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Study of ECG process while machining Al_2O_3/Al – IPC using grey-Taguchi methodology

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A B S T R A C T

The present paper attempts to optimize machining parameters of electrochemical grinding (ECG) while machining alumina-aluminum interpenetrating phase composites by Grey-Taguchi methodology. Control parameters like electrolyte concentration, voltage, depth of cut and electrolyte flow rate have been considered to ensure two conflicting responses – higher material removal rate and lower surface roughness simultaneously by a single parametric combination. The L_9 orthogonal array design is followed for the purpose of experimentation. The well-known S/N ratio analysis is performed along with ANOVA to establish the prominent variables that govern the responses separately. Finally Grey Relational Analysis is performed to optimize multiple performances in which different levels combinations of the factors are ranked based on grey relational grade. Surface roughness is given more importance than the *MRR* considering basic objective of the process. The analysis reveals that substantial improvement in machining performance takes place following this technique. The experimental investigation approach for evaluating the optimum ECG parametric combination during machining of composites materials can act as useful and an efficient guideline for manufacturing of products using such material. The study highlights the effects of different process variables on multiple performances for complex process like ECG.

A R T I C L E I N F O

Keywords:
Electrochemical grinding
Aluminum interpenetrating phase
Composites
Taguchi
Analysis of variance
Grey relational analysis

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1. Introduction

Manufacturing industries all across the globe is passing through dramatic changes caused by globalization, rapid proliferation in communication and IT enabled services. These changes essentially call for several modifications in the traditional way of working to survive in this complex business environment. Use of emerging and non-conventional techniques of machining and alternative materials is one of the major steps to cope with the changes. Electrochemical grinding ECG, a useful non-conventional hybrid machining process, used for machining difficult-to-machine alloys, hardened, fragile and thermal sensitive parts [1]. The reason for such a combination and the development of a hybrid machining process is mainly to make use of the combined advantages and to avoid or reduce some adverse effects the constituent processes produce when they are individually applied. The material removal is due to the combined effect of electrochemical dissolution and mechanical abrasion and found to be superior over conventional grinding.

Further, the process being based on electrochemical dissolution of work material, the machined surfaces are free from burr and residual stress, eliminating costly and time consuming secondary operations and reducing rejection caused by stress and cracks. ECG has high material removal rate as compared to the conventional grinding when working with the tough-to-machine materials, such as high temperature resistant Co-Ni alloys, high tensile strength materials, metal matrix composites etc. [2].

Interpenetrating phase composites IPC are a new class of composite materials in which phases are three-dimensionally 3D continuous and each phase spans or percolates throughout the microstructure. Such materials are envisaged as very promising category of composites since it exhibits multifunctional characteristics-offering improved combinations of mechanical and physical properties and enhanced damage tolerance [3]. The alumina-aluminum (Al_2O_3–Al) system is one of the most studied ceramic-metal IPC systems. Al_2O_3–Al IPCs produced by these processes have a random, usually isotropic, spatial distribution of phases [4].

The material removal in the ECG process can be attributed to (i) purely mechanical abrasion (ii) electrochemical removal combined with mechanical abrasion with zero over cut (iii) electrochemical removal coupled with mechanical means with over cut greater than zero (iv) absolutely electrochemical reaction [5]. Input variables like voltage, electrolyte flow rate, electrolyte concentration and depth of cut significantly contribute to both material removal rate *MRR* and surface finish R_a. Few research works have been carried out to establish the optimal process variables so as to achieve better surface finish and higher material removal rate [6, 7]. Nevertheless there is hardly any mathematical model involving process variables that can successfully describe neither *MRR* or R_a. Both the objective being conflicting in nature, it is very difficult to achieve them simultaneously by a single set of process variables. The present work is aimed at optimization of process variables in regard to high *MRR* and lower R_a concurrently following grey relational analysis technique during ECG of Al_2O_3–Al IPC.

