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Multi-Objective Optimization of Electrochemical Machining of Al 7075 (T6)/10% Al2o3 Composite using Taguchi Based Grey Relational Analysis

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Abstract—*Electrochemical machining (ECM), one of the non-conventional machining processes, is used for machining of difficult-to-machine materials and intricate profiles. Use of optimal ECM process parameters can significantly reduce the ECM operating, tooling, and maintenance cost and will produce components with higher accuracy. This paper investigates the influence of process parameters on the metal removal rate (MRR), surface roughness (SR) and diameteral overcut (DOC), to fulfill the effective utilization of electrochemical machining of stir casted aluminium composites using Grey Relational Analysis (GRA). Experiments were conducted based on Taguchi's L_9 orthogonal array (OA) with three process parameters viz. electrolyte concentration, voltage, and electrolyte flow rate with three levels each on Al 7075 T6/10% Al_2O_3 composite. The performance measures considered were material removal rate, surface roughness and diameteral overcut. GRA converts the multi response variable to a single response viz. Grey relational grade and, therefore, simplifies the optimization procedure. It has been observed that electrolyte flow rate is the significant process parameter that affects the ECM.*
The optimal combination are voltage 20 V, electrolyte concentration 40(g/l) and electrolyte flow rate 4 l/min for maximum MRR, minimum surface roughness and minimum diameteral overcut (DOC).

Keywords: *ECM, Aluminium matrix composite, Orthogonal array, Taguchi's methodology, Grey relational analysis, Multi-objective parametric optimization.*

1. INTRODUCTION

Aluminium matrx Composites are gaining increasing attention for applications in aerospace, defense, and automobile industries. These materials have been used in automobile brake rotors and various components in combustion engines. The limitation of Aluminum Composites is that the machining of these composites is very difficult due to the highly abrasive nature of ceramic reinforcements [1]. AMC_S are generally produced by mechanical mixing of reinforcement into the molten aluminum alloy base through stir casting and are tailored made according to some special applications by varying volume fraction [2]. Electrochemical machining (ECM) was developed to machine difficult-to-cut materials [1]. ECM is opposite of galvanic coating or deposition process [2] .ECM is controlled anodic dissolution at atomic level of the work piece, that is electrically conductive, through an electrolyte which is quite often water based neutral salt solution [3]. Because of various complex physio-chemical and hydrodynamic phenomena that occur in the machining gap during the course of machining, the machining rate at any instant depends not only on the inter-electrode gap, but also on other process parameters [4]. The other parameters are applied voltage, feed rate, electrolyte concentration, electrolyte flow rate, current, type of electrolyte, tool shape etc. They directly influence the metal removal rate and surface quality of the work piece during machining. Optimal quality of the work piece in ECM can be generated through combinational control of various parameters [5].

One of the major advantage of ECM is that there is no tool wear; Hard conductive materials can be machined into complicated profiles and work-piece structure suffer no thermal damages and have burr free surface [6].

Current engineering applications require materials that are stronger, lighter and less expensive. A good example is the current interest in the field of automotive, aeronautics, defense etc. The components made up of these materials offers economy with improved engine performance [7]. Aluminium matrix composites have been noted to offer such tailored property combinations required in a wide range of engineering applications [8]. Some of these desirable property combinations include: high specific strength, low coefficient thermal expansion, high thermal resistance, good damping capacities, superior wear resistance, high specific stiffness and satisfactory levels of corrosion resistance [9]. Aluminium matrix composites (Al 7075 (T6)/10% Al_2O_3) are a new generation of composites that have the potentials of satisfying the recent demands of advanced engineering applications. These demands are met due to improved mechanical properties, amenability to conventional processing technique and possibility of reducing production cost of aluminium composites [10].

