ANNALS of Faculty Engineering Hunedoara – International Journal of Engineering
Tome XVIII [2020] | Fascicule 2 [May]

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INVESTIGATION OF Al/Gr/Cp10 WEDM USING ARTIFICIAL NEURAL NETWORK BASED GREY RELATIONAL ANALYSIS

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Abstract: Machining is very important process in any industry. To maintain the quality of the machined product along with the accuracy and the material removal rate obtained during the machining complex part is a challenging task for any industry. Wire electric discharge machining (WEDM) is an advance machining process which helps to improve the machining environments and will hell to meet the customer satisfaction. On other side the customer demands light, durable, high strength, economical products. To overcome this, an attempts has been made to introduce an Aluminium based metal matrix composite (MMC) with 10 % (By weight) of graphite. Therefore, the present work is focused on the optimization of surface roughness, material removal rate and the overcut dimensions during the WEDM of Al/Gr10Cp MMC. Artificial neural network (ANN) based Grey relational analysis (GRA) i.e. GRA-ANN coupled with the Taguchi has been used for the analysis. Experiments were carried out using Taguchi's L_{27} orthogonal array (OA) to analyze the impact of pulse on time (PON), pulse off time (POFF), wire feed rate (WFR) and wire tension (WT). A multiple regression models with 1st and 2nd order have been developed for the GRA-ANN responses. From the developed models, it has been observed that the model with 2nd order is superior to the 1st order model. Both the developed models show the acceptable correlations between experimental and predicted GRA-ANN response. The presented methodology has been proved to be effective and efficient method for solving the multi-response optimization problems.
Keywords: Regression, Al/Gr MMC, Artificial neural network, Multi-response optimization, Taguchi method, Back propagation neural network

1. INTRODUCTION

Wire-electrical discharge machining (WEDM) is a very advance machining process which work very effectively and efficiently for machining a complex shape products. The various researchers investigated the WEDM process for different materials some of them are highlighted in the followings. Arun Kumar et al. [1] investigated the impact of various process parameters on surface roughness and maximizing the material removal rate. The three input parameters with three levels are considered for the responses analysis the signal-noise ratio is calculated for the material removal rate and the surface roughness. From his experimental findings, it has been observed that the depth of cut is the most influencing parameter for the MRR response and feed is the most influencing parameter for surface roughness response. Chia-Chi Sun [2] used technique for order performance by similarity to ideal solution (TOPSIS) for the multi-response optimization of the process. The fuzzy analytic hierarchy process coupled with TOPSIS technique used for the performance evaluation of the process. The model developed on the basis of fuzzy environment with triangular fuzzy number. Yu. Huang et al [3] used Taguchi's L18 orthogonal array of the experimentation. The responses such as material removal rate and the surface roughness has been optimized by using the signal-noise ratio. The material used for the processing was high hardness tool steel YG15.

ANNALS of Faculty Engineering Hunedoara – International Journal of Engineering
ISSN 1584 - 2665 (printed version); ISSN 2601 - 2332 (online); ISSN-L 1584 - 2665

