Influence of Input Parameters on Characteristics of Electro Chemical Machining Process

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Abstract: Proper selection of manufacturing conditions is one of the most important aspects in the die sinking Electrochemical Machining process, as these conditions determine important characteristics such as Material Removal Rate and Surface Roughness. The material used in the study was LM25Al/10%SiCp composite. Experiments have been carried out to establish an empirical relationship between process parameters and responses in ECM process using Response Surface Methodology. The developed empirical relationships predict the machining conditions within the experimental domain. Analysis of variance (ANOVA) is employed to indicate the level of significance of machining parameters. The contour plots are generated to study the effect of process parameters as well as their interactions. MRR is influenced by applied voltage and tool feed rather than other parameters. Electrolyte concentration has most significant factor on Ra rather than other parameters.

Keywords: Electrochemical machining (ECM); response surface methodology (RSM); metal removal rate (MRR); surface roughness (Ra).

1. Introduction

Electrochemical machining (ECM) is a non-contact, electrochemical dissolution process that is used to shape the anode metal, namely the workpiece, the cathode, namely the tool, is normally moved toward the anode at constant feed rate, and the electrolyte flows at high speed through the gap to carry away the dissolved metal [1]. ECM is mainly used to cut hard or difficult to cut metals, where the application of a more traditional process is not convenient. Those difficult to cut metals demand high energy to form chips, which can result in thermal effects due to the high temperatures inherent to the process in the chip–tool interface. The difficulties to cut super alloys and other hard-to-machine materials by conventional process have been largely responsible for the development of the ECM process [2]. ECM has been used widely in the manufacturing of semiconductor devices and this process is also used in aerospace and electronic industries [3]. Metal matrix composites (MMCs) are now beginning to make an important contribution to major industries such as transportation, electronics, sports, tooling, and machinery. Although the properties of MMCs, in many respects, are superior to those of their monolithic counterparts, the extremely hard abrasive, low electrical conductivity, and high thermal resistance nature of the ceramic reinforcement phase remains a major obstacle in the shaping of these materials whether

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or not conventional or unconventional techniques are used [4]. To machine MMCs, using conventional means could be problematic due to abrasive nature of the reinforcement [5]. In view of difficulties encountered-e.g. high tool wear and high tooling cost, during conventional machining, hence non-contact metal removal processes such as ECM offer an effective alternative.

In this study Response surface methodology (RSM) has been used to plan and analyze the experiments. It is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response. It is a sequential experimentation strategy for empirical model building and optimization. By conducting experiments and applying regression analysis, a model of the response to some independent input variables can be obtained. Based on the model of the response, a near optimal point can then be deduced. RSM is often applied in the characterization and optimization of processes [6]. The objective of using RSM is not only to investigate the response over the entire factor space, but also to locate the region of interest where the response reaches its optimum or near optimal value. By studying carefully the response surface model, the combination of factors, which gives the best response, can then be established [7].

2. Experimental study

ECM machine has been used to analyze the influence of predominant machining parameters, i.e. applied voltage, electrolyte concentration, electrolyte flow rate and tool feed rate during ECM operation on the desired machining performance characteristic, i.e. metal removal rate (MRR) and surface roughness (Ra) of machined product. The material used in these experiments was LM25 Al/10% SiCp composite produced through stir-casting. This composite has an excellent strength-to-weight ratio, high wear resistance, good corrosion resistance and is widely used in the aerospace industry. The dimensions of the specimens were 30mm diameter and 6 mm height. The experiments were conducted on METATECH electro chemical machining equipment. The tool was made up of copper with a square cross section. The electrolyte used for experimentation was fresh aqueous solution of sodium nitrate (NaNO₃) with varying electrolyte concentration because of its high conductivity and non-passive characteristic. The weight of test pieces was measured before and after machining by using a precision weighing machine and machining time was set in the machine for calculating material removal rate. The material removal rate (MRR) and surface roughness was observed for various sets of experiments with different combinations of process parameters based on response surface methodology (RSM).