The optimization of process parameters is essential for the achievement of high response of production. Optimal quality during ECM can be generated through combinational control of various process parameters [3]. To select the process parameters properly, literature identifies techniques such as mathematical modeling based on statistical analysis or neural computing in order to establish the relationship between the machining measures and the parameters, Neto *et al.* (2006) presented the study of the intervening variables in electrochemical machining using sodium chloride (NaCl) and sodium nitrate ($NaNO_3$) electrolytic solution. They have also studied MRR, roughness and over-cut. The results show that feed rate is the significant parameter affecting the material removal rate [11]. Munda and Bhattacharyya (2008) have optimized pulse on/off ratio, voltage, electrolyte concentration, voltage frequency and tool vibration frequency to optimize multiple performance characteristics such as MRR and radial overcut using RSM [12]. Asokan *et al.* (2008) have developed a regression and artificial neural network (ANN) model of process performance (MRR and surface roughness) with control parameters (current, voltage, flow rate and inter-electrode gap) in ECM of hardened steel [13].

The present study deals with the application of Taguchi method coupled with grey relational analysis performance during ECM of Al 7075(T6)/10% Al_2O_3 to determine the optimal parametric settings in order to obtain maximum MRR, low surface roughness and diameteral overcut.

An orthogonal array (L9) with three replicates is generated using the Taguchi methodology to carry out the experimental runs with no interaction in L9. The process parameters namely electrolyte concentration (g/l), applied voltage (V) and electrolyte flow rate (l/min) are considered as independent variables. The results were analysed using Grey Relational Analysis technique. Analysis of variance (ANOVA) is also carried out to observe the level of significance of factors. Confirmation tests were later carried out to check the validation of optimal process parameters settings.

2. GREY RELATIONAL ANALYSIS

Taguchi technique (Taguchi, 1990) is a powerful tool for designing high quality system at minimum cost based on orthogonal array (OA) experiments that provide much reduced variance for the experiments with an optimum setting of process control parameters [14]. Taguchi method is suitable for single response optimization, but optimization of multiple performance characteristics is different from of a single performance characteristics [15].For multi-response optimization, grey relational analysis coupled with Taguchi method is employed. The grey system theory has been first proposed by Deng (1989) [16]. GRA is based on geometrical mathematics, which compliance with the principles of normality, symmetry, entirety, and proximity [17].

The algorithm of grey relational analysis is illustrated as follow [17-18]

- Calculation of the grey relational generation in which the set of experimental results are normalized in between 0 and 1.
- Calculation of the grey relational coefficient from the normalized data to represent the correlation between the desired and actual experimental data.
- Calculation of the grey relational grade by averaging the grey relational coefficients.
- As grey relational grade is to be maximized, the S/N ratio is calculated using higher-the-better (HB) Criterion.
- To perform statistical analysis of variance (ANOVA) for the input parameters with the grey relational grade and to find which parameter significantly affects the process performance.
- Selection of the optimal levels of process parameters.
- Confirmation test to verify the optimal process parameters setting.

3. EXPERIMENTAL PROCEDURE

3.1. Experimental set up

The experimental runs were conducted on Electrochemical Machining set up by modifying existing setup of ECM. The ECM set up has input supply of 210 single phase AC, 50 Hz. Output supply is 0-20 A, DC at any voltage from 0-27 V. The ECM set up consists of tool holder and tool feed, working tank, tank, pump and work holding device, control panel, Electrolyte and circulation system. The tool, i.e. the cathode, is connected to a direct voltage source with the workpiece acting as the anode. A charge exchange takes place between the cathode and the anode in an aqueous electrolyte solution which targets specific areas of the workpiece.