The comparative analysis showed that effectiveness of Taguchi's approach in the WEDM process.
M.P. Jenarthanani et al [4] optimized the glass-fibre reinforced plastic (GFRP) composites using desirability function analysis. L27 OA has been used for the experimentation with feed rate, fibre orientation angle and the helix angle as input parameters and surface roughness, machining force and the surface delimitation factor as output parameters. J.R. Mevada et. al. [5] investigated on two responses i.e. MRR and Surface roughness. This investigation was carried out to find best optimal level for higher material removal rate at lower surface roughness for Inconel 600 material. The experiments have been conducted by varying pulse on time, pulse off time and peak current.
Meenu Gupta et. al.[6] investigated glass fibre reinforced plastics composite material for the experimentation. Taguchi's L18 OA's has been used for the plan experimental design. The parameters such as rake angle, nose radius, feed rate, cutting speed, depth of cut along with the different working environments has used for optimizing the responses by using principal component analysis.
Mohammadrwza Shabgard et al. [7] used ABAQUS code finite element software to find out the temperature distribution of the surface work piece and the tool for the electrical discharge machining. From the experimental results it has been observed that the pulse on time and pulse current are the most influencing parameters. Murahari Kolli et al. [8] used Taguchi method to analyze the impact of dielectric fluid on discharge of WEDM of titanium alloy. The various responses considered are Material Removal Rate (MRR), Surface Roughness (SR), Tool wear rate (TWR) and Recast Layer Thickness (RLT).The effect of cutting parameters such as cutting speed, feed and depth of cut has been analysed by Mangesh Phate et. al. [9-13] used dimensional analysis approach along with the linear programming (LPP) to optimize the surface roughness of Al 6063 work piece. The LPP technique used only for the single response optimization. Phate et. al. [14] used artificial neural network and the fuzzy grey approach in the analysis of WEDM of Al based MMC. Mangesh Phate and Shraddha Toney [15,16] used artificial neural network (ANN) for analyzing the performance of turning process for the ferrous and non-ferrous material. 13-10-1 network has been used for the analyzing the performance of machining response such as material removal rate and the power consumption.
Pujara Srinivasa Rao et. al. [17] investigated the influence of machining parameters in WEDM of aluminium alloy on the residual stresses generated on the surface . The parametric analysis has been used to find out the best set of input parameters which minimize the residual stresses on the components. Rajesh Khanna et. al. [18] used brass rod of 2mm diameter as an electrode (tool). The experiments conducted for measuring the response such as tool wear rate. The parameters such as pulse on time, pulse off time and the fluid pressure has been studied for the process optimization. The Taguchi's plan of design of experiments was implemented for the data experimentation. The experimental findings showed that the pulse on time and the pulse of time combined effect affect the wire EDM process.
Ravindranadh Bobbili et. al. [19] evaluated the significance machine variables such as pulse-on time, flushing pressure, input power, thermal diffusivity and latent heat of vaporization on responses such as material removal rate and the surface roughness. Buckingham's pi theorem used for the model formulation of the material such as aluminium alloy 7017 and rolled homogeneous armour. Shailesh et. al. [20] used grey-fuzzy logic based hybrid optimization tool to find out the best set of input parameters to improve the surface integrity in the WEDM of AISI P20 steel. The response surface method has been used to find out the impact of parameters such as pulse on time, pulse off time, current and the tool lift time as input parameters. Senthil Kumar et. al.[21] used rational grey analysis technique (RGA) for the multi response optimization. The various responses are tool wear, surface roughness and the material removal rate while the influencing parameters are cutting speed, feed and the depth of cut with three levels. Taguch's L9 orthogonal array's was selected for the experimentation and the data collection. The experimental findings showed that the use of GRA coupled with the Taguchi improved the performance.
Vinod Kumar et. al. [22] worked on WEDM of Monel -400 i.e. nickel copper base alloy. The parameters such as current, pulse-on time, pulse off time and servo voltage have been considered to measure the performance of parameters such as surface roughness and the material removal rate. ANOVA has been used for the analysis of the WEDM process. The experimental results showed that the current (103 A), Pulse on time (113 micro sec), pulse off time (37 micro sec) and the voltage (50 V) was the optimum combination. Chia-Chi Sun [23] used technique for order performance by similarity to ideal solution (TOPSIS) for the multi-response optimization of the

process .The fuzzy analytic hierarchy process coupled with TOPSIS technique used for the performance evaluation of the process. The model developed on the basis of fuzzy environment with triangular fuzzy number.

2. MATERIAL AND METHODS

The details related to the material preparation and the experimental method adopted for the investigation is discussed in the following section.

— Preparation of Al/GrCp10 MMC

The experiments were conducted using EZEECUT NXG –Wire cut EDM with 320 x 400mm axis travel and 360 x 600 maximum work piece diameters. Brass wire with diameter 0.25 mm used with accuracy of 0.1 mm. Al/GrCp10 was used as a work piece material. A work piece of dimensions 200 x 75 x 10 mm used as a work piece material while brass wire used as the tool electrode materials. A picture of experimental methodology is as shown in Figure 1. The graphite has very high intensity, higher temperature resistance, and high thermal shock resistance property, very low coefficient of thermal expansion, very low density and excellent commitment against the corrosion and radiation performance. The AlGrCp10 MMC is prepared by stir casting process.

