Vol. XII & Issue No.12 December - 2019
INDUSTRIAL ENGINEERING JOURNAL

PREDICTION AND ANALYSIS OF SURFACE ROUGHNESS IN WEDM OF AL/GR/CP5 MMC USING RSM & ANN

Dr. M.R. Phate

Ms. Shraddha B Toney

Vikas R. Phate

Abstract

Wire electric discharge machining i.e. WEDM is very popular non-conventional machining process. Most of the machining industries preferred WEDM as an economical and effective machining process. Along with the use of aluminium, its composite are going to be very popular and fulfill the industrial need. To maximize the use of WEDM for getting the economical and precise outcomes, analysis is very important. There are so may process parameters concern with the WEDM process, but it was really a tough job to correlate all the process parameters. Hence the parameters such as P-on time (TON), P-off time (TOFF), wire federate (WFR) and the input current (IP) has been finalized for the investigation. The new aluminium based metal matrix with graphite (5%) as a filler metal was selected for the investigation. Taguchi L_{27} (3^3) design of experimentation plan has been employed to carried out the experimentation. Two modelling techniques i.e. response surface method (RSM) and soft computing technique i.e. artificial neural techniques has been adopted for the analysis. From the experimental findings, it has been observed that both RSM and ANN have efficiently predicted the response with an acceptable agreement measure in terms of correlation coefficient. Feed forward back propagation neural network was employed for the analysis through ANN while the second degree response surface model was formulated for response surface method. Analysis of variance (ANOVA) was carried out to know the impact of various process parameters. But the ANN was superior to the RSM model hence recommended for the investigation of such process.

keywords: Al/Gr/Cp5 MMC,ANN, ANOVA,RSM,WEDM.

1. INTRODUCTION

At the moment, the use of lightweight materials such as aluminum, magnesium and their composites are effectively sprouting in various fields like space equipments, automobiles, and medical, household and other metal concern industries. The demand of these materials are going to be increase drastically sue to the properties such as higher value of thermal and electrical conductivity, high weight to strength ratio, low density , higher value of damping coefficient etc. Hence, it is today's need to focus on the fabrication and processing of such materials. The present work focus on the fabrication and wire cut electric discharge machining (W-EDM) of new aluminum based metal matrix composite (MMC) with 5 % graphite (by weight). The fabricated MMC is designated as Al/Gr/Cp5 MMC. V. Kavimani et al. [1] has develop new MMC using magnesium as a alloying materials. The experimental investigation has been carried out to know the impact of various process parameters. The response parameters were material removal rate and the surface roughness. The approach of Taguchi based grey relation analysis (GRA) was employed for the investigation. Mangesh et al [2] has developed aluminium based MMC with the silicate percentage (15 to 20 by weight). The WEDM process was analysed to find out the impact of process parameters and to know the ease machining conditions. The approach of dimensional analysis and the soft computing technique i.e. artificial neural network were employed for the modelling and prediction. B. Singh et al [3] investigated the impact of WEDM process parameters during the machining of Nimonic 263 material. The modelling techniques like response surface method and artificial neural network were employed for the analysis. N. Sharma et al [4] has investigated the WEDM process parameters for the machining of High speed low alloy steel (HSLA). The modelling technique such as response surface method (RSM) and the optimization technique such as genetic algorithm (GA) were employed for the investigation. Mangesh et al. [5] has optimized the WEDM process for the Al/SiCp20 MMC using the Fuzzy based grey rational analysis. Taguchi approach has been employed for the experimentation and the result analysis.

Tea Sung Jun et.al. [6] analysed the influence of residual strains in Al 2024/AlSiCp composite linear friction welds using an eigen strain based finite element approach. Ilhan Asilturk et.al. [7] has used the multiple regressions and the artificial neural network technique for analyze the machining process for improving the surface quality of the work piece. Debaprasanna et.al. [8] has employed the machinability of AlSiC MMC during the WEDM process using principal component analysis. The various performance parameters consider for the investigation were surface roughness, material removal rate, tool wear and the circularity. I.M.Jamadar et.al. [9] formulated DA approach and ANN based on feed forward back propagation training network to analyse the responses due to the defects in the bearing components. Ravindranadh Bobbili et.al. [10] examined the impact of various process parameters on MRR and the roughness using dimensional analysis (DA) and the artificial neural network (ANN) approach. Senthilkumar N. et.al [11] employed a grey relational fuzzy grade technique (GRFG) along with the well known Taguchi method to analyze the impact of machining process parameters and the carbide inserts approach angle on various process parameters. Vinod Kumar et.al. [12] adopted RSM and desirability function to analyse the impact of the pulse on time, pulse off time, discharge current and the servo voltage on material removal rate and the surface roughness. The desirability function approach has been employed to find out the optimum process parameters during the WEDM of Monel-400 material. Phate et al. [13-14] has employed the ANN based models for the machining of nonferrous materials. Their experimental findings showed the efficiency and effectiveness of back propagation neural network. Rao et al. [15] has used teaching –learning algorithm (TLBO) to find out the optimize the WEDM process parameters. Nain et al. [16] has used speed low alloy steel (HSLA) which has a wide application in the space and die manufacturing. The research was carried out by the authors to investigate the impact of various WEDM process parameters on the machining response parameters. The research was carried out by the various researchers to fine out the best set of WEDM process parameters. Saha et al. [17] has implemented particle swarm optimization (PSO) for the optimization of Udimet-L605 material WEDM performance. M.V.Bhadrarao et al. [18] has investigated the optimum process parameters for the turning of low carbon steel with dry, flood and minimum quantity lubricant (MQL) during the machining. A. Sharma et al. [19] has investigated the turning process parameters on surface finish, tool wear and the specific energy consumption during the turning of AISI 4140 Alloy. Response surface method (RSM) was employed for analysing the impact of turning process parameters. N. Bhanot et al.[20] has done the sustainability assessment of turning process using internet of things concepts. The basic aim of the study was to improve the performance of tool during the turning process.