2. The Taguchi method and grey relational analysis

The Taguchi method is a well organised approach to improve product/process design by optimizing a single response through level settings of significant parameters that affect the response [8-10]. However, increase in process variables eventually augments the number of experiments to be conducted, thereby increasing the time and cost. To get rid of such situations, the Taguchi method recommends that a small numbers of experiments using special design orthogonal arrays are sufficient for this purpose. S/N ratio is one of the major attributes of Taguchi based quality engineering that is based on the premise of variability reduction and the improvement of measurement [11]. Based on the nature of objective(s), it can have three distinct categories – higher-the-better, lower-the-better and nominal-the-better. Nevertheless, the larger S/N ratio is always favorable irrespective of the above categories. Although, this procedure yield very good result for a single performance characteristic with great ease, it is difficult for optimizing several responses simultaneously which are contradicting in nature. This necessitates computation of an overall S/N ratio by suitable transformation function. Such problems however, can be solved successfully following grey relational analysis (GRA).

The grey system theory was proposed by Deng in 1980's [12] and it is widely used for analyzing a system in which the model is uncertain or the information is incomplete implying a combination of known and unknown information's [13, 14]. It also provides an efficient solution to complicated interrelationships among multiple response parameters [15]. Based on the grey theory, a system can be investigated by means of relational coefficient, relational grade so as to take final decision regarding selection of optimum variables combination based on highest grade. The grey relational analysis is very much effective to evaluate the multiple response parameters by converting individual responses to a single grey relational grade.

Chen et al. [16] used this technique to establish optimal cutting parameters while rough cutting processes in side milling for SKD61 tool steels to improve tool life and *MRR* by 54 % and 9.7 %, respectively, employing low spindle speed, moderate level of feed per tooth and radial depth of cut while maintaining highest level of depth of cut. Kuo et al. [17] followed this approach for an IC packaging company in order to find out the best plant layout among eighteen alternatives by considering six attributes and for a hybrid flow shop environment for ranking nine dispatching rules having five attributes. Lin & Lin [18] optimized the process variables like work piece polarity, pulse on time, duty factor, open discharge voltage, discharge current, and dielectric fluid on the responses such as material removal rate, surface roughness, and electrode wear ratio following GRA while machining SKD11 alloy steel by copper electrode in EDM. The analysis shows significant improvements in performances following optimized process variables combination. Tsao [19] adopted Grey-Taguchi method to optimize milling parameters while machining A6061P-T651 aluminum alloy so as to reduce surface roughness and flank wear. Lin [20] recommended low level of cutting speed, feed and depth of cut to enhance tool life and to reduce cutting force and surface roughness during turning of S45C steel by P20 tungsten carbide inserts. Few other similar works are available in Yan-min et al. [21], Kao and Hocheng [22] respectively.

3. Plan of experimentation

In this paper an experimental study has been carried out on specimen of Al_2O_3–Al IPC material to optimize the machining parameters of Electrochemical grinding for maximum *MRR* and minimum R_a following GRA. During machining of composite materials by *ECG*, *MRR* and R_a have got different grades of importance. In case of finishing operation R_a is given more priority than *MRR*.

These conflicting response parameters require different levels setting of the machining parameters for their optimization. So proper machining parameter set up for simultaneous optimization of the responses is critical. Four process variables, i.e., electrolyte concentration *C*, voltage *V*, depth of cut *D* and electrolyte flow rate *F* have been chosen as input parameters and their levels and combinations are varied in conformance with L_9 orthogonal array. According to GRA technique, the characteristic that a larger value represents the better machining performance, such as higher *MRR*, is called larger-the-better type problem. On the other hand, the characteristic for which smaller value indicates better machining performance such as R_a is addressed as smaller-the-better type problem. Table 1 exhibits the different levels of control parameters during machining operation. Other factors like feed, types of power supply, electrolyte temperature which may affect the measured performance were kept constant during experimentation. Sodium chloride solution was used as electrolyte. The work piece was a flat rectangular plate of dimension 23 mm × 15 mm × 10 mm thick. Power supply maintained was DC continuous.

