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OPTIMIZATION OF MRR AND SURFACE ROUGHNESS OF IN SITU FORMED AA7075/TiB_2 COMPOSITE – GREY BASED TAGUCHI METHOD

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ABSTRACT

This paper presents the multi-response optimization of Wire EDM process parameters using grey based Taguchi method. Taguchi's L9 orthogonal array design technique has been employed for experimental investigation. The different machining parameters (Pulse on time, Pulse off time, Peak current, Wire feed) on Material Removal Rate (MRR) and Surface Roughness of AA7075/ TiB2 (3wt%) Metal Matrix Composite were optimized. Taguchi's Signal-to-Noise (S/N) ratio are determined based on their performance characteristics. A grey relation grade is obtained by using S/N ratio. Based on grey relational grade value, optimum levels of parameters have been identified by using response table and response graph and the significant contributions of controlling parameters are estimated using analysis of variances (ANOVA). Confirmation test is conducted for the optimal machining parameters to validate the test result. The proposed method is having prediction accuracy and competency.

Key words: Wire EDM process, ANOVA, Taguchi's method.

INTRODUCTION

Aluminum Metal Matrix Composites (AMMCs) with ceramic particulate reinforcement have gained the attention of the present era. Aluminum metal matrix composites emerged from the perpetual need for lighter weight, higher performance components in aerospace, automotive and aircraft industries. AMCs are progressively replacing conventional aluminum alloys in many applications due to its superior properties including high wear resistance, low thermal expansion, high strength to weight ratio, etc.[1,2] The ceramic particles SiC and Al_2O_3 were extensively used as reinforcements over a long period since the inception of AMCs. Several kind of potential ceramics particles such as TiC,

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SiO_2, ZrB_2, B_4C etc. reinforcements are used to produce aluminum matrix composites (AMCs).

These kinds of composites are generally hard to machine by conventional machining techniques. It causes serious tool wear due to the presence of abrasive reinforcing particles and thus reduced tool life[3,4]. However, non-traditional machining processes have been used successfully by researchers to machine MMCs[5]. Wire Electric Discharge Machining (WEDM) finds extensive applications in various fields like tool and die manufacturing industries, automotive industries and space applications[6]. The wire electrode and work piece never make contact therefore, there is virtually no cutting force on the part. Hence free from mechanical stresses.

Garg et al.[7] reported a detailed survey on review of wire EDM on Metal Matrix Composites stated that there is not so much work in WEDM on MMC's. Sathiskumar et al.[8] reported a machining of Al 6063 composite reinforced with SiC_p (5,10 and 15 vol%) and observed that the MRR decreases with increase in the volume fraction of reinforcements (SiC_p) and the surface roughness R_a increases with increase in reinforcements in the MMC's. Nilesh & Brahmankar[9] investigated the performance parameters such as kerf width, cutting rate and surface finish of the MMC Al6061/Al_2O_{3p} (10 and 22 vol%) and concluded that the volume fraction, pulse on-time, pulse off-time and servo reference voltage plays a vital role in cutting speed, surface roughness and kerf width. M. Rozenek et al.[10] carried out machining studies on AlSi7Mg/SiC and AlSi7Mg/Al_2O_3 MMC's and concluded that machining feed rate of WEDM cutting composites significantly depends on the kind of reinforcement. Mahapatra & Amar[11] investigated about the performance measures such as surface roughness, kerf and MRR of D2 tool steel on WEDM by optimizing the process parameters using Taguchi's method. Selection of optimum machining process parameter combinations for obtaining higher material removal rate and better surface finish is a challenging task when processed in WEDM.

Optimization problems are solved by conventional and non-conventional optimization techniques[14]. Conventional techniques may be broadly classified into two categories: In the first category, experimental techniques that include statistical design of experiment, such as Taguchi method, and response surface design methodology. In the second category, iterative mathematical search techniques, such as linear programming, non-linear programming and dynamic programming algorithms are included. Non-conventional meta-heuristic search-based techniques, which are used by researchers in recent times are based on genetic algorithm (GA), tabu search (TS), simulated annealing (SA).

