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PARAMETRIC OPTIMIZATION IN ELECTROCHEMICAL MACHINING USING UTILITY BASED TAGUCHI METHOD

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Abstract

The present work deals the application of Taguchi method with utility concept to optimize the machining parameters with multiple characteristics in electrochemical machining (ECM) of Al/B_4C composites. L_{27} orthogonal array was chosen for the experiments. METATECH ECM setup is used to conduct the experiments. The ECM machining parameters namely applied voltage, electrolyte concentration, electrode feed rate and percentage of reinforcement are optimized based on multiple responses, i.e., material removal rate, surface roughness and radial over cut. The optimum machining parameters are calculated by using utility concept and results are compared with ANOVA. The results show that the feed rate is the most influencing parameter which affects the multiple machining characteristics simultaneously. The optimum parametric combination to maximize the material removal rate and to minimize surface roughness and radial over cut simultaneously are, applied voltage 16 V, feed rate 1.0 mm/min, electrolyte concentration 30 g/L and reinforcement content 5 wt%. Experimental results show that the responses in electrochemical machining process can be improved through this approach.

Keywords: Electrochemical machining, utility function, Taguchi method, ANOVA.

1. Introduction

Aluminium metal matrix composites (AMMCs) have high strength to weight ratio, low wear rate and low thermal coefficient of expansion and are used in aerospace, biomedical, defence, automotive industries, etc. [1]. Since abrasive properties of the reinforced particles, high tool wear associated with the conventional machining of AMMCs and hence the machining is difficult or costly [2]. Electrochemical machining is the one of the unconventional machining process

Nomenclatures

A	Applied voltage
Al	Aluminium
B	Tool feed rate
B_4C	Boron carbide
C	Electrolyte concentration
D	Percentage of reinforcement
DF	Degrees of freedom
k	Number of responses
MS	Mean sum of squares
n	Number of observations
NaCl	Sodium chloride
P_i	Preference number of response 'i'
p	Probability
q	Number of machining parameters
S/N ratio	Signal-to-noise ratio
SS	Sum of squares
$\bar{T}$	Overall mean of the response
U	Utility value
W_i	Weight of a response 'i'
x_i	Any value of response 'i'
x_i^*	Predicted optimum value of response 'i'
$x_i^/$	Minimum or maximum acceptable value of response 'i'
Z	Constant

Greek Symbols

γ_m	Mean utility value
γ_o	Mean utility value at optimum conditions
$\gamma_{predicted}$	Predicted utility value
μ	Estimated mean of the response

Abbreviations

AMMC	Aluminium metal matrix composite
ANOVA	Analysis of variance
ECM	Electrochemical machining
IEG	Inter electrode gap
MRR	Material removal rate
ROC	Radial over cut
SR	Surface roughness

used for machining extremely hard materials into complex shapes which is difficult to machine by conventional methods [3]. In ECM process machining is done by the controlled movement of the tool into the workpiece, which produces the tool shape in the worpiece by mass migrational transport [4].

Effect of intervening variables like, feed rate, electrolyte, flow rate of the electrolyte and voltage on the responses material removal rate, roughness and over-cut were studied in electrochemical machining of SAE-XEV-F Valve-Steel and find out feed rate is the main parameter which effects on the material removal rate [5]. Senthil Kumar, et al., studied the effect of various process parameters like applied voltage, electrolyte concentration, feed rate and percentage of reinforcement on the response material removal rate in electrochemical machining of A356/SiCp composites [6].

Multiple regression analysis and artificial neural networks (ANN) were used for the multi-objective optimization of ECM process [7]. Later on, grey relational analysis was used to optimize multi-responses viz. material removal rate, overcut, cylindricity error and surface roughness in electrochemical machining of EN31 steel and observed that feed rate is the most influencing parameter in multi-response optimization [8]. Moreover, ANN had also been used by Abuzeid et al., for the prediction of ECM process parameters with applied voltage, feed rate and electrolyte flow rate as inputs and material removal rate and surface roughness as outputs [9]. Surface roughness and passivation strength of electrolyte in electrochemical polishing of 316L stainless steel were optimized using grey relational analysis and observed that electrolyte composition plays a vital role on the surface roughness [10].

The present work investigates the effect of applied voltage, electrode feed rate, electrolyte concentration and percentage of reinforcement on multi performance characteristics (responses) in electrochemical machining of Al/B_4C composites using utility based Taguchi method.

