MACHINABILITY STUDY ON AL- 10% TIC COMPOSITES AND OPTIMUM SETTING OF DRILLING PARAMETERS IN ELECTROCHEMICAL MICRO MACHINING USING GREY RELATIONAL ANALYSIS

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***Abstract*— This paper investigates the influence of the process parameters like machining voltage, electrolyte concentration, frequency on the over cut and Material Removal Rate (MRR) on drilling of Al-10% TiC Metal Matrix composites using Electrochemical Micro Machining (EMM) through taguchi methodology and grey relational analysis. Based on the analysis, optimum levels of parameters were determined and the same to validate through the confirmation test. Experimental results are in close agreement with the developed model. The confirmation results reveal that, there is considerable improvement in Material Removal Rate, Overcut. Grey relational grade are improved by 89.5 %, 57.9% and 95.16 % respectively. It is observed that the machining performance can be effectively improved with respect to initial parametric setting.**

***Keywords*— Metal Matrix Composite, Material removal rate, Overcut, Electrochemical micromachining (EMM), Taguchi, ANOVA, Grey relational analysis.**

I. INTRODUCTION

MMC's have became the most demanding materials in many industrial applications including electronics, bio medicine, optics, bio technology, home appliances, Fuel injection system components, ordnance components mechanical machine parts, because of their high modules, low ductility, high thermal conductivity, low thermal expansion, high strength-to-weight ratio, high toughness, high-impact strength, high wear resistance, low sensitivity to surface flaws, and high surface durability. Stir casting method is very popular in MMC's fabrication due to its unique advantages (Hashim *et al.*, 1999). The hard particles present in the matrix, poor machining properties of MMC and drilling of MMCs are challenging tasks for the manufacturing engineers. To meet these issues various micro manufacturing methods have been developed. Among the various micromachining, EMM appears to be potential one because it produces good surface finish, no tool wear, no thermal damage to the work piece, higher machining rate, better precision, control and capability to machine wide range of materials and complex shapes can be machined for extremely hard materials (Malapati and Bhattacharyya, 2011). Spieser and Ivanov (2013) to address the problems met by the EMM technology developers and to present the current state-of-the-art solutions. Rajurkar *et al.* (1999) have discussed, the principal issues in ECM development, tool design, pulse current, micro-shaping, finishing, numerically controlled, environmental concerns, hybrid processes, and recent industrial applications. Paczkowski and Sawicki (2008) present the theoretical analysis of the ECM process of curvilinear surfaces. Micro drilling is an essential process in the electronics, aviation, and semiconductor industries. Since micro drills have low rigidness and a high aspect ratio, precise drilling parameters are required to prevent tool breakage from excessive thrust force or torque. Have made an attempt to machine the alumina ceramic to investigate the effects of drilling parameters on hole characteristics (Chang and Lin, 2012). The EMM micro hole making process satisfies the quality requirements with respect to their geometrical characteristics like over-cut, taper, aspect ratio or metallurgical characteristics like heat affected zone and micro-cracking (Bhattacharyya *et al.*, 2001). Mithu *et al.* (2014) found that, the material removal rate, machining time, and the size of fabricated micro hole are significantly influenced by the micro tool dimension. Tang and Yang (2013) observed, given the same voltage, with an increasing cathode feed rate, the MRR was shown to increase while the surface roughness value and the side gap decreased. Under the same cathode feed rate, the MRR decreases, while the side gap and the surface roughness increase as the electrochemical machining application voltage increases. Mithu *et al*. (2011) focus on effects of applied frequency and duty cycle in electrochemical micro drilling on nickel plate. The EMM is still in its initial stages of development and a lot of research needs to be done to improve MRR, surface quality and accuracy by optimizing the various process parameters (Bhattacharyya *et al.*, 2007). Being a complex process, it is very difficult to determine optimal parameters for improving cutting performance. Jain *et al.* (2012) have studied the effects of process parameters

