ISSN 2278-0149
Vol.3, No.3, July 2014

International Journal of
Mechanical Engineering and Robotics Research

IJMERR

www.ijmerr.com

International Journal of Mechanical Engineering and Robotics Research

India

Email : editorijmerr@gmail.com or editor@ijmerr.com

International Journal of Mechanical Engineering and Robotics Research

ISSN 2278 – 0149 www.ijmerr.com
Vol. 3, No. 3, July 2014

Research Paper

OPTIMIZATION OF MACHINING PARAMETERS IN ECM OF Al/B_4C COMPOSITES USING GENETIC ALGORITHMS

A Giribabu[1]*, Sadineni Rama Rao[2] and G Padmanbhan[1]

*Corresponding Author: A Giribabu, ✉ gbabu.mech@gmail.com

Performance criteria namely Material Removal Rate (MRR), Surface Roughness (SR) and Radial Over Cut (ROC) in electrochemical machining process greatly affected by the machining parameters like electrical parameters, electrode parameters, electrolyte parameters and workpiece properties. In the present work applied voltage (electrical parameter), tool feed rate (electrode parameter), electrolyte concentration (electrolyte parameter) and reinforcement content (workpiece property) are considered as input machining parameters. Multiple linear regression models are developed for MRR, SR and ROC. Optimum machinating parameters to maximize MRR, minimize SR and minimize ROC are found out using genetic algorithms.

Keywords: Al/B_4C composites, Electrochemical machining, Genetic algorithms, Optimization

INTRODUCTION

Electrochemical Machining (ECM) is a non-traditional machining process used mainly to cut hard or difficult to cut metals, where the application of a more traditional process is not convenient. It offers several special advantages including higher machining rate, better precision and control, and a wider range of materials that can be machined.

Goswami *et al.* (2013) studied the cutting of Mild Steel and Aluminum using Electrochemical Machining (ECM) with an electrode by using Taguchi approach. Beravala *et al.* (2011) developed mathematical model of ECM process parameters (electrolyte flow rate, electrode feed rate and voltage's effect) in relation with process output (MRR, surface finish and overcut). Analysis of Variance has been carried out to identify the significant effect of input parameters on output. Labib *et al.* (2011) studied the integration of a Fuzzy Logic Controller (FLC) with ECM drilling rig to control feed rate of the tool and the flow rate of the electrolyte with the objective of improving the

1 SV University College of Engg, Tirupathi, AP, India 517502.
2 Department of Mechanical Engineering, SVCET, RVS Nagar, Chittoor, AP, India 517127.

machining performance and accuracy of FLC. Surface characteristics in electrochemical machining of titanium are investigated experimentally, utilizing cross flow electrolyte system (Dhobe *et al.*, 2011). Abuzied *et al.* (2012) developed artificial neural network models for electrochemical machining process. Applied voltage, feed rate and electrolyte flow rate are considered as input process parameters and metal removal rate and surface roughness are considered as output responses. Nayak *et al.* (2012) used Multi-layer Feed Forward Neural Network (MFNN) and Least Square Support Vector Machine (LSSVM) to model the electrochemical machining process. Flow rate of electrolyte, feed rate, and voltage are considered as input process parameters and MRR and SR are predicted. Santhi *et al.* (2013) used Desirability Function Analysis (DFA), fuzzy set theory with trapezoidal membership function and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method to optimize the electro chemical machining process parameters for titanium alloy (Ti_6Al_4V).

In any machining process optimization of process parameters is essential for achieving high rate of production with good quality, which is the preliminary basis for survival in today's dynamic market conditions. Optimal quality of the workpiece in ECM can be generated through combinational control of various process parameters (Sorkhel and Bhattacharyya, 1994). Munda and Bhattacharyya (2008) investigated the electrochemical micromachining through response surface methodology approach with metal removal rate and radial over cut as objective measures and developed mathematical models. Both objectives were dealt separately and analyzed with reference to machining parameters. Process parameters were optimized in electrochemical machining of Al/5%SiC composites by using Taguchi and ANOVA methods (Rao and Padmnabhan, 2012). Non dominated Sorting Genetic Algorithm (NSGA-II) was used for optimization of process parameters in electrochemical machining of Al/15%SiC composites (Kao and Hocheng, 2003).

In the present work genetic algorithms are used to optimize the machining parameters such as applied voltage, tool feed rate, electrolyte concentration and reinforcement content in electrochemical machining of Al/B_4C composites.