2. The Utility-Based Taguchi Method

Taguchi method works only for optimization of single response problems. The utility concept is used to convert multi response problems into single response. In the present work, utility-based Taguchi optimization method follows the optimization method developed by Taguchi. The procedure of the utility-based Taguchi optimization method is shown in Fig. 1. In Fig. 1 steps 1, 2 and 7 are procedure of Taguchi method and steps 3 to 6 are procedure of utility concept.

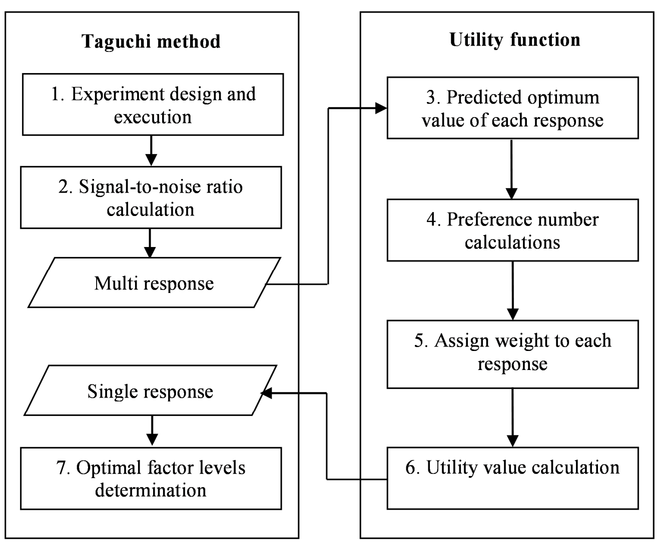

Fig. 1. Procedure of utility-based Taguchi method.

2.1. Experimental design and execution

A large number of experiments are required when classical parameter design is used and the complexity increases with increasing the number of process parameters [11]. Taguchi method solves this problem with a special design of orthogonal arrays (OA). Entire process parameters space is studied with only a small number of experiments by using Taguchi's OA [12]. Therefore, in the optimization problems selection of OA is the first step and the experiments are conducted according to the selected OA.

2.2. Signal-to-noise ratio calculation

In the Taguchi method, the term 'signal' represents the desirable value (mean) for the output characteristic and the term 'noise' represents the undesirable value (standard deviation, SD) for the output characteristic. Therefore, the S/N ratio is the ratio of the mean to the SD. There are several S/N ratios available, depending on the type of characteristic; lower the better (LB), nominal the best (NB), or higher the better (HB) [13].

The S/N ratio for higher-the-better criterion is given by Taguchi as:

$$S/N = -10log_{10}\left[\frac{1}{n}\sum\frac{1}{y^2}\right] \tag{1}$$

The S/N ratio for lower-the-better criterion is given by Taguchi as:

$$S/N = -10log_{10}\left[\frac{\sum y^2}{n}\right] \tag{2}$$

where 'y' is the observed data and 'n' is the number of observations.

2.3. Optimum value of each response

The optimum value of performance characteristic is predicted at the optimal levels of significant process parameters. The estimated mean of the performance characteristic 'i' can be determined as [14]:

$$\mu_i = \overline{A_{opt}} + \overline{B_{opt}} + \overline{C_{opt}} + \overline{D_{opt}} + \cdots - (q-1)\overline{T} \tag{3}$$

where $\overline{A_{opt}}$ is the average value of the performance characteristic 'i' at the optimum level of process parameter 'A', 'q' is the number of process parameters and '$\overline{T}$' is the overall mean of the performance characteristic 'i'.

2.4. Preference number calculations

After obtaining the optimum values, a preference scale is constructed for each response. In multi objective problems the range and unit of one performance characteristic may differ from others. To reduce the variability in performance characteristics, preference numbers are used. According to Gupata and Murthy [15] the preference scale should be a logarithmic one. The minimum acceptable quality level for each response is set out at 0 preference number and the best available quality is assigned a preference number of 9. If a log scale is chosen the preference number (P_i) is given by Eq. (4).

$$P_i = Z \log \frac{x_i}{x_i^{/}} \tag{4}$$

where 'x_i' is any value of performance characteristic or attribute 'i', $x_i^{/}$ is minimum or maximum acceptable value of performance characteristic or attribute 'i' and 'Z' is a constant.

