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PERFORMANCE EVOLUTION AND SELECTION OF CONTROLLABLE PROCESS VARIABLES IN ECM FOR AL, B_4C METAL MATRIX COMPOSITES

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Abstract

In recent years, the need for light weight MMCs products are becoming more valuable in aerospace, electronics, nuclear power plants and defence industries because of their specific properties. The machining of MMCs is a big concern and still an area of research. Al, B_4C is one of the widely accepted MMC having specific properties like wear and impact resistance. This composite shows difficulty while machining with non- conventional processes due to various reasons such as higher surface roughness, tool wear rate and machining cost. In this experimental work, ECM has been selected for machining of Al,B4C composite to get better product quality & satisfactory machining characteristics. The voltage, feed rate, B_4C %age of reinforcement and electrolyte concentration were selected as process constraints to

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conduct experimental trials. The Surface roughness, MRR and radial over cut were considered as output responses. The experimental outcomes were optimized by multi-parametric optimization using DoE and Grey relational analysis. The optimized parameters by multi-parametric optimization showed the considerable improvement in the process.

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1. Introduction

ECM (Electro Chemical Machining) generally known as anodic cutting is the latest and most useful modern machining. Because of its machining capability of machining metal alloys, fragile parts, complex shapes and insignificant tool wear; ECM is mostly utilized to machine harder and tougher materials with stress free conditions. ECM process is the reverse process of Electroplating (i.e. If two electrode plates are placed in a bath containing conducting liquid and direct current is supplied across them, the metal depletes from the anode (+ve) plate to the cathode (-ve) plate) with certain modification. [1, 2]

The ECM process used a shaped tool or electrode which is linked to the cathode (-ve) terminal & workpiece is connected to the anode (+ve) terminal. The spark gap of 0.05 to 0.03 mm is kept between the tool electrode and material which allows the passage of an electrolytic neutral salt solution (i.e. Sodium chloride, sodium nitrate and sodium chlorate) between the gap. D.C. of ranges from 1-20 V current is supplied to the tool and work piece. An electronic ion is pulled from the material surface when sufficient energy, i.e. 6eV is available. The -ve ions present in the electrolyte solution reacts with the +ve ions and form metallic hydroxide compounds. Therefore, the metal is anodically dissolved with the formation of sludge and MRR is generated by "Faraday's Law of electrolysis" as shown in Fig 1. [2, 5]

MMCs are the composites which are reinforced with fibers & ceramics and consists metal matrices, reinforced with fibers. It consists of the primary phase, i.e. metal matrix & secondary phase i.e. reinforcement. The primary phase consists of the bulk form of composite material; it holds the imbedded phase and conceals it. When an external force is employed primary phase distribute the force with secondary phase. The secondary phase increases the properties of the material, i.e. increase in strength, improvement in corrosion and shock resistance. In this experimental study, Al (matrix metal) is primary phase and B_4C reinforced metal is the secondary phase. [5, 8]

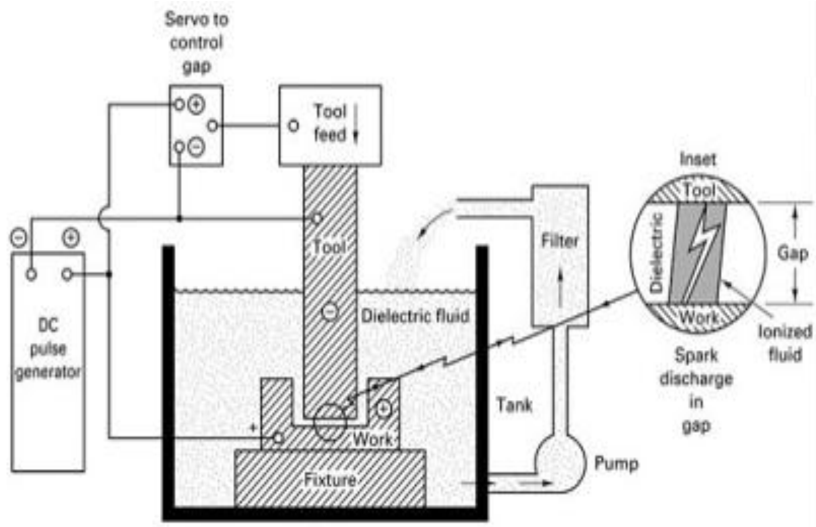

Fig.1. Schematic view of *ECM*

The Aluminium metal matrix has several industrial applications and it deals with two types of reinforcements i.e. AL_2O_3 (aluminium oxide) and SiC (silicon carbide). Because B_4C has a low specific gravity, hardness below than the diamond and boron nitride & thermal expansion similar to the SiC, therefore, B4C is used as an alternative to SiC and AL_2O_3. It has advantages for various applications such as wear and impact resistance and neutron absorption; therefore, B_4C is used in reinforcement phase. The interfacial reactions in Al composites depend mainly on fabrication method, chemical composition of the matrix and condition of fabrication. The properties of the interface changes by composition methods utilized. [9-13]