EXPERIMENTAL DETAILS

The working principle of ECM process is shown in Figure 1. In order to establish the input-output relationships of ECM process, four machining parameters, namely tool feed rate, applied voltage, electrolyte concentration

Figure 1: Working Principle of ECM

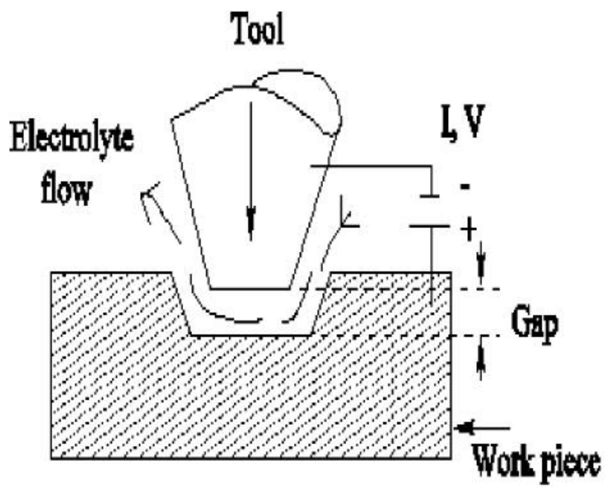


Table 1: Machining Parameters and Their Levels

Machining Parameters	Unit	Level		
		1	2	3
Applied Voltage (X_1)	Volts	12	16	20
Feed Rate (X_2)	mm/min	0.2	0.6	1.0
Electrolyte concentration (X_3)	g/L	10	20	30
Percentage of Reinforcement (X_4)	wt%	2.5	5.0	7.5

and percentage of reinforcement are considered as input parameters.

Further, the material removal rate, radial over cut and surface roughness in machining is considered as the responses. The ranges of the selected input parameters, used in this study (Rao and Padmanabhan, 2013) are shown in Table 1. Interested readers can refer (Rao and Padmanabhan, 2013) for more details of the experimental description. Table 2 shows the experimental results obtained from Taguchi design.

GENETIC ALGORITHMS

Genetic Algorithms (GAs) are general-purpose search algorithms that use the principles of natural genetics to evolve solutions of the problems. The basic idea is to maintain a population of knowledge structure that evolves over the time through a process of competition and controlled variation. Each structure in the population represents a candidate solution to the specific problem and has an associated fitness to determine which structures are used to form new ones in the process of competition. The new individuals are created using genetic operators, such as crossover and mutation. GAs are robust and have great measure of success in search and optimization problems.

As the name suggests, GA represents a new programming paradigm that tries to mimic the process of natural evolution, to solve the computing and optimization problems. In a GA, a population of chromosomes, which are usually strings of bits, is randomly selected. This population is transformed into a new population by a sort of natural selection based on the use of operators inspired by the natural genetic operators. The three operators defined by Holland are the reproduction, crossover, and mutation.

Figure 2 shows a schematic diagram explaining the working cycle of a genetic algorithm. The natural selection is based on the output of a function called the fitness function. Only the fit chromosomes survive and are allowed to reproduce off-springs. Among those surviving chromosomes, the fitter chromosome reproduces more off-springs than the less fit ones. In crossover, there is an exchange of properties between two parents and as a result of which, two children will be