The experiment is performed in a retrofitted (microprocessor controlled) surface grinder that utilizes a diamond-impregnated metal bonded grinding wheel of 150 mm diameter and 12.27 mm width. The width of the layer containing the diamond was 3 mm and the abrasive grit size was 100. A DC motor rotating at a speed of 3500 rpm drove the grinding wheel mounted at the end of the spindle. During machining, current was recorded that appeared on the ammeter connected to the electrical circuit. A stepper motor (Type: STM – 1100), having torque 1 Nm and angular resolution of 1.8 °/ step with voltage phase: 24 V DC and current 0.67 A was used for the feed drive mechanism of the worktable.

Mechanical and other properties of work piece material, i.e., Al_2O_3/Al IPC composites are exhibited in Table 2. *MRR* was measured by dividing the difference in weight of the workpiece before and after machining by the time duration of machining. An electronic weighing machine of accuracy 0.02 mg of Mettler Toledo make (model no-AG285) was used for this purpose. R_a was measured with Perthometer-M1 of Mahr GmbH make.

Table 1 Input variables with their levels

Input Variables	Unit	Levels		
		Level 1	Level 2	Level 3
Concentration *C*	g/l	20	25	30
Voltage *V*	V	15	20	25
Depth of cut *D*	mm	0.04	0.08	0.12
Electrolyte flow rate *F*	l/s	0.10	0.20	0.30

Table 2 Properties of the Al_2O_3/Al IPC work material

Properties	Values (synthesis condition is 1150 ^{0}/24 h)
Compressive strength (MPa)	576
Micro hardness no. (VHN)	364
Bend strength (MPa)	458 ± 15
Elastic modulus (GPa)	67
Fracture origin principal	Separation at Al_2O_3/Al grain boundary
Bulk density (g/cm^3)	3.54
Conductivity (10^5ohm^{-1}cm^{-1} at RT)	0.4
Grain size (μm)	Al_2O_3 – 4.27 & Al– 1.42

3.1 Orthogonal array experiment

To select an appropriate orthogonal array for experiments, the total degrees of freedom need to be computed. The degrees of freedom are defined as the number of comparisons between machining parameters that need to be made to determine which level is better and specifically how much better it is. For example, a three-level machining parameter counts for two degrees of freedom. The degrees of freedom associated with interaction between two machining parameters are given by the product of the degrees of freedom for the two machining parameters. In the present study, the interaction between the machining parameters is neglected. An L_9 orthogonal array with 4 columns and 9 rows is used. This array has eight degrees of freedom and it can handle three-level process parameters. Nine experiments are required to study the entire linear motion guide parameter space when the L_9 orthogonal array is used. The experimental layout for the machining parameters using the L_9 orthogonal array along with the responses is shown in Table 3.

Table 3 Parametric combinations for experimental run and the responses

	Control Parameters				Responses	
Experiment	*C*	*V*	*D*	*F*	*MRR*	R_a (μm)
1	20	15	0.04	0.1	0.067	0.168
2	20	20	0.08	0.2	0.141	0.214
3	20	25	0.12	0.3	0.053	0.837
4	25	15	0.08	0.3	0.125	0.195
5	25	20	0.12	0.1	0.151	0.516
6	25	25	0.04	0.2	0.079	0.924
7	30	15	0.12	0.2	0.373	0.206
8	30	20	0.04	0.3	0.524	0.157
9	30	25	0.08	0.1	0.093	0.402

4. Results analysis using Taguchi methodology

In this section, the experimental results are analyzed to investigate the contribution of different process variables on various responses by using S/N ratio and ANOVA. The S/N ratio converts several repetitions into one value that manifests the amount of variations and the mean response. The ANOVA is an important and potential technique to establish the prominence of various factors and their levels (main effects) on the response. The optimum level of a factor is the level that provides highest values of S/N ratio. ANOVA is a statistical technique that helps estimate the significance of variables by variance ratio (F-value) and to compute percentage contribution of each factor. The result analysis is carried out by statistical software MINITAB, version 13.

4.1 Analysis of test results for MRR

The Signal to noise ratio (S/N) analysis for *MRR* (g/min) is carried out on the basis of larger is the better option.