2. MATERIAL & METHOD

In this section, the description about the MMC fabrication and the experimentation with the parameters associated with the WEDM investigation has been discussed.

2.1. Al/Gr/Cp5 MMC

Aluminium is a very popular material which is use in automobile industries, space equipments and some defence equipments due to its unique properties such as light in weight, excellent corrosion resistance, high thermal and electrical conductivity, high strength at low temperature etc. The aluminium based metal matrix composites has got the good acceptability due to its high strength and weight ratio. In the present work, the filler material used to fabricate the MMC was graphite (5% by weight). The experimentation was carried out on Electronics Ultracut WEDM (Make: Pune). A rectangular plate of 80x55x20mm was preferred for the fabrication and the processing. A brass wire of 0.25mm diameter was used as an electrode. The process variable and their levels are as shown in the following Table 1. The geometry of the work piece is as shown in the fig1. The experimental setup is as shown in fig. 2.

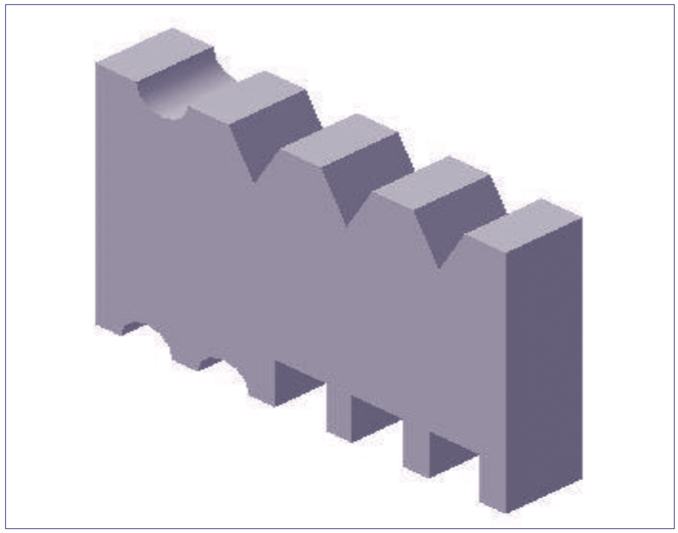

Fig. 1. Geometry of the Al/Gr/Cp MMC.

S.N.	Process Parameters	Sym-bols	Levels		
			Low(1)	Medium (2)	High (3)
1	P_on time (micro-sec)	TON	108	110	112
2	P-off (micro-sec)	TOFF	52	54	56
3	Wire feed rate (mm/min)	WFR	4	5	6
4	Input current (Amp)	IP	11	12	13

Table 1. WEDM process parameters and their levels.

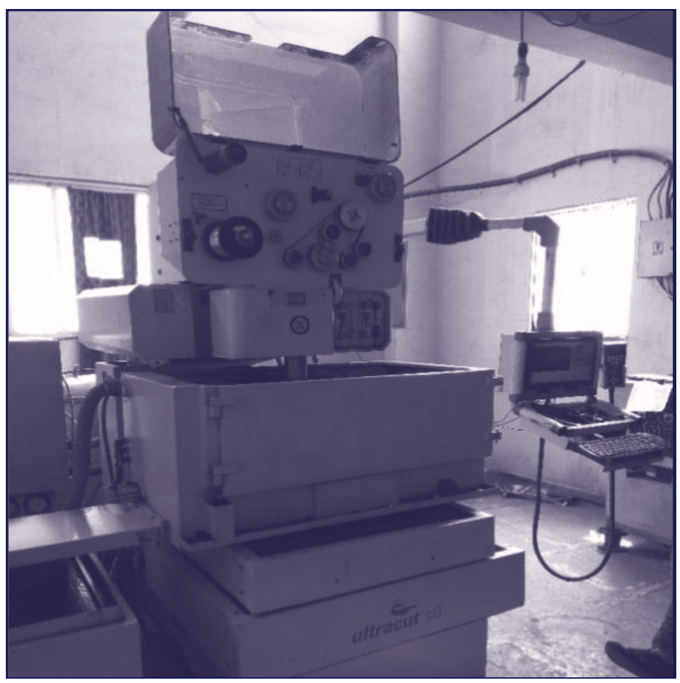

Fig. 2. WEDM experimental for processing Al/Gr/Cp MMC.

2.2. Experimentation

Four parameters (Table 1) were chosen for the investigation. Taguchi's L_{27} (3^3) plan of experimentation was employed for collecting the data. Three replicate were carried out for each experiment and the average value was noted as the response value. The observations are as shown in Table 2.

2.3. Response Surface Method (RSM)

Response surface method (RSM) is the statistical technique use to correlate the two variables with the response variable. The seconds order mathematical equation is created in this method. This is an industrial tool widely used for the investigation. Minitab software is used for the RSM analysis.

The generalized second degree RSM equation as given by the equation (1).

$$X = a_0 + a_1y_1 + a_2y_2 + a_3y_3 + a_4y_4 + a_{11}y_1^2 + a_{22}y_2^2 + a_{33}y_3^2 + a_{44}y_4^2 + a_{12}y_1y_2 + a_{13}y_1y_3 + a_{14}y_1y_4 + a_{23}y_2y_3 + a_{24}y_2y_4 + a_{34}y_3y_4. \quad (1)$$

Where, X is the response variable is X is the value of input variables and a0,a1,a2.................a34 are the regression coefficient. Response surface method (RSM) two degree model with four process parameters (with coded data or levels and uncoded data or actual value) and the surface roughness as a response parameter is given by the Equation 2 and 3 respectively.

$$R_a = 2.693 - 0.031 * \mathrm{TON} + 1.180 * \mathrm{TOFF} - 0.820 * \mathrm{WFR} + 0.896\& * \mathrm{IP} + 0.1587\mathrm{TON}^2 - 0.2979 * \mathrm{TOFF}^2 + 0.1137 * \mathrm{WFR}^2 - 0.0963 * \mathrm{IP}^2 \quad (2)$$

$$R_a = 2.693 - 0.031 * \mathrm{TON} + 1.180 * \mathrm{TOFF} - 0.820 * \mathrm{WFR} + 0.896\& * IP + 0.1587\mathrm{TON}^2 - 0.2979 * \mathrm{TOFF}^2 + 0.1137 * \mathrm{WFR}^2 - 0.0963 * \mathrm{IP}^2$$