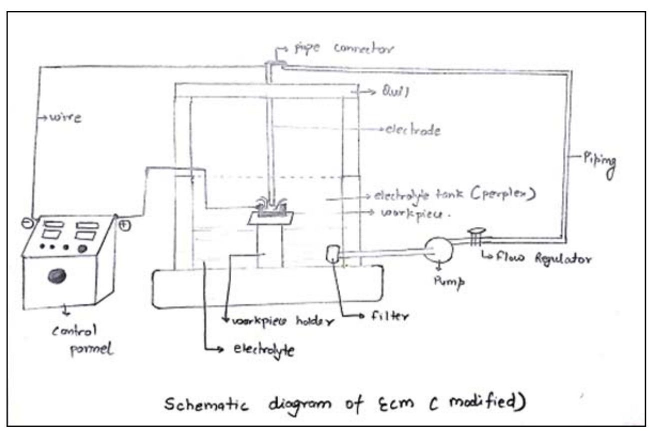

Fig. 1: Schematic Diagram of ECM

Fig. 2: Set up of ECM

3.2. Work piece, tool electrode and electrolyte

Rectangular blocks of dimensions 70x70x10 mm^3 of Al 7075(T6)/10% Al_2O_3 is used as work piece. The composite was prepared by stir casting technique. The base material was Aluminum Alloy 7075 (T6) and Alumina (Al_2O_3) 10% as reinforcement. The T6 designation implies that aluminium alloy has been solution heat treated and artificial aged to maximum mechanical properties levels. The aging temperature of T6 is 176 °C.

The tool electrode used were of copper having hollow cylindrical in shape with 8 mm outer diameter and 5 mm inner diameter and 500 mm length. Copper offer wide range of properties including excellent electrical and thermal conductivity, outstanding corrosion resistance, good strength and fatigue resistance, and appearance. The electrolyte is an component of ECM and carries out the vital functions such as the current flow between the tool and the work-piece, removes the products of machining from the cutting region, and dissipates heat produced in the operation. Electrolytes must have high electrical conductivity, low toxicity and low corrosiveness. Nacl solution is used as Electrolyte in the present study.

3.3. Design of Experiment

In this study, the experimental plan has three controllable variables, namely, voltage (V), electrolyte concentration (g/l) and electrolyte flow rate (l/min). On the basis of preliminary experiments conducted by using one variable at a time approach, the feasible range for the machining parameters was defined as shown in Table 1.

Table 1: Parameter and their levels

S. No	Process Parameter	Symbol (unit)	Level		
			1	2	3
1	Voltage	V (V)	20	30	3
2	Electrolyte Concentration	EC (g/l)	22.5	35	4
3	Electrolyte Flow Rate	EFR (l/min)	25	40	5

The experimental runs were performed using Taguchi's L9 orthogonal array as shown in Table 2.

Table 2: L9 Orthogonal Array

Run	Voltage (V)	EC. (g/l)	EFR (l/min)
1	20	30	3
2	20	35	4
3	20	40	5
4	22.5	30	4
5	22.5	35	5
6	22.5	40	3
7	25	30	5
8	25	35	3
9	25	40	4

3.4. Grey Relational Analysis

3.4.1. Grey relational generation

The first step in grey relational analysis is to perform the grey relational generation in which the results of the experiments are normalized in the range of 0 and 1 [12].

For normalization of MRR data, higher-the-better (HB) criterion and for diameteral overcut and surface roughness parameters, lower-the-better (LB) criterion are used as MRR is to be maximized and diameteral overcut and surface roughness is to be minimized.

Normalization using higher-the-better (HB) criterion:

$$\mathbf{X_i(k)} = \frac{\mathbf{y_i(k) - min y_i(k)}}{\mathbf{max y_i(k) - min y_i(k)}} \tag{1}$$

Normalization using lower-the-better (LB) criterion:

$$\mathbf{Xi(k)} = \frac{\mathbf{max y_i(k) - y_i(k)}}{\mathbf{max y_i(k) - min y_i(k)}} \tag{2}$$

here *xi(k)* is the value after grey relational generation, min *yi(k)* is the smallest value of *yi(k)* for the *kth* response, and max *yi(k)* is the largest value of *yi(k)* for the *kth* response. An ideal sequence is *x0(k) (k=1,2,3,……..,9)* for the response.

Larger normalized results correspond to the better performance and the best normalized result should be equal to 1(ideal).

3.4.2. Grey relational coefficient

Grey relational coefficients are calculated to express the relationship between the ideal (best = 1) and the actual experimental results. The grey relational coefficient $\xi(k)$ can be calculated as:

$$\xi i(k) = \frac{\Delta_{\min} + \Psi \Delta_{max}}{\Delta_{0i}(k) + \Psi \Delta_{max}} \quad (3)$$

where,

$\Delta_{\min}$ and $\Delta_{\max}$ are respectively the minimum and maximum values of the absolute differences Δ_{0i} of all comparing sequences.