The corresponding S/N ratio is expressed as

$$\eta_1 = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{MRR^2}\right) \tag{1}$$

The S/N ratio for *MRR* is shown in Table 4. It is observed that voltage and electrolyte concentration both has significant effects on *MRR* while depth of cut and flow rate has only marginal effect. The S/N ratio plot for *MRR* is shown in Fig. 1.

Table 4 S/N Ratio table for MRR

Level	*C*	*V*	*D*	*F*
1	–22.0029	–16.7020	–17.0464	–20.1764
2	–18.8432	–13.0165	–18.5693	–15.8763
3	–11.6032	–22.7308	–16.8336	–16.3966
Delta	10.3997	9.7143	1.7357	4.3001
Rank	1	2	4	3

From S/N ratio graph it is observed that the *MRR* attains its peak with the parametric combination of C3-V2-D3-F2. *MRR* follows a continuous increasing trend with electrolyte concentration since higher concentration facilitates the ionization of aluminum into the solution. However, *MRR* initially increases with the voltage to reach its peak value and then decrease. With the increase in the machining voltage, the decomposition potential increases to attain an optimum level beyond which over potential adversely affects the *MRR*. Increase in the depth of cut causes inter-grit space of the rotating grinding wheel to be reduced thereby clogging the space between wheel and the work surface that results in reduction in *MRR*. However further increase in depth of cut causes mechanical abrasion to predominate thereby enhancing the *MRR*. The graph exhibits that *MRR* increases with an increase in the flow rate. At higher electrolyte flow rate, the rate of electrolytic dissolution is high hence the *MRR* increases. Very high flow rate in contrast retards the dissolution due to insufficient time of the process to take place hence slight decline in *MRR*.

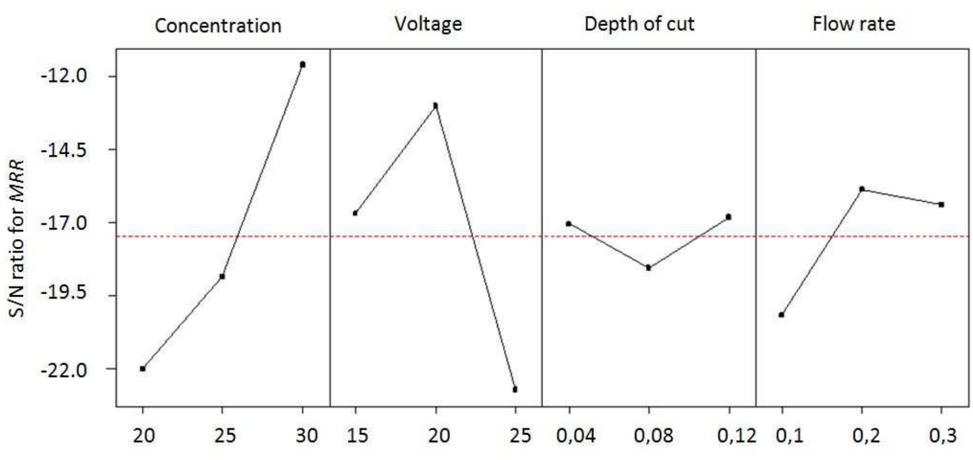

Fig. 1 S/N ratio graph for *MRR*

Table 5 Sum of *MRR* S/N ratios at each level of each factor

Level	Factors			
	C	*V*	*D*	*F*
−1	–66.0086	–50.1061	–51.1394	–60.5293
0	–56.5298	–39.0495	–55.7077	–47.6289
1	–34.8095	–68.1923	–50.5008	–49.1897
Total	–157.348	–157.348	–157.348	–157.348

The average of factor levels for *MRR* is presented in Table 5 which helps conclude the aforementioned parametric combinations for optimum result.

Table 6 shows the ANOVA results for *MRR*. The S/N ratio findings are also corroborated by ANOVA results as exhibited from F-values and percentage contribution of the process variables.

