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Multi-objective Optimization of Electrochemical Machining of Hardened Steel Using NSGA II

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Abstract

Electrochemical machining (ECM) is one of the non-conventional machining processes which is mostly used to machine difficult-to-machine materials such as super alloys, Ti-alloys, stainless steel, alloy steel etc. The major requirement of the process is that work piece should be electrically conducting in nature. A large number of parameters influence material removal rate (MRR) and surface roughness (SR) of parts produced by ECM. Usually, tool makers use thumb rules and machine manuals to set optimal parameters for the process. In this work, response surface methodology is adopted to study the effect of four important parameters such as current, voltage, flow rate of electrolyte and inter-electrode gap on MRR and SR. Statistically validated regression equation are developed relating response like MRR and SR with input parameters. Finally, a non-dominated sorted genetic algorithm is used to find out the optimal process parameters that simultaneously maximize MRR and minimize SR. The set of Pareto solutions provide flexibility to the tool makers to choose the best setting depending on applications.

Keywords: Electrochemical machining (ECM); Material Removal Rare (MRR); Surface Roughness (SR); Response Surface Methodology (RSM); Non-dominated Sorted Genetic Algorithm (NSGA)

1. Introduction

According to Faraday's law of electrolysis, if an electrode and work piece are placed in an electrolyte bath and a potential difference is applied, metal molecules from anode ionize to lose electrons and break free of the work piece, and travel through the electrolyte to cathode.

Mathematically, $m = It\varepsilon / F$ (1)

where, m = weight (g) of a material

I = current (A)

t = time (sec)

ε = gram equivalent weight of material

F = Faraday's constant of proportionality (=96500 coulomb)

Practically, ECM parts are subjected to less amount of thermal stress (as the operating temperature is low) or mechanical stress (as ideally no contact occur between tool and work piece during machining) but in real practice sparks occur which is to be avoided to minimize the tool wear. ECM process is primarily used for manufacturing components of complex shape used in aerospace and defense industries, offshore petroleum industries and medical engineering.

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Electrochemical drilling, electrochemical deburring, electrochemical grinding and electrochemical polishing are some modifications of electrochemical machining. Due to complexity of the ECM process, it is difficult to control all the machining parameters at a time to achieve desired optimal responses. A different set of input parameters need to be selected depending upon the responses to be optimized. Acharya et al. [1] have optimized MRR, tool life and geometrical inaccuracy subjected to temperature, choking and passivity constraint in electrochemical machining process using goal programming approach. Jain and Jain [2] have optimized three most important process parameters such as tool feed rate, electrolyte flow velocity, and applied voltage to minimize geometrically inaccuracy subjected to temperature, choking, and passivity constraints using real-coded genetic algorithms. Asokan et al. [3] have used grey relational analysis for simultaneous optimization of MRR and SR. Chakradhar and Venu Gopal [4] have also used grey relational analysis to optimize MRR, SR, overcut and cylindricity error considering electrolyte concentration, feed rate, applied voltage as input parameters, each of three levels. All the methods need weight estimation for each response for simultaneous optimization of multiple responses. Normally, weights are extracted from the experts, sometimes producing erroneous optimal values. To alleviate such problems, the current paper adopts a non-dominated sorted genetic algorithm (NSGA II) to produce set of Pareto optimal solution. All the solution in the Pareto front are optimal solutions; however, its application to a particular situation depends on the users.

2. Experimental procedure

A. Experimental Setup

Experiments were conducted on the electrochemical machining set up supplied by Metatech industries India shown in Figure 1. The ECM setup consists of three parts called machining chamber, control panel and electrolyte circulation system. In the machining chamber, work piece is fixed and the cathode (tool) is attached to a driving lead screw which is controlled by a servo feed mechanism. To avoid short circuits, there is a current sensing circuit interfaced between the tool and the stepper motor controller circuit which is used to reverse the downward motion of the tool immediately in case current exceeds the input limit. The necessary process parameters like current, voltage, flow rate and IEG can be varied through the control panel. The electrolyte is pneumatically pumped through a reservoir.

Figure . Electrochemical Machining Setup

B. Selection of work piece, tool material and electrolyte

Cylindrical blank of 20 mm diameter and 40 mm height made of hardened steel which is a high carbon alloy steel with high degree of hardness with compressive strength and abrasion resistance is selected as work piece. Tool is made of copper. 10% NaCl along with 0.2% H_2O_2 is chosen as electrolyte such that no deposition occurs on the cathode. Unwanted machining due to stray current can be avoided on application of epoxy powder resin coating on the tool except the base of the tool.