Table 1: List of Process Parameters with their levels.

S.N	Variables	Symbol	Levels		
			Low	Medium	High
1	Pulse in time	PON (Micro-sec)	108	110	112
2	Pulse off time	POFF (Micro-sec)	52	54	56
3	Wire feed rate	WFR(mm/min)	6	9	12
4	Wire tension	WT(kg)	0.8	1	1.2

— Experimental Plan

In this work, Taguchi's L_{27} orthogonal arrays (OA) using design of experiments (DOE) is used for the experimentation considering four governing parameters such as pulse on time, pulse off time, wire feed rate and the wire tension that are varied through three levels. Table 1 shows the selected level of parameters and their values for experimentation. Table 2 shows the different levels of machining parameters and the observed responses. Figure 1 shows the experimental methodology used for the present work.

— Grey Relational Analysis (GRA)

In multi-response optimization, the impact and the correlations between various parameters are very multifarious and not understandable. Hence to avoid the complexity and reduced the uncertainty of optimization grey relational analysis (GRA) has been used in the present so that the multi-response is converted into single response i.e. grey relational grade (GRG). The basic methodology adopted for the GRA is discussed in the following section.

Step 1 : Data Normalization as per the response objectives

The first step in the GRA is normalization of the available date to minimize the effect of diverse units used in the experimentation and also to minimize the variability in the process parameters. In this steps all the values are converted in to the normalized range i.e. (0 to 1 range). There are two types of response incurred in the Engineering study. The objectives of the first type are to minimize the response value while the objectives of the other are to maximize the value of the response. For the first type of response (Minimization type of objectives) lower-the –better characteristics is used for the normalization by using following Eqn.1.

$$Y_i^*(k) = \frac{MaxY_i(k) - Y_i(k)}{MaxY_i(k) - MinY_i(k)} \quad (1)$$

For the second type of response (Maximization type of objectives) higher-the –better characteristics is used for the normalization by using following Eqn.2.

$$Y_i^*(k) = \frac{Y_i(k) - MinY_i(k)}{MaxY_i(k) - MinY_i(k)} \quad (2)$$

where, i =1,2,3,---------m; and k=1,2,3,----------n, m is the number of experiments (i.e.27) and the n is the number of response (i.e.3).$Y_i(k)$ is the original data set , $Y_i^*(k)$ is the normalised data set, max $Y_i(k)$ is the maximum response value of the $Y_i(k)$ and min $Y_i(k)$ is the minimum response value of the $Y_i(k)$. The normalised value of all the original response variables is as shown in Table 3.

Table 2: Experimentation as per Taguchi's L_{27} Orthogonal array (OA).

RUN	PON	POFF	WFR	WT	MRR	Overcut	Ra
1	108	52	6	0.8	12.696	0.3512	3.735
2	108	52	6	0.8	13.524	0.3865	3.523
3	108	52	6	0.8	13.254	0.3685	3.354
4	108	54	9	1	10.365	0.3045	2.935
5	108	54	9	1	9.635	0.3125	3.215
6	108	54	9	1	10.254	0.3102	3.365
7	108	56	12	1.2	14.325	0.3025	3.125
8	108	56	12	1.2	13.654	0.3125	3.254
9	108	56	12	1.2	12.365	0.3025	3.056
10	110	52	9	1.2	16.325	0.3201	3.524
11	110	52	9	1.2	15.868	0.3185	3.425
12	110	52	9	1.2	16.023	0.3251	3.325
13	110	54	12	0.8	12.854	0.2985	3.102
14	110	54	12	0.8	13.021	0.2925	3.012
15	110	54	12	0.8	12.854	0.3021	3.215
16	110	56	6	1	16.356	0.3562	3.452
17	110	56	6	1	15.985	0.3485	3.356
18	110	56	6	1	15.421	0.3525	3.452
19	112	52	12	1	19.524	0.3254	3.568
20	112	52	12	1	20.524	0.3365	3.689
21	112	52	12	1	19.568	0.3452	3.758
22	112	54	6	1.2	21.521	0.3651	3.875
23	112	54	6	1.2	20.652	0.3568	3.758
24	112	54	6	1.2	21.324	0.3652	3.689
25	112	56	9	0.8	17.635	0.2985	3.564
26	112	56	9	0.8	18.325	0.3025	3.658
27	112	56	9	0.8	18.458	0.3125	3.758