Run	Input Parameters				Response
	TON	TOFF	WFR	IP	(Ra)
1	108	56	4	11	3.71
2	108	56	4	11	3.72
3	108	56	4	11	3.95
4	108	54	5	12	4.06
5	108	54	5	12	4.04
6	108	54	5	12	4.01
7	108	52	6	13	4
8	110	52	6	13	3.95
9	110	52	6	13	3.98
10	110	56	5	13	4.81
11	110	56	5	13	4.79
12	110	56	5	13	4.75
13	110	54	6	11	3.8
14	110	54	6	11	3.8
15	110	54	6	11	3.8
16	110	52	4	12	4.63
17	112	52	4	12	4.61
18	112	52	4	12	4.5
19	112	56	6	12	4.9
20	112	56	6	12	4.89
21	112	56	6	12	4.85
22	112	54	4	13	4.5
23	112	54	4	13	4.4
24	112	54	4	13	4.49
25	112	52	5	11	4.03
26	112	52	5	11	4.02
27	112	52	5	11	4.01

Table 2. Experimental data and plan of experimentation.

2.4. Artificial Neural network (ANN)

Artificial neural network (ANN) is a soft computing technique use for the analysis of various systems. It is the network of various nodes distributed in the various layers. The function of ANN is synonymous to the working of human brain and the functioning of the sense organs. The human brains sense the data from the sense organs and process it and send the signal in terms of response. The basic structure of ANN is as shoen in the following figure 3. The network is divided into three basic layers i.e. input layer – received the data through nodes and send it to the nest level where the weights are assigned to the data and normalized the data. The number of nodes and the layers are depends on the type of data, its nature, processing time time and the accuracy accepted from the data. In the present work, feed forward back propagation neural network was employed to analyse the data.

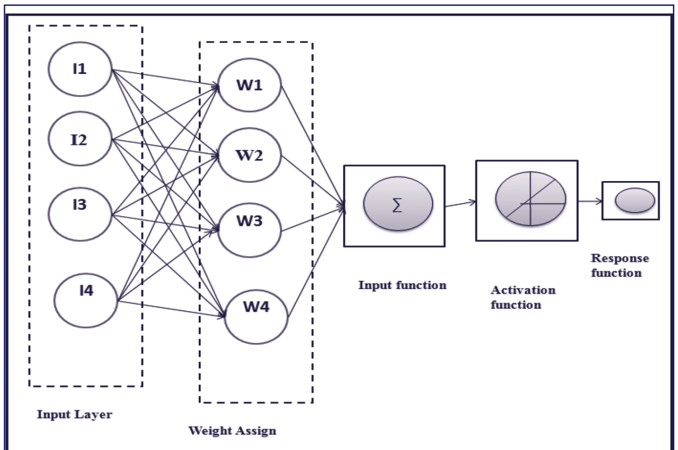

Fig. 3. Basic structure of ANN.

3. RESULTS & DISCUSSION

3.1 Response Surface Method (RSM)

Four graphs such as Pareto chart, normal plot, and the fits plot and the residual plot obtained during the data analysis through RSM are as shown in figs. 2(a)-2(d).

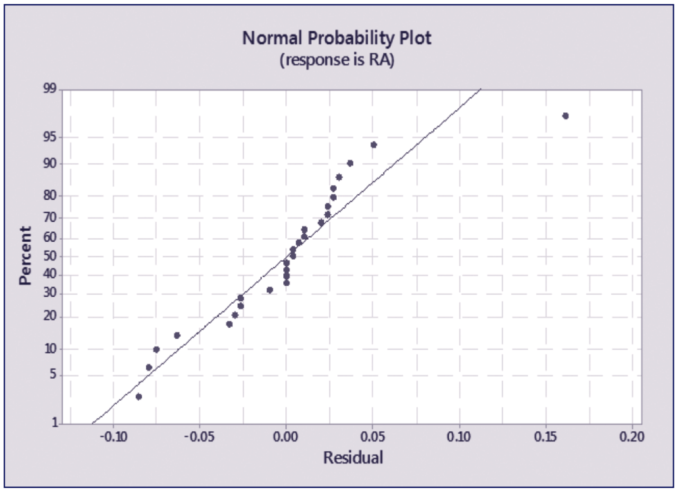

Fig. 3 (a) Normal probability plot.

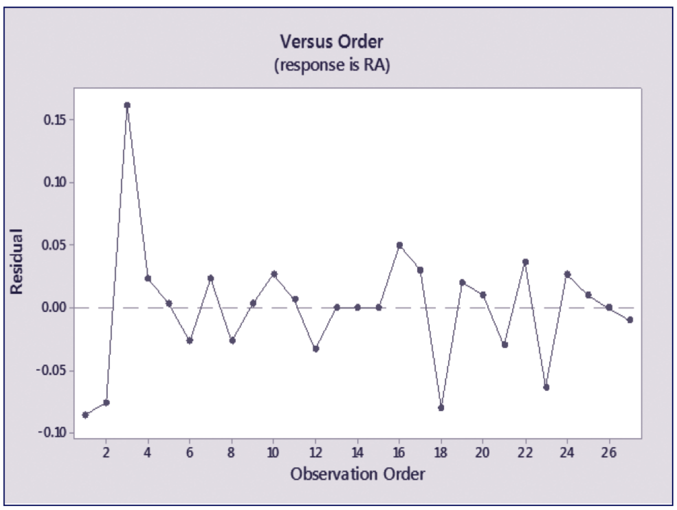

Fig. 3 (b) Residual plot.