such as voltage, electrolyte concentration, pulse duty cycle, and feed rate on the machined hole diameter. Thanigaivelan and Arunachalam (2010) conducted an experimental study on the influence of shape of tool electrode tip on machining rate and overcut for 304 Stainless Steel has been presented. The tool electrode tips of different shapes like flat, conical with rounded and truncated cone were used for this study. The micro ECM process is complex, and it is not easy to decide the optimal machining parameters for improving the output quality. The optimization of process parameters is essential for the realization of a higher productivity, which is the preliminary basis for survival in today's dynamic market conditions. Optimal quality of the work piece in ECM can be generated through combinational control of various process parameters. Various empirical models for Material Removal Rate (MRR), Tool Wear Rate (TWR), Overcut (OC) and Surface Roughness (SR) of the work piece have been published in the past (Jeyapaul *et al.*, 2006; Yadav and Yadava, 2013). In these models it has been proved that Grey relational analysis is a powerful tool for representing the relationship between input parameters and the process responses (Manivannan *et al.*, 2011; Noorul Haq *et al.*, 2008). The theory of grey systems is a new technique for performing prediction, relational analysis and decision making in many areas. Electrochemical Micro Machining of MMC's through Grey analysis, not much more in the past researchers.

In view of the above, an attempt has been made in this present investigation, the influence of voltage, electrolyte concentration, and frequency on MRR and overcut of the Aluminum matrix composites using Electro chemical micro machining through Taguchi methodology and Grey relational analysis. Optimization of cutting parameters is important for achievement of high quality. Taguchi's method of experimental design is one of the widely accepted techniques for offline quality assurance of products and processes. Grey relational analysis is a unique statistical tool and it has potential for savings in experimental time and cost on product or process development and quality improvement.

II. EXPERIMENTAL DETAILS

A. Preparation of the Hybrid Composites

The material used in this investigation is Al- 10% TiC , which was getting from stir casting route. It is well suitable for high temperature application due their high thermal conductivity. The aluminum matrix was reinforced with 10 % wt of TiC. The average particle size TiC was 50 microns. The aluminum alloy was preheated in a resistance furnace at 450º C for 2 to 3 hour before melting. TiC also preheated in a resistance furnace at 1100º C for 2 hour. The preheated aluminum were first heated above the liquidus temperature to melt them completely, and then slightly cooled below the liquidus to maintain the slurry in the semisolid state. This procedure has been adopted while stir casting aluminum composites (Riaz Ahamed *et al.*, 2008). The preheated reinforcements were added and mixed manually. Manual mixing was used because it was very difficult to mix using automatic device when the alloy was in a semisolid state. The composite slurry was then reheated to a fully liquid state, and mechanical mixing was carried out for about 20 min at an average mixing speed of 200–300 rpm. The final temperature was controlled to be within 750°C±20°C, and pouring temperature was controlled to be around 700°C. After thorough stirring, the melt was poured into steel molds of size 100x100x10 mm and allowed to cool to obtain cast sheet. The SEM image of Al-TiC as shown in Fig. 1.

B. Electrochemical Micro Machining

Electrochemical micro machining (EMM) (Fig. 2) is one of the nonconventional machining processes. It offers the unique advantage of better accuracy with high surface integrity of hard-machined components; also it has wider application because it produces good quality surfaces without affecting the metallurgical properties of the work material. During ECM, there will be reactions occurring at the electrodes i.e. at the anode or work-piece and at the cathode or the tool along with within the electrolyte. Ion and electrons crossing phase boundaries (the interface between two or more separate phases, such as liquid-solid) would result in electron transfer reaction carried out at both anode and cathode. The tool electrode feed mechanism, with resolution of 2 µm along Z – axis designed with stepper motor and 8051 micro controller. The electrolyte supply system consists of filter and pump arrangement. A pulsed power supply of 20 V and 30 A with capability for varying voltage, current, and pulse width stainless steel electrode of 452 µm diameter was used (Thanigaivelan *et al.*, 2012). The electrolyte concentrations used in this study was sodium nitrate ($NANO_3$) and Al- TiC of thickness of 0.5 mm as work piece. Based on the literature review and preliminary experiments conducted, the initial process parameters and their corresponding levels are chosen. The work piece thickness 0.4 mm, machining current 0.6 A as fixed for entire experiment. Table 1 shows the machining parameters and their level indentified for this investigation. MRR was derived as work piece removal weight over machining time. Overcut of the micro hole has been related with the machining accuracy, hence it is the difference between the diameters of the tool electrode and machined micro hole. With the support of optical microscope the radius of the machined micro – hole was measured which is shown in Fig. 3.