At optimum value (x_i^*) of attribute i, $P_i = 9$.

$$\text{So, } Z = \frac{9}{\log \frac{x_i^*}{x_i^{/}}} \tag{5}$$

2.5. Assign weight to each response

Weight is nothing but relative importance of each performance characteristic. It depends on the customer's requirement or on the end use of product. The assigned weight should satisfy the following condition:

$$\sum_{i=1}^{k} W_i = 1 \tag{6}$$

where, W_i is the weight assigned to the performance characteristic 'i' and the sum of the weights for all performance characteristics is equal to 1.

2.6. Utility value calculation

The utility of a product on a particular characteristic measures the usefulness of that particular characteristic of the product. The overall utility (U) of a product is the sum of utilities of each of the quality characteristics and is given by

$$U = \sum_{i=1}^{k} W_i P_i \tag{7}$$

2.7. Optimal factor levels for utility value

From S/N ratio analysis of utility values, optimal level of performance characteristics is determined. Since utility is a higher-the-better (HB) type of quality characteristic, S/N ratios are calculated using Eq. (1). The optimal level of the utility value is the level with the greatest S/N value.

3. Experimentation

A 25 mm diameter and 20 mm length LM6 Al/B_4C composite samples were fabricated with the help of stir casting technique with different percentage of reinforcement of B_4C (2.5, 5.0 and 7.5 wt%). LM6 is an Aluminium-Silicon alloy containing 11-13% Si and small amount of Mg, Mn, Fe, Cu, Ni, Zn, Ti, etc. Twenty seven experiments were conducted on METATECH ECM setup using Taguchi L_{27} orthogonal array. METATECH ECM setup is shown in Fig. 2. The setup consists of a control panel for changing the voltage, current, feed rate etc.; a machining chamber in which tool and workpiece are fixed; a pump for circulating the electrolyte and tool feed system (servo system) to maintain constant gap between the tool and workpiece. A circular cross section tool coated with epoxy on the lateral surface was used. NaCl solution with different concentration was used as an electrolyte since NaCl solution has no passivation effect on the job [16]. Electrolyte was pumped to the machining zone through the central hole of the tool. An electrolyte flow rate of 30 liters per minute, and an inter electrode gap of 0.5 mm was maintained constant for all the experiments.

Fig. 2. Electrochemical machining setup.

The responses like, material removal rate (MRR), surface roughness (SR) and radial over cut (ROC) were measured by varying the predominant machining parameters namely applied voltage; electrode feed rate, electrolyte concentration and reinforcement content (i.e. wt% of B_4C). The selected factors and their levels are given in Table 1. The MRR was measured by weight loss using Eq. (8). The diameter of the machined hole was measured using digital vernier caliper and the ROC was obtained from this data by using Eq. (9). The surface roughness was measured using a Talysurf tester.

MRR= (weight before machining – weight after machining) / machining time (8)

ROC = (Hole diameter – Tool diameter) / 2 (9)

Table 1. Machining parameters and their levels.

Machining parameters	Symbol	Unit	Level		
			1	2	3
Applied Voltage	A	Volts	12	16	20
Feed rate	B	mm/min	0.2	0.6	1.0
Electrolyte concentration	C	g/lit	10	20	30
Reinforcement content	D	wt%	2.5	5.0	7.5

4. Taguchi and Utility Analysis

4.1. Experimental design and execution

Experiments were conducted by varying the predominant machining parameters namely, applied voltage; electrode feed rate, electrolyte concentration and reinforcement content. Taguchi L_{27} orthogonal array and the measured responses are given in Table 2. Effect of machining parameters on the responses is discussed in the following subsections.

Table 2. Taguchi L_{27} orthogonal array and measured response values and their S/N ratios.