Raj Kumar et al investigated the effect of D.C. voltage by using NaCl, NaNO3 aqueous solution at high speed. The authors concluded that 10-25 V voltage is suitable for ECM. [5] Neto et al investigated the effect of feed rate on valve steel and concluded that the value for SR decreases with the lower feed rate. [6] Ashokan et al investigated the ECM parameters using grey relational combined with an ANN method to analyze the effect of machining parameters such as current, voltage, flow rate and gap of hardened steel. [4] Rao et al concluded that the rate of MRR increase with feed rate, voltage and electrolytic concentration & decrease with %age of reinforcement. [11] Senthil Kumar et al demonstrated a mathematical model by using RSM and NSGA for improvement of ECM parameters for Al, SiC composites. [10]

Based on the literatures, it is found that no plausible works are conducted on multi-parametric optimization using DoE and Grey relational method of machining Al_2B4_C metal matrix composite in the ECM process [9, 10]. Taguchi method, TOPSIS and GA (Genetic Algorithm) had been utilized to optimize the process parameters in ECM process. [17-20]. Design of experiments (DoE) and regression analysis was performed by the application of Taguchi's orthogonal array. In this work, MRR, Surface roughness and radial over cut has been considered. Even though, the goal of the ECM could be to acquire the supreme MRR after machining suitable parameters. The said problem has been described by multi-objective optimization by using Grey relational analysis.

2. Experimental Plan

Design-of-experiments (DoE) needs cautious scheduling, practical layout of the trials, Taguchi has identical procedures for every DoE application steps and also DoE can dramatically decrease the amount of trials. Thus,

Table 1. Allocated values of ECM parameters and their levels

Parameter		**Units**	**Level-1**	**Level-2**	**Level-3**
A	Voltage (V)	Volts	12	16	20
B	Feed rate (F)	mm/min.	0.2	0.6	1.0
C	Electrolyte concentration	g/lit.	10	20	30
D	%age of Reinforcing	Wt%	2.5	5.0	7.5

The four important machining parameters, i.e. Voltage (V), Feed rate (F), electrolyte immersion and %age of reinforcing had selected for the governing parameter, and each parametric quantity had three levels denoted by level 1, level 2 and level 3, as designated in the Table 1. These important parameters were selected from the previous literatures.

2.1. *Running Experiment*

MCMAC Meta Tech Electrochemical machine was used for the experimentation as shown in Fig. 2. EN1706 aluminium alloys circular bar having a 25mm diameter was used as a primary metal. The aluminium alloy was reinforced by B_4C secondary phase in different Wt% through liquid state processing (i.e. Squeeze casting). In this process, the molten metal is forced into a fibrous and squeezed until solidification is accomplished. As per DoE the experiments were conducted with a 20 V rated ECM machine and the work piece was used in the form of a cylinder. The workpiece and the electrodes were linked up with +ve and -ve polarity in the D.C power source respectively. Circular cross sectional Copper tool with internal hole for the electrolyte flow was used for experimental work. The values for surface roughness were measured with the help of the surface roughness tester. The mass of the workpiece before and after machining for every trial run was measured with digital weight-balance (up to 0.001 gram accuracy).

Fig.2. *Meta Tech Electrochemical Machining* Setup

The mathematical relation used to evaluate the Surface roughness (SR) is given below:

$$SurfaceRoughness(Ra) = \frac{1}{\mathrm{L}}\int_0^L |Zx|\langle dx\rangle \quad (\mu m) \qquad (1)$$

Where; Ra is the surface roughness value measured in µm, L = evaluation length; Z (x) = profiles height function.

The formula used to find the Radial over cut (ROC) is given below:

$$ROC = \frac{\text{DIA. of hole in material - DIA. of tool}}{2} \quad \text{(mm)} \tag{2}$$

The formula used to find the Workpiece Removal Rate (MRR) is given below:

$$MRR = \frac{\text{Weight of material removal}}{\text{Time}} \text{(g / min)} \tag{3}$$

After machining of AlB_4C composite, radial over-cut of the material was evaluated with a digital vernier caliper. Each sample was evaluated by thrice and mean values were considered.

3. Taguchi Analysis

To design the experiments, the first step is selection of appropriate Orthogonal Array, Assign each factor to columns, identify each trial circumstance, and decides the set up and repeating of trial circumstances. An OA Design matrix table is generated.

3.1. *Experimentation*

In the present experimentation work, L_{27} ($3^{\wedge 3}$) OA was chosen. L27 Orthogonal Array has 27 parametric combination therefore the total number of 27 experiments were conducted to measure the interactions between the various factors. The parameter combinations using the L_{27} or OA are shown in Table 2.