Table 6 ANOVA of *MRR*

Process parameter	DOF	Sum of squares	Adjusted mean square	F-Value	Contribution %
C	2	170.555	85.278	8.877	48.28
V	2	144.296	72.148	7.510	40.84
D	2	5.377	2.688	0.280	1.50
F	2	33.049	16.525	1.720	9.35
Total	8	353.277			
Error	(4)	38.426	9.6065		

The F-value and the percentage contribution of electrolyte concentration and voltage are substantially high implying that a change in these design parameters has significant consequences on the *MRR* with the former being more prominent in this regard. Other two variables emerge as insignificant.

4.2 Analysis of test results for R_a

The signal to noise ratio (S/N) analysis for R_a is modeled on the basis of smaller is the better.
The corresponding S/N ratio is expressed as

$$\eta_2 = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} R_a^2\right) \tag{2}$$

The S/N ratio for R_a is shown in Table 7. It is found from "delta-values" of the process variables that voltage is the most influencing parameter that governs *Ra* considerably. The overall ranking is portrayed in the above table. The S/N plot for R_a is shown in Fig. 2. The best combination for lower *Ra* is C3-V1-D2-F3.

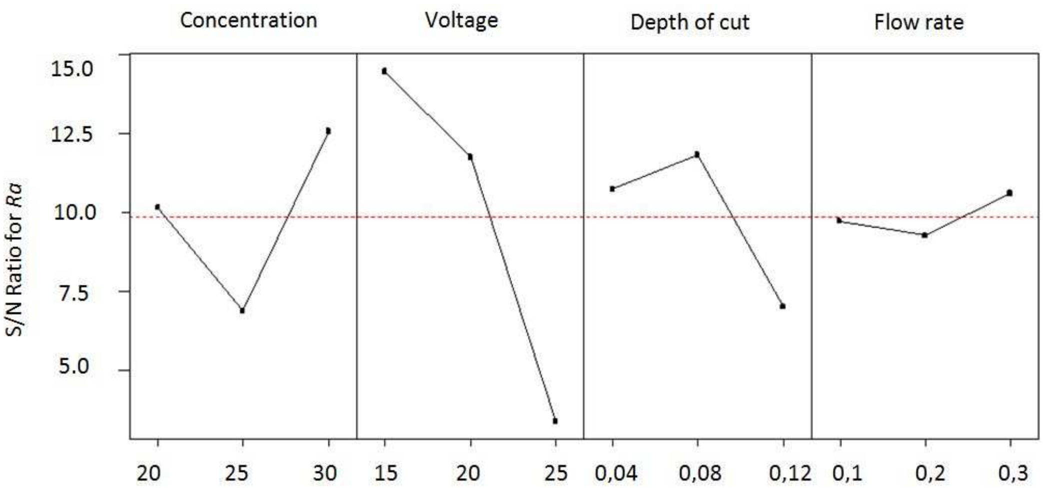

Fig. 2 S/N ratio graph for R_a

Table 7 S/N Ratio Table for R_a

Level	C	V	D	F
1	10.1437	14.4719	10.7541	9.7188
2	6.8776	11.7402	11.8355	9.2670
3	12.5734	3.3825	7.0051	10.6089
Delta	5.6958	11.0894	4.8305	1.3420
Rank	2	1	3	4

The S/N ratio graph shows that minimum surface irregularities are obtained by employing a combination of C3-V1-D2-F3. Increase in the machining voltage enhances surface roughness quite significantly. This is owing to the fact that higher machining voltage accompanied by increased current density causes more ionization of aluminum into the solution, exposing Al_2O_3 texture that makes the work surface rough. At the lowest level of concentration, electrochemical dissolution is low and the process is primarily governed by mechanical abrasion. With the increase in the concentration the dissolution rate increases that causes the Al_2O_3 texture to expose resulting in poor surface finish. Further increase in the variable the dissolution rate is also encouraged to yield better surface finish. Increase in the depth of cut, the surface roughness initially decreases steadily. Further increase of the same helps mechanical abrasion to predominate rather than electrochemical dissolution resulting in poor surface finish. Surface roughness almost remains unaffected by electrolyte flow rate.