Exp. No.	Process parameters				Responses			S/N ratios		
	A	B	C	D	MRR	SR	ROC	MRR	SR	ROC
1	1	1	1	1	0.268	4.948	0.96	-11.437	-13.889	0.354
2	1	1	2	2	0.335	5.002	0.94	-9.4991	-13.983	0.537
3	1	1	3	3	0.227	4.591	0.79	-12.879	-13.238	2.047
4	1	2	1	1	0.353	4.920	0.75	-9.0445	-13.839	2.499
5	1	2	2	2	0.448	4.498	0.65	-6.9744	-13.060	3.742
6	1	2	3	3	0.420	4.725	0.80	-7.5350	-13.488	1.938
7	1	3	1	1	0.689	4.555	0.67	-3.2356	-13.170	3.478
8	1	3	2	2	0.545	4.356	0.64	-5.2721	-12.782	3.876
9	1	3	3	3	0.703	4.232	0.65	-3.0609	-12.531	3.742
10	2	1	1	2	0.321	4.882	0.91	-9.8699	-13.772	0.819
11	2	1	2	3	0.329	4.823	0.94	-9.6561	-13.666	0.537
12	2	1	3	1	0.488	4.254	1.05	-6.2316	-12.576	-0.424
13	2	2	1	2	0.379	4.540	0.76	-8.4272	-13.141	2.384
14	2	2	2	3	0.302	4.431	0.69	-10.400	-12.930	3.223
15	2	2	3	1	0.583	3.998	0.99	-4.6866	-12.037	0.087
16	2	3	1	2	0.615	4.274	0.75	-4.2225	-12.617	2.499
17	2	3	2	3	0.619	4.346	0.70	-4.1662	-12.762	3.098
18	2	3	3	1	0.812	3.598	0.93	-1.8089	-11.1212	0.630
19	3	1	1	3	0.282	5.472	0.91	-10.995	-14.7629	0.819
20	3	1	2	1	0.599	4.797	1.10	-4.4515	-13.6194	-0.823
21	3	1	3	2	0.603	4.640	1.16	-4.3937	-13.3304	-1.289
22	3	2	1	3	0.526	5.214	0.85	-5.5803	-14.3434	1.412
23	3	2	2	1	0.688	4.897	1.03	-3.2482	-13.7986	-0.257
24	3	2	3	2	0.732	4.531	1.08	-2.7098	-13.1239	-0.668
25	3	3	1	3	0.688	5.002	0.64	-3.2482	-13.9829	3.876
26	3	3	2	1	0.887	4.389	0.99	-1.0415	-12.8473	0.087
27	3	3	3	2	0.944	3.989	1.00	-0.5006	-12.0173	0.060

4.1.1. Effect of machining parameters on material removal rate

Effect of machining parameters on MRR is shown in Fig. 3. MRR increases with increase in voltage (A), feed rate (B) and electrolyte concentration (C) and decreases with increase in percentage of reinforcement (D). With increase in applied voltage, the machining current in the inter electrode gap (IEG) increases, which leads to the enhancement of MRR. Increase in feed rate reduces the IEG that leads to increase in the current density in the gap. This effect causes rapid anodic dissolution which increases the MRR. With increasing the electrolyte concentration the electrical conductivity of the electrolyte increases and also that releases large number of ions in IEG, which results in higher machining current in IEG and causes higher MRR. With increasing the percentage of reinforcement, the electrical conductivity of the work piece decreases, because the reinforced particles are poor conductors than the base material. Thus increase in the percentage of reinforcement leads to lower metal removal rate.

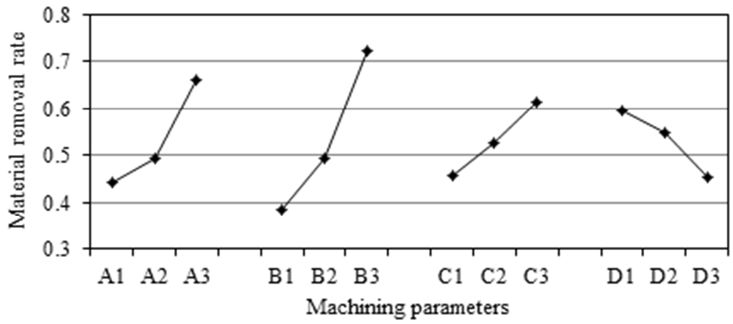

Fig. 3. Effect of machining parameters on material removal rate.

4.1.2. Effect of machining parameters on surface roughness

Figure 4 shows the effect of machining parameters on surface roughness. At low voltage, the current density in IEG is low which results in etching pits, leads to rough surface. Moreover, high voltage causes excessive heating of the workpiece which deteriorates the surface finish. Therefore, lower surface roughness values are obtained at middle level of voltage. With increasing the feed rate the metal dissolution is steady and uniformity in anodic dissolution results good surface finish. At low electrolyte concentration depletions of ions occurs which leads to poor surface finish. Thus increasing the electrolyte concentration improves the surface finish. With increase in percentage of reinforcement the electrical conductivity of the workpiece decreases due to non-conductive nature of the reinforced particles and these reinforced particles are not participated in electrolytic action, but the surrounding matrix material is removed by electrolysis process which gives poor surface finish.