Figure 2: Working Cycle of a Genetic Algorithm

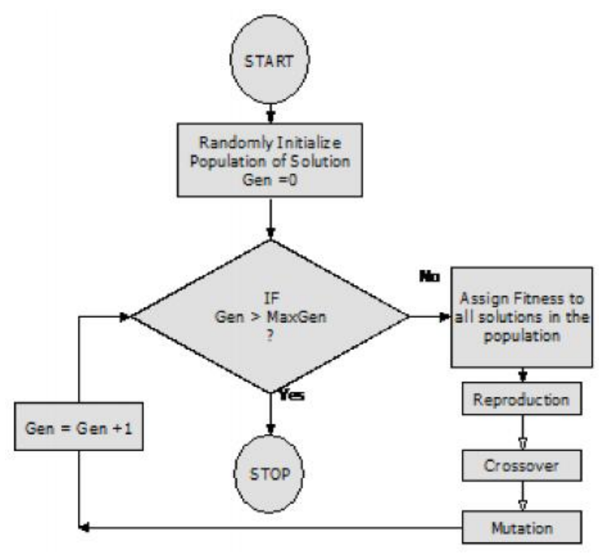


Table 2: Experimental Data According to Taguchi L_{27} Orthogonal Array Design

Exp. No.	Factors				Responses		
	X_1	X_2	X_3	X_4	MRR (g/min)	SR («m)	ROC (mm)
1	1	1	1	1	0.268	4.948	0.96
2	1	1	2	2	0.335	5.002	0.94
3	1	1	3	3	0.227	4.591	0.79
4	1	2	1	1	0.353	4.920	0.75
5	1	2	2	2	0.448	4.498	0.65
6	1	2	3	3	0.42	4.725	0.80
7	1	3	1	1	0.689	4.555	0.67
8	1	3	2	2	0.545	4.356	0.64
9	1	3	3	3	0.703	4.232	0.65
10	2	1	1	2	0.321	4.882	0.91
11	2	1	2	3	0.329	4.823	0.94
12	2	1	3	1	0.488	4.254	1.05
13	2	2	1	2	0.379	4.540	0.76
14	2	2	2	3	0.302	4.431	0.69
15	2	2	3	1	0.583	3.998	0.99
16	2	3	1	2	0.615	4.274	0.75
17	2	3	2	3	0.619	4.346	0.70
18	2	3	3	1	0.812	3.598	0.93
19	3	1	1	3	0.282	5.472	0.91
20	3	1	2	1	0.599	4.797	1.10
21	3	1	3	2	0.603	4.640	1.16
22	3	2	1	3	0.526	5.214	0.85
23	3	2	2	1	0.688	4.897	1.03
24	3	2	3	2	0.732	4.531	1.08
25	3	3	1	3	0.688	5.002	0.64
26	3	3	2	1	0.887	4.389	0.99
27	3	3	3	2	0.944	3.989	1.00

created. The mutation operator flips some of the bits in a chromosome. When the generation of a new population is completed, stopping criterion is evaluated. If the stopping criterion is met, the algorithm stops.

MATHEMATICAL MODELING

Multiple linear regression models are developed using the experimental data in the form of

$MRR/SR/ROC = K + K_1(X_1) + K_2(X_2) + K_3(X_3) + K_4(X_4)$; where k, k_1, k_2, k_3 and k_4 are constants.

Responses like MRR, SR and ROC in ECM of Al/B_4C composites are expressed as a linear function of the input variables and are given in un-coded form as:

$$MRR = -0.166 + 0.0272X_1 + 0.424X_2 + 0.00776X_3 - 0.0284X_4 \quad ...(1)$$

$$SR = 5.04 + 0.0153X_1 - 0.648X_2 - 0.0292X_3 + 0.0551X_4 \quad ...(2)$$

$$ROC = 0.611 + 0.0265X_1 - 0.249X_2 + 0.00683X_3 - 0.0329X_4 \quad ...(3)$$

OPTIMIZATION

In the present work genetic algorithms are used for optimization of varies responses like material removal rate, surface roughness and radial over cut in electrochemical machining process. By using the multiple linear regression equations fitness functions are formulated. In the present work MRR is a maximizing function, SR and ROC are minimizing functions. The objective functions are maximized and minimized by using GA toolbox in MATLAB software. The fitness function in MATLAB environment is as follows:

Function MRR/SR/ROC = simple_fitness(X)

$$MRR = (-0.166 + 0.0272*X_1 + 0.424*X_2 + 0.00776*X_3 - 0.0284*X_4)\ \hat{}\ -1 \quad ...(4)$$

$$SR = 5.04 + 0.0153*X_1 - 0.648*X_2 - 0.0292*X_3 + 0.0551*X_4 \quad ...(5)$$

$$ROC = 0.611 + 0.0265*X_1 - 0.249*X_2 + 0.00683*X_3 - 0.0329*X_4 \quad ...(6)$$

Subjected to constraints

$$12 \leq X_1 \leq 20 \quad ...(7)$$

$$0.2 \leq X_2 \leq 1 \quad ...(8)$$

$$10 \leq X_3 \leq 30 \quad ...(9)$$

$$2.5 \leq X_4 \leq 7.5 \quad ...(10)$$

RESULTS AND DISCUSSION

As the performance of GA depends on its parameters, a thorough study is carried out to determine the optimal parameters. Table 3 shows the GA parameters that are found to yield the best results.