The average of factor levels for R_a is presented in Table 8 to justify the significance of various operational parameters and their levels.

Table 8 Sum of R_a S/N ratios at each level of each factor

Level	Factors			
	C	V	D	F
-1	30.431	43.4158	32.2624	29.1563
0	20.6329	35.2207	35.5065	27.801
1	37.7202	10.1476	21.0152	31.8268
Total	88.7841	88.7841	88.7841	88.7841

The findings of S/N ratio are supported by ANOVA results shown in Table 9. The F-value of voltage stands at healthy 9.685 having percentage contribution of 68.91 as evident from ANOVA. The percentage contribution of depth of cut and concentration are 11.98 and 16.86 respectively.

Voltage has emerged as single design parameter that has paramount importance on the surface finish (F-value greater than 4).

Table 9 ANOVA for surface roughness R_a

Process Parameter	DOF	Sum of Squares	Adjusted Mean Square	F-Value	Contribution %
C	2	49.012	24.506	2.370	16.86
V	2	200.289	100.144	9.685	68.91
D	2	38.558	19.279	1.864	11.98
F	2	2.797	1.399	0.135	0.96
Total	8	290.657			
(Error)	(4)	41.355	10.340		

5. Multi-objective model using grey relational analysis

The main procedure of grey relational analysis (GRA) is firstly translating the performance of all alternatives into a comparability sequence. This step is called grey relational generating. According to these sequences, a reference sequence (ideal target sequence) is defined. Then, the grey relational coefficient between all comparability sequences and the reference sequence is calculated. Finally, based on these grey relational coefficients, the grey relational grade between the reference sequence and every comparability sequences is calculated. If a comparability sequence translated from an alternative has the highest grey relational grade between the reference sequence and itself, that alternative will be the best choice.

If the range and unit in one data sequence of a response parameter differ from the others then data preprocessing in grey relational analysis is required. If the sequence range is excessively large and the standard value is too high, then the effect of some factors needs to be ignored. The process of transferring the original data sequence to a comparable sequence is called normalization. The original data are normalized into the range between zero and one. If higher value indicates the better performance such as *MRR* then it is normalized as per equation,

$$X_{ij} = \frac{Y_{ij} - \text{Min}\left[Y_{ij} \quad i = 1,2, \dots n\right]}{\text{Max}\left[Y_{ij} \quad i = 1,2, \dots n\right] - \text{Min}\left[Y_{ij} \quad i = 1,2, \dots n\right]} \tag{3}$$

If lower value indicates better performance such as R_a then it is expressed as,

$$X_{ij} = \frac{\text{Max}\left[Y_{ij} \quad i = 1,2, \dots n\right] - Y_{ij}}{\text{Max}\left[Y_{ij} \quad i = 1,2, \dots n\right] - \text{Min}\left[Y_{ij} \quad i = 1,2, \dots n\right]} \tag{4}$$

The grey relational coefficient is determined to express the relationship between reference and actual normalized experimental data. Reference data is the best data which is expressed as X_0. The grey relational coefficient can be calculated as

$$Y\left(X_{oj}, X_{ij}\right) = \frac{\nabla_{\min} + \xi \nabla_{\max}}{\nabla_{ij} + \xi \nabla_{\max}} \left[i = 1,2, \dots n \;\&\; j = 1,2, \dots m\right] \tag{5}$$

where,

$$\nabla_{ij} = \left|X_{oj} - X_{ij}\right|, \nabla_{min} = \text{Min}\left[\nabla_{ij} \quad i = 1,2, \dots n \;\&\; j = 1,2, \dots m\right] \tag{6}$$

and

$$\nabla_{max} = \text{Max}\left[\nabla_{ij} \quad i = 1,2, \dots n \;\&\; j = 1,2, \dots m\right] \tag{7}$$

ζ is the distinguishing coefficient that is defined in the range between 0 to 1. Generally, the distinguishing coefficient can be adjusted to fit the practical requirements.