Step 2 : Grey Relational Coefficient

The next step after normalizing the original data in the GRA is to find out the grey relational coefficient. Following Equ.3. is used to calculate the same. This value represents the correlation between the actual and ideal normalized response value.

$$\xi_i^*(k) = \frac{\Delta\min + \xi\Delta\max}{\Delta_i(k) + \xi\Delta\max} \tag{3}$$

Where, $\Delta_i(k)$ is the deviation sequence of the reference sequence which is given by following Equ.4-6.

$$\Delta_i(k) = \left\| Y_i^*(k) - Y_i(k) \right\| \tag{4}$$

$$\Delta\max = \max\max\left\| Y_i^*(k) - Y_i(k) \right\| \tag{5}$$

$$\Delta\min = \min\min\left\| Y_i^*(k) - Y_i(k) \right\| \tag{6}$$

ξ is the identification coefficient generally taken as 0.5.

Step 3 : Grey relational grade (GRG)

The grey relational grade is calculated by using Equ.7. i.e. the average of grey relational coefficient of all the responses .

$$\gamma_i(k) = \frac{1}{n}\sum_{k=1}^{n}\xi_i^*(k) \tag{7}$$

3. ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is a very effective and efficient technique to simulate or analyze very complex and difficult engineering system. The ANN working methodology is based on the human nervous system where the inputs are sending to the control unit. In the present work there are four input parameters and one output parameters as discussed in the previous section. Various networks has tried for getting the best results and finally 4-20-1 (Four input-20 hidden layer-one output) was chosen for getting the higher value of the correlation and the minimum errors. The ANN simulation will be discussed in the following section.

ANN approach is superior approach than the any other approach (10-14). The ANN working methodology is divided into three section i.e. training section, testing section and the validation section. The various parameters related to the network performance during the trainging phase is as shown in Figure 1,2 and 5 performance parameters are as shown in Figure 1,2 and 5. ANN model with 4-20-1 architecture was best fitted with the actual system. The correlation coefficient obtained for this architecture was approximately equal to 0.9681. 19 (70%) of response values were used as training, 4 (15%) of *response* values were used as validation and 4(15%) of response values were used to test data. The regression curves for the ANN simulation during the training, testing, validation and for the overall phase is as shown in figure 3. The performance of the ANN simulation is as shown in Figure 4.

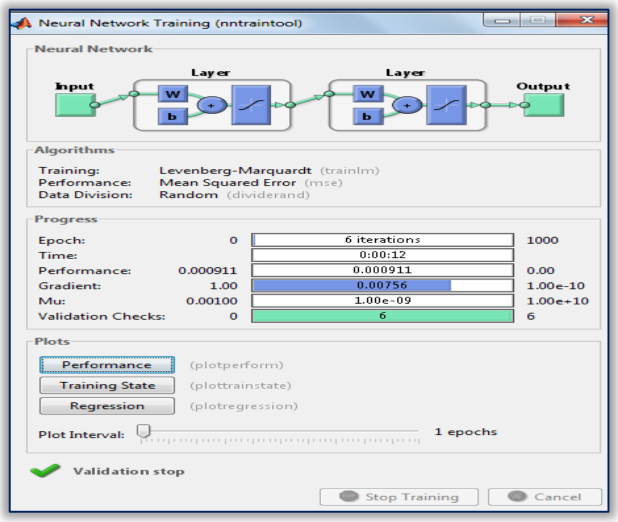

Figure 1. ANN training parameters details

Table 3: Calculation for Grey relational Coefficient and Grey relational grade.