Table 2. DoE (Design of Experiment) Matrix of L_{27} ($3^{\wedge 3}$) Orthogonal array (OA) and measured values for output responses

Sl. No.	Voltage (A)	Feed Rate (B)	Electrolyte Concentration (C)	%age of Reinforcing (D)	Surface Roughness (μm)	ROC (mm)	MRR (g/min.)
1.	12	0.2	10	2.5	4.95	0.97	0.269
2.	12	0.2	20	5	5.00	0.95	0.337
3.	12	0.2	30	7.5	4.60	0.80	0.227

4.	12	0.6	10	2.5	4.92	0.76	0.353
5.	12	0.6	20	5	4.50	0.65	0.448
6.	12	0.6	30	7.5	4.73	0.80	0.42
7.	12	1	10	2.5	4.60	0.68	0.689
8.	12	1	20	5	4.36	0.65	0.545
9.	12	1	30	7.5	4.23	0.64	0.703
10.	16	0.2	10	5	4.90	0.92	0.321
11.	16	0.2	20	7.5	4.80	0.95	0.329
12.	16	0.2	30	2.5	4.30	1.04	0.488
13.	16	0.6	10	5	4.55	0.77	0.379
14.	16	0.6	20	7.5	4.40	0.70	0.302
15.	16	0.6	30	2.5	4.00	1.00	0.583
16.	16	1	10	5	4.30	0.76	0.615
17.	16	1	20	7.5	4.35	0.71	0.619
18.	16	1	30	2.5	3.60	0.94	0.812
19.	20	0.2	10	7.5	5.50	0.92	0.282
20.	20	0.2	20	2.5	4.80	1.10	0.599
21.	20	0.2	30	5	4.60	1.17	0.600
22.	20	0.6	10	7.5	5.21	0.86	0.526
23.	20	0.6	20	2.5	4.90	1.03	0.688
24.	20	0.6	30	5	4.50	1.08	0.73
25.	20	1	10	7.5	5.00	0.65	0.68
26.	20	1	20	2.5	4.40	0.99	0.887
27.	20	1	30	5	4.00	1.10	0.944

For accurate measurements minimum three values were taken for each specimen and the mean value was selected. The mean values of the SR, Radial over cut and MRR are shown in the table 3.

4. Taguchi Analysis

DOE is the first step of experimental work and a statistical technique introduced by R.A. Fisher (1920). In DOE the change in corresponding output variables is measured by changing the values of Input variables and used to find the most efficient and effective conclusions by designing, planning and organizing.

To design the experiments, the first step is selection of appropriate Orthogonal Array, Assign each factor to columns, identify each trial circumstance, and decides the order and repetitions of trial circumstances. Taguchi analysis is used for the selection of best-optimized parameter value for the individual process parameter and to measure the influence of each parameter at different levels. [10]

The ANOVA mathematical relation (Lower is the better) used to evaluate the S/N ratio of surface roughness and radial over cut is given below:

$$\eta_{LB} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \qquad (4)$$

The ANOVA mathematical relation (Higher is the better) utilized to evaluate the S/N ratio of the Material removal rate (MRR) is given below:

$$\eta_{HB} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}y_i\right] \qquad (5)$$

The S/N ratio n_{ij} for the i^{th} performance characteristics in the j^{th} experiment is evaluated by the following relation:

$$\eta_{ij} = -10\log[L_{ij}] \qquad (6)$$

Where; y = observed data and n= no. of trials

4.1. *Dominance of Input parameters on Surface roughness*

The main effect plot for means (for surface roughness) generated by Minitab 16 Software is shown in the Figure 3. This graph indicates the effect of individual input parameters on the surface roughness. In this analysis “Smaller is better” S/N ratio was used. This graph shows the best optimized values for surface roughness.