The approach adopted by Taguchi is popular for solving optimization problems in the field of manufacturing engineering[12,13,16-18]. Taguchi method utilizes experimental design called orthogonal array design, and S/N ratio which serve the objective function to be optimized within experimental domain. Traditional Taguchi method solve only single response optimization problem. But most of real time engineering application problems are multi-response in nature. In multiple response optimum setting of control factors, it can be observed that an increase/improvement of one response may cause change in another response, beyond the acceptable limit. To solve multi-response optimization problems, it is convenient to convert all the objectives into an equivalent single objective function. This equivalent objective function, which is the representative of all the quality characteristics of the product, is to be optimized. The more frequently used approach is to assign a weighting for each responses. The weighted Signal to Noise ratio of each quality characteristics is used to compute the performance measures[15]. In practice it is not competent because it uses engineering judgment and past experiences to optimize multiple responses. The combined approaches are proposed by many researchers to overcome these limitations[18,25,26].

The grey relational analysis theory, initialized by Deng[20], makes use of this to handle uncertain systematic problem with only partial known information. This theory is used for solving the complicated interrelationships among the multiple responses. The grey relational coefficient can express the relationship between the desired and actual experimental results. A grey relational grade is obtained to evaluate the multi-response. Optimization of the complicated multi-response can be converted into optimization of a single grey relational grade. The integrated grey based Taguchi method combines advantages of both Taguchi method and grey relational analysis. This method was successfully applied to optimize the multi-response of complicated problems in manufacturing processes[19,21,27,28]. Furthermore, ANOVA is performed to see which process parameters are statistically significant[22]. In this study, the effect of WireEDM process parameters on MRR and surface roughness are reported using grey based Taguchi method.

Grey based taguchi method

The integrated Grey based Taguchi method combines the algorithm of Taguchi method and grey relational analysis to determine the optimum process parameters for multiple responses.

Taguchi method

The concept of the Taguchi method is that the parameter design is performed to reduce the sources of variation on the quality characteristics of product, and reach a target of process robustness[15]. It utilizes the orthogonal arrays from experimental design theory to study a large number of variables with a small number of experiments[12,13]. Furthermore, the conclusions drawn from small scale experiments are valid over the entire experimental region spanned by the control factors and their level settings. A loss function is defined to calculate the deviation between the experimental value and the desired value. The value of the loss function is further transformed into an S/N ratio. Usually, there are three categories of performance characteristic in the analysis of the S/N ratio, i.e. lower-the-better, higher-the-better, and nominal-the-best. The S/N ratio η_{ij} for the i^{th} performance characteristic in the j^{th} experiment can be expressed as:

$$\eta_{ij} = -10 \log (L_{ij}) \qquad \ldots(1)$$

The loss function L_{ij} for higher-the-better performance characteristic can be expressed as:

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{y_{ijk}^{2}} \qquad \ldots(2)$$

L_{ij}-Loss function of the ith process response in the jth experiment, k- number of tests,

y_{ijk}-Experimental value of the ith performance characteristic in the jth experiment at the kth tests

For lower-the-better performance characteristic, the loss function L_{ij} can be expressed as:

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^{2} \qquad \ldots(3)$$

For nominal-is-best performance characteristics, the S/N ratio can be expressed as:

$$\eta_{ij} = 10\log\left(\bar{y}^{2} / \sigma\right) \qquad \ldots(4)$$

The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the performance characteristic, a larger S/N ratio corresponds to a better performance characteristic. This S/N ratio value can be considered for the optimization of single response problems. However, optimization of multi-response cannot be straightforward as in the optimization of a single response[23,24]. The higher S/N ratio for one response may correspond to the lower S/N ratio for another response. To overcome the limitation combined approaches are proposed by researchers. In this, grey based Taguchi method is adopted to optimize the multi-response.

Grey relational analysis

The grey relational analysis based on the grey system theory can be used to solve the complicated interrelationships among the multiple responses effectively. In a grey system, some information is known and some information is unknown. It is applied in optimization of WEDM process, EDM process, chemical-mechanical polishing process and drilling operation with multi-responses[18,19,21,26].