RUN	Normalization			Deviation Sequence			Grey relational Coefficient			Grey Relational Grade		Rank
	MRR	OVT	Ra	MRR	OVT	Ra	MRR	OVT	Ra	Cal	ANN	
1	0.149	0.258	0.376	0.851	0.742	0.624	0.370	0.402	0.445	0.406	0.413	26
2	0.374	0.327	0.000	0.626	0.673	1.000	0.444	0.426	0.333	0.401	0.409	27
3	0.554	0.304	0.191	0.446	0.696	0.809	0.529	0.418	0.382	0.443	0.448	25
4	1.000	0.061	0.872	0.000	0.939	0.128	1.000	0.348	0.797	0.715	0.721	2
5	0.702	0.000	0.787	0.298	1.000	0.213	0.627	0.333	0.701	0.554	0.558	15
6	0.543	0.052	0.812	0.457	0.948	0.188	0.522	0.345	0.726	0.531	0.540	20
7	0.798	0.395	0.894	0.202	0.605	0.106	0.712	0.452	0.825	0.663	0.673	5
8	0.661	0.338	0.787	0.339	0.662	0.213	0.596	0.430	0.701	0.576	0.582	12
9	0.871	0.230	0.894	0.129	0.770	0.106	0.795	0.394	0.825	0.671	0.670	4
10	0.373	0.563	0.706	0.627	0.437	0.294	0.444	0.534	0.630	0.536	0.544	19
11	0.479	0.524	0.723	0.521	0.476	0.277	0.490	0.513	0.644	0.549	0.556	18
12	0.585	0.537	0.653	0.415	0.463	0.347	0.547	0.519	0.590	0.552	0.559	17
13	0.822	0.271	0.936	0.178	0.729	0.064	0.738	0.407	0.887	0.677	0.686	3
14	0.918	0.285	1.000	0.082	0.715	0.000	0.859	0.411	1.000	0.757	0.760	1
15	0.702	0.271	0.898	0.298	0.729	0.102	0.627	0.407	0.830	0.621	0.634	8
16	0.450	0.565	0.322	0.550	0.435	0.678	0.476	0.535	0.425	0.479	0.491	23
17	0.552	0.534	0.404	0.448	0.466	0.596	0.527	0.518	0.456	0.501	0.511	22
18	0.450	0.487	0.362	0.550	0.513	0.638	0.476	0.493	0.439	0.470	0.483	24
19	0.327	0.832	0.650	0.673	0.168	0.350	0.426	0.748	0.588	0.588	0.592	9
20	0.198	0.916	0.532	0.802	0.084	0.468	0.384	0.856	0.516	0.586	0.591	10
21	0.124	0.836	0.439	0.876	0.164	0.561	0.363	0.753	0.471	0.529	0.528	21
22	0.000	1.000	0.228	1.000	0.000	0.772	0.333	1.000	0.393	0.575	0.571	13
23	0.124	0.927	0.316	0.876	0.073	0.684	0.363	0.872	0.422	0.553	0.550	16
24	0.198	0.983	0.227	0.802	0.017	0.773	0.384	0.968	0.393	0.582	0.577	11
25	0.331	0.673	0.936	0.669	0.327	0.064	0.428	0.605	0.887	0.640	0.631	6
26	0.231	0.731	0.894	0.769	0.269	0.106	0.394	0.650	0.825	0.623	0.615	7
27	0.124	0.742	0.787	0.876	0.258	0.213	0.363	0.660	0.701	0.575	0.571	14

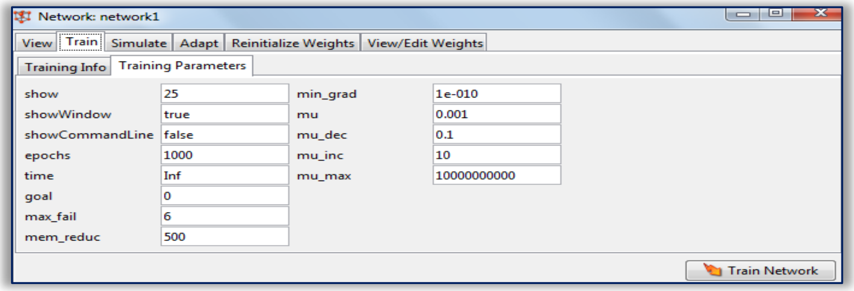

Figure 2. ANN train network selected

4. RESULTS

Full factorial experimentation required large number of experimentation. To minimize the cost of experimentation a well-known Taguchi's L_{27} (OA's) has been used for the experimentation. Analysis of variance used to find out the impact of each input parameters on the response variables. The ANOVA is as shown in Table 5. The findings obtained from the ANOVA can be used for the improvement of the WEDM process.