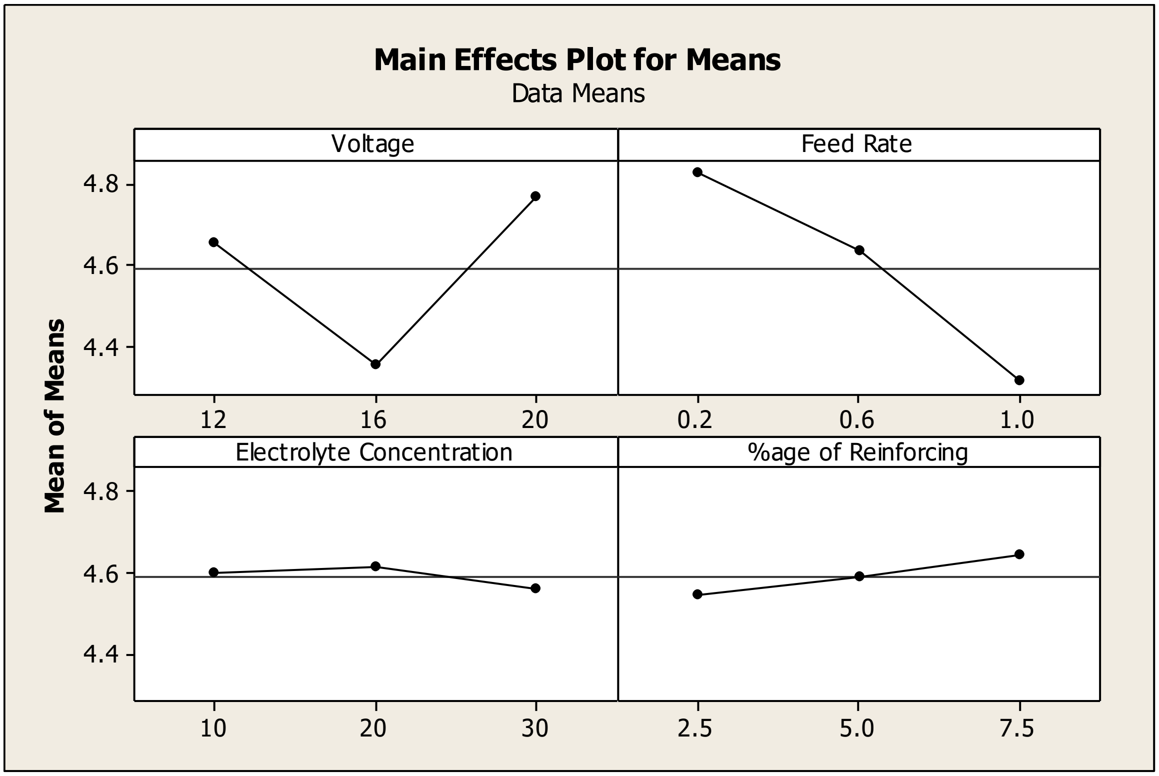

Fig.3. Main effect plot for means *(Surface Roughness)*

The best optimized level values for surface roughness are:

Optimized Parameters	**Voltage (A)**	**Feed Rate (B)**	**Electrolyte Concentration (C)**	**%age of Reinforcing (D)**
Level	2	3	3	1

Table 3. Surface Roughness Response table for means (Smaller is better)

Level	**Voltage (A)**	**Feed Rate (B)**	**Electrolyte Concentration (C)**	**%age of Reinforcing (D)**
1	4.654	4.828	4.601	4.544
2	4.356	4.634	4.617	4.589

3	4.768	4.316	4.560	4.644
Delta	0.412	0.512	0.057	0.100
Rank	2	1	4	3

The surface roughness response table for means is shown in the Table 3. This table represents the most significant parameter and least significant parameter for surface roughness (SR). The table clearly indicates that the feed rate and voltage are the most significant parameters for surface roughness whereas the %age of reinforcing and electrolyte concentration has the least significance.

The influence on surface roughness in relation to change of ECM process parameters is illustrated in Figure 4.

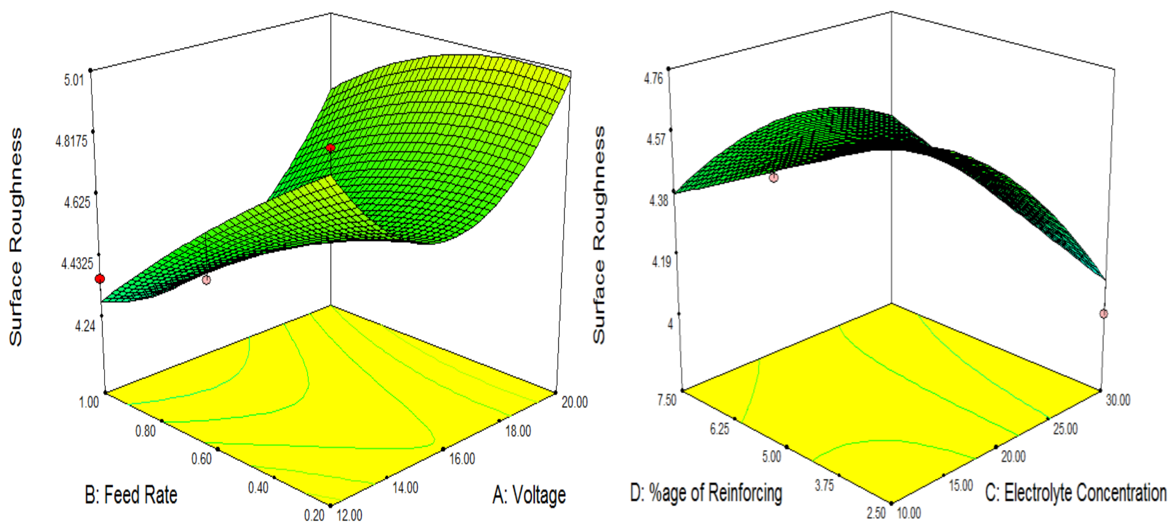

Fig.4. Influence on surface roughness in relation to change of (i) *Voltage and feed rate* and (ii) *electrolyte concentration and %age of reinforcing*