C. Selection of the machining parameters and their levels

In this experiment, four process parameters such as current, applied voltage, flow rate, inter-electrode gap (IEG) are considered as input parameters. The gap between the two electrodes (tool and work piece) is called IEG. As the IEG decreases, current density increases and vice versa. The actual values and coded values of parameters are given in Table 1.

To run the experiment smoothly, the parametric levels for any chosen factor (X) need to be coded using the equation 1.

$$Coded\ Value\ (X_i) = \frac{2X-(X_{max}+X_{min})}{\frac{X_{max}-X_{min}}{2}} \quad (2)$$

where, coded value for X_i is -2, -1, 0, 1, and 2, X_{max} and X_{min} is maximum and minimum value of actual variable and X is the actual value of corresponding variable.

Table . Electrochemical machining process parameters and their levels

Process parameter (unit)	Symbols	Codes				
		-2	-1	0	1	2
Current (A)	*A*	200	220	240	260	280
Voltage (V)	*B*	20	24	28	32	36
Flow rate (m^3/min)	*C*	5	6	7	8	9
IEG (mm)	*D*	0.1	0.2	0.3	0.4	0.5

D. Response Surface Methodology

The experimental design is based on second order central composite rotatable design. Central composite design (CCD) is chosen over other designs as it is insensitive to missing data and used for estimating a quadratic model. A total of 31 numbers of experiments are conducted consisting of 16 orthogonal points, 8 axial points and 7 centre points. A quadratic model is given in equation 3.

$$Y = \beta_0 + \sum_{i=1}^{p} \beta_i X_i + \sum_{i=1}^{p} \beta_{ii} X_i^2 + \sum_{i<j} \sum \beta_i X_i X_j + \varepsilon \quad (3)$$

where, Y : response values corresponds to input variables Xi

X_i^2 - square terms of parameters

X_iX_j - interaction terms of parameters

$\beta_0, \beta_i, \beta_{ii},$ - unknown regression coefficients

ε : error

The experiments are conducted as per the experimental layout shown in Table 2. The responses such as MRR and SR are obtained calculating weight loss before and after machining using a precision electronic balance (least count 0.001 g) and Talysurf respectively.

Table . Experimental layout

	Machining parameters				Response parameters	
Expt. No.	Current (A)	Voltage (V)	Flow rate (m/sec)	IEG (mm)	MRR (mg/min)	SR (μm)
1	220	24	6	0.2	2.575	2
2	260	24	6	0.2	2.85	2.3
3	220	32	6	0.2	2.67	2.1
4	260	32	6	0.2	2.96	2.5
5	220	24	8	0.2	2.57	2.1
6	260	24	8	0.2	2.7	2.1
7	220	32	8	0.2	2.65	2.2
8	260	32	8	0.2	2.91	2.3
9	220	24	6	0.4	2.65	2.1
10	260	24	6	0.4	2.87	2.3
11	220	32	6	0.4	2.82	2.1
12	260	32	6	0.4	3.1	2.5
13	220	24	8	0.4	2.57	2.1
14	260	24	8	0.4	2.62	2
15	220	32	8	0.4	2.52	2.1
16	260	32	8	0.4	2.71	2.1
17	200	28	7	0.3	2.5	2.1
18	280	28	7	0.3	3.05	2.5
19	240	20	7	0.3	2.51	2
20	240	36	7	0.3	2.71	2.2142
21	240	28	5	0.3	2.9483	2.3118
22	240	28	9	0.3	2.75	2.1

23	240	28	7	0.1	2.655	2.21
24	240	28	7	0.5	2.64	2.1
25	240	28	7	0.3	2.625	2.1429
26	240	28	7	0.3	2.59	2.1
27	240	28	7	0.3	2.67	2.2
28	240	28	7	0.3	2.61	2.18
29	240	28	7	0.3	2.69	2.16
30	240	28	7	0.3	2.64	2.15
31	240	28	7	0.3	2.74	2.12

3. Results and discussions

An analysis of variance (ANOVA) was conducted on responses such as MRR and SR shown in Tables 3 and 4 respectively. The insignificant parameters are removed from the model. The ANOVA for MRR indicates coefficient of determination is adequate since obtained R^2, Adj. R^2 and predicted R^2 values are 90.17%, 87.17% and 80.37% respectively. Similarly, obtained R^2, Adj. R^2 and predicted R^2 values are 97.51%, 95.85% and 92.95% respectively for the response SR. It is to be noted that lack of fit is not significant in both cases. The normality plots for residuals shown in Figure 2 and 3 respectively for MRR and SR shows that residuals lie around the mid-line.