In multi-response optimization problem, to analyse the impact of various process parameters on the response variables are very complex and not clear from the available data.

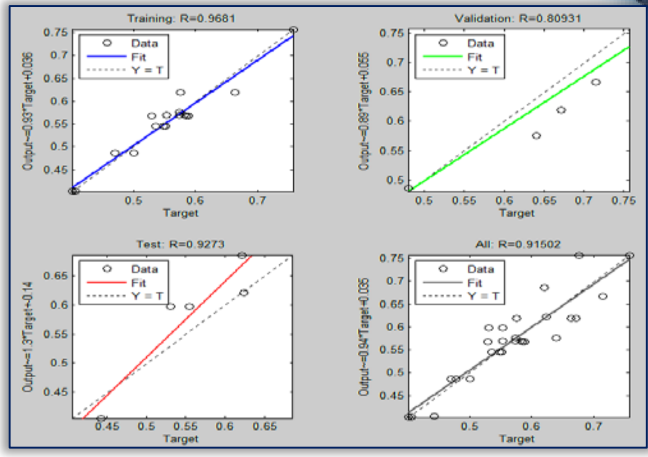

Figure 3. ANN regression plots during training, testing and validation phase

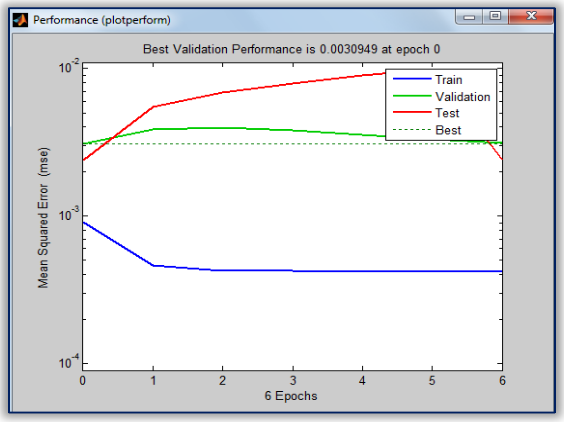

Figure 4. ANN performance curves

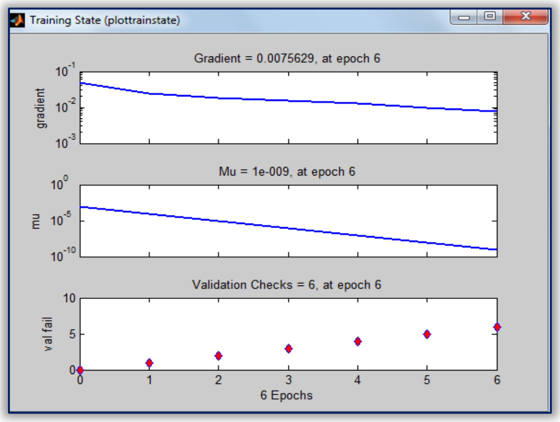

Figure 5. ANN training state plots

Table 4: Response table for mean ANN based grey relational grade

Level	PON	POFF	WFR	WT
1	0.5485	0.5102	0.4915	0.5674
2	0.5672	0.6110	0.5810	0.5476
3	0.5785	0.5730	0.6217	0.5791
Delta	0.0299	0.1008	0.1301	0.0315
Rank	4	2	1	3