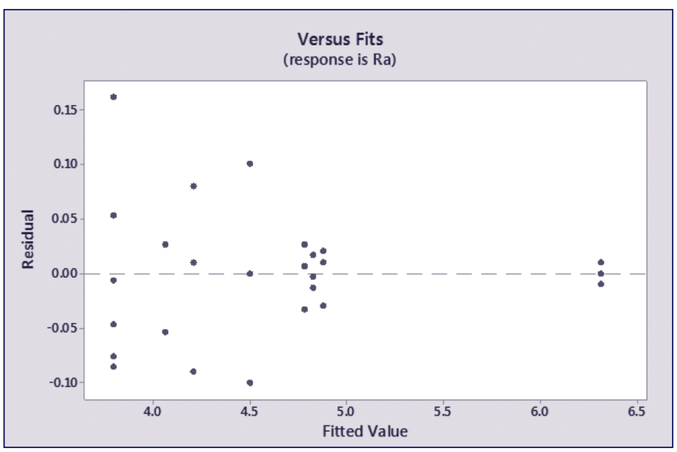

Fig. 3 (c) Fits plot.

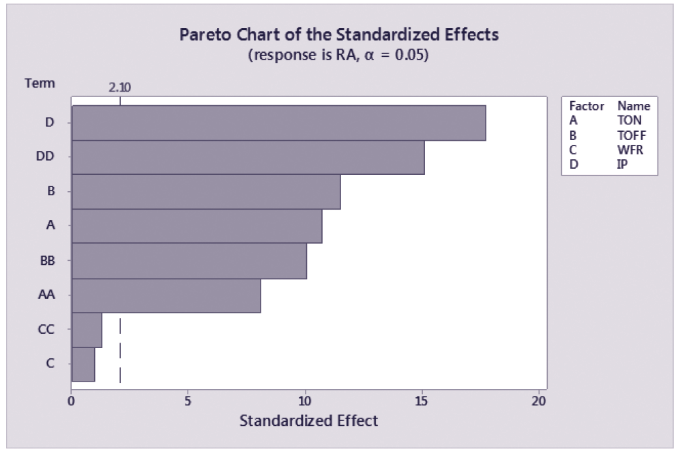

Fig. 3 (d) Pareto chart of the standardized effect.

Fig. 3. Plots obtain during the data analysis through RSM.

Source	DOF	Adj. SS	ADj.MS	F-value	P-Val-ue
Model	8	14.4664	1.80830	374.30	0.000
Linear	4	0.7362	0.18405	38.10	0.000
TON	1	0.1565	0.15652	32.40	0.000
TOFF	1	0.5330	0.5330	110.33	0.000
WFR	1	0.0166	0.0166	3.45	0.080
IP	1	0.0300	0.0300	6.21	0.23
Square	4	0.8170	0.20425	42.28	0.000
TON^2	1	0.1512	0.1512	31.29	0.000
$TOFF^2$	1	0.5326	0.5326	110.25	0.000
WFR^2	1	0.0776	0.0776	16.06	0.001
IP^2	1	0.0556	0.0556	11.51	0.003
Error	18	0.0870	0.00483		
Total	26	14.5533			
S =0.06950 Rsq :0.9940				Rsq(adj):0.9914 Rsq(pred):0.9866	

Table 2. Analysis of variance (ANOVA) to find out the impact of process parameters.

Fig 3(a) shows the normal plots of residuals where the error or residuals emerge on the inclined straight line. The normality test shows the formulation of good RSM model. It is a graph between % probability vs residuals. The residual plot 3(b) show the error between actual response and the RSM based response w.r.t. the observations. Fits is the measure of model closeness w.r.t the actual response The fits plot is as shown in fig 3(c). Pareto chart use to find out the magnitude and the impact of the effect. In the Pareto chart, the horizontal bar that crosses the reference line are known as a significant. The bars D (IP),DD(IP*IP),B(TOFF),A(TON),BB(TOFF*TOFF) and AA(TON*TON) are significant impact on the surface roughness while CC (WFR*WFR) and C (WFR)are not significant. Surface plots are as shown in Fig Fig 3(a)-3(f). Surface plots are the three dimensional representation of three variables in which the response variables is plotted on Z axis while the two variables are on the X and y axis respectively. The remaining variables are keep constant at their mean value during the analysis. In other world, it is the representation of interaction effect of two variables on the response variables. From fig. 3(a), it can seen that the surface roughness increases with increase in the process parameter pulse on time (TON). Hence it is directly affects the Ra. The other variable wire feed rate (WFR) has insignificant impact on the Ra. The process parameter input current (IP) is directly affects the response as shown in Fig 3(b). The parameters pulse off time (TOFF) in increase when the feed rate increase from level 2 to 3 and it goes on decreasing from level 1 to 2 as shown in fig 3(c-d). From figure 3(e-f), it can be observed that the parameter pulse off time (TOFF) has direct impact on the Ra value.

The contour plots are the slices along the axis or two dimensional; representations of the surface plots. The various plots are as shown in fig 5 (a-f).

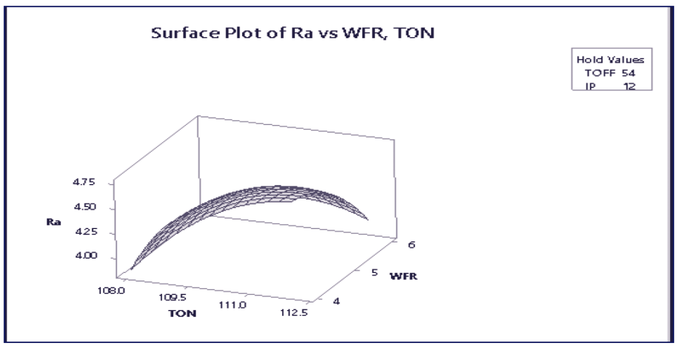

Fig. 4 (a) Surface plot of Ra vs TON, WFR.

