation obtained after the ANN simulation is 0.98276, 0.98885 and 0.99557 respectively.

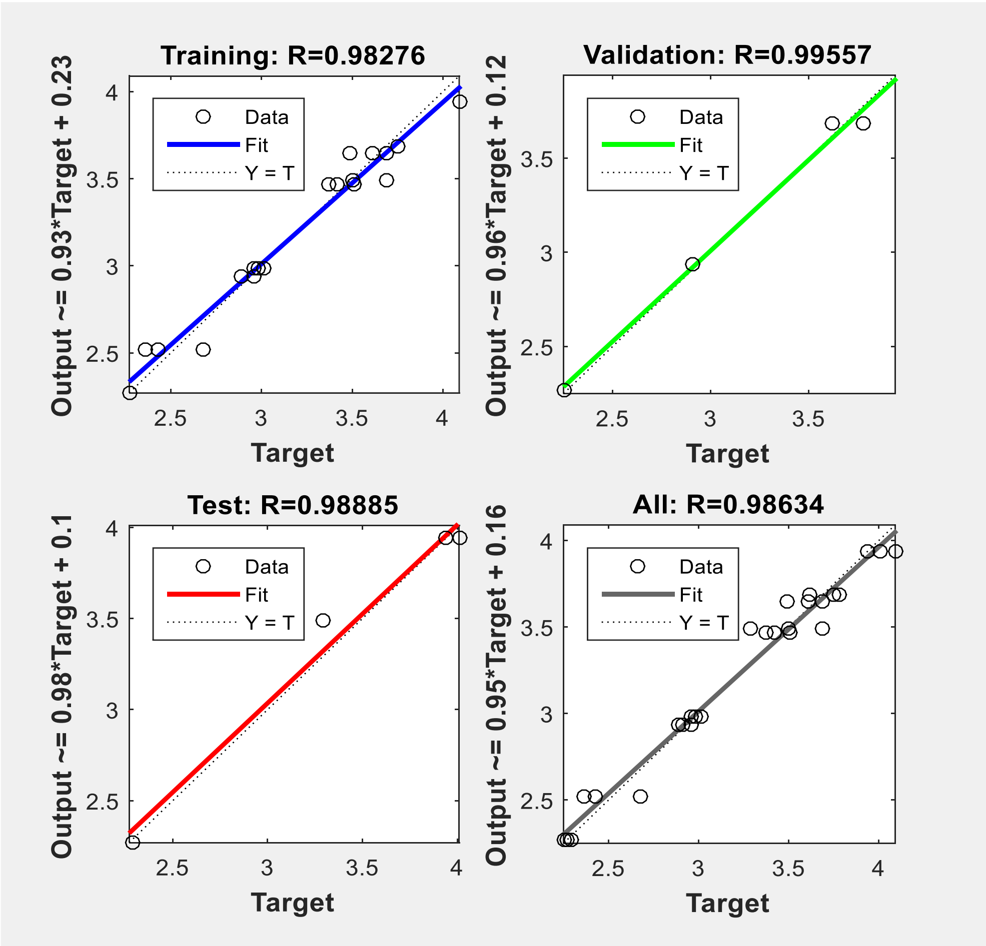


Figure 8: ANN based regression plot for response 'Ra'