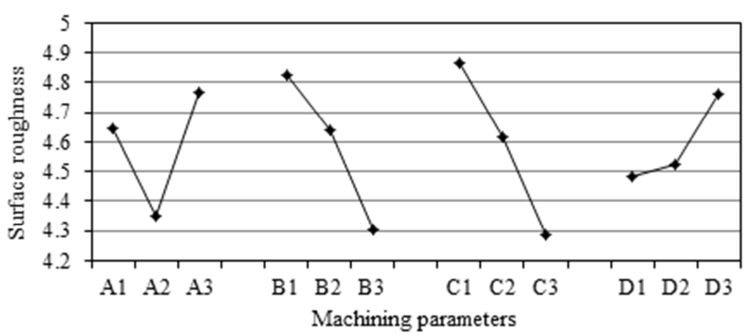

Fig. 4. Effect of machining parameters on surface roughness.

4.1.3. Effect of machining parameters on radial over cut

Effect of machining parameters on ROC is shown in Fig. 5. ROC increases with increasing applied voltage (A) and electrolyte concentration (C) and decreases with increasing feed rate (B) and reinforcement content (D). A higher electrolyte concentration leads to the formation of greater volume of reaction products, e.g. sludge's and precipitations and also inhibits the initiation of gas bubbles, e.g. O_2, H_2, etc. These phenomenal effects lead to the possibility of the passage of stray current to the machining periphery thereby increase the ROC. At higher feed rates the operational stability occurs which reduces the metal removal in the lateral of the hole, causing the reduction in ROC. The increase in voltage causes greater electrolyzing current to be available in the IEG, as well as causing a greater stray current intensity, which leads to higher ROC. Electrical conductivity of the work piece decreases with the increase in percentage of reinforcement. This causes the reduction in metal removal rate in radial direction, which leads to lower ROC.

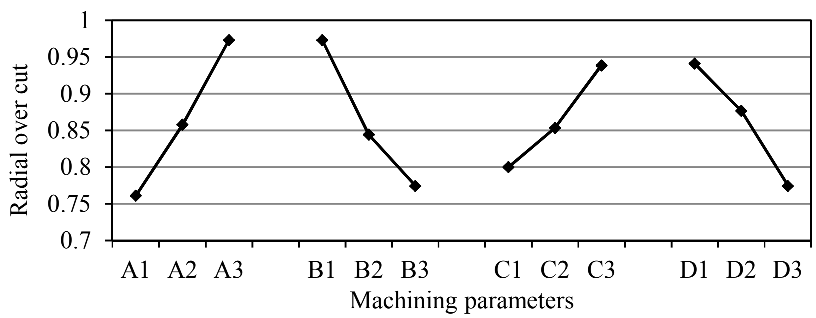

Fig. 5. Effect of machining parameters on radial over cut.

4.2. Signal-to-noise ratio calculation

In the present work, the S/N ratio for MRR is calculated using higher-the-better criterion by using Eq. (1) and the S/N ratio for ROC and SR is calculated using lower-the-better criterion by using Eq. (2). The calculated S/N ratios of the responses MRR, SR and ROC are given in Table 2.

4.3. Predicted optimum value of each response

Mean of each response for each level of factor is shown in Table 3. The average of the S/N ratio of the responses MRR, SR and ROC for each level of each factor is shown in Table 4. Regardless of the category of the performance characteristics, a greater S/N value corresponds to a better performance. Therefore, the optimal level of the machining parameters is the level with the greatest S/N value. From Table 3 and Table 4 based on the analysis of means and S/N ratios, the optimal machining parameter levels are $A_3\,B_3\,C_3\,D_1$, $A_2\,B_3\,C_3\,D_1$ and $A_1\,B_3\,C_1\,D_3$ for MRR, SR and ROC, respectively. The optimal level of each machining parameter is bolded in Tables 3 and 4.

Table 3. Average response value by factor levels (mean).