Ψ is a distinguishing coefficient, $0 \leq \psi \leq 1$, the purpose of which is to weaken the effect of $\Delta_{\max}$ when it gets too big, and thus enlarges the difference significance of the relational coefficient[12]. The suggested value of the distinguishing coefficient, Ψ, is 0.5, due to the moderate distinguishing effects and good stability of outcomes. Therefore, Ψ is adopted as 0.5 for further analysis in the present study**.**

3.4.3. Grey Relational Grade

The grey relational grade is obtained by:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad (4)$$

where n is the number of process responses. Higher value of grey relational grade implies stronger relational degree between the ideal sequence $x_0(k)$ and the given sequence $xi(k)$.

4. EXPERIMENTATION

The data was collected after carrying out the experimental runs using L9 orthogonal array having three replicates. The material removal rate (MRR) (g/min) was measured using weight difference per unit machining time. The weight is measured by using Analytical Digital Indicator Electronic Balance with least count of 0.001 g. It has been manufactured by Chanzhou Xingyun Electronic equipement Co. Ltd. Surface Roughness measurement is done using a stylus-type profilometer, Talysurf. Least count of Taylor Hobson, surface roughness tester is 0.01µm.Diameteral overcut is calculated by averaging the diameter of the hole machined after ECM. It was measured using vernier caliper which has the least count of 0.02mm.The experimental results are shown in Table 3.

4.1. Results and Discussion

Table 4 shows the normalization of experimental results which are calculated by using equations (1) & (2). Table 5 shows Grey Relational Grade (GRG) calculated by using equation (4). Thus, multi-response optimization problem is converted into single response optimization problem, which is not feasible with Taguchi's methodology. The ranking has also been done.

Table 4: Normalization of Experimental Results

Run	MRR			Surface Roughness			DOC		
Ideal value	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*
1	0.9428	0.6540	0.7966	0.4931	0.4933	0.4737	0.6991	1.0000	0.5565
2	1.0000	0.5903	0.7286	0.9319	0.6014	0.5358	1.0000	0.6897	0.6718
3	0.4737	1.0000	0.5126	0.5948	0.5993	0.6817	0.7973	0.4862	0.8281
4	0.7113	0.4866	1.0000	0.8524	0.5541	1.0000	0.5431	0.4737	0.6059
5	0.7078	0.6004	0.4737	0.9907	0.6857	0.5267	0.5801	0.4780	0.7953
6	0.5236	0.7456	0.5386	1.0000	1.0000	0.9146	0.4737	0.5660	1.0000
7	0.7059	0.4737	0.6113	0.4737	0.4737	0.4863	0.6020	0.7207	0.4737
8	0.5756	0.6614	0.8446	0.7260	0.5228	0.6714	0.8016	0.4887	0.7832
9	0.5757	0.6547	0.6493	0.7361	0.9140	0.6382	0.8826	0.4887	0.5411

Table 5: Grey Relational Grade

Run No.	GRG	Order
1	0.6788	4
2	**0.7500**	**2**
3	0.6637	7
4	**0.6919**	**3**
5	0.6487	8
6	**0.7513**	**1**
7	0.5579	9
8	0.6750	6
9	0.6756	5

The maximum value of GRG is 0.7513 and has been ranked first, followed by 0.7500 and 0.6919 and has been ranked second and third respectively.

5. ANALYSIS OF VARIANCE

ANOVA is very useful for revealing the level of significance of influence of factor(s) or interaction of factors on a particular response [16]. In the present study, ANOVA is performed using Minitab 17® and as shown in Table 6. Response table of GRG showing ranking is shown in Table 7. As per Table 6, the contribution of EFR (l/min) is best, followed by V (V).