Table 3: Genetic Algorithm Optimal Parameters

Parameters	MRR	SR	ROC
Population size	20	40	40
Crossover fraction	1	0.2	0.5
Probability of mutation	0.05	0.03	0.02
No. of generations	100	100	100

The optimal parameter values of the machining parameters for maximizing the MRR are X_1 = 20 V, X_2 = 1 mm/min, X_3 = 30 g/L, X_4 = 2.5 wt% and the corresponding MRR is 1.037 g/min.

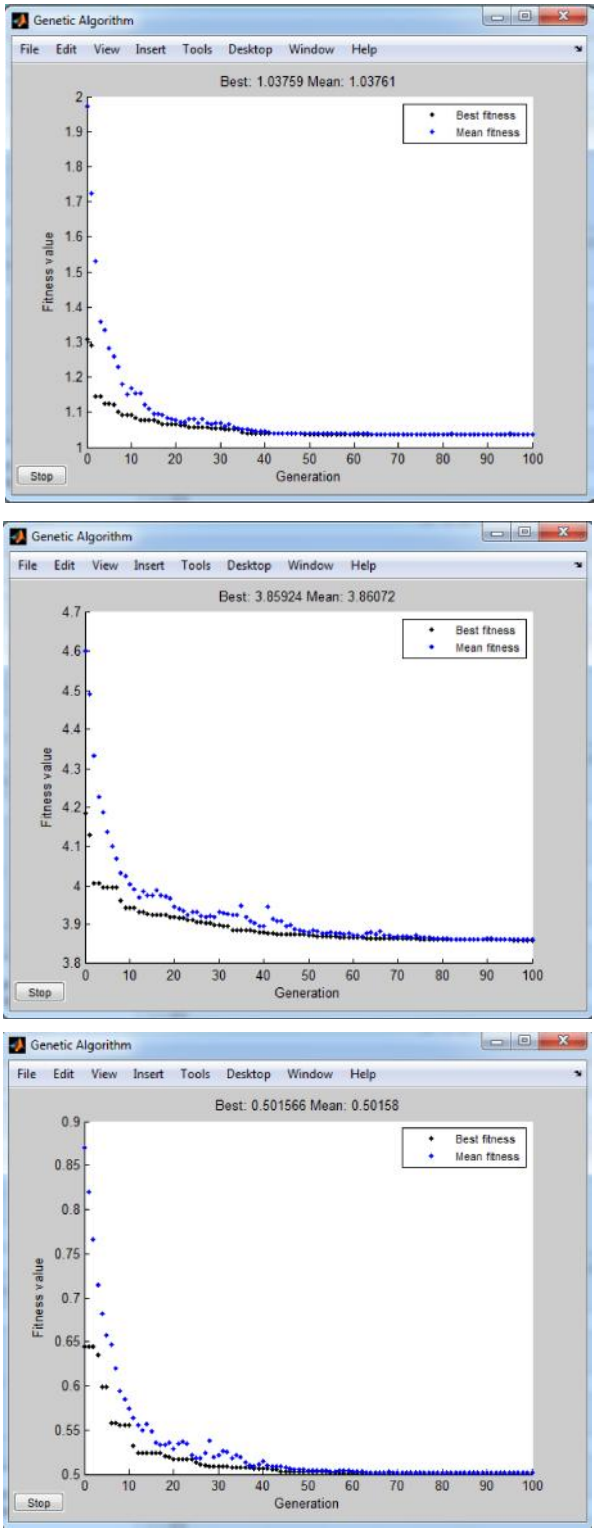
The optimal parameter values of the machining parameters for minimizing the SR are X_1 = 13.4 V, X_2 = 1 mm/min, X_3 = 29.98 g/L, X_4 = 2.5 wt% and the corresponding SR is 3.859 μm.

The optimal parameter values of the machining parameters for minimizing the ROC are X_1 = 12 V, X_2 = 1 mm/min, X_3 = 10 g/L, X_4 = 7.5 wt% and the corresponding ROC is 0.501 mm.

Figure 3 shows the performance of genetic algorithm, i.e., fitness verses generations for material removal rate, surface roughness and radial over cut.

It is also clear from Figure 3 that the convergence rate at the earlier stage is much higher than that of the later stage. Mean fitness and best fitness values decrease very rapidly in the initial stage (1 to 30 generations). As

Figure 3: Performance of GA: Fitness vs No. of Generation for (a) MRR, (b) SR and (c) ROC



the number of generations increases, rate of changes in these two fitness values decrease rapidly and programs are so designed that GA terminates when no significant improvement occurs in the solution. Usually maximum number of generations is set before the program starts.