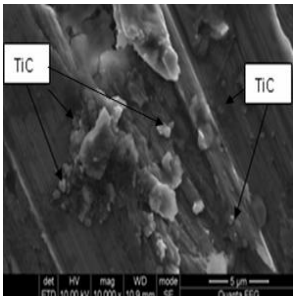

Fig. 1. SEM image of Al-TiC

Fig 2. EMM Set up

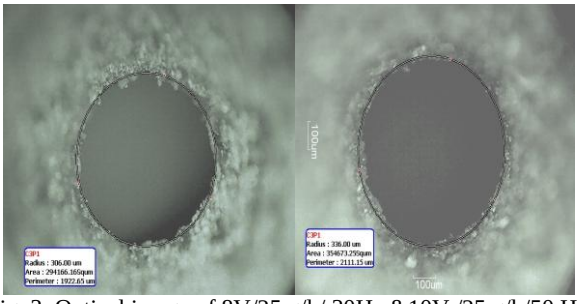

Fig. 3. Optical image of 8V/25 g/l / 30Hz &10V /25 g/l /50 Hz

Table 1: Machining parameters

	Factors	Level 1	Level 2	Level 3
A	Voltage (V)	6	8	10
B	Electrolyte Concentration (g/l)	20	25	30
C	Frequency (Hz)	30	40	50

III METHODOLOGY

A. Grey Relational Analysis.

The Grey theory established by Dr. Deng includes Grey relational analysis, Grey modeling, prediction and decision making of a system in which the model is unsure or the information is incomplete. It provides an efficient solution to the uncertainty, multi-input and discrete data problem. The relation between machining parameters and machining performance can be found out using the Grey relational analysis. And this kind of interaction is mainly through the connection among parameters and some conditions that are already known. Also, it will indicate the relational degree between two sequences with the help of Grey relational analysis. Moreover, the Grey relational grade will utilize the discrete measurement method to measure the distance.

Grey analysis does not attempt to find the best solution, but does provide techniques for determining a good solution, an appropriate solution for vogue problems. When the range of the sequence is too large or the standard value is too enormous, it will cause the influence of some factors to be neglected. Also, in the sequence, if the factors' goals and directions are different the relational analysis might also produce incorrect results. Therefore, preprocessing of all the data is necessary. It does not involve complicated mathematical theory or computation and thus can be employed by the engineers without a strong statistical background.

The Grey number in Grey system represents a number with less complete information. The Grey element represents an element with incomplete information. The Grey relation is the relation with incomplete information. There are several aspects for the theory of Grey system:

1. Grey generation: This is data processing to supplement information. It is aimed to process those complicate and tedious data to gain a clear rule, which is the whitening of a sequence of numbers.
2. Grey modeling: This is done by step 1 to establish a set of Grey variation equations and Grey differential equations, which is the whitening of the model.
3. Grey prediction: By using the Grey model to conduct a qualitative prediction, this is called the whitening of development.
4. Grey decision: A decision is made under imperfect countermeasure and unclear situation, which is called the whitening of status.
5. Grey relational analysis: Quantify all influences of various factors and their relation, which is called the whitening of factor relation.
6. Grey control: Work on the data of system behavior and look for any rules of behavior development to predict future's behavior, the prediction value can be fed back into the system in order to control the system.

The Grey relational analysis uses information from the Grey system to dynamically compare each factor quantitatively. This approach is based on the level of similarity and variability among all factors to establish their relation. The relational analysis suggests how to make prediction and decision, and generate reports that make suggestions for the vendor selection. This analytical model magnifies and clarifies the Grey relation among all factors. It also provides data to support quantification and comparison analysis. In other words, the Grey relational analysis is a method to analyze the relational grade for discrete sequences. This is unlike the traditional statistics analysis handling the relation between variables. Some of its defects are: (1) it must have plenty of data; (2) data distribution must be typical; (3) a few factors are allowed and can be expressed functionally. But the Grey relational analysis requires less data and can analyze many factors that can overcome the disadvantages of statistics method.