4.2. *Dominance of Input parameters on ROC*

The main effect plot for means (for ROC) generated is shown in the Figure 5. This graph indicates the effect of individual input parameters on the ROC (Radial over Cut). In this analysis "Smaller is better" S/N ratio was used. This graph shows the best optimized values for ROC.

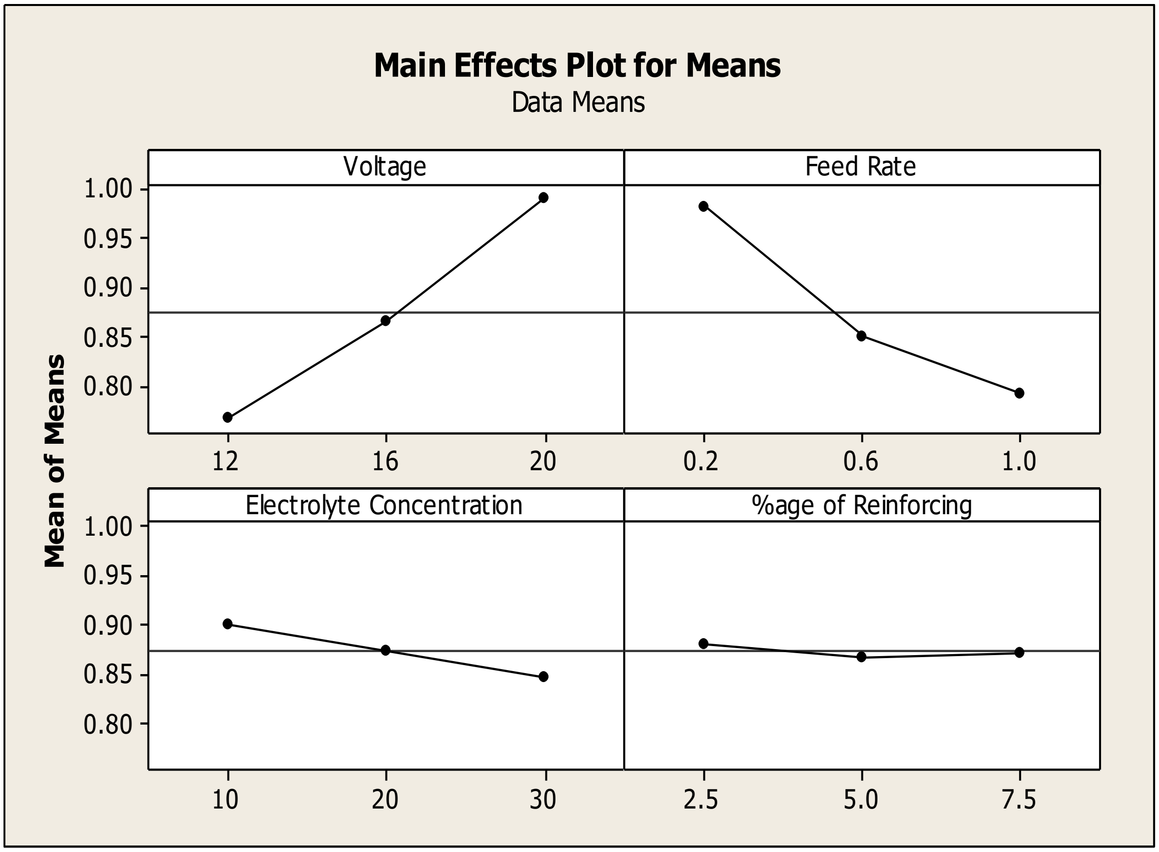

Fig.5. Main effect plot for means *(ROC)*

The best optimized level values for ROC are:

Optimized Parameters	**Voltage (A)**	**Feed Rate (B)**	**Electrolyte Concentration (C)**	**%age of Reinforcing (D)**
Level	1	3	3	2

Table 4. ROC Response table for means (Smaller is better)

Level	**Voltage (A)**	**Feed Rate (B)**	**Electrolyte Concentration (C)**	**%age of Reinforcing (D)**
1	0.7667	0.9800	0.9000	0.8811
2	0.8656	0.8500	0.8733	0.8678
3	0.9889	0.7911	0.8478	0.8722
Delta	0.2222	0.1889	0.0522	0.0133

Rank	1	2	3	4

The ROC response table for means is shown in the Table 4. This table represents the most significant parameter and least significant parameter for ROC. The table clearly indicates that the voltage and feed rate has the most significance on ROC whereas the %age of reinforcing has least significance.