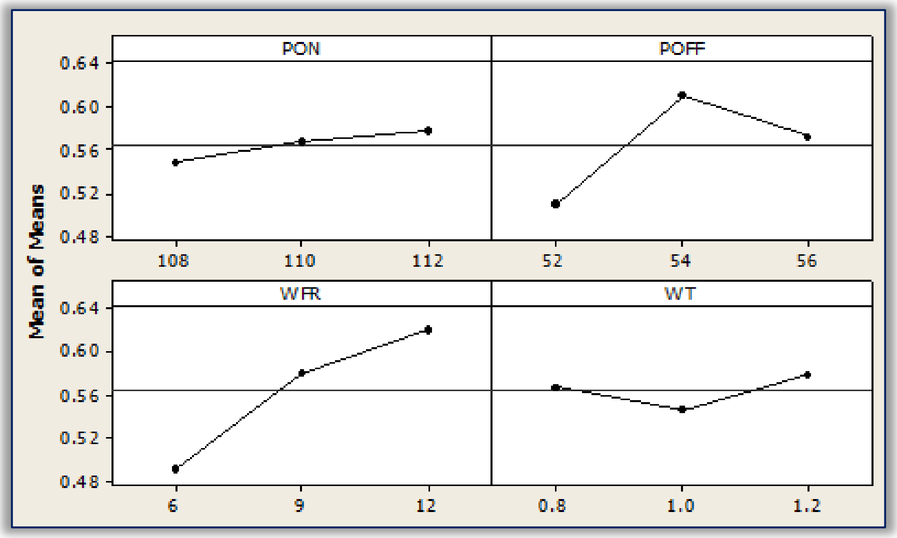

Figure 6. Main effects plots for mean ANN based GRG

The optimal value of input process parameters is obtained using higher value of grey relational grade which gives the better working performance. After the optimal set of parameters is find out, the next step is to perform the ANOVA. The ANOVA is used to find out the impact of individual process parameters on the response variables. ANOVA helps us to give important information on the experimental results. It also helps to find out the percentage contribution to know the effect on individual parameters. The probability of significance (P-value) is calculated on the basis of obtain F value in the ANOVA table. The ANOVA is as shown in Table 5. P-value less than 0.05 indicate the significance impact of variable on the response variables.

From the value of ANN based grey relational grade (GRG) (Table 3), the impact of each process parameters at various levels are plotted and shown in Figure 5. The mean value of GRG is as shown in Table 4. The optimal combinations of input variables are chosen based on the highest value of GRG as shown in Table3. The higher value of the grey relational grade (GRG) implies a stronger correlation to the reference sequence and better performance. Thus, the optimum setting for the multi-response problem is observed for the observation number 14 with the GRG value of 0.760.

The optimum setting for the present study is PON (2)-POFF (2)-WFR (3)-WT(1) level or PON (110 micro-sec)-POFF(54 micro-sec)-WFR(12 mm/revolution)-WT(0.8 kg) which gives the minimum value of surface roughness, minimum value of overcut and the maximum value of material removal rate.

Table 4 shows the mean GRG for each level. The result shows that the wire feed rate is the most influencing parameters affects the GRG as compare to the pulse off and the wire tension and pulse on time. The sequence of important parameters on multi-responses are wire feed rate-pulse off time-wire tension and the pulse on time respectively. From ANOVA table 5, it has been observed that the pulse on time and wire tension does not show any significance on both responses simultaneously.

Table 5: Analysis of Variance (ANOVA) for the mean ANN based GRG

Source	DF	Sq. SS	Adj. SS	Adj. MS	F ratio	P values	Remarks
Regression	8	0.135126	0.135126	0.016891	8.47	0.0000	Significant
Linear	4	0.098568	0.098568	0.024642	12.36	0.0000	Significant
PON	1	0.004036	0.004036	0.004036	2.02	0.172	Insignificant
POFF	1	0.017723	0.017723	0.017723	8.89	0.008	Significant
WFR	1	0.076192	0.076192	0.076192	38.21	0.000	Significant
WT	1	0.000617	0.000617	0.000617	0.31	0.585	Insignificant
Square	4	0.036558	0.036558	0.009140	4.58	0.010	Significant
PON*PON	1	0.000082	0.000082	0.000082	0.04	0.841	Insignificant
POFF*POFF	1	0.028951	0.028951	0.028591	14.52	0.001	Significant
WFR*WFR	1	0.003567	0.003567	0.003567	1.79	0.198	Insignificant
WT*WT	1	0.003958	0.003958	0.003958	1.98	0.176	Insignificant
Residual Error	18	0.035897	0.035897	0.001994			
Total	26	0.171023					
S=0.0446575	Press=0.0807689		R-sq=0.9701				
			R-Sq(Preq)=0.9277				
			R-sq(adj)=0.9668				