The grey relational grade can be determined as the average of the grey relational coefficients associated with each response parameter. It can be expressed as follows:

$$\Gamma(X_0, X_i) = \frac{1}{m} \sum_{j=1}^{m} Y\left(X_{oj}, X_{ij}\right) \tag{8}$$

where, m is the number of response parameter.

In relation to the present work the two responses, i.e., *MRR* and R_a have got different level of importance. ECG primarily being a finishing operation, emphasis is given on R_a rather than on *MRR* leading to an assignment of biased weights to the two attributes. In this experimentation 70 % and 30 % weights are assigned to *MRR* and R_a, respectively. Generally, a high value of the grey relational grade corresponds to a strong relation between the reference data sequence and the comparative sequence. As mentioned above, the reference data is the best response of the experimental results. Therefore, a higher value of the grey relational grade means that the corresponding machining parameters are closer to the optimal levels. In other words, the optimization of machining parameters associated with the complex multiple response parameters can be converted into the optimal resolution of single grey relational grade.

Table 10 presents the results of grey relational coefficients, grey relational grades, and their ranks. The results show that experiment number 8 has the largest grey relational grade. So it is expected that the machining parameter setting of this experiment will fulfill multiple response parameters optimization.

Table 10 Grey relational coefficients and grades

No.	Normalizing		Delta		Grey coefficient		Grey grade	Rank
	MRR	R_a	*MRR*	R_a	*MRR*	R_a		
1	0.024605	0.990291	0.975395	0.009709	0.235221	0.98632	0.7610	3
2	0.154657	0.949691	0.845343	0.050309	0.261930	0.932949	0.7316	5
3	0.000000	0.399823	1.000000	0.600177	0.230769	0.538388	0.4461	8
4	0.126538	0.966461	0.873462	0.033539	0.255654	0.954277	0.7447	4
5	0.172232	0.683142	0.827768	0.316858	0.266012	0.688395	0.5617	7
6	0.045694	0.323036	0.954306	0.676964	0.239176	0.508365	0.4276	9
7	0.562390	0.956752	0.437610	0.043248	0.406719	0.941812	0.7813	2
8	0.827768	1.000000	0.172232	0.000000	0.635281	1.000000	0.8906	1
9	0.070299	0.783760	0.929701	0.216240	0.243962	0.763992	0.6080	6

6. Determination of optimum machining parameters

In this section, optimal machining parameters with considerations of the multiple performance characteristics are obtained and verified. ANOVA for multiple performance characteristics is carried out to investigate the prominent variables that have significant consequences. Table 11 clearly exhibits that voltage (63.22 %) and concentration (25.03 %) have pronounced effect on the multiple performances.

Table 11 ANOVA for multiple performances

Process Parameter	DOF	Sum of Squares	Adjusted Mean Square	F-Value	Contribution %
C	2	0.050730	0.025351	4.2650	25.03
V	2	0.128020	0.064012	10.7700	63.22
D	2	0.019030	0.009518	1.6013	9.40
F	2	0.004740	0.002370	0.4000	2.35
Total	8	0.202500		17.0363	
(Error)	4	0.023776	0.005940		

The grade corresponding to each control factor at their levels are calculated as shown in Table 12 and subsequently the overall mean is calculated. Then the absolute value which is the difference between the maximum and minimum value of each factor considering different levels of grey relational grade is computed as shown in Table 12. The optimum level setting for the control factor is selected corresponding to the maximum value of the level of each factor of Table 12. Total mean value of the grey relational grade is 0.6614.

Fig. 3 shows the grey relational grade graph, where the dashed line in this graph is the value of the total mean of the grey relational grade. The larger the grey relational grade, the better are the multiple performance characteristics. However, the relative importance among the process parameters for the multiple performance characteristics still needs to be known, so that the optimal combinations of the process parameter levels can be determined.