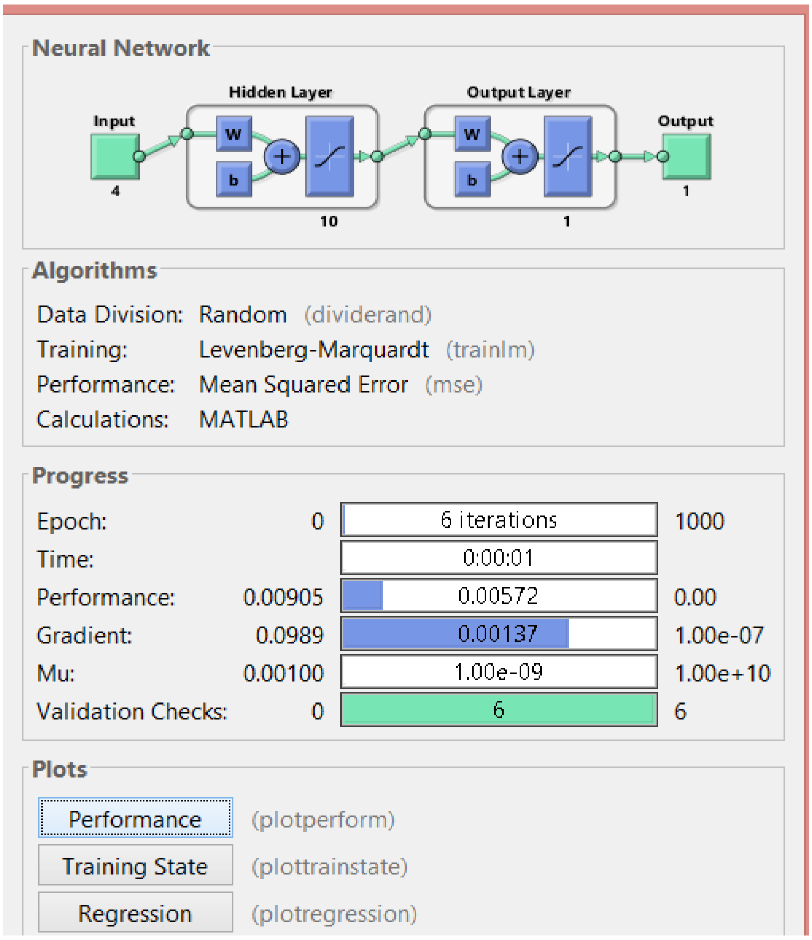


Figure 9: ANN parameters used for ANN simulation.

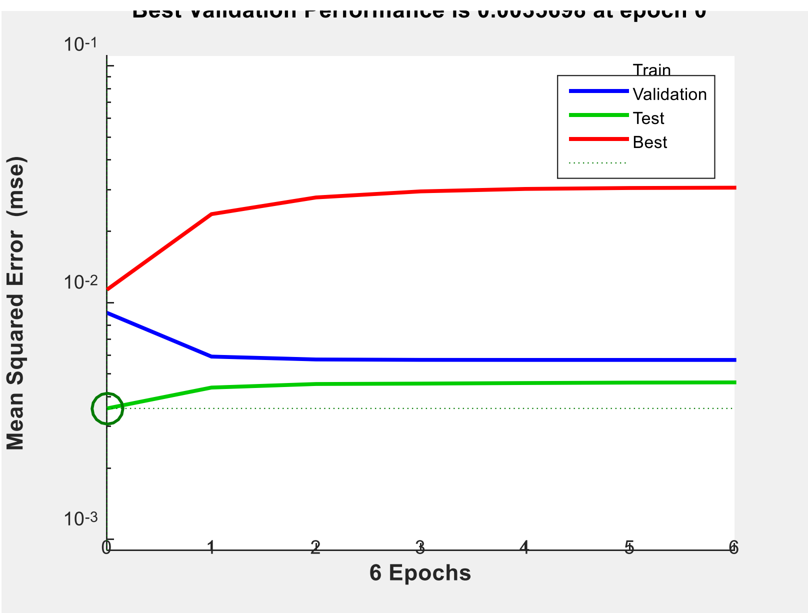


Figure 10: ANN performance during the simulation.

To update the weights in various layers, BPNN transmits the error in backward direction. The error is nothing but the deviation of actual response from computed response. BPNN is used to map correlation between inputs and output variables. The decision regarding the number of hidden layers is depends on the parameters associate in analysis. The presented work has four independent (input) and one dependent (output) parameter, hence three layer networks is preferred. Levenberg-Marquardt (LM) i.e. TRAINLM and used as a training function, learning function 'LEARNGDM' and transfer function 'TANSIG' has tested and prove the significant during the analysis. The ANN performance is as shown in the figure 9 and 10.

CONCLUSION

In the presented work, machining of AlSiCp5 was presented. The well known machining i.e. EDM ease has been carried out in the analysis. From the analysis, it has been concluded that the RSM is a very competent method of modelling. ANOVA was implemented to carry out the impact analysis of enlisted parameters on 'Ra'. The 'P' value has some significant, if 'p' value is ≤ 0.005 then the associate parameter has not sensible to response. While if the value of 'p' > 0.005 shows that the concerned parameters are insignificant. The value of correlation coefficient is 0.9764 , which is a good competent relation. The value of correlation coefficient is 0.9863, which shows the good competent relation between actual and RSM based response. An acceptable value of correlation coefficient (0.9863) was observed between the ANN predicted response and the experimental response. Out of both the soft computing techniques, ANN is better than the RSM.

ACKNOWLEDGEMENT

Authors would like to acknowledge industries for entire support and the facilities for doing this research work. Authors would also like to acknowledge all well wishers and my family members for their entire support.