B. Optimization steps using grey relational analysis

Twenty seven experimental runs (L_{27}) based on the Orthogonal Array (OA) of Taguchi methods have been carried out. The multi-response optimization of the process parameters viz. MRR, Over cut has been performed for making a micro hole in the process of micro-ECM of Al- TiC metal matrix composites, each experiment was replicated twice. Machining time, over cut, MRR noted for every trial. In this study higher MRR and Lower over cut are desired. Therefore MRR is Larger is better and Overcut is Smaller is better chosen for this study.

Step 1: Calculate S/N Ratio for the corresponding responses using the following formula.

Larger is better

The signal-to-noise (S/N) ratio is calculated for each factor level combination.

$$S/N = -10 \log_{10} [\Sigma (1/Y^2_{ij}) / n)] \quad (1)$$

This is applied for problem where maximization of the quality characteristic of interest is sought. This is referred as the larger-the-better type problem.

Nominal is best (I)

The signal-to-noise (S/N) ratio is calculated for each factor level combination. The formula for the nominal-is-best I S/N ratio using base 10 log is:

$$S/N = -10 \log (10\, s^2) \quad (2\text{ a})$$

where s is the standard deviation of the responses for all noise factors for the given factor level combination.

Nominal is best (II)

The signal-to-noise (S/N) ratio is calculated for each factor level combination. The formula for the nominal-is-best II S/N ratio using base 10 log is:

$$S/N = 10 \log((Y^2) / s^2) \quad (2b)$$

where Y is the mean of responses for the given factor level combination, s is the standard deviation of the responses for the given factor level combination, and n is the number of responses in the factor level combination.

This is called nominal-the-best type of problem where one tries to minimize the mean squared error around a specific target value. Adjusting the mean on target by any means renders the problem to a constrained optimization problem.

Smaller is better

The signal-to-noise (S/N) ratio is calculated for each factor level combination.

$$S/N = -10 \log_{10} [\Sigma\, (Y^2_{ij})/n)] \quad (3)$$

where Y_{ij} is the observed response value where i=1, 2, ..., n ; j =1, 2., .. k and n is the number of responses in the factor level combination. This is termed as the smaller-the-better type problem where minimization of the characteristic is intended.

Step 2: Y_{ij} is normalized as Z_{ij} ($0 \le Z_{ij} \le 1$) by the following formula to avoid the effect of adopting different units and to reduce the variability. It is necessary to normalize the original data before analyzing them with the grey relation theory or any other methodologies. An appropriate value is deducted from the values in the same array to make the value of this array approximate to 1. Since the process of normalization affects the rank, we also analyzed the sensitivity of the normalization process on the sequencing results. Thus, we recommend that the S/N ratio value be adopted when normalizing data in grey relation analysis.

$$Z_{ij} = \frac{\max\limits_{i=1,2,\cdots,n}(Y_{ij}) - Y_{ij}}{\max\limits_{i=1,2,\cdots,n}(Y_{ij}) - \min\limits_{i=1,2,\cdots,n}(Y_{ij})} \quad (4)$$

(To be used for S/N ratio with smaller the better manner)

$$Z_{ij} = \frac{Y_{ij} - \min\limits_{i=1,2,\cdots,n}(Y_{ij})}{\max\limits_{i=1,2,\cdots,n}(Y_{ij}) - \min\limits_{i=1,2,\cdots,n}(Y_{ij})} \quad (5)$$

(To be used for S/N ratio with Larger the better manner)

$$Z_{ij} = \frac{(Y_{ij} - Target) - \min\limits_{i=1,2,\cdots,n}(|Y_{ij} - Target|)}{\max\limits_{i=1,2,\cdots,n}(|Y_{ij} - Target|) - \min\limits_{i=1,2,\cdots,n}(|Y_{ij} - Target|)} \quad (6)$$

(To be used for S/N ratio with nominal the best manner)

Step 3: Calculate Grey relational Co-efficient for the normalized S/N ratio values.