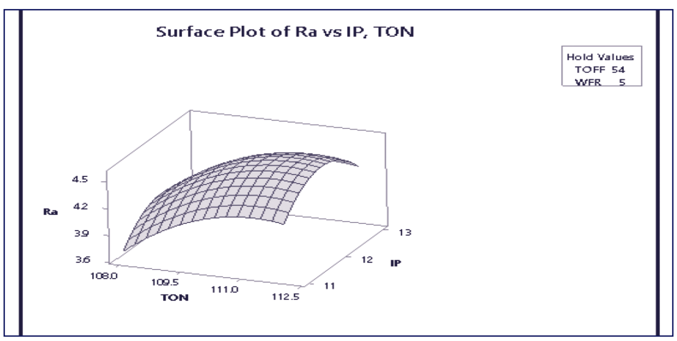

Fig. 4 (b) Surface plot of Ra vs IP, TON

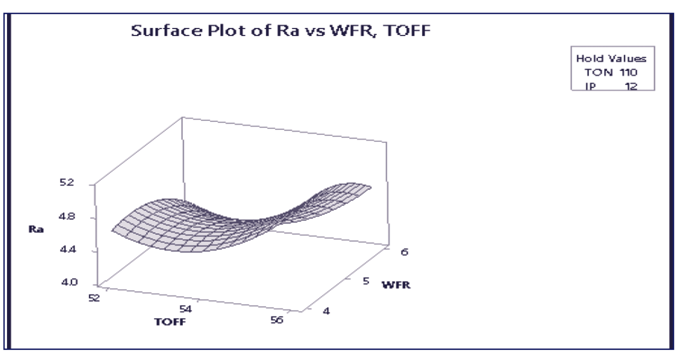

Fig. 4 (c) Surface plot of Ra vs TOFF, WFR.

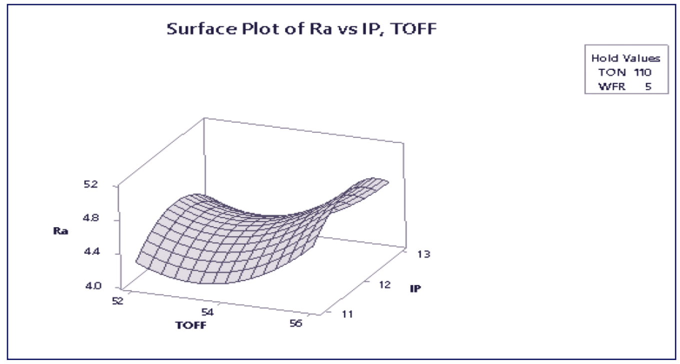

Fig. 4 (d) Surface plot of Ra vs IP, TOFF.

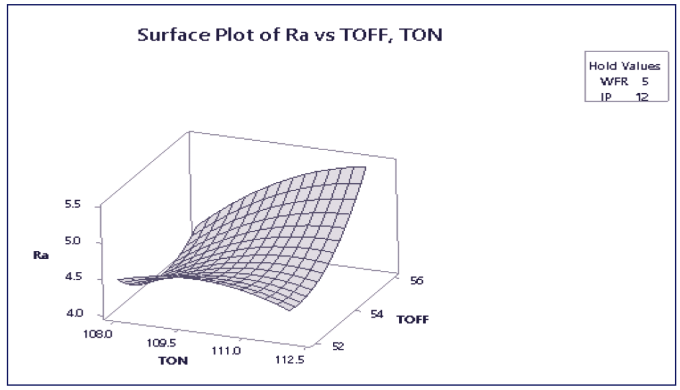

Fig. 4 (e) Surface plot of Ra vs TON, TOFF.

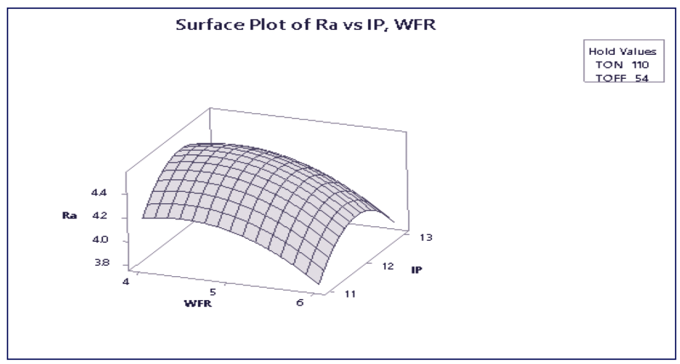

Fig. 4 (f) Surface plot of Ra vs IP,WFR.

Fig. 4. Surface plots obtain during the data analysis through RSM.

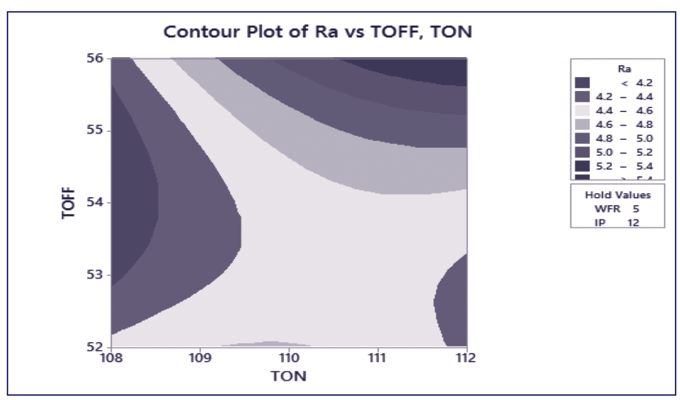

Fig. 5 (a) Contour plot of Ra vs TON,TOFF.

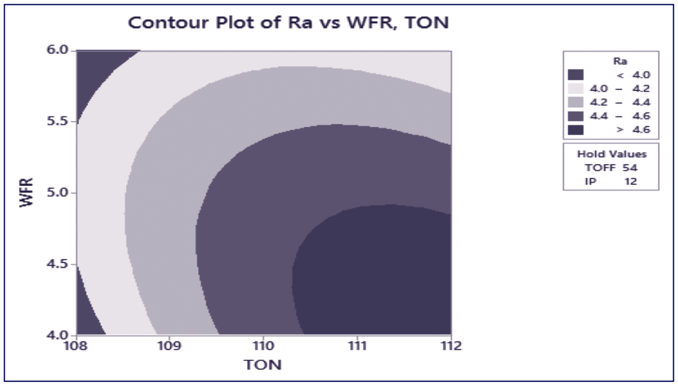

Fig. 5 (a) Contour plot of Ra vs TON,WFR.