3. Response surface methodology

The RSM is an empirical modeling approach for determining the relationship between various process parameters and responses with the various desired criteria and searching the significance of these process parameters on the coupled responses [8]. It is a sequential experimentation strategy for building and optimizing the empirical model. Therefore, RSM is a collection of mathematical and statistical procedures that are useful for the modeling and analysis of problems in which response of demand is affected by several variables and the objective is to optimize the response [9]. The general second order polynomial response surface mathematical model, which analyses the parametric influences on the various response criteria, can be described as follows:

$$Y_{u} = b_{o} + \sum_{i=1}^{k} b_{i} x_{i} + \sum_{i=1}^{k} b_{ii} x^{2}_{i} + \sum_{j>1}^{k} b_{ij} x_{i} x_{j}$$
(1)

Where Yu represents the corresponding response, e.g. MRR and Ra of the ECM process in the present research. The code values of ith machining parameters for Uth experiment are represented by x_{iu}. The values of n indicate the number of machining parameters. The terms bi, b_{ii} and b_{ii} are the second order regression co-efficient. The second term under the summation sign of this polynomial equation attributes to linear effects, whereas the third term of the above equation corresponds to the higher order effects and lastly the forth term of the equation includes the interactive effects of the parameters. Using this quadratic model of y in this study is not only to investigate over the entire factor space, but also to locate region of desired target where the response approaches its optimum or near optimal value. The necessary data for building the response models are generally collected by the design of experiments. In this study, the collection of experimental data adopts the central composite design (CCD) in order to fit the quadratic model of y. The CCDs are most popular due to the following attributes: (1) CCDs can ruin sequentially; (2) CCDs are efficient, providing information on experiment variable effect on overall experimental error in a minimum number of runs; (3) CCDs are very flexible [10]. The pertinent process parameters selected for the present investigation are electrolyte Concentration (X_1) , electrolyte flow rate (X_2) , applied voltage (X_3) , tool feed rate (X_4) were considered as controlling variables. Their effects on material removal rate (MRR) and surface roughness (Ra) are tested through a set of planned experiments based on central composite second order rotatable design. The levels of each factor were chosen as -2,-1, 0, 1, 2 in closed form to have a rotatable design. For the four variables, the design required 31 experiments with the 16 factorial points, 8 axial points to form a central composite design with $\alpha=2$, 7 centre points. The design was generated and analyzed using MINITAB 14.0 statistical package. Table 1 shows the factors and their levels in coded and actual values. The experiment has been carried out according to the designed experimental based on CCD as depicted in Table 2.

4. Result and discussion

The 31 experiments were conducted and the values of MRR and Ra along with design matrix were tabulated in Table 2. For analysis the data, the checking of goodness of fit of the model is very much required. The model adequacy checking includes test for significance of the regression model, test for significance on model coefficients and test for lack of fit. For this purpose, analysis of variance (ANOVA) is performed.

DARAMETERS	LEVELS				
TANAMETERS	-2	-1	0	+1	+2
Electrolyte Concentration (X_1) , g/lit	10	15	20	25	30
Electrolyte flow rate (X ₂), lit/min	5	6	7	8	9
Applied Voltage (X ₃), (volts)	12	13	14	15	16
Feed rate (X_4) , (mm/min)	0.2	0.4	0.6	0.8	1

Table 1. Experimental parameters and their levels

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Ex.No.	X_1	X_2	X ₃	X_4	MRR g/min	$R_a \mu m$
1	-1	-1	-1	-1	0.0509	4.712
2	1	-1	-1	-1	0.0521	3.143
3	-1	1	-1	-1	0.0548	3.914
4	1	1	-1	-1	0.0546	3.214
5	-1	-1	1	-1	0.0567	3.845
6	1	-1	1	-1	0.0568	3.345
7	-1	1	1	-1	0.0579	3.754
8	1	1	1	-1	0.0581	3.452
9	-1	-1	-1	1	0.0503	3.643
10	1	-1	-1	1	0.0521	3.312
11	-1	1	-1	1	0.0538	3.111
12	1	1	-1	1	0.0546	3.215
13	-1	-1	1	1	0.0558	3.014
14	1	-1	1	1	0.0567	3.158
15	-1	1	1	1	0.0576	2.586
16	1	1	1	1	0.0587	3.555
17	-2	0	0	0	0.0501	4.124
18	2	0	0	0	0.0576	3.567
19	0	-2	0	0	0.0511	4.242
20	0	2	0	0	0.0589	2.891
21	0	0	-2	0	0.0514	3.678
22	0	0	2	0	0.0634	2.873
23	0	0	0	-2	0.0521	3.637
24	0	0	0	2	0.0562	1.819
25	0	0	0	0	0.0569	2.814
26	0	0	0	0	0.0582	2.934
27	0	0	0	0	0.0587	2.611
28	0	0	0	0	0.0576	2.725
29	0	0	0	0	0.0574	2.734
30	0	0	0	0	0.0581	2.912
31	0	0	0	0	0.0589	2.913