$$\gamma(y_o(k), y_j(k)) = \frac{\Delta\min + \xi\Delta\max}{\Delta_{oj}(k) + \xi\Delta\max} \quad (7)$$

where

1. j=1,2,.....n; k = 1,2…..m, n is the number of experimental data items and m is the number of responses.
2. $y_o(k)$ is the reference sequence ($y(k)$=1, k=1,2...m); $y(k)$ is the specific comparison sequence.
3. $\Delta_{oj} = \|y_o(k)-y_j(k)\|$ is the absolute value of the difference between $y_o(k)$ and $y_j(k)$
4. $\Delta\min = \min\limits_{\forall i}\min\limits_{\forall k}\|y_o(k) - y_j(k)\|$ is the smallest value of $y_j(k)$.
5. $\Delta\max = \max\limits_{\forall i}\max\limits_{\forall k}\|y_o(k) - y_j(k)\|$ is the largest value of $y_j(k)$.
6. ζ is the distinguishing coefficient, which is defined in the range 0= ζ =1 (the value may adjusted based on the practical needs of the system)

Step 4: Generation of Grey relational grade

$$\bar{\gamma}_j = \frac{1}{k}\sum_{i=1}^{m}\gamma_{ij} \quad (9)$$

where $\bar{\gamma}_j$ is the grey relational grade for the jth experiment and k is the number of performance characteristics.

Finally the grades are considered for optimizing the multi response parameter design. The results are given in the Table 4. The higher grey relational grade reveals that the corresponding experimental result is closer to the ideally normalized value. It has been observed that trial no. 25 has the best multiple response characteristics among the 27 trials, because it has the highest grey relational grade shown in Table 2.

Step 5: Determine the optimal factor and its level combination. The higher grey relational grade implies the better product quality; therefore, 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. For example, to estimate the effect of factor i, we calculate the average of grade values (AGV) for each level j, denoted as AGV_{ij}, then the effect, E_i, is defined as:

$$E_i = \max (AGV_{ij}) - \min (AGV_{ij}) \quad (9)$$

If the factor i is controllable, the best level j*, is determined by

$$J^* = \max_j (AGV_{ij}) \quad (10)$$

The response table of Taguchi method is employed here to calculate the average grey relational grade for each machining parameter level. It is done by sorting the grey relational grades corresponding to levels of the machining parameter in each column of the orthogonal array, and taking an average on those with the same level. Using the same method, calculations are performed for each machining parameter level and the response table is constructed as shown in Table 3. Figure4 shows the effect of EMM parameters on multi response characteristics.

C. Implementation of the solution methodology

Step 1: Calculate the S/N ratios for a given response and predicted S/N ratios of the starting conditions using one of the Eqs. (1), (2) and (3) depending upon the type of quality characteristics. The computed S/N ratios for each quality Characteristic are shown in Table 2.