Table 12 Response table for determination of optimum level setting

Factors	Level 1	Level 2	Level 3	ABS (max-min)	Rank
C	0.6462	0.57799	0.7600	0.18201	2
V	0.7623	0.7280	0.4939	0.2684	1
D	0.6931	0.6948	0.5964	0.0984	3
F	0.6436	0.6468	0.6938	0.0502	4
Total mean value of the grey relational grade is 0.6614					

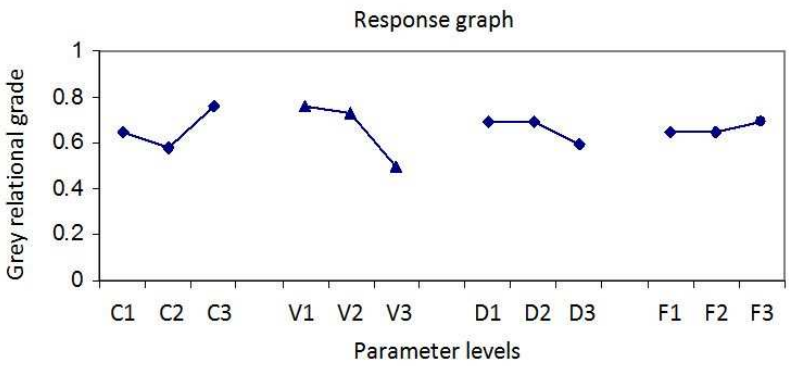

Fig. 3 Grey relational grades

6.1 Confirmation test

Once the optimal level of the machining parameters is selected, the final step is to predict and verify the improvement of the performance characteristic using the optimal level of the machining parameters. The estimated grey relational grade $\hat{\Psi}$ using the optimal level of the machining parameters can be calculated as:

$$\hat{\Psi} = \Psi_m + \sum_{i=1}^{q} (\overline{\Psi}_i - \Psi_m) \tag{9}$$

Where, Ψ_m is the total mean of the grey relational grade, $\overline{\Psi}_i$ is the mean of the grey relational grade at the optimal level, and q is the number of the machining parameters that significantly influence the multiple performance characteristics.
Table 13 shows the results of the confirmation experiment employing the optimal machining parameters. It is found that *MRR* increases by 0.45 g/min and improvement in the R_a is by 0.008 µm.

Table 13 Results of machining performance using the initial and optimal machining parameters

	Initial machining parameters	Optimal machining parameters	
		Prediction	Experiment
Setting levels	C1-V1-D1-F1	C3-V1-D1-F3	C3-V1-D1-F3
MRR (g/min)	0.067	0.524	0.517
R_a (µm)	0.168	0.157	0.160
Grey relation grade	0.7610	0.8906	0.8831
Improvement of the grey relation grade: 0.1204			

7. Conclusion

The present paper attempts to optimize the machining variables by combining grey relational analysis and the Taguchi method while machining of Alumina-Aluminium IPC by ECG. The S/N ratio shows that high concentration and low voltage augurs well for both high *MRR* and lower R_a. Based on the results of analysis, it is concluded that voltage and electrolyte concentration plays significant role in governing high *MRR* and low R_a. Increase in the machining voltage encourages decomposition potential to attain an optimum level beyond which over potential adversely affects the *MRR*. As the machining voltage increases, the current density increases and more and more aluminum gets dissolved into the solution exposing Al_2O_3 texture that results in rough surface. *MRR* follows an increasing trend with electrolyte concentration owing to the fact that it facilitates more aluminum to be ionized into the solution. At the lowest level of concentration, electrochemical dissolution is low hence mechanical abrasion is predominant. With the increase in the concentration the dissolution rate increases. This causes the Al_2O_3 texture to expose which makes the surface rough. The other two variables namely depth of cut and electrolyte flow rate are insignificant to affect the responses.

The grey relational analysis converts optimization of the multiple characteristics into optimization of a single function called grey relational grade, which simplifies the computation. The grey analysis establishes the ranks of output for different variables combinations. It is found that both *MRR* and R_a improve considerably (as evident from computational results) by using optimal machining variables combinations. It is concluded that the grey relational analysis is a powerful method to study the effects of different process variables on multiple performance for complex process like ECG. Future work in this emerging area can be considered with other parameters for the present responses as well as for other responses such as cutting force, amount of overcut etc. to capture the process in full perspective.

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