Table 2. Experimental design matrix and results

4.1. Analysis of material removal rate

The fit summary recommended that the quadratic model is statistically significant for analysis of MRR. The results of the quadratic model for MRR is given in Table 3. The value of R^2 and

adjusted R^2 are 90.31% and 81.83%. This means that regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (MRR). The associated *p*-value for the model is lower than 0.05 (i.e. $\alpha = 0.05$, or 95% confidence) indicates that the model is considered to be statistically significant. The standard percentage point of F distribution for 99% confidence limit is 7.87. As shown in Table 4 the F- value 5.22 for lack of fit is smaller than the standard value. Thus the lack-of-fit term is significant. In the same manner, the main effect of X₁ (electrolyte concentration), X₂ (electrolyte flow rate), X₃ (applied voltage), X₄ (tool feed rate), second order effect of X₁ (electrolyte concentration), X₂ (electrolyte flow rate) and X₄ (tool feed rate) are significant model terms. The other model terms are can be regard as not significant effect due to their "Prob. > *F*" value greater than 0.05. Figure 1 displays the normal probability plot of the residuals for MRR. It shows the regression model is fairly well fitted with the observed values. Using the results presented in Table 3, the form of the derived model is as follows:

 $MRR = -0.12006 + (0.002112 X_1) + (0.01753 X_2)$

+ $(0.00931X_3)$ + $(0.01989 X_4)$ - $(0.00004 X_{12})$

 $-(0.000744X_{22}) - (0.000144 X_{32}) - (0.02391X_{42})$

 $-(0.000026X_1 X_2) - (0.000016X_1 X_3) + (0.000206X_1 X_4)$

- $(0.000381X_2 X_3) + (0.000281X_2 X_4) + (0.000281X_3 X_4)$

Term	Coefficient	Т	Р
Constant	-0.12006	-1.744	0.100
X1	0.002112	1.815	0.088
X2	0.01753	2.822	< 0.012
X3	0.00931	1.204	0.246
X4	0.01989	0.694	0.498
X_1^2	-0.00004	-4.039	< 0.001
X_2^2	-0.000744	-2.913	< 0.010
X_3^2	-0.000144	-0.563	0.581
X_4^2	-0.02391	-3.745	< 0.002
X _{1*} X ₂	-0.000026	-0.384	0.706
X _{1*} X ₃	-0.000016	-0.238	0.815
$X_{1*} X_4$	0.000206	0.604	0.554
X _{2*} X ₃	-0.000381	-1.117	0.281
$X_{2^{*}} X_{4}$	0.000281	0.165	0.871
X _{3*} X ₄	0.000281	0.165	0.871

(2)

Source of variation	Degree of freedom	Sum of squares	Mean sum of squares	F-value	p-value
Linear	4	0.000019	0.00005	2.60	0.075
Square	4	0.000060	0.000015	8.09	0.001
Interaction	6	0.000003	0.000001	0.31	0.922
Lack of fit	10	0.000003	0.000003	5.22	0.028
Error	6	0.000003	0.000001		
Total	30				

Table 4. Analysis of variance for MRR

Figure 2 exhibits the influence of applied voltage and feed rate on material removal rate (MRR). Increase in applied voltage, passive film formed on the anode surface is get teared and allows more electrochemical reaction, which enhances the chemical dissolution of the matrix material and results in loosening the particles, thus facilitating the removal of the ceramic particles. Under such conditions, a more MRR is obtained [5]. Increase in tool feed rate, interelectrode gap (IEG) becomes narrower, and the resistance between cathode and anode becomes lower [11]. Hence MRR increases.

Figure 3 illustrates the effect of electrolyte concentration and electrolyte flow rate on MRR. Increase in electrolyte concentration, rate of electrochemical action is high [5]. Hence more MRR is obtained. MRR increases with increase in electrolyte flow rate. This due to increase in electrolyte flow rate removes the reaction products from the Inter-electrode gap (IEG) and also fresh electrolyte directed into IEG which increases the conductivity of the electrolyte [12].