The influence on ROC in relation change of voltage, feed rate, electrolyte concentration and %age of reinforcing levels is illustrated in Figure 6.

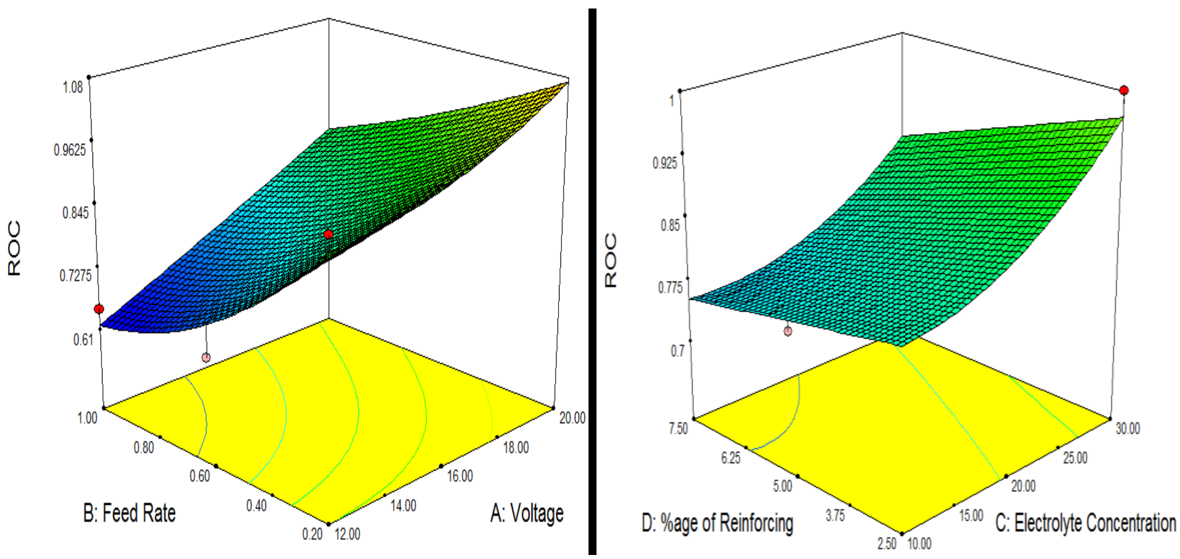

Fig.6. Influence on ROC in relation to change of (i) *Voltage and feed rate* and (ii) *electrolyte concentration and %age of reinforcing*

4.3. *Dominance of Input parameters on MRR*

The main effect plot for means (for MRR) generated is shown in the Figure 7. This graph indicates the effect of individual input parameters on the MRR (Material removal rate). In this analysis "Larger is better" S/N ratio was used. This graph shows the best optimized values for MRR.

The MRR (Material removal rate) table for means is shown in the Table 5. This table represents the most significant parameter and least significant parameter for MRR. The table clearly indicates that the feed rate and voltage has the most significance on MRR whereas the electrolyte concentration has the least significance.

The best optimized level values for MRR are:

Optimized Parameters	Voltage (A)	Feed Rate (B)	Electrolyte Concentration (C)	%age of Reinforcing (D)
Level	3	3	2	3