	Material removal rate				Surface roughness			
Level	A	B	C	D	A	B	C	D
1	0.443	0.389	0.462	**0.601**	4.647	4.823	4.867	**4.484**
2	0.508	0.496	0.532	0.551	**4.350**	4.639	4.615	4.524
3	**0.661**	**0.727**	**0.617**	0.460	4.770	**4.305**	**4.284**	4.760
Delta	0.218	0.339	0.155	0.142	0.421	0.519	0.583	0.276
	Cell mean = 0.5373				Cell mean = 4.5890			

Radial over cut

Level	A	B	C	D
1	**0.761**	0.967	**0.796**	0.934
2	0.842	0.842	0.849	0.872
3	0.973	**0.768**	0.932	**0.770**
Delta	0.212	0.199	0.137	0.164
	Cell mean = 0.8588			

Table 4. Average response value by factor levels (S/N ratio).

	Material removal rate				Surface roughness			
Level	A	B	C	D	A	B	C	D
1	-7.660	-8.824	-7.340	**-5.021**	-13.33	-13.65	-13.72	**-12.99**
2	-6.608	-6.512	-6.079	-5.763	**-12.74**	-13.31	-13.27	-13.09
3	**-4.019**	**-2.951**	**-4.867**	-7.502	-13.54	**-12.65**	**-12.61**	-13.52
Delta	3.641	5.873	2.473	2.482	0.80	1.00	1.12	0.53

Radial over cut

Level	A	B	C	D
1	**2.468**	0.347	**2.063**	0.685
2	1.584	1.615	1.606	1.370
3	0.350	**2.440**	0.733	**2.348**
Delta	2.118	2.094	1.330	1.663

The predicted optimal value of each response characteristics can be determined [14] as:

$$MRR = A_3 + B_3 + C_3 + D_1 - 3 \times \text{mean} = 0.661 + 0.727 + 0.617 + 0.601 - 3 \times 0.5373 = 0.9941$$

$$SR = A_2 + B_3 + C_3 + D_1 - 3 \times \text{mean} = 4.350 + 4.305 + 4.284 + 4.484 - 3 \times 4.5890 = 3.6560$$

$$ROC = A_1 + B_3 + C_1 + D_3 - 3 \times \text{mean} = 0.761 + 0.768 + 0.796 + 0.770 - 3 \times 0.8588 = 0.5186.$$

4.4. Preference number calculation

After obtaining the optimum value, a preference scale is constructed for each response. The preference scale should be a logarithmic one [15]. Zero is the preference number of the minimum acceptable quality level and 9 is the preference number of the best available quality level for each response. For the log scale the preference number (P_i) is calculated by using Eqs. (4) and (5).

- **Material removal rate**

x^{*}_{MRR}= predicted optimum value of MRR = 0.9941 g/min

$x^{/}_{MRR}$= minimum acceptable value of MRR = 0.2 g/min

(since all MRR values greater than 0.2).

Using x^{*}_{MRR}, $x^{/}_{MRR}$values and Eqs. (4) and (5), the preference scale for MRR is given by

$$P_{MRR} = 12.9236 \ log \frac{x_{MRR}}{0.2} \quad (10)$$

- **Surface roughness**

x^{*}_{SR}= predicted optimum value of SR = 3.6560 µm

$x^{/}_{SR}$= maximum acceptable value of SR = 6.0 µm

(since all SR values are less than 6.0).

Using x^{*}_{SR}, $x^{/}_{SR}$ values and Eqs. (4) and (5), the preference scale for SR is

$$P_{SR} = -41.8322 \ log \frac{x_{SR}}{6.0} \quad (11)$$

- **Radial over cut**

x^{*}_{ROC}= predicted optimum value of ROC = 0.5186 mm

$x^{/}_{ROC}$= maximum acceptable value of ROC = 1.5mm

(since all ROC values are less than 1.5).

Using x^{*}_{ROC}, $x^{/}_{ROC}$ values and Eqs. (4) and (5), the preference scale for ROC is given by

$$P_{ROC} = -19.5118 \ log \frac{x_{ROC}}{1.5} \quad (12)$$

The preference number of the responses MRR, SR and ROC is calculated by using Eqs. (10), (11) and (12) respectively and are given in Table 5.

4.5. Assign weight to each response

In the present study it is given equal importance to all responses and hence equal weight has been assigned to them. The weights assigned to various responses are $W_{MRR} = W_{SR} = W_{ROC} = 1/3$.

Table 5. Preference number and utility value of the responses.