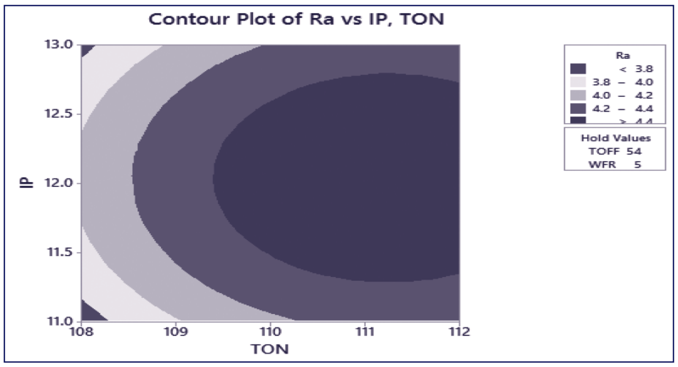

Fig. 5 (c) Contour plot of Ra vs IP,TON.

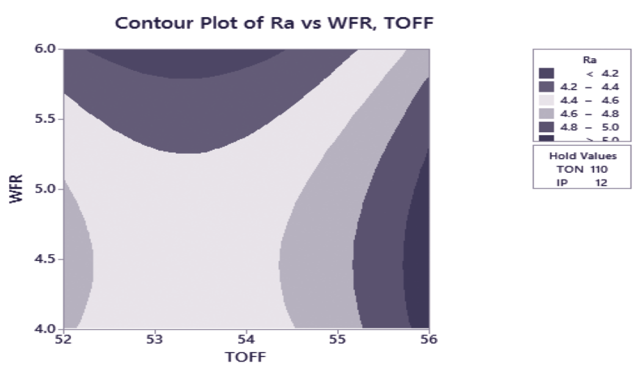

Fig. 5 (d) Contour plot of Ra vs TOFF,WFR.

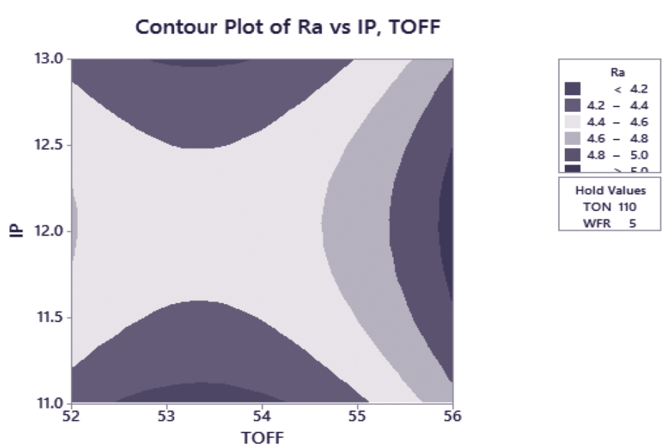

Fig. 5 (e) Contour plot of Ra vs IP,TOFF.

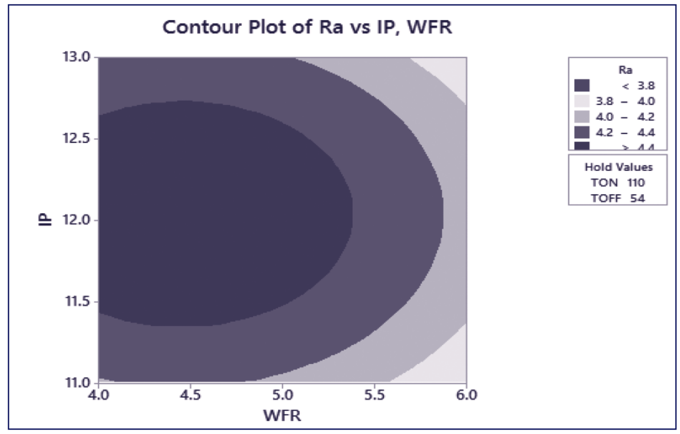

Fig. 5 (f) Contour plot of Ra vs IP,WFR.

Fig. 5. Contour plots obtain during the data analysis through RSM.

3.2 Artificial Neural network (ANN)

The feed forward back propagation neural network (BPNN) is employed with three layers. The number of layer depends on the number of inputs and the response parameters. In the present work there were four inputs and one response variable. Hence three layer ANN is preferred. Levenberg-Marquardt (LM) i.e. TRAINLM was used as a training function. The learning function 'LEARNGDM' was used for learning process. The transfer function 'TANSIG' was used for the analysis. The number of neurons selected was 10.

The ANN network works in the three layers, Training, testing and the validation of the network. The performance of the train network is as shown in the fig.6 and 7. The accuracy of the train network is measured in terms of the correlation coefficient obtain for the data. The regression curve , correlation and the correlation coefficient is as shown in figure 8.

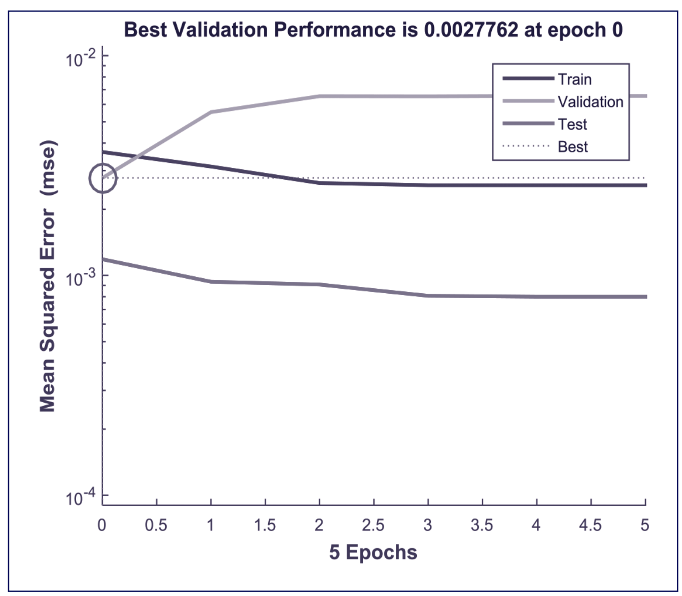

Fig. 6. ANN performance curve between MSE and epochs.