Data pre-processing is the first stage in grey analysis since the range and unit in one data sequence may differ from the others. Data pre-processing is a means of transferring the original sequence to a comparable sequence. Depending on the characteristics of a data sequence, there are various methodologies of data pre-processing available for this analysis.

Experimental data y_{ij} is normalized as Z_{ij} ($0 \le Z_{ij} \le 1$) for the i^{th} performance characteristics in the j^{th} experiment can be expressed as:

For S/N ratio with Larger-the-better condition

$$Z_{ij} = \frac{y_{ij} - \min\left(y_{ij}, i = 1, 2, ...n\right)}{\max\left(y_{ij}, i = 1, 2, ...n\right) - \min\left(y_{ij}, i = 1, 2, ...n\right)} \quad \ldots(5)$$

For S/N ratio with smaller-the-better

$$Zij = \frac{\max\left(y_{ij}, i = 1, 2, ...n\right) - y_{ij}}{\max\left(y_{ij}, i = 1, 2, ...n\right) - \min\left(y_{ij}, i = 1, 2, ...n\right)} \quad \ldots(6)$$

For S/N ratio with nominal-the-best

$$Zij = \frac{(y_{ij} - \text{Target}) - \min(\left|y_{ij} - \text{Target}\right|, i = 1, 2, ...n)}{\max(\left|y_{ij} - \text{Target}\right|, i = 1, 2, ...n) - \min(\left|y_{ij} - \text{Target}\right|, i = 1, 2, ...n)} \quad \ldots(7)$$

According to Deng[20] [i], larger normalized results correspond to better performance and the best normalized result should be equal to one. Then, the grey relational coefficients are calculated to express the relationship between the ideal (best) and the actual experimental results.

The grey relational Co-efficient γ_{ij} can be expressed as –

$$\gamma_{ij} = \frac{\Delta\min + \xi\Delta\max}{\Delta_{oj}(k) + \xi\Delta\max} \quad \ldots(8)$$

Where,

a. j = 1,2…n; k = 1,2…m, n is the number of experimental data items and m is the number of responses.

b. yo(k) is the reference sequence (yo(k) = 1, k = 1,2…m); yj(k) is the specific comparison sequence.

c. $\Delta_{oj} = \left\| y_o(k) - y_j(k) \right\|$ = The absolute value of the difference between yo(k) and yj(k)

d. $\Delta_{\min} = \min\limits_{\forall j \in i} \min\limits_{\forall k} \left\| y_o(k) - y_j(k) \right\|$ is the smallest value of yj(k)

e. $\Delta_{\max} = \max\limits_{\forall j \in i} \max\limits_{\forall k} \left\| y_o(k) - y_j(k) \right\|$ is the largest value of yj(k)

f. ξ is the distinguishing coefficient which is defined in the range $0 \leq \xi \leq 1$ (the value may adjusted based on the practical needs of the system)

The Grey relational grade $\overline{\gamma}_j$ is expressed as:

$$\overline{\gamma_j} = \frac{1}{k}\sum_{i=1}^{m} \gamma_{ij} \quad \ldots(9)$$

Where $\overline{\gamma}_j$ is the grey relational grade for the j^{th} experiment and k is the number of performance characteristics. The grey relational grade shows the correlation between the reference sequence and the comparability sequence. The evaluated grey relational grade varies from 0 to 1 and equals 1 if these two sequences are identically coincident. The higher grey relational grade implies the better product quality; on the basis of grey relational grade, the factor effect can be estimated and the optimal level for each controllable factor can also be determined. The structure of the integrated grey based Taguchi algorithm is illustrated in Fig. 1.