Exp. No.	Preference number			Utility	Order
	MRR	SR	ROC		
1	1.642652	3.502257	3.783134	2.976014	26
2	2.895078	3.305060	3.961602	3.387247	25
3	0.710745	4.862740	5.435286	3.669590	22
4	3.188830	3.605356	5.875744	4.223310	21
5	4.526465	5.234538	7.088797	5.616600	11
6	4.164233	4.340067	5.328657	4.610986	16
7	6.942419	5.005761	6.831901	6.260027	4
8	5.626503	5.817327	7.220224	6.221351	5
9	7.055321	6.341995	7.088797	6.828704	2
10	2.655477	3.746219	4.236553	3.546083	24
11	2.793642	3.967114	3.961602	3.574119	23
12	5.006471	6.247797	3.023500	4.759256	15
13	3.587710	5.065687	5.763466	4.805621	13
14	2.313026	5.507188	6.582562	4.800926	14
15	6.004803	7.375371	3.522286	5.634153	10
16	6.304715	6.162583	5.875744	6.114347	7
17	6.341102	5.859082	6.460590	6.220258	6
18	7.864347	9.290517	4.052265	7.069043	1
19	1.928448	1.673504	4.236553	2.612835	27
20	6.156762	4.065317	2.629155	4.283745	19
21	6.194118	4.669865	2.178947	4.347643	18
22	5.427340	2.550937	4.814748	4.264342	20
23	6.934267	3.690485	3.186523	4.603758	17
24	7.282204	5.101737	2.784698	5.056213	12
25	6.934267	3.305060	7.220224	5.819850	9
26	8.360194	5.680213	3.522286	5.854231	8
27	8.709757	7.416314	3.437090	6.521054	3

4.6. Utility value calculation

The utility value of experiments has been calculated [17] by using Eq. (13) and is given in Table 5.

$$U = P_{MRR} \times W_{MRR} + P_{SR} \times W_{SR} + P_{ROC} \times W_{ROC} \quad (13)$$

Figure 6 shows the utility value for MRR, SR and ROC, and it can be clearly observed that experiment 18 has the highest utility value. Therefore, the parameters of experiment 18 have the near optimal parameters setting for the best multi-performance characteristics such as MRR, SR and ROC.

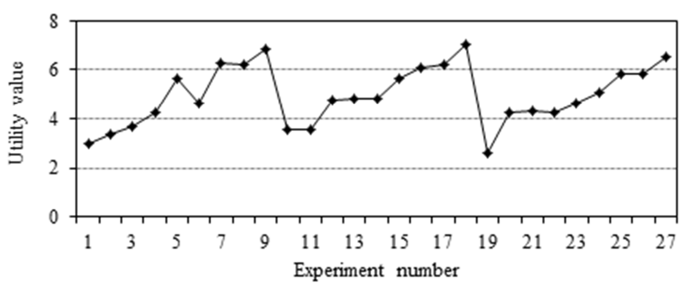

Fig. 6. Utility value for MRR, SR and ROC.

4.7. Optimal factor levels for utility value

The effects of each machining parameter at different level can be separated by the orthogonal experimental design. For example, the mean of utility value for the applied voltage at level 1, 2 and 3 can be calculated by taking the average of the utility values for the experiments 1–9, 10–18 and 19–27, respectively. The mean of the utility value for each level of other machining parameters can be computed in the similar manner and is given in Table 6. In Table 6, the data in bold type is the optimal parameter level, i.e. A_2 B_3 C_3 D_2. The difference between the maximum and minimum value (Range) of the utility is also indicated in Table 6. The factor which has the maximum range is the most influencing factor on the multi-performance characteristics. The maximum range value in Table 6 is 2.444, and the corresponding control factor, i.e. the feed rate, has the strongest effect on multi-performance characteristics. The order of importance of the controllable factor to the multi-performance characteristics in the electrochemical machining process, in sequence, can be listed as: Feed rate, electrolyte concentration, applied voltage and reinforcement content. Fig. 7 shows the utility value for different machining parameters at different levels. Basically, the larger the utility value is, the closer will be the product quality to the ideal value. Thus the larger utility value is desired. From Fig. 7 it is inferred that A_2 B_3 C_3 D_2 is the optimum parameter level for multi-response optimization.

Table 6. Utility response table for each level of machining parameters.