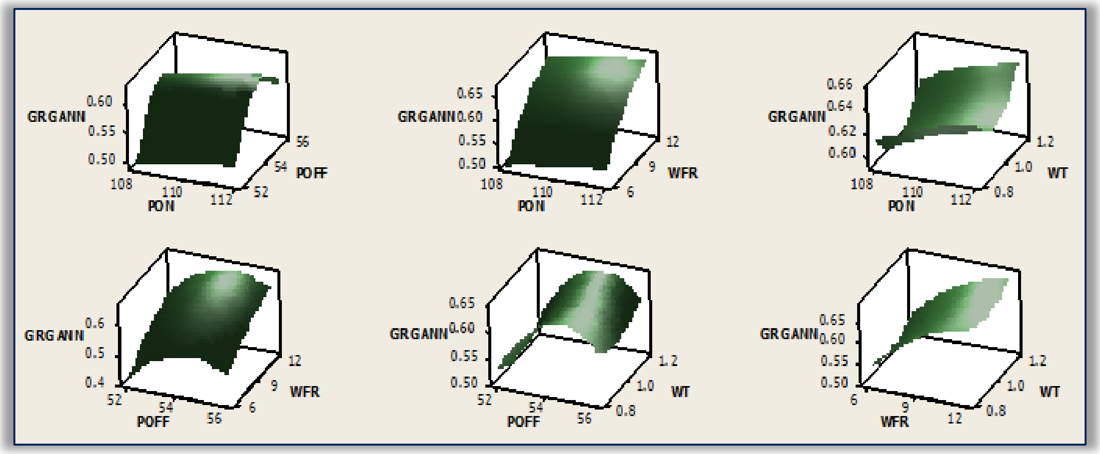

Figure 6. Response surface plot for the ANN based GRG

The main effect plot for the mean GRG ANN is as shown in figure 6. From Figure 6, the effects of each process parameters at different levels are plotted and shown in figure 5. From the main effect plot, it is revealed that GRG increases with increase in pulse on time and wire feed rate. However the effect of pulse on time and the wire tension is marginal. Grey relational grade is increase with increase in wire feed rate drastically.

Response surface model (RSM) has been developed for GRG response at 95% confidence level. The correlation coefficient (R^2) has been used to check the adequacy of the developed model. The value of (R^2) close to one indicates the greater representation of the system by using RSM equation. The response surface model (RSM) is as given by the equation 5.

$$\begin{aligned} GRG(ANN) &= -62.7017 + 0.211183 * PON + 1.89119 * POFF + 0.0704527 * WFR \\ &-1.25494 * WT - 9.25893X10^{-4} * PON^2 - 0.01736657 * POFF^2 - 0.00270921 * WFR^2 + 0.642107 * WT^2 \end{aligned} \quad (5)$$

5. DISCUSSION AND CONCLUSION

This presented work helps to find out the best set of process parameters for making multi-criteria optimization in WEDM of Al/GrCp10 MMC through ANN based grey relational analysis coupled with the Taguchi's orthogonal array. The second order RSM model has been developed for the ANN based GRA to correlate the various process parameters. Based on the analysis, following conclusions are drawn.

— The optimum setting for the process parameters are PON (2)-POFF (2)-WFR (3)-WT(1) level or PON (110 micro-sec)-POFF(54 micro-sec)-WFR(12 mm/revolution)-WT(0.8 kg) which gives the minimum value of surface roughness (3.012 micro-mm), minimum value of overcut(0.2925mm) and the maximum value of material removal rate(13.021 mm^3/min).
— From ANOVA , it has been observed that the wire feed rate is the most influencing parameters affects the GRG as compare to the pulse off and the wire tension and pulse on time. The sequence of important parameters on multi-responses are wire feed rate-pulse off time-wire tension and the pulse on time respectively.
— ANN used to improve the results obtained through traditional method.

The proposed ANN based GRG coupled with the Taguchi method has been proved to be very efficient and effective method for solving multi-response optimization

Acknowledgment

The authors would like to acknowledge Kakade Laser, Narhe, Pune, Maharashtra, India for providing the work shop facility and the support for the completion of this work

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ANNALS of Faculty Engineering Hunedoara – International Journal of Engineering
ISSN 1584 - 2665 (printed version); ISSN 2601 - 2332 (online); ISSN-L 1584 - 2665

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