CONCLUSION

The machining parameters for electrochemical machining of Al/B_4C composites are optimized with L_{27} orthogonal array and genetic algorithms. From the investigation, the following conclusions can be drawn:

Multiple linear regression models were developed for material removal rate, surface roughness and radial over cut.

The recommended levels of ECM machining parameters for maximizing metal removal rate are the applied voltage 20 V, feed rate 1 mm/min, electrolyte concentration 30 g/L and reinforcement content 2.5 wt%.

The recommended levels of ECM machining parameters for minimizing surface roughness are the applied voltage 13.4 V, feed rate 1 mm/min, electrolyte concentration 29.98 g/L and reinforcement content 2.5 wt%.

The recommended levels of ECM machining parameters for minimizing radial over cut are the applied voltage 12 V, feed rate 1 mm/min, electrolyte concentration 10 g/L and reinforcement content 7.5 wt%.

REFERENCES

1. Abuzied H H, Awad M A and Senbel H A (2012), "Prediction of Electrochemical Machining Process Parameters Using Artificial Neural Networks", *International*

Journal on Computer Science and Engineering, Vol. 4, No. 1, pp. 125-132.

2. Beravala H S, Barot R S, Pandey A B and Karhadkar G D (2011), "Development of Predictive Mathematical Model of Process Parameters in Electrochemical Machining Process", National Conference on Recent Trends in Engineering & Technology, B.V.M. Engineering College, Gujarat, India.

3. Dhobe S D, Doloi B and Bhattacharyya B (2011), "Analysis of Surface Characteristics of Titanium During ECM", *International Journal of Machining and Machinability of Materials*, Vol. 10, No. 4, pp. 293-309.

4. Goswami R, Chouhan R and Chaturvedi V (2013), "The Implementation of Taguchi Approach on ECM Process Parameters for Mild Steel and Aluminum", *International Journal of Research in Engineering & Applied Sciences*, Vol. 3, No. 2, pp. 53-62.

5. Labib A W, Keasberry V J, Atkinson J and Frost H W (2011), "Towards Next Generation Electrochemical Machining Controllers: A Fuzzy Logic Control Approach to ECM", *Expert Systems with Applications*, Vol. 38, No. 6, pp. 7486-7493.

6. Munda J and Bhattacharyya B (2008), "Investigation into Electrochemical Micromachining (EMM) Through Response Surface Methodology Based Approach", *International Journal of Advanced Manufacturing Technology*, Vol. 35, pp. 821-832.

7. Nayak K C, Tripathy R K and Panda S R (2012), "Relevance Vector Machine Based Prediction of MRR and SR for Electro Chemical Machining Process", *International Journal of Mechanical Engineering and Technology*, Vol. 3, No. 3, pp. 394-403.

8. Rao P S and Hocheng H (2003), "Optimization of Electrochemical Polishing of Stainless Steel by Grey Relational Analysis", *Journal of Materials Processing Technology*, Vol. 140, pp. 255-259.

9. Rao S R and Padmnabhan G (2012), "Application of Taguchi Methods and ANOVA in Optimization of Process Parameters for Metal Removal Rate in ECM of Al/5%SiC Composites", *International Journal of Engineering Research and Applications*, Vol. 2, No. 3, pp. 192-197.

10. Rao S R and Padmanabhan G (2013), "Optimization of Machining Parameters in ECM of Al/B_4C Composites", *Journal of Manufacturing Science and Production*, Vol. 13, No. 3, pp. 145-153.

11. Santhi M, Ravikumar R and Jeyapaul R (2013), "Optimization of Process Parameters in Electro Chemical Machining (ECM) Using DFA-Fuzzy Set Theory-TOPSIS for Titanium Alloy", *Multidiscipline Modeling in Materials and Structures*, Vol. 9, No. 2, pp. 243-255.

12. Sorkhel S K and Bhattacharyya B (1994), "Parametric Control for Optimal Quality of the Workpiece Surface in ECM", *Journal of Material Processing Technology*, Vol. 40, pp. 271-286.

International Journal of Mechanical Engineering and Robotics Research

Hyderabad, INDIA. Ph: +91-09441351700, 09059645577

E-mail: editorijmerr@gmail.com or editor@ijmerr.com

Website: www.ijmerr.com

ISSN 2278-0149