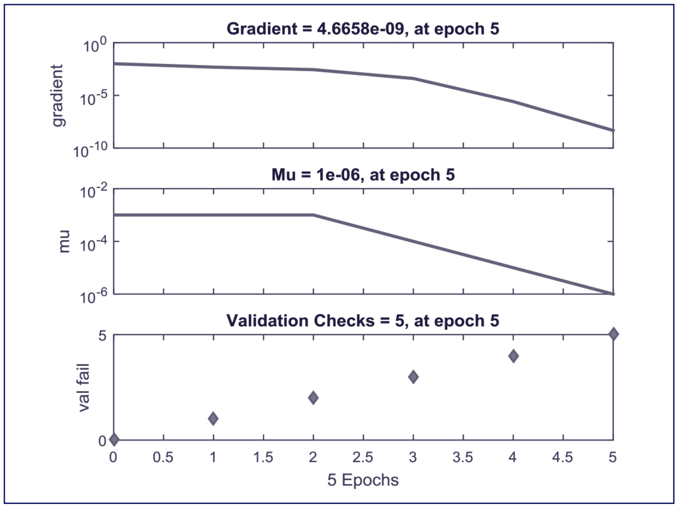

Fig. 7. ANN performance curve between gradient and epochs.

The comparison between the surface roughness obtained through the response surface method (RSM) and artificial neural network (ANN) predicted was as shown in figure 9.

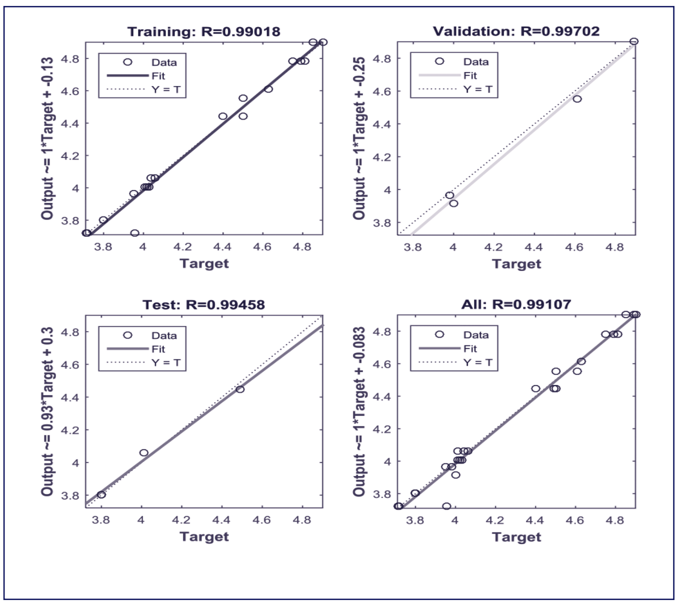

Fig. 8. ANN regression cures for training, testing, validation and overall data.

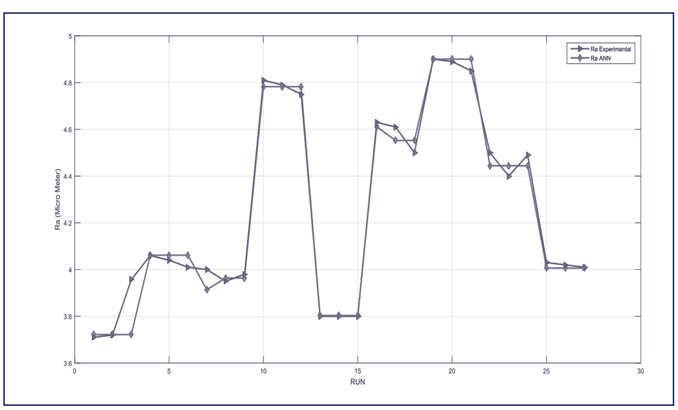

Fig. 9. Comparison between RSM and ANN based Ra.

Conclusion

In the presented work, the new aluminium based MMC (Al/Gr/Cp5) was presented. The WEDM processes have been examined to find out the impact of various process parameters. The two advanced modelling techniques i.e. response surface method and the artificial neural network has been employed for the analysis. From the experimental findings, it has been observed that the RSM is a very effective and efficient method adopted for the modelling and analysis of WEDM process. Analysis of variance showed the impact of or the contribution of various process parameters along with their interaction effect. The 'P' value shows the variable impact either significant ($p \leq 0.005$) and the insignificant parameters where ($p > 0.005$). A good acceptable value of correlation coefficient (0.9866) was observed between the RSM predicted response and the experimental response. The artificial neural network (ANN) based models also showed the effectiveness to represent the process. A good acceptable value of correlation coefficient (0.9970) was observed between the ANN predicted response and the experimental response. From the analysis, it has been concluded that the RSM and ANN both the techniques are efficient and effectively model and analyse the system. But the soft computing techniques i.e. ANN is more superior than the RSM. Hence recommended for the analysis of similar kind of problem analysis. The novelty in the presented work is the fabrication of Al/Gr MMC with 5 % graphite and ease of manufacturing using WEDM process. The work will help the worldwide researcher to use the Al /Gr MMC for the various application such as in automobile industries .

ACKNOWLEDGEMENT

Authors would like to acknowledge the Kakde laser industries for the facilities provided during the execution of the presented work. Authors would like to acknowledge the family members for their supports.