Figure 1. Normal probability plot residuals for MRR



Figure 2. Effect of applied voltage and tool feed rate on MRR



Figure 3. Effect of electrolyte concentration and electrolyte flow rate on MRR

4.2. Analysis of surface roughness

For surface roughness, the fit summary recommended that the quadratic model is statistically significant for analysis. The results of the quadratic model for Ra is given in Table 5. The value of R^2 and adjusted R^2 are 91.44% and 83.94%. This means that regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (MRR). The associated *p*-value for the model is lower than 0.05 (i.e. $\alpha = 0.05$, or 95% confidence) indicates that the model is considered to be statistically significant. The standard percentage point of F distribution for 99% confidence limit is 7.87. As shown in Table 6 the Fvalue 5.17 for lack of fit is smaller than the standard value. Thus the lack-of-fit term is significant. In the same manner, the main effect of X_1 (electrolyte concentration), X_2 (electrolyte flow rate), X_3 (applied voltage), X_4 (tool feed rate), second order effect X_1 (electrolyte concentration), X_2 (electrolyte flow rate), X_3 (applied voltage), interaction effect of factor X_1 (electrolyte concentration) and X₂ (electrolyte flow rate), X₁ (electrolyte concentration) and X₄ (tool feed rate) are significant model terms. The other model terms are can be regard as not significant effect due to their "Prob. > F" value greater than 0.05. Figure 4 displays the normal probability plot of the residuals for Ra. It shows the regression model is fairly well fitted with the observed values. Using the results presented in Table 5, the form of the derived model is as follows:

 $Ra = 71.444 - (1.30X_1) - (4.786 X_2)$

 $\begin{array}{l} - (5.016X_3) - (4.7606X_4) + (0.0109 X_{12}) \\ + (0.2037 X_{22}) + (0.131 X_{32}) - (0.147X_{42}) \end{array}$

 $+ (0.0291 X_1 X_2) + (0.0351 X_1 X_3) + (0.2473 X_1 X_4)$

+ $(0.0838 X_2 X_3)$ + $(0.0159 X_2 X_4)$ - $(0.1191 X_3 X_4)$ (3)

Figure 5 displays the effect of applied voltage and tool feed rate on Ra. Ra decreases above 0.3 mm/min of feed rate; it is due to increase in tool feed rate current density in the IEG increases, leads to lower Ra [13]. At low applied voltage, machining current in the IEG is lower, leads to non uniform anodic dissolution. Thus results in pits and slots that are formed by different etching characteristics of grains and grain boundaries due to low current density which is shown in Figure 6. However, at higher zone of applied voltage surface roughness of the machined surface is decreases. It is due to conductivity of electrolyte increases with increase in current density.

Figure 7 exhibits the response contour graph of surface roughness with respect to electrolyte flow rate and electrolyte concentration. Increase in electrolyte concentration surface roughness becomes decreases up to 25 gm/lit, further increase in electrolyte concentration, generation of machined products is more, which changes the property of electrolyte and act as lower concentration leads to higher surface roughness. Increase in electrolyte flow rate surface roughness decreases. This is due to the larger the flow rate is, the more rapidly the electrolytic products and heat can be flushed away from the machining zone and has also been attributed to the successive entrance of a fresh electrolyte into the machining gap[14].

5. Conclusions

The following conclusions can be drawn from the above investigations:

Increase in applied voltage and tool feed rate leads to an increase current density in the interelectrode gap (IEG), and hence MRR increases. With increase in electrolyte concentration and electrolyte flow rate mobility of ions is more which increase the speed of the chemical reaction results more MRR.

With increase in electrolyte concentration Ra decreases up to 25 gm/lit and further increase in electrolyte concentration, the property of the electrolyte changes and act as lower concentration leads to higher surface roughness. With increase electrolyte flow rate the reaction products and gas bubbles generated in the IEG flushes out properly leads to decrease surface roughness.