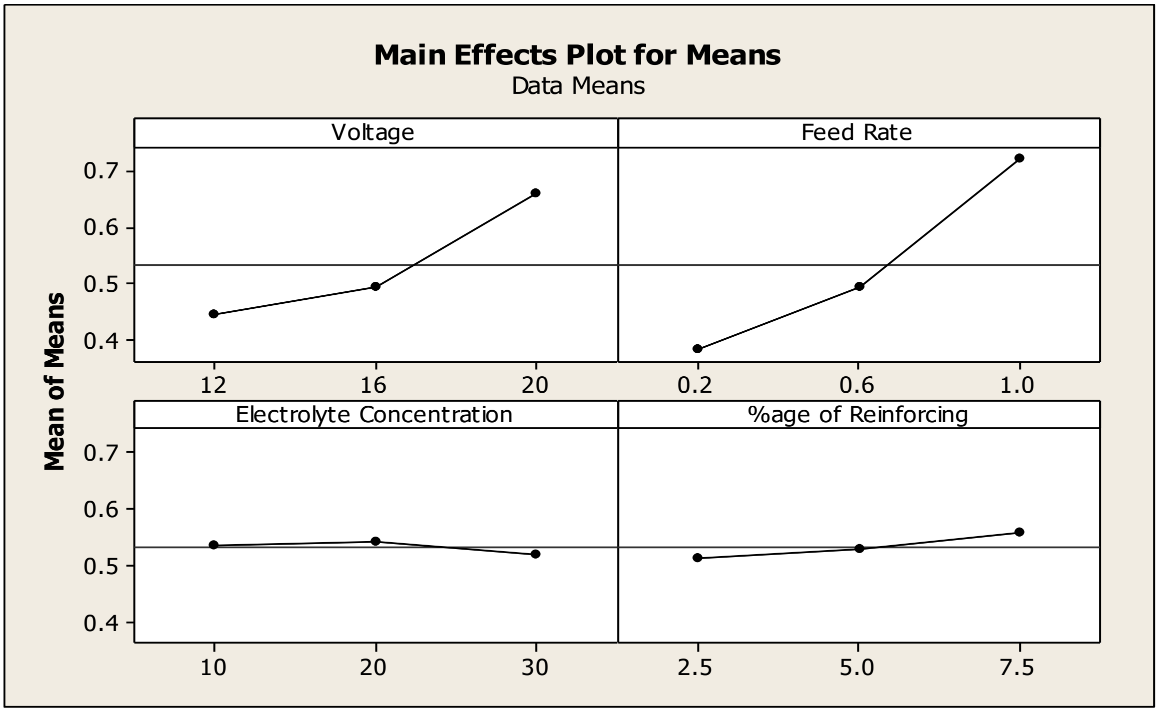

Fig.7. Main effect plot for means *(MRR)*

Table 5. MRR Response table for means (Larger is better)

Level	Voltage (A)	Feed Rate (B)	Electrolyte Concentration (C)	%age of Reinforcing (D)
1	0.4434	0.3836	0.5359	0.5120
2	0.4942	0.4921	0.5411	0.5276
3	0.6596	0.7216	0.5202	0.5577
Delta	0.2161	0.3380	0.0209	0.0457

Rank	2	1	4	3

The influence on MRR in relation to change of ECM process parameters is illustrated in Figure 8.

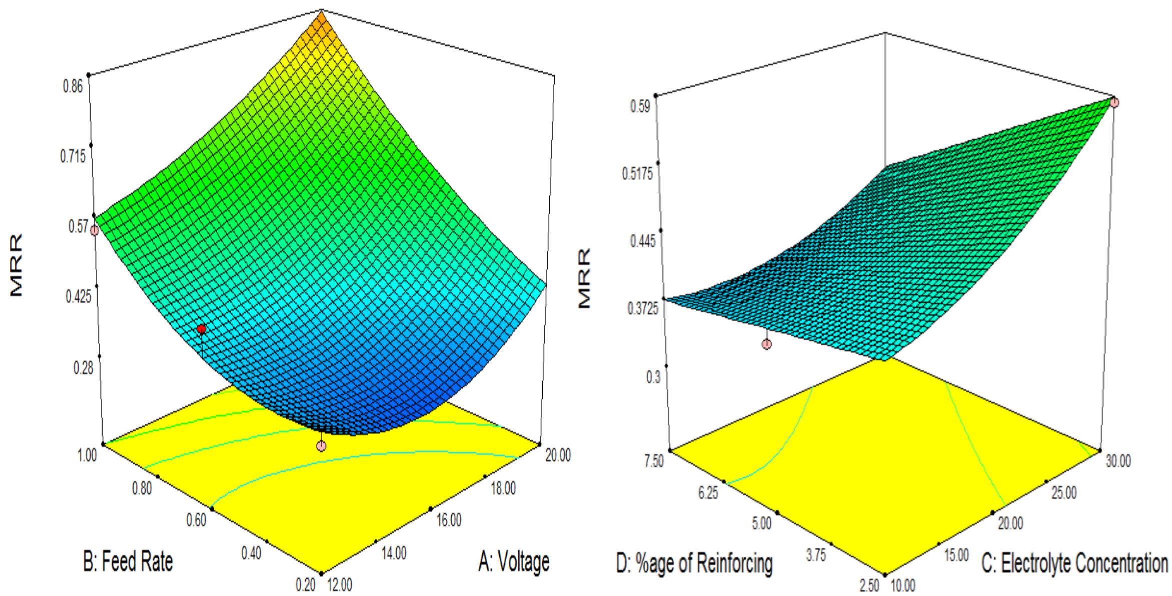

Fig.8. Influence on MRR in relation to change of (i) *Voltage and feed rate* and (ii) *electrolyte concentration and %age of reinforcing*

5. Multi-parametric Optimization using the Grey relational method

The steps used for multi-parametric optimization using the Grey relational analysis is discussed below; [18]

a) Normalization of the all experimental results: The normalized values for output responses were calculated by using the standard formula:

$$Normalized\ Results\ (X_{ij}) = \frac{(y_{ij}) - (\min_j y_{ij})}{(max_j\, y_{ij}) - (min_{ij}\, y_{ij})}$$

(7)

Where,

y_{ij} = ith experiment results in jth experiment.