Table 2. S/N ratios for each quality characteristic

Trial No	A	B	C	MRR mg/min	Overcut μ m	S/N Ratio for MRR	S/N Ratio for Overcut	Normalized S/N ratio MRR	Normalized S/N ratio Overcut	Grey relational co-efficient MRR	Grey relational co-efficient Overcut	Grey grade
1	6	20	30	0.19	212.46	-14.4249	-46.5455	1	1	0.3333	0.3333	0.3333
2	6	20	40	0.21	167.32	-13.5556	-44.471	0.8699	0.7659	0.365	0.395	0.38
3	6	20	50	0.29	141.67	-10.752	-43.0256	0.4502	0.6028	0.5262	0.4534	0.4898
4	6	25	30	0.36	156.2	-8.87395	-43.8736	0.1691	0.6985	0.7473	0.4172	0.5822
5	6	25	40	0.34	125.62	-9.37042	-41.9812	0.2434	0.4849	0.6726	0.5077	0.5901
6	6	25	50	0.29	143.44	-10.752	-43.1334	0.4502	0.6149	0.5262	0.4485	0.4873
7	6	30	30	0.35	145.65	-9.11864	-43.2662	0.2057	0.6299	0.7085	0.4425	0.5755
8	6	30	40	0.31	173	-10.1728	-44.7609	0.3635	0.7986	0.579	0.385	0.482
9	6	30	50	0.33	169.86	-9.62972	-44.6018	0.2822	0.7806	0.6392	0.3904	0.5148
10	8	20	30	0.27	129.4	-11.3727	-42.2387	0.5431	0.514	0.4793	0.4931	0.4862
11	8	20	40	0.2	171.1	-13.9794	-44.665	0.9333	0.7878	0.3488	0.3883	0.3686
12	8	20	50	0.28	138.92	-11.0568	-42.8553	0.4958	0.5835	0.5021	0.4615	0.4818
13	8	25	30	0.19	116	-14.4249	-41.2892	1	0.4068	0.3333	0.5514	0.4424
14	8	25	40	0.39	138.14	-8.17871	-42.8064	0.065	0.578	0.8849	0.4638	0.6744
15	8	25	50	0.22	155.86	-13.1515	-43.8547	0.8094	0.6963	0.3819	0.4179	0.3999
16	8	30	30	0.36	89.4	-8.87395	-39.0268	0.1691	0.1515	0.7473	0.7675	0.7574
17	8	30	40	0.28	152	-11.0568	-43.6369	0.4958	0.6717	0.5021	0.4267	0.4644
18	8	30	50	0.27	76.6	-11.3727	-37.6846	0.5431	0	0.4793	1	0.7397
19	10	20	30	0.17	162.72	-15.391	-44.2288	1.1446	0.7386	0.304	0.4037	0.3539
20	10	20	40	0.23	187	-12.7654	-45.4368	0.7516	0.8749	0.3995	0.3637	0.3816
21	10	20	50	0.21	161.16	-13.5556	-44.1451	0.8699	0.7291	0.365	0.4068	0.3859
22	10	25	30	0.31	149	-10.1728	-43.4637	0.3635	0.6522	0.579	0.434	0.5065
23	10	25	40	0.29	109.5	-10.752	-40.7883	0.4502	0.3503	0.5262	0.5881	0.5571
24	10	25	50	0.22	146	-13.1515	-43.2871	0.8094	0.6323	0.3819	0.4416	0.4117
25	10	30	30	0.36	78.62	-8.87395	-37.9107	0.1691	0.0255	0.7473	0.9515	**0.8494**
26	10	30	40	0.41	158.45	-7.74432	-43.9978	0	0.7125	1	0.4124	0.7062
27	10	30	50	0.33	149.66	-9.62972	-43.5021	0.2822	0.6565	0.6392	0.4323	0.5358

Table 3. Grey relational grade

	Process parameters	Level 1	Level 2	Level 3
A	Voltage	0.4928	**0.5349***	0.5209
B	Elec. concentration	0.4068	0.5169	**0.6250***
C	Frequency	**0.5230***	0.5116	0.4941

*Optimum Levels

Mean grey grade = **0.51621**

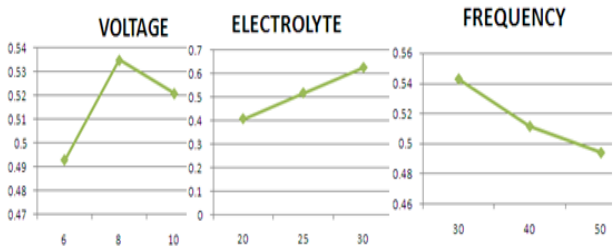

Fig. 4 – Effect of EMM Process parameter

Step 2: Normalize the S/N ratio values by Eqs. (4), (5) and (6). The results are given in Table 2.

Step 3: Perform the grey relational analysis. From the data in Table 2, calculate the grey relational co-efficient for the normalized S/N ratio values by using Eq. (7). The value for $\xi\Delta max$ is taken as 0.5 in Eq. (7). Since all the process parameters are of equal weighting. The results are given in Table 2.

Step 4: Next, the grey relational grade can be computed by Eq. (8). Finally, the grades are considered for optimizing the multi response parameter design problem. The results are given in the Table 4.