Table 3. ANOVA for MRR

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob. > F)	
Model	0.656168	7	0.093738	30.12652	< 0.0001	significant
A-current	0.325501	1	0.325501	104.6126	< 0.0001	
B-voltage	0.074259	1	0.074259	23.86619	< 0.0001	
C-flow rate	0.112285	1	0.112285	36.08736	< 0.0001	
D-IEG	0.000126	1	0.000126	0.040508	0.8423	
$C \times D$	0.039502	1	0.039502	12.69539	0.0017	
A^2	0.033108	1	0.033108	10.64051	0.0034	
C^2	0.079589	1	0.079589	25.57898	< 0.0001	
Residual	0.071564	23	0.003111			
Lack of Fit	0.055571	17	0.003269	1.226387	0.4273	not significant
Pure Error	0.015993	6	0.002665			
Cor Total	0.727733	30				

Table 4. ANOVA for SR

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	0.536942	12	0.044745	58.75605	< 0.0001	significant
A-current	0.18375	1	0.18375	241.287	< 0.0001	
B-voltage	0.073527	1	0.073527	96.55019	< 0.0001	
C-flow rate	0.072997	1	0.072997	95.8537	< 0.0001	
D-IEG	0.011267	1	0.011267	14.79456	0.0012	
$A \times B$	0.015625	1	0.015625	20.5176	0.0003	
$A \times C$	0.105625	1	0.105625	138.699	< 0.0001	
$A \times D$	0.005625	1	0.005625	7.386338	0.0141	
$B \times D$	0.005625	1	0.005625	7.386338	0.0141	
$C \times D$	0.015625	1	0.015625	20.5176	0.0003	
A^2	0.036807	1	0.036807	48.33261	< 0.0001	
B^2	0.004557	1	0.004557	5.983413	0.0249	
C^2	0.004269	1	0.004269	5.60518	0.0293	
Residual	0.013708	18	0.000762			
Lack of Fit	0.006759	12	0.000563	0.486281	0.8644	not significant
Pure Error	0.006949	6	0.001158			
Cor Total	0.55065	30				

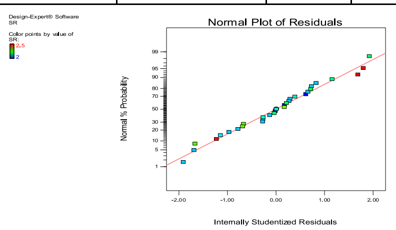

Figure 2. Normal Plot of Residuals for MRR

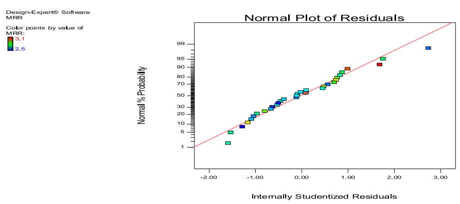

Figure 3. Normal Plot of Residuals for SR

Figure 4 shows the surface plot for MRR in relation to the process parameters such as current and voltage. It shows that on increasing voltage from lower level to higher level, MRR increases. Similarly, on increasing current, MRR increases. However, increase of current causes rapid increase in MRR as compared to increase in voltage. Figure 5 shows the surface plot for SR in relation to the process parameters such as current and flow rate. Figure shows that increasing flow rate, SR increases for lower current setting but decreases for higher current setting. Increasing current value, SR increases suddenly for lower value of flow rate. Figure 6 shows the surface plot for SR in relation to the process parameters such as current and IEG. It shows that there is not that much variation in SR value for increasing IEG value for lower value of current but for higher value of current, decrease in SR is observed on increasing IEG value. Figure 7 shows the surface plot for MRR in relation to the process parameters such as flow rate and IEG. With increase in flow rate from lower level to higher level, MRR decreases for higher IEG value but for lower level of IEG value, MRR decreases up to a limit and then increases while increasing flow rate.

From RSM, empirical relationship between response and factors in coded forms are given as follows:

$$MRR=2.65+0.12\times A+0.056\times B-0.068\times C-.002292\times D-0.050\times C\times D+0.034\times A^2+0.052\times C^2 \quad (4)$$

$$SR=2.15+0.087\times A+0.055\times B-0.055\times C-0.022\times D+0.031\times A\times B-0.081\times A\times C-0.019\times A\times D-0.019\times B\times D-0.031\times C\times D+0.036\times A^2 \quad (5)$$

Objective of the experiment is to maximize MRR and minimize SR simultaneously. Here, eq-4 is the optimization function for MRR which is to be maximized and eq-5 is the optimization function for SR which is to be minimized.