Table 6: ANOVA of GRG

Factors	DOF	SS	MS	F-Value	Contribution (%)
V	2	0.007499	0.003750	14.29	**28.56**
EC	2	0.005287	0.002644	10.08	20.15
EFR	2	0.012933	0.006466	24.65	**49.28**
Error	2	0.000525	0.000262		2.005
Total	8	0.026243			100

Table 7: Response table for GRG

Levels	Voltage(V)	Elec. Conc. (g/l)	Elec. flow rate (l/min)
1	**-3.142**	-3.878	-3.088
2	-3.147	-3.224	**-3.035**
3	-3.963	**-3.150**	-4.130
Delta	.822	.728	1.095
Rank	**2**	3	**1**

The response table for GRG [Table 7] also shows the ranking of process parameters. The factor EFR (l/min) has been ranked first, followed by Voltage (V) ranked second. The optimal parametric setting are A1B3C2.It is observed that electrolyte flow rate is the significant factor for maximizing the material removal rate and minimizing the surface roughness and diameteral overcut followed by voltage. An increase electrolyte flow rate increases the material removal rate and reduces the surface roughness nd overcut. Figure 4 shows the main effect plot based on grey relational grade where dashed line shows the value of total mean of grey relational grade. It is evident that as the voltage increases, MRR decreases because at higher voltage, electric field between the electrode increases which draws high current and causes short circuit nditions. This also increases the surface roughness and doc [19].The increase in concentration in electrolyte results in increase in MRR due to increase in conductivity of the electrolyte. Higher conductivity of electrolyte helps to increase more chemical energy between the tool and the work material which causes the removal of work material more quickly and also reduces the surface roughness and diameteral overcut [20]. As the flow rate increases the intensity of flow increases which cause deeper crater on the machined surface, hence the MRR increases but sludge is not removed therefore surface roughness increases along with doc. The optimal parametric settings can also be visualized as A1B3C2.

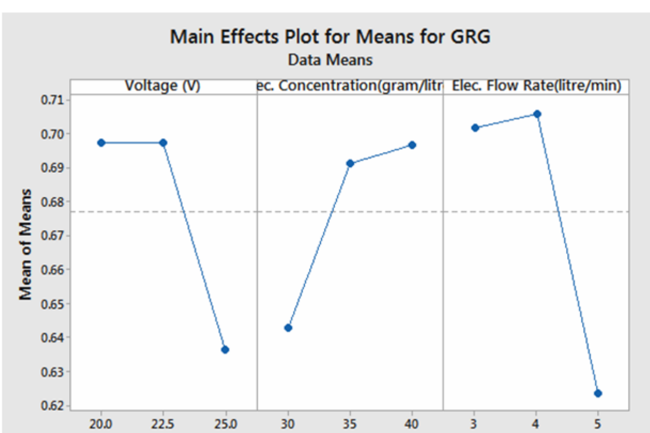

Fig. 4: Main effect plot for GRG

6. CONFIRMATION TEST

A validation test is performed to see whether any improvement in results is obtained through the condition suggested by the optimum parameter analysis compared to the initial condition. As observed in table 8, MRR increases from 0.032675 g/min to 0.034825, surface roughness reduces from4.302 to 3.015 and diameteral overcut reduces from 2.1763 to 2.1264. Based on the above above results, it is clearly observed quality characteristics can be greatly improved through this study.

Table 8: Result of Confirmation Test

	Process Parameter	MRR	SR	DOC
Initial design	A1B3C3	0.032675	4.302	2.1763
Optimal design	A1B3C2	0.034825	3.015	2.1264

7. CONCLUSION

In the present study, Grey relational analysis is successfully employed in conjunction with Taguchi design of experiments to optimize this multiple response problem. The optimal parameter combination is obtained as A1B3C2 (the lowest level of voltage i.e. 20V, highest level of electrolyte concentration i.e. 40 g/l and mid level of electrolyte flow i.e. 4 l/min). As a result, the target performance characteristics, i.e. material removal rate can be maximized and the diameteral overcut and surface roughness can be minimized through this method. The effectiveness of this approach is verified by experiment and analysis of variance.

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