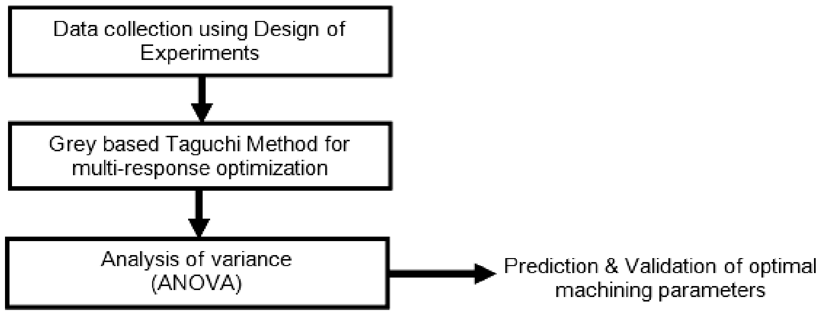

Fig. 1: Structure of grey based taguchi method

Determination of optimal machining parameters

Experimental details

MMC's used in this process AA7075/TiB_2 (3wt %) are fabricated by the in-situ process. Detailed fabrication procedure and in situ TiB_2 formation of particles are available elsewhere[29,30]. The material composition of unreinforced AA7075 is given in Table 1. Rough cut machining of unreinforced AA7075 and MMC's are done by Electronica Sprint cut model EPULS 40A DLX wire EDM. The brass wire of 0.25 mm diameter is taken as cathode. De-ionized water is used as dielectric fluid. The work piece is rectangular in shape with 6mm thickness. Photograph of the composite AA7075/TiB_2 (3% wt) is shown in Fig. 2 and 3 shows the photograph of machined piece.

Table 1: Composition of AA7075-T6

	Al	Zn	Mg	Cu	Cr	Fe	Si	Ti	Others
Weight %	90.4	5.26	2.11	1.48	0.22	0.2	0.10	0.06	Balance

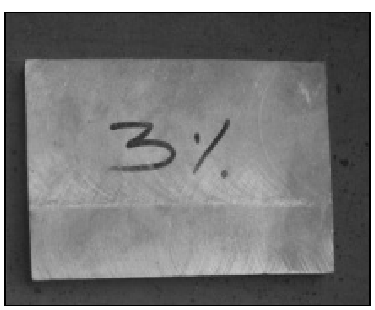

Fig. 2: Prepared casting in plate form with different wt% of TiB_2

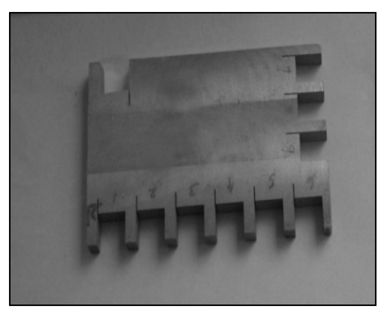

Fig. 3: Photograph of Machined work piece sample

From the outcomes of literature review, it is understood that the process parameters which made significant impact on the performance are peak current pulse on time, pulse off time and wire feed. The experiments were conducted as per the Taguchi's L_9 orthogonal array. The levels of the process parameters and their orthogonal array with process parameters values are given in Table 2 and 3.

Table 2: WEDM Process parameters table

S. No.	Parameter	Symbol	Unit	Level 1	Level 2	Level 3
1	Pulse-on time	A (Ton)	μs	120	125	130
2	Pulse-off time	B (Toff)	μs	45	50	55
3	Peak current	C (Ip)	A	150	190	230
4	Wire feed	D (F)	m/min	8	9	10

Table 3: Taguchi's L_9 orthogonal array and process parameters values

Experiment No.	Orthogonal array (L_9)				Output responses	
	Pulse on Time (Ton) μs	Pulse off Time (Toff) μs	Peak Current (Ip) (amps)	Wire Feed (F) (m/min)	Material removal rate (MRR) g/min	Surface roughness R_a
1	1	1	1	1	0.0532	3.38
2	1	2	2	2	0.0525	4.06
3	1	3	3	3	0.0598	3.74
4	2	1	2	3	0.0545	3.38
5	2	2	3	1	0.0536	4.52
6	2	3	1	2	0.0462	3.33
7	3	1	3	2	0.0488	3.51
8	3	2	1	3	0.0488	3.83
9	3	3	2	1	0.0472	3.22

Optimization of machining parameters

The output parameters used to assess the WEDM performance are MRR and R_a. MRR can be calculated by the following formula[11, 31].

$$MRR = V_c \, B \, t \, \rho, \text{ g/min} \quad (10)$$

Where, V_c – Cutting speed, mm/min

B – Width of cut, mm

t – Work piece thickness, mm

ρ – Density of the composite kg/m^3 (3% - 2754.6)

Surface roughness of WEDM machined components was measured using Mitutoyo Surftest SJ-210. Surface roughness of the three sides of the machined surface was measured and the average value was taken.