Where, A,B,C,D are the symbols used for current, voltage, flow rate and IEG respectively.

Unlike single objective optimization in which a single optimal solution is obtained, a set of optimal solutions is obtained in case of multi-objective optimization known as pareto-optimal solution. Each of the pareto-optimal solution is equally good. Depending on one's requirement and according to the problem environment, corresponding input values for factors are taken to achieve a suitable solution. Real-world problems require simultaneous optimization of several incommensurable and often conflicting objectives. Often, there is no single optimal solution; rather there is a set of alternative solutions. These solutions are optimal in the wider sense that no other solutions in the search space are superior to another when all objectives are considered. They are known as pareto-optimal solutions. The image of the efficient set in the objective space is called non-dominated set. For example, consider a minimization problem and two decision vectors a, b ε X, the concept of pareto optimality can be defined as follows: a is said to dominate b if:

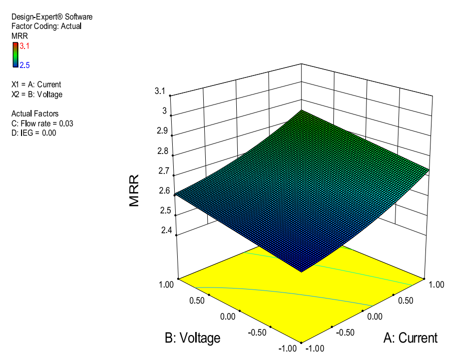

Figure . Surface plot current Vs voltage for MRR

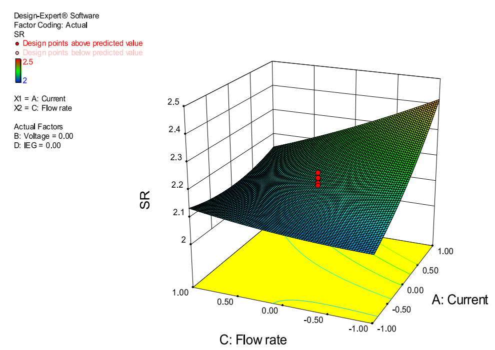

Figure . Surface Plot Current Vs Flow Rate for SR

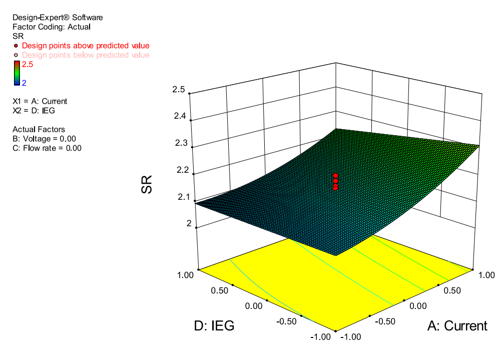

Figure . Surface Plot Current Vs IEG for SR

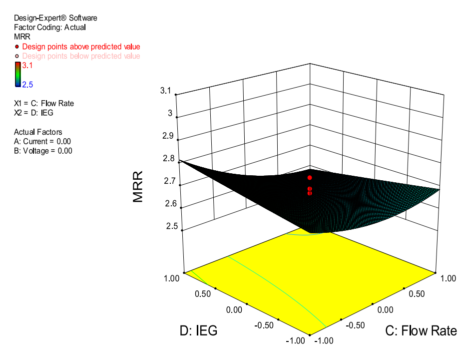

Figure . Surface Plot Flow Rate Vs IEG for MRR

$i = \{1, 2, 3, \ldots, n\} : fi(a) \leq fi(b)$ and
$j = \{1, 2, 3, \ldots, n\} : fi(a) < fi(b)$

Conditions which a solution should satisfy to become dominant are; (i) any two solutions of *X* must be non-dominated with respect to each other, (ii) any solution not belonging to *X* is dominated by at least one member of *X*. All the objective function vectors, which are not dominated by any other objective function vector of a set of Pareto-optimal solutions are called non-dominated set with respect to that set of Pareto-optimal solutions. There are two goals in a multi-objective optimization: (i) convergence to the Pareto-optimal set; and (ii) maintenance of diversity and distribution in solutions. Non-dominated Sorting Genetic Algorithm II (NSGA II) is a multi-objective genetic algorithm based on the concept of non-dominated sorting [5-6]. NSGA II algorithm is based on both non-dominated sorting and crowding sorting to obtain the required non-dominated set. This algorithm can be used for constrained optimization problems with binary coding and real parameters. The appropriate objective function in terms of selected variables is coded in the algorithm and a non-dominated set out of the entire population after a specific number of generations is generated.