Step 5 From the value of grey relational grade in Table 2, by using Eq. (9), the main effects are tabulated in Table 3 and the factor effects are plotted in Fig. 4.

Step 6: Considering maximization of grade values (Table 3/ Fig. 4), we can obtain the optimal parameter conditions $\mathbf{A_2B_3C_1}$..

V. MAJOR RESULTS AND INFERENCES

A. Analysis of Variance (ANOVA)

After the Grey relational analysis, ANOVA is performed to identify the process parameters that influence the MRR and Over cut of this investigation (Table 4). This analysis is carried out for significance level of α = 0.05, i.e., for a confidence level of 95%. The results of ANOVA, the Voltage and Electrolyte concentration are the significant machining parameters for affecting the MRR and Overcut. Based on the F value (111.74), voltage is the most significant factor that influences the MRR and overcut with 80.02 % contribution. The second ranking factor is Electrolyte concentration, which contributes 11.05 %.As machining voltage is increased, the machining rate is increased. The machining rate reaches its maximum value at a particular voltage and

decreased because electrode surface is gradually covered by bubbles generated at increased voltage. It is observed that a power supply which maintains a constant voltage and current throughout the machining process is the most effective for electrochemical machining. With the increase in electrolyte concentration, ions associated with the machining operation in the ma chining zone also increase. A higher concentration of ions reduces the localization effect of electrochemical material removal reactions. This leads to the higher overcut and thus reduces the machining accuracy. Figure 5 shows the interaction between the Voltages, Electrolyte concentration, Frequency to MRR Overcut respectively. Figure 6 Show the residual plots for Grey grade. Figure 7 shows the percentage contributions of factors on Grey relational grade.

Table 4. ANOVA for Grey Relation Grade

Factors	DOF	Sumof squares	Mean square	F value	$F_{0.05}$	%of contribution	
Voltage	2	0.374791	0.187395	111.74	0.000	**80.02**	significant
Elec. Concentration	2	0.051750	0.025875	15.43	0.000	**11.05**	significant
Frequency	2	0.008243	0.004121	2.46	0.111	01.76	
Error	20	0.033543	0.001677			07.17	
Total	26	0.468326				100 %	

S = 0.0409529 R-Sq = 92.84% R-Sq(adj) = 90.69%

Table 5: Conformation test table for MRR & Overcut

	Initial levels of machining parameters	Optimal combination levels of machining parameters	
		Prediction	Experiment
Level	$A_1B_1C_1$	$A_2B_3C_1$	$A_2B_3C_1$
MRR	0.19		0.36
Overcut	212.46		89.4
Grey relational grade	0.3333	0.6505	0.7574