REFERENCES

[1] Kumar, A.P., Bharat, C.R., 2014, Multi response optimisation of process parameters in turning of GFRP using TOPSIS method. *Hindawi Pub. Corp, Int. Sch. Res. Nots*. 101-110.

[2] Chia-Chi, S.,2010, A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS method. Exp.Sys. wt. *App*. **37**, 7745-7754.

[3] Huu-Phan, N., Van-Dong,P.,Ngoc-Vu,N.,2018, Application of TOPSIS to Taguchi method for multi-characteristic optimization of electrical discharge machining with titanium powder mixed into dielectric fluid. Int. J. of Adv. Manuf. Tech. **98**, 1179-1198.

[4] Jenarthanani,M., Jeyapaul, R., 2013, Optimization of machining parameters on milling of GFRP composites by desirability function analysis using Taguchi method. Int. J. of Engg. Sci. & Tech. **5(4)**, 23-36.

[5] Mevada, J., 2013, A Comparative Experimental Investigation on Process Parameters Using Molybdenum,Brass and Zinc-Coated Wires in Wire cut EDM. Int. J. of Sci. & Engg. Res. **4(7)**, 1398-1407.

[6] S. Suresh Kumar a, M. Uthayakumar a,S. Thirumalai Kumaran a, Temel Varol b, Aykut Canakci b, "Investigating the surface integrity of aluminum based composites machined by EDM", Defence Technology(Elsevier), 15,2019, 338-343.

[7] B. Surekha, T. Sree Lakshmi, Hemalata Jena, Priyaranjan Samal, "Response surface modelling and application of fuzzy grey relational analysis to optimise the multi response characteristics of EN-19 machined using powder mixed EDM, Australian Journal of Mechanical Engineering (Taylor & Fransis), 2019, 1–11

[8] Taher A., Shehabeldeena b, Jianxin Zhoua, Xu Shena, Yajun Yina,Xiaoyuan Jia, "Comparison of RSM with ANFIS in predicting tensile strength of dissimilar friction stir welded AA2024 -AA5083 aluminium alloys", Procedia Manufacturing, 37, 2019, 555-562

[9] Aysegul Bodur, Senol Sahin, Yildiz Sahin, Melih Inal, "Modeling of the Flexural Strength of Low Flow Polypropylene Talc / Colemanite Hybrid Composite Materials with Taguchi and ANFIS Methods" , IFAC Papers online, 51-30, 2018, 271–276

[10] Jibin T. Philip, Deepak Kumar, Jose Mathew, Basil Kuriachen, "Experimental Investigations on the Tribological Performance of Electric Discharge Alloyed Ti–6Al–4V at 200–600 °C", Journal of Tribology, 142, 2020, 061702 (1-15).

---

[11] N. Manikandan, K.Balasubramanian, D. Palanisamy, P.M. Gopal, D., Arulkirubakaran, J.S. Binoj, "Machinability Analysis and ANFIS modelling on Advanced Machining of Hybrid Metal Matrix Composites for Aerospace Applications" , Materials and Mfg. Processes, 34, 2019, 1866-1881.

[12] Devarasiddappa Devarajaiah1, Chandrasekaran Muthumari1, "Fuzzy logic-integrated PSO methodology for parameters optimization in end milling of Al/SiCp MMC", Journal of the Brazilian Society of Mechanical Sciences and Engineering, 41, 2019, 1-12.

[13] Tamang, S.K.a, Chandrasekaran, M.a, "Modeling and optimization of parameters for minimizing surface roughness and tool wear in turning Al/SiCp MMC, using conventional and soft computing techniques" , Advances in Production Engineering & Mgmt., 10, 2015, 59–72

[14] Prosun Mandal , Subhas Chandra Mondal, "Surface characteristics of mild steel using EDM with Cu-MWCNT composite electrode", Materials and mfg. processes, 34, 2019, 1326-1332.

[15] Ravindranadh Bobbili, V. Madhu, A.K. Gogia, "Multi response optimization of wire-EDM process parameters of ballistic grade aluminium alloy", Engineering Science and Technology, an International Journal, 18, 2015, 720-726

[16] P. N. L. Pavani1, C. L. V. R. S. V.Prasad, and K.Ramji, "Experimental Study & Optimization of Machining Parameters in Turning of AISI 1040 Steel with Micro-grooved WC Cutting Tools." , Engineering Journal, 24, 2020, 155-169.

[17] Huu-Phan Nguyen, Ngoc-Vu Ngo , Quoc–Tuan Nguyen, "Optimizing process parameters in edm using low frequency vibration for Material removal rate and surface roughness" , Journal of King Saud University – Engineering Sciences, 2020,1-8.