Machining parameter	Utility value Level 1	Level 2	Level 3	Max−Min (Range)
A	5.109	**5.379**	4.943	0.436
B	3.967	5.052	**6.411**	2.444
C	4.747	5.143	**5.541**	0.794
D	5.231	**5.250**	4.950	0.300
Mean value of utility = 5.1436				

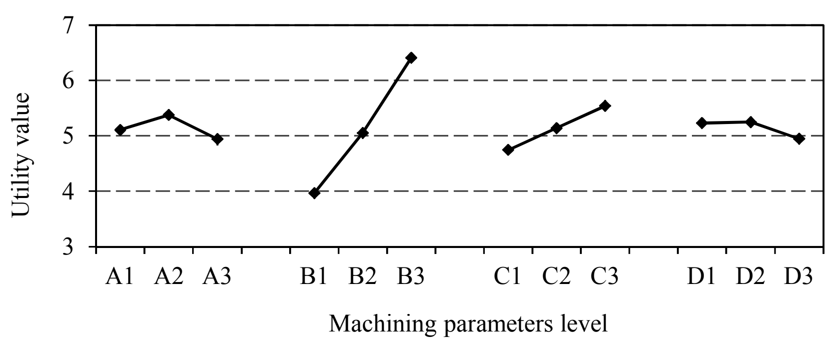

Fig. 7. Effect of ECM parameters on multiple performances.

5. Analysis of Variance

Analysis of variance (ANOVA) is a statistical tool used to investigate the significance of the all parameters and their interactions by comparing the mean square with an estimate of the experimental error at a specific confidence level.

The relative influence of the parameters is measured by total sum of square value (SS_T) and is given by:

$$SS_T = \sum_{i=1}^{n}(n_i - n_m)^2 \quad (14)$$

where 'n' is the number of experiments in the orthogonal array, n_i is the mean S/N ratio for the ith experiment and n_m is the total mean S/N ratio of all experiments. Further, the Fisher's F-ratio, the ratio between the regression mean square and the mean square error, is used to identify the most significant factor on the performance characteristic. Table 7 shows the results of ANOVA for utility value. In Table 7, the applied voltage, feed rate and electrolyte concentration are the significant factors which influence the utility (multi-performance) since their p values are below 0.05.

Table 7. Results of ANOVA for utility value.

Source	DF	SS	MS	F	*P*
A	2	0.8714	0.4357	3.81	0.042
B	2	26.9903	13.4951	117.98	0.000
C	2	2.8367	1.4184	12.40	0.000
D	2	0.5090	0.2545	2.23	0.137
Error	18	2.0589	0.1144		
Total	26	33.2663			

6. Confirmation Experiment

Improvement of performance characteristic at optimum level is verified by conducting the confirmation experiment. The estimated utility value $\gamma_{predicted,}$ using the optimum level of machining parameters can be calculated as:

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{q}(\gamma_o - \gamma_m) \quad (15)$$

where γ_m is total mean of utility value, γ_o is mean of utility value at optimum level and q is the number of parameters that significantly affect the performance characteristic.

Table 8 shows the results of confirmation experiment using the optimal electrochemical machining parameters. As shown in Table 8 the material removal rate is increased from 0.268 g/min to 0.798 g/min, the surface roughness is improved from 4.948 µm to 3.859 µm and the radial over cut is decreased from 0.96 mm to 0.73 mm and the overall utility value is improved from 3.34552 to 7.3157. It is clearly noticed that the performance characteristics in ECM are considerably improved through this work.

Table 8. Confirmation experiment.

Response	Initial data	Optimal machining parameters	
		Prediction	Experiment
	(A_1 B_1 C_1 D_1)	(A_2 B_3 C_3 D_2)	
MRR	0.268		0.798
SR	4.948		3.859
ROC	0.960		0.730
Utility value	3.3455	7.1503	7.3157

7. Concluding Remarks

In the present work utility based Taguchi method was used to solve multi response optimization problem in electrochemical machining of Al/B_4C composites. Applied voltage, feed rate, electrolyte concentration and reinforcement content were considered as input machining parameters and material removal rate, surface roughness and radial over cut were considered as the performance measures of the electrochemical machining process. Utility function was used to transform multi-objective problem into single objective problem and then Taguchi method is used to solve this single objective problem.

The optimum machining parameter values to maximize the MRR and to minimize SR and ROC simultaneously are, applied voltage 16 V (level 2), feed rate 1.0 mm/min (level 3), electrolyte concentration 30 g/L (level 3) and reinforcement content 5 wt% (level 2). From the results of ANOVA, the most influencing parameter for multi-response optimization was feed rate followed by electrolyte concentration and applied voltage. Confirmation experiment shows that the performances can be improved greatly through this study.

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