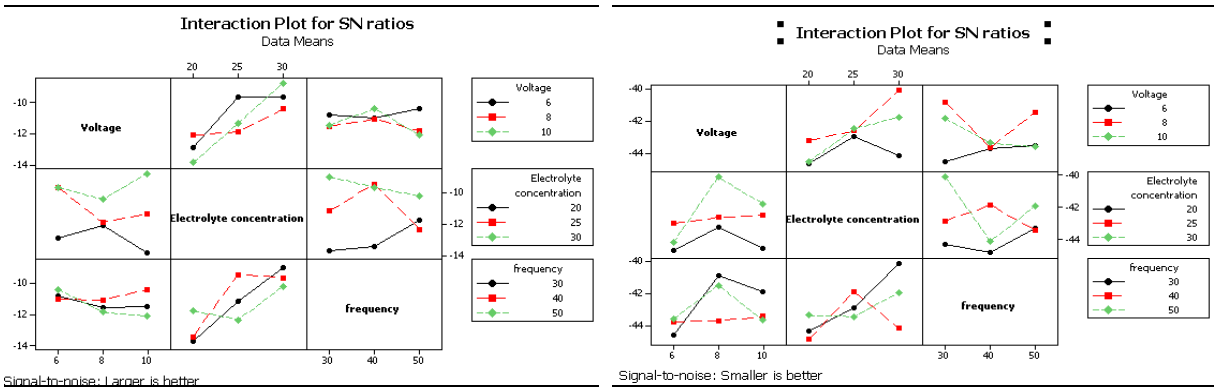

Fig. 5: Interaction Plot for MRR & Overcut

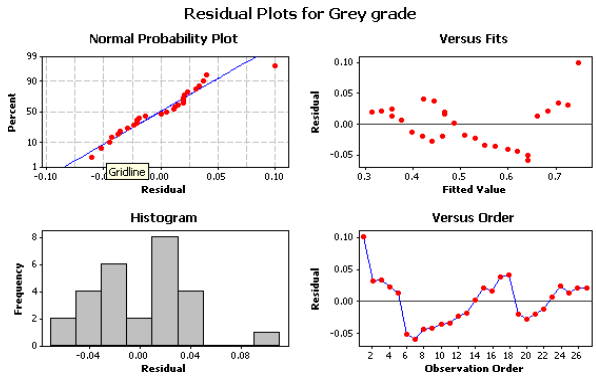

Fig. 6. Residual Plot for Grey grade

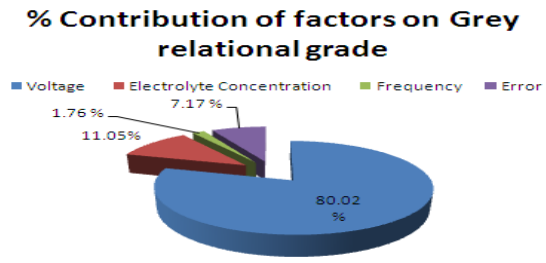

Fig. 7. Percentage contribution of factors on Grey relational grade

B. Confirmation Test

After identifying the most influential parameters, the final phase is to verify the predicted results (MRR and Overcut) by conducting the confirmation test. The $A_2B_3C_1$ is an optimal parameter combination of the EMM process via the GRA. Therefore, the combination $A_2B_3C_1$ was treated as a confirmation test. The predicted Grey relational grade can be calculated using the optimum parameters as

$$\alpha_{predicted} = \alpha_m + \sum_{i=1}^{3}(\alpha_o - \alpha_m)$$

where $\alpha_{predicted}$ is the grey relational grade for predicting the optimal EMM Parameter, α_o is the average grey relational grade of the optimal level of a certain significant factor, α_m is the over all mean grey relational grade .

$\alpha_{predicted}$ =0.51621+(0.5349-0.51621)+(0.6250-0.51621)+ (0.5230 - 0.51621)=**0.6505**

V. CONCLUSIONS

The Present investigation is focused on optimization and analysis electrochemical micro machining of Al-6063 /10 % wt of TiC metal matrix composites machining parameters. From the study of result in EMM was using Taguchi methodology and Grey relational analysis. It does not involve complicated mathematical theory or computation and thus can be employed by the engineers without a strong statistical background. The experimental process parameters and levels are fixed through preliminary experiments. The range of parameters used in the experiment has a significant impact on the output parameters such as MRR and overcut. The results may change provided if any process parameters is included such as pulse on time, flushing rate and tool vibration etc. The conclusion provided in this manuscript holds good for parameters such as voltage, elec concentration and frequency. Hence for this Electrochemical machining set up, Voltage are the most significant factor that influences the MRR and overcut with 80.02 % contribution. The second ranking factor is Electrolyte concentration, which contributes 11.05 %.

The following can be concluded from the present study.

1. Based on the confirmation test, improvement in Material Removal Rate, Overcut are 89.5% and 57.9 % respectively..
2. Grey relational grade is improved by 95.16 %.
3. The parameter combination suggested for the higher MRR and lesser overcut is machining Voltage, 8 V, Electrolyte concentration, 30 g/l, Frequency, 30 Hz
4. The results of ANOVA, the Voltage and Electrolyte concentration are the most significant machining parameters for affecting the MRR and Overcut.
5. Confirmation test results proved that the determined optimum combination of machining parameters satisfy the real requirements of EMM operation of hybrid metal matrix composites.

ACKNOWLEDGMENT

The authors are thankful for the technical support of this project by Sona College of Technology, Salem, and Tamilnadu, India.

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Received: February 17, 2014
Accepted: March 26, 2014
Recommended by Subject Editor: Eduardo Dvorkin