Term	Coefficient	Т	Р			
Constant	71.44	6.132	< 0.000			
X_1	-1.3083	-6.643	< 0.000			
X ₂	-4.7868	-4.551	< 0.000			
X ₃	-5.0167	-3.832	< 0.001			
X_4	-4.7606	-0.982	< 0.034			
X_{1}^{2}	0.0109	6.328	< 0.000			
X_2^{-2}	0.2037	4.714	< 0.000			
X_3^2	0.1370	3.031	< 0.008			
X_4^2	-0.1470	-0.136	0.893			
$X_{1*} X_2$	0.0291	2.517	< 0.023			
X _{1*} X ₃	0.0351	3.036	0.008			
$X_{1*} X_4$	0.2473	4.28.	< 0.001			
X _{2*} X ₃	0.0838	1.451	0.166			
X _{2*} X ₄	0.0159	0.055	0.957			
X _{3*} X ₄	-0.1191	-0.412	0.686			

 Table 5. Test for significance of Ra

Table 6. Analysis of variance for Ra

Source of variation	Degree of freedom	Sum of squares	Mean sum of squares	F-value	p-value
Linear	4	3.2929	0.8232	15.14	0.000
Square	4	3.3358	0.8339	15.61	0.000
Interaction	6	1.9311	0.3218	6.03	0.002
Lack of fit	10	0.7657	0.07657	5.17	0.029
Error	6	0.0889	0.01482		
Total	30				



Figure 5. Effect of voltage and feed rate on Ra



Figure 6. Pits occur on the surface



Figure 7. Effect of Electrolyte concentration and Electrolyte flow rate on Ra

References

- [1] Zhu, D., Xu, Z., Xu, Q., and Liu, J. 2010. Investigation on the flow field of W-shape electrolyte flow mode in electrochemical machining. *Journal of applied chemistry*, 40: 525-32.
- [2] Neto, J. C. D. S., Silva, E. M. D., and Silva, M. B. D. 2006. Intervening Variables in electrochemical machining. *Journal of Material Processing Technology*, 179: 92-96.
- [3] Asokan, P., Ravi, Kumar, R., Jeyapaul, R., and Santhi, M. 2008. Development of multi-objective optimization models for electrochemical machining process. *International Journal of Advanced Manufacturing Technology*, 39: 55-3.
- [4] Ding, X., Liew, W. Y. H., and Liu, X. D. 2005. Evaluation of machining performance of MMC with PCBN and PCD tools. *Wear*, 259, 7-12: 1225-34.
- [5] Liu, J. W., Yue, T. M., and Guo, Z. N. 2009. Wire electrochemical discharge machining of Al2O3 particle reinforced Aluminum Alloy 6061. *Material Manufacturing Process*, 24: 446-53.
- [6] Kansal, H. K., Sehijpa, S., and Kumar, P. 2005. Parametric optimization of powder mixed electrical discharge machining by response surface methodology. *Journal of Material Processing Technology*, 169: 427-436.
- [7] Kanagarajan, D., Karthikeyan, R., and Palanikumar, K. 2007. Parametric optimization of electro discharge machining characteristics of WC/Co composites by response surface methodology. *Journal of Engineering Manufacture*, 222: 807-815.
- [8] Montgomery, D. C. 1997. "Design and Analysis of Experiments". fourth ed., Wiley, New York.
- [9] Chiang, K. T., Chang, F. P., and Tsai, D. C. 2007. Modeling and analysis of the rapidly resolidified layer of SG cast iron in the EDM process through the response surface methodology. *Journal of Material Processing Technology*, 182: 525-533.
- [10] Kuppan, P., Rajadurai, A., and Narayanan, S. 2006. Experimental investigation into electrical discharge deep hole drilling of Inconel 718 using graphite electrode. *in:Proceedings of the 17th All India machine tool design and research conference, Roorke, Delhi*, 923-927.
- [11] Sarkar, B. R., Doloi, B., and Bhattacharyya, B. 2006. Parametric analysis on electrochemical discharge machining of silicon nitride ceramics. *International Journal of Machine Tools Manufacture*, 28, 9-10: 873-81.
- [12] Sen, M. and Shan, H. S. 2005. Analysis of hole quality characteristics in the electro jet drilling process. *International Journal of Machine Tools Manufacture*, 45:137-52.
- [13] El-Taweel, T. A. 2008. Modelling and analysis of hybrid electrochemical turning magnetic abrasive finishing of 6061 Al/Al2O3 composite. *International Journal of Advanced Manufacturing Technology*, 37: 705-14.
- [14] Pa, P. S. 2008. Design of effective plate-shape electrode in ultrasonic electrochemical finishing. *International Journal of Advanced Manufacturing Technology*, 34, 1-2: 70-8.