Initially, the S/N ratios for a given responses are computed using one of the (1), (2), (3) and (4) depending upon the type of quality characteristics. Surface roughness have lower-the-better and MRR have higher-the-better criterion.

The normalized values for each response S/N ratios are estimated using (5), (6) and (7). The computed S/N ratios for each quality characteristic and the normalized values of S/N ratios are shown in Table 4.

Table 4: S/N Ratios and grey relational coefficients of responses and grey relational grade

Exp. No.	S/N ratios		Normalized values of S/N ratios		Grey relational coefficient of		Grey relational grade
	MRR	Surface Roughness	MRR	Surface Roughness	MRR	Surface Roughness	
1	-25.483	-10.58	0.5472	0.8596	0.5248	0.7807	0.6528
2	-25.589	-12.17	0.4996	0.3151	0.4998	0.4220	0.4609
3	-24.471	-11.45	1.0000	0.5616	1.0000	0.5328	0.7664
4	-25.271	-10.58	0.6420	0.8596	0.5828	0.7807	0.6818
5	-25.421	-13.09	0.5748	0.0000	0.5404	0.3333	0.4369
6	-26.706	-10.44	0.0000	0.9075	0.3333	0.8439	0.5886
7	-26.237	-10.90	0.2098	0.7500	0.3875	0.6667	0.5271
8	-26.228	-11.66	0.2137	0.4897	0.3887	0.4949	0.4418
9	-26.525	-10.17	0.0809	1.0000	0.3523	1.0000	0.6762

Grey relational coefficient for each response has been calculated using (8). The value for ξ is taken as 0.5 since both the process parameters are of equal weight. The results are shown in Table 4. The grey relational grade can be calculated by using (9), which is the overall representative of both the responses shown in Table 4. Now, the multi-response optimization problem has been transformed into a single equivalent objective function optimization problem using this approach. The higher grey relational grade is said to be close to the optimal. The mean response table for overall grey relational grade is shown in Table 5 and is represented graphically in Fig. 4. The mean grey relational grade for the parameters at levels 1, 2 and 3 can be calculated by averaging the grey relational grades for the experiments 1-9. With the help of the Table 5 and Fig 5, the optimal parameter combination has been determined. The optimal factor setting condition is $A_1B_3C_2D_2$. Using the grey relational grade value, ANOVA is formulated for identifying the significant factors. The results of ANOVA are presented in Table 5. From ANOVA, it is clear that T_{off} (74.5%) influences more on Wire EDM of AA7075/TiB_2 (3wt %) followed by Wire feed (14.28%), and T_{on} (8.5%).

Table 5: Response table (mean) for overall grey relational grade

Factors	Level-1	Level-2	Level-3
A	**0.6267**	0.5691	0.5484
B	0.6205	0.4465	**0.6771**
C	0.5611	**0.6063**	0.5768
D	0.5547	**0.6627**	0.5707