These empirical equations (4 and 5) between the responses and the input parameters are used for multi-objective optimization in MATLAB environment. Here, an initial population size of 60 is taken and optimization is carried out by setting simple crossover and bitwise mutation with a crossover probability Pc=0.8, migration interval of 20, migration fraction of 0.2 and pareto fraction of 0.35. According to the algorithm, ranking and sorting of solutions are done and the final pareto-optimal setting is shown in the Table 5. It should be noted that all the solutions are equally good and any set of input parameters can be taken to achieve the corresponding response values depending upon manufacturer's requirement.

Table 5. Solutions based on Pareto optimal setting

.	Response parameters		Corresponding machining parameters			
Sl No	MRR (mg/min)	SR (μm)	Current (A)	Voltage (V)	Flow rate (m/sec)	IEG (mm)
1	2.749828	1.673698	275.2101	20.71278	8.999219	0.482568
2	3.198721	2.101709	279.5522	23.32491	8.976085	0.126695
3	2.769919	1.680615	276.4584	20.9672	8.998464	0.481128
4	3.255515	2.23568	279.7239	25.89591	8.96866	0.106567
5	3.230397	2.172791	279.6177	24.35276	8.951081	0.104636
6	3.166659	1.99901	278.3403	20.9497	8.985216	0.11248
7	3.376665	2.536274	279.6874	34.40102	8.96704	0.103662
8	3.09228	1.940367	279.0597	20.95621	8.947892	0.18764
9	3.319106	2.445868	279.372	33.67126	8.975588	0.148523
10	3.15048	1.997471	279.0422	21.16344	8.950338	0.132481
11	3.194073	2.088415	279.1198	22.93647	8.977205	0.120738
12	2.867542	1.739993	278.8144	21.08739	8.992992	0.415406
13	3.011759	1.871321	278.6615	21.14723	8.979709	0.270875
14	3.21116	2.153828	279.5567	24.33508	8.948781	0.122361
15	2.973877	1.832867	279.2298	21.18863	8.983008	0.316355
16	3.397741	2.586133	279.8118	35.98911	8.944807	0.101202
17	3.184038	2.032683	279.515	21.62172	8.972013	0.116242
18	3.338062	2.483721	279.2952	33.02396	8.941836	0.112169
19	2.83488	1.71268	279.1855	21.36481	8.994856	0.455965
20	3.397873	2.586134	279.8125	35.99204	8.945248	0.101223
21	2.897818	1.761571	279.2571	21.03519	8.986945	0.38992

4. Conclusions

In the present paper, MRR and SR is estimated experimentally for electrochemical machining using hardened steel as work piece. A central composite design of response surface methodology is used for experimental plan. Empirical equations for MRR and SR in terms of four important ECM parameters such as current, voltage, flow rate and IEG are obtained. The equations are tested for statistical validity. Response plots are analyzed to study the effect of various parameters on responses. Finally, NSGA II is used to obtain pareto-optimal solutions for simultaneous maximization of MRR and minimization of SR. Validation of optimum results can be done by doing electrochemical machining for the corresponding input parameters.

5. References

[1] Acharya, B.G., Jain, V.K., Batra, J.L., 1986. Multi-objective optimization of ECM process, Precision Engineering, 8(2), p.88–96.

[2] Jain, N.K., Jain, V.K., 2007. Optimization of electro-chemical machining process parameters using genetic algorithms, Machining Science and Technology, 11, p.235-258.

[3] Asokan, P., Kumar, R. Ravi, Jeyapaul, R., Santhi, M., 2008. Development of multi-objective optimization models for electrochemical machining process, Int J Adv Manuf Technol, 39, p.55-63.

[4] Chakradhar, D., Venu Gopal, A., 2011. Multi-Objective Optimization of Electrochemical machining of EN31 steel by Grey Relational Analysis, *International Journal of Modeling and Optimization 1(2).*

[5] Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on

Evolutionary Computation , 6(2), p.182-197.
[6] Padhee, S., Nayak, N.R., Panda, S.K., Dhal, P.R., Mahapatra, S.S., 2012. Multi-objective parametric optimization of powder mixed electro-discharge machining using response surface methodology and non-dominated sorting genetic algorithm, Indian Academy of Sciences 37(2), p.223-240.