Table 6. Calculated values for Grey Relational Grade

Sl. No.	Voltage (A)	Feed Rate (B)	Electrolyte Concentration (C)	%age of Reinforcing (D)	Grey relational Grade
1.	12	0.2	10	2.5	0.402732959
2.	12	0.2	20	5	0.413283745
3.	12	0.2	30	7.5	0.484886387
4.	12	0.6	10	2.5	0.499590682
5.	12	0.6	20	5	0.644352369
6.	12	0.6	30	7.5	0.499036468
7.	12	1	10	2.5	0.656027763
8.	12	1	20	5	0.676274294
9.	12	1	30	7.5	**0.74642138**
10.	16	0.2	10	5	0.426015173
11.	16	0.2	20	7.5	0.42480168
12.	16	0.2	30	2.5	0.471968302
13.	16	0.6	10	5	0.524135868
14.	16	0.6	20	7.5	0.579962553
15.	16	0.6	30	2.5	0.542731965
16.	16	1	10	5	0.599971608
17.	16	1	20	7.5	0.631943249
18.	16	1	30	2.5	**0.734538041**
19.	20	0.2	10	7.5	0.391732585
20.	20	0.2	20	2.5	0.43921751
21.	20	0.2	30	5	0.443611035
22.	20	0.6	10	7.5	0.461990766
23.	20	0.6	20	2.5	0.470624454
24.	20	0.6	30	5	0.50550866
25.	20	1	10	7.5	0.660052978
26.	20	1	20	2.5	0.61300212

27.	20	1	30	5	0.689966962

(b) Calculation for the Grey relational coefficients: The standard formula used for the computation of Grey relational coefficients is given below:

$$\delta_{ij} = \frac{min_i min_j |x°_i - x_{ij}| + \xi max_i max_j |x°_i - x_{ij}|}{|x°_i - x_{ij}| + \xi max_i max_i |x°_i - x_j|}, \ 0 < \xi < 1$$

(8)

Where,

$x°_i$ = ideal normalized result

(c) Calculation for the Grey relational grade: The grades are evaluated by the average of Grey relational coefficient using the formula given below:

$$\alpha_j = \frac{1}{m} \sum_{i=1}^{m} \delta_{ij} \qquad (9)$$

Where,

α_j = Grey relational grade,

m = No. of execution grade characteristics

Table 7. Grey relational grade response table

Process Parameters	**Level-1**	**Level-2**	**Level-3**
A	0.558067339	0.548452049	0.519523008
B	0.43313882	0.525325976	0.6675776
C	0.513583376	0.543717997	0.568741023
D	0.536714866	0.542314228	0.547013302
Average Grey relational Grade= 0.542014132			

(d) Calculation of the optimum levels: optimum levels are calculated to find the significant parameter.

(e) Selection of the optimal levels of parameters by taking the highest values of levels for each parameter from the optimum level table.

The highest value of process parameters for each parameter showed the best optimized value.

(f) Confirmation of experiment and verification of the optimized process parameters.

5.1. *Confirmation of Experiment*

After obtaining the optimized values of process parameters the last step is to confirm the experimentation. The estimated Grey relational grade can be calculated from the following given relation:

$$\hat{\alpha} = \alpha_m + \sum_{i=1}^{q} (\overline{\alpha}_i - \alpha_m) \qquad (10)$$

Where,

α_m = Total mean of the Grey relational grade,

q = No. of process parameters.

Table 8. Grey relational grade response table

Predicted Value		**Experimental Value**
Level	$A_1B_3C_3D_3$	$A_2B_3C_3D_1$
Surface Roughness (µm)	3.60	4.23
ROC (mm)	0.94	0.65
MRR (g/min.)	0.812	0.545
Grade	0.734538041	0.746421358
Improvement in Grey relational Grade= 0.01188		

4. Conclusion

The ECM process parameters for AMMCs namely Al, B_4C had optimized by using DoE and grey relational analysis. The optimal solution had calculated for Surface Roughness (SR), MRR and radial over-cut. An attempt had also been made to attain Max. and Min. MRR, radial over cut & SR evaluation of process parameters respectively. The feed rate and voltage has the most significance on surface roughness, ROC and MRR whereas the electrolyte concentration and %age of reinforcing has the least significance.

The optimized outcomes had also been examined through a real experiment and established to be satisfactory. The optimized parameters for the response of SR, MRR, and radial over cut in ECM process are: 12 Volts of applied voltage (V), 1.0 mm/min. Feed rate (F), 30 g/l electrolytic concentration & 7.5 Wt% of B_4C reinforcement. The Grey relational technique simplifies the optimization method by convert of the multi response variables to a single response grade by normalizing. Thus, the experimental results showed the considerable advancement in the process.

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