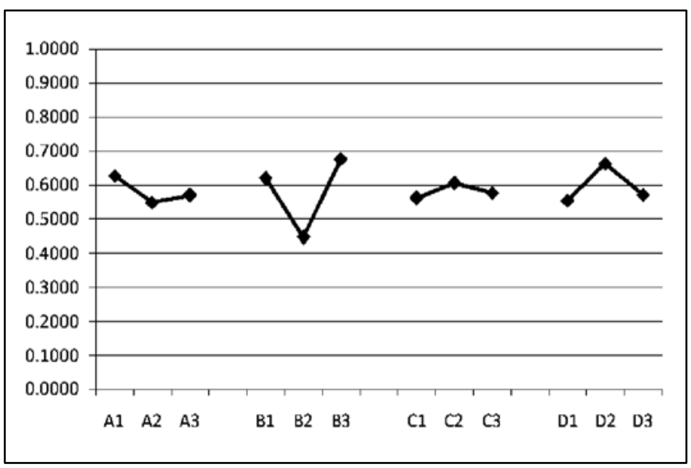

Fig. 4: The response graph for each level of machining parameters

Table 6: Results of the anova

Source of variation	Degree of freedom	Sum of squares	Mean square	F ratio	p – Value	Contribution (%)
Ton	2	0.010	0.0049	3.295		8.50
Toff	2	0.087	0.0433	28.877		74.50
IP	2	0.003	0.0016			
Wire Feed	2	0.017	0.0083	5.534		14.28
Error (IP)	2	0.003	0.0015			2.72
Total	8	0.116				100.00

Predicted optimum condition

In order to predict the optimum condition, the expected mean at the optimal settings (μ) is calculated by using the following model.

$$\mu = \overline{A}_1 + \overline{B}_3 + \overline{C}_2 + \overline{D}_2 - 3 \times \overline{T}_{gg} \qquad \ldots(11)$$

Where, $\overline{A}_1$, $\overline{B}_3$, $\overline{C}_2$ and $\overline{D}_2$ are the mean values of the grey relational grade with the parameters at optimum levels and $\overline{T}_{gg}$ is the overall mean of average grey grade. The expected mean (μ) at optimal setting is found to be 0.7702.

Confidence interval (CI) is calculated as

$$CI = \sqrt{F_\alpha(1, f_e)V_e\left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \qquad \ldots(12)$$

$$= \pm\, 0.2156$$

Where, F_α (1, f_e) is the F ratio at a significance level of α%, α is the risk, f_e is the error degrees of freedom, V_e is the error mean square, n_{eff} is the effective total number of tests and R is the number of confirmation tests

$$n_{eff} = \frac{\text{Total number of observations}}{\text{1+Total degrees of freedom associated with items used in estimating } \mu} \qquad \ldots(13)$$

Therefore 95% confidence interval of the predicted optimum condition is given by following model, where μ = the Grey relational grade values after conducting the confirmation experiments with optimal setting point, i.e., $A_1B_3C_2D_2$

$$(0.7702-0.2156) < \mu < (0.7702 + 0.2156)$$

$$(0.5546) < \mu < (0.9858)$$

Confirmation test

Once the optimal level of the process parameters has been determined, then the final step is to predict and verify the improvement of the responses using the optimal level of process parameters. Table VII shows the comparison of the multi-response for initial and optimal machining parameters. The initial designated levels of machining parameters are A_1, B_2, C_2 and D_2 which is the second experiment shown in the Table III. As noted from Table VII, the surface roughness Ra is decreased from 4.06 µm to 3.42 µm and the MRR is increased from 0.0525 g/min to 0.0582 g/min respectively. The estimated grey relational grade is increased from 0.5063 to 0.7849, which is the largest value obtained in all the experimental results in Table IV. It is clearly shown that the multi-responses in the Wire Electrical Discharge Machining process are together improved by using this method.

Table 7: The comparison results of initial and optimal wire EDM responses

Initial Wire EDM parameters		Optimal Wire EDM parameters	
		Prediction	Experiment
Levels	A1B2C2D2	A1B3C2D2	A1B3C2D2
MRR (g/min),	0.0525	-	0.0582
Surface roughness (Ra)	4.06	-	3.42
Taguchi based grey relational grade	0.5063	0.7702	0.7849
Improvement of taguchi based grey relational grade		0.2639	0.2786

CONCLUSION

Experiments are designed and conducted on Wire Electrical Discharge Machine with AA7075/TiB_2 (3 wt %) as work material to optimize the machining parameters. The MRR and surface roughness are the responses. The proposed Grey based Taguchi method is constructive in optimizing the multi-responses. It is identified that T_{off} (74.5%) influences more followed by Wire feed (14.28%), and T_{on} (8.5%). Confirmation test results proved that the determined optimum condition of WireEDM machining parameters satisfy the real requirements.

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