[18] S Debnath1, G R K Sastry2, R Naresh Rai3, "Multi-Objective Decision Making Optimization for Electro Discharge Machining Process of Al-4.5Cu-SiC Composite Using Fuzzy-Topsis" , Journal of Scientific & Industrial Research, 22, 2019, 468-476.

[19] Mangesh R. Phate , Shraddha B. Toney, "Modeling and prediction of WEDM performance parameters for Al/SiCp MMC using dimensional analysis and artificial neural network", Engineering Science and Technology, an Internationl Journal, 22, 2019.

[20] Sreenivasa Rao M, Venkaiah N, "Parametric optimization in machining of Nimonic-263 alloy using RSM and particle swarm optimization", Procedia Materials Science, 10, 2015, 70-79

[21] S. Suresh Kumar, M. UthayakumarS., Thirumalai KumaranP., Parameswaran, E.Mohandas2, "Electrical Discharge Machining of Al (6351)-5% SiC-10% B4C Hybrid Composite: A Grey Relational Approach, Materials and Mfg Processes, 29, 2014, 1395-1400.

[22] Dr. P. Nageswara Rao, Dr. R. Kotaiah , Dr. D. Venkateswarlu, "Experimental Investigation of EDM Parameters on Al-LM6/SiC/B4C Hybrid Composites" , Applied Mechanics and Materials, 877, 2018, 149-156.

[23] M.K. Pradhan, Manish Gangil , Prabhat Ranjan Kumar, "Application of MCDM for Optimization of EDM of LM6 Silicon Carbide Boron Carbide Hybrid Composite", Conference: 6th International and 27th All India Manufacturing Technology, Design and Research (AIMTDR) conference, 1, 2016, 557-562.

[24] P. Sahani , S.K. Karak, B. Mishra , D. Chakravarty,D. Chaira, "Effect of Al addition on SiC–B4C cermet prepared by pressureless sintering and spark plasma sintering methods", Int. Journal of Refractory Metals and Hard Materials , 57, 2016, 31-41.

[25] Anil Kumar Bodukuria, K. Eswaraiahb, Katla Rajendara,V. Sampath, "Fabrication of Al—SiC—B4C metal matrix composite by powder metallurgy technique and evaluating mechanical properties" , Perspectives in Science, 8, 2016, 428-43.

[26] Phate, M., S. Toney, and V. Phate. 2020. "Investigation on the Impact of Silicon Carbide and Process Parameters on Wire Cut-EDM of Al/SiCp MMC." Journal of Industrial Engineering and Production Research. 31 (2): 177– 187.

[27] Phate, V., R. Malmathanraj, and P. Palanisamy. 2019a. "Classification and Weighting of Sweet Lime (Citrus Limetta) for Packing Using Computer Vision System." Journal of Food Measurement and Characterization 13: 1451–1468.

[28] Phate, M., S. Toney, and V. Phate. 2019b. "Optimization Performance Parameters of OHNS Die Steel Using Dimensional Analysis Integrated with Desirability Function." Journal of Industrial Engineering and Production Research 30 (1): 11–23.

[29] Phate, M., S. Toney, and V. Phate. 2019c. "Investigation on the Impact of Silicon Carbide and Process Parameters on Wire Cut-EDM of Al/SiCp20 MMC." Industrial Engineering of Journal 12 (12): 1–13.

[30] Phate, M., and B. Toney. 2019. "Modeling and Prediction of WEDM Performance Parameters for Al/SiCp MMC Using Dimensional Analysis and Artificial Neural Network." Engineering Science and Technology, an International Journal 22 (2): 468–476.

[31] Phate, M., S. Toney, and V. Phate. 2019a. "Analysis of Machining Parameters in WEDM of Al/SiCp20 MMC Using Taguchi Based Grey-Fuzzy Approach." Modeling and Simulation in Engineering 1483169: 562–566. Hindawi Pub.

[32] Mangesh Phate, Shraddha Toney & Vikas Phate (2020): Prediction and optimization of tool wear rate during electric discharge machining of Al/Cu/Ni alloy using adaptive neuro-fuzzy inference system, e05308: 1–10, Heliyon,6.

[33] Mangesh Phate , Shraddha Toney & Vikas Phate (2022): Modeling and investigating the impact of EDM parameters on surface roughness in EDM of Al/Cu/Ni Alloy, 20, PP : 1226-1239,Australian Journal of Mechanical Engineering.