REFERENCES

[1] *V. Kavimani, K. S. Prakash, and T. Thankachan, "Multi-objective optimization in WEDM process of Graphen-SiC-magnesium Composite through hybrid Techniques", Measurements, vol. 145, Pages : 335-349,2019.*

[2] *M. Phate and S. Toney, "Modeling & Prediction of WEDM Performance Parameters for Al/SiCp MMC using Dimensional Analysis and Artificial Neural Network", Engineering Science & Technology, An International Journal, vol. 22,Pages : 468-476,2019.*

[3] *B. Singh and J. P. Mishra, "Surface Finish Analysis of Wire Electric Discharge Machined Specimens by RSM and ANN Modeling", Measurements, vol. 137, Pages : 225-237,2019.*

[4] *N. Sharma, R. Khanna and R.D.Gupta, "WEDM Process Investigation for HSLA by Response Surface methodology and Genetic Algorithm ", Engineering Science &*

Technology, An International Journal, vol. 18,Pages : 171-177,2015.

[5] *M. R.Phate, S.B.Toney and V.R.Phate, "Analysis of Machining Parameters in WEDM of Al/SiCp20 MMC using Taguchi based Grey Fuzzy approach", Modelling and Simulation in Engineering, vol. 1483169,Pages : 1-13,2019.*

[6] *S.J. Tea, F. Rotundo, X. Song, L. Ceschini and A.M Korsunsky, "Residual Strains in AA2024/AlSiCp Composite linear Friction Welds.", Materials and Design,Vol.31 ,Pages : 117-120,2010.*

[7] *A. Ilhan, S. Neseli and M.A. Ince, "Optimization of Premaster affecting Surface Roughness of Co28Cr6Mo medical material during CNC lathe machining by using Taguchi and RSM methods.", Measurements,Vol.78 ,Pages : 120-128,2016.*

[8] *P. Debaprasanna, S.S. Mahapatta and J.L. Sahu, "A Hybrid approach for Multi-respsone Optimization of non-conventional machining on Al/SiCp MMC.", Measurements,Vol.46, Issue 9 ,Pages : 3581-3592,2014.*

[9] *I.M. Jamadar and D.P. Vakharia,"A Novel Approach Integrating Dimensional Analysis and neural network for the detection of Localized Faults in Toller bearing.", Measurements,Vol.94, Issue 1 ,Pages : 177-185,2015.*

[10] *R. Bobbili, V. Madhu and A. Gogia," Modelling and Analysis of material Removal Rate and Surface Roughness in Wire-Cut EDM of Armour Materials.", Engineering Science & Technology, An International Journal, Vol. 18, Issue 4,Pages : 664-668,2015.*

[11] *N. Senthilkumar, J. Sudha and V. Muthukumar," A grey-Fuzzy Approach for Optimizing machining Parameters and the Approach Angle in Turing AISI 1045 Steel.", Advance in production Engineering & Managements, Vol. 10, Issue 4,Pages : 195-208,2015.*

[12] *V. Kumar and K. Jangra," An Experimental Analysis and Optimization of Machining rate and Surface Characteristics in WEDM of Monel-400 using RSM and Desirability Approach.", Journal of Industrial Engineering International, Vol. 11, Pages : 297-307,2015.*

[13] *M.R.Phate and V.H.Tatwawadi," ANN based Model Development for Material Removal Rate in Dry Turning in India Contest.", World Academy of Science Engineering & Technology, International Journal Mechanical and Manufacturing Engineering , Vol. 8,Issue 1 Pages : 7-13,2014.*

[14] *M.R.Phate and V.H.Tatwawadi," ANN based Model Prediction of Human Energy in Conventional Machining of Nonferrous Material from India Industry prospective.", Journal of Production Engineering , Vol. 17,Issue 1 Pages : 1-6,2014.*

[15] *V.R. Rao and V.D. Kalyabkar," Parameter Optimization of Modern Machining Processes using Teaching -Learning based Optimization Algorithm.", Engineering Application of Artificial Intelligence, Vol. 26,Issue 1 Pages : 524-531,2013.*

[16] *S.S.Nain, D. Garg and S.Kumar," Investigation for obtaining the optimal Solution for improving the Performance of WEDM of Super alloy Udimet-L605 using Particle Swarm Optimization.", Engineering Science and Technology an International Journal, Vol. 18 Pages : 56-59,2016.*

[17] *A. Saha and S.C. Mondal," Multi objective optimization in WEDM process of nanostructure hard facing Material through Hybrid Techniques.", Measurements, Vol. 94 Pages : 161-171,2018.*

[18] *M.V.Bhadrarao, V.A.Shaikh and B.T.Patil," Recent Trends in the Effective utilization of Minimum Quality Lubrication (MQL) in turning Low Carbon Steels.", Industrial Engineering Journal, Vol. XI , Issue 2,Pages : 29-33,2018.*

[19] *A. Sharma, S. Singh and A.S. Sidhu," Multi-objective optimization of Cutting Parameters to Minimize Energy Consumption in Dry Turning of AISI 4140 Alloy.", Industrial Engineering Journal, Vol. XI , Issue 6,Pages : 20-26,2018.*

[20] *N. Bhanot, M. Singh, M. Panday, P. Stood and S. Dhawan," A Conceptual IoT framework for Sustainability Assessment of Turning Process with respect to Quality and Production Control.", Industrial Engineering Journal, Vol. 12 , Issue 4,Pages : 1-17,2019.*

AUTHORS

Dr. Mangesh Ravindra Phate, PhD (Mechanical), All India Shri Shivaji Memorial Society's, College of Engineering, Pune – 411 001, (MS), India
Email: mangeshphate03@gmail.com / mrphate@aissmscoe.com / 0985033 03148

Ms. Shraddha Bhanudasrao Toney, ME (Computer), STE's, Sinhgad Institute of Technology & Science, Narhe, Pune, (MS), India
Email: toneyshraddha@gmail.com

Vikas Ravindra Phate, ME (Electronics), Government Polytechnic, Murtijapur, Akola, (MS), India
Email: vikas.phate13@gmail.com