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Research paper

Effect of process variables on surface roughness in electrochemical machining of stainless steel 304

Abbas Fadhil Ibrahim [1], Mostafa Adel Abdullah [1], Safaa Kadhim Ghazi [1], O. H. Hassoon [1]*

[1] Metallurgical and Production Engineering Department, University of Technology/Baghdad
**Corresponding author E-mail: 70048@uotechnology.edu.iq*

Abstract

The electrochemical machining process is largely used in industry operations to manufacture components used in automotive, aerospace and medical applications. The optimal conditions of this process can significant reducing the electrochemical machining operating, maintenance cost, tooling, and producing of components with high accuracy. The more requirements of the processes are that work piece must be electrical conduct. Due to various independent variables in this process, difficulties are presented in the chosen and analysis of the experimental results. In this work, the response surface methodology and analysis of variance method are applied to optimize ECM process and to study the more effective parameters (current, inter- electrode gap, and concentration of electrolyte) on surface roughness of stainless steel 304 workpiece. An empirical equation formula is proposed based on the experimental results and the statistical model that used to predict the surface roughness. The R2 (ability the Input variables to prediction the output variables) of the predictive model was 92.6%. The experimental results were shown that the current considered the most effective factor to minimize the Ra, while the electrolyte concentration considered the second affect factor.

Keywords: *ECM; RA; Response Surface Methodology; Stainless Steel.*

1. Introduction

ECM machining is a non-contacting process of electrochemical dissolution that is used for shape the anode material, name the workpiece, the cathode, name the tool, its normally move toward the anode at a constant federate, and the electrolyte is flowed at high speed in the gap to carry away the dissolved material [1]. Electrochemical machining is a method using a current to remove the material from the workpiece. The chemical reaction takes position on the electrode, and the potential difference is applied across the anode and cathode (tool electrode), the material is dissolving from the anode [2].

This process is generally used for machining hard materials and complex shape. Moreover, it not generates burrs, which has a long tool life, no internal stress, higher surface quality, and material removal rate. Electrochemical Machining is an anodic solution process based on the electrolysis phenomenon. The temperature generates during the cutting is dissipating on the tool, the chip of workpiece and environments, affecting the surface shape of the workpiece. Different from other cutting processes, this process works as a noncontact between work-piece and tool. Electrochemical is electrolysis that reaction is responsible for the mechanism of chip removal [3]. On the other hand, response surface methodology applies in the optimization and characterization of processes [4]. The objectives of using response surface methodology are not only to investigate the response over the input factors space, but also locates the region of interest where the response reaches its optimum [5].Jain and Jain used a real-code genetic algorithms to optimize three most important process factors like electrolyte flow velocity, tool feed rate and applied voltage to minimize geometrically inaccuracy to temperature, choking, and passivity constrains [6]. Asokan et al (2008) used grey analysis for optimization of material removal rate and roughness [7]. Chakradhar and Venugopal (2011) implemented a grey relational analysis to optimize the surface roughness and material removal rate, overcut and cylindricity error considering electrolyte concentration, feed, and input voltage, each of three levels [8]. Abbas Fadhil Ibrahim (2016) studied the effect of process factors on material removal rate (MRR) and surface roughness (Ra), and the optimization of process factors in ECM by using Taguchi theory [9]. S Abhijith et al (2018) optimized the surface roughness parameters namely Ra and Rt using the multi-objective optimization methods using Grey Relational Analysis (GRA) and Response Surface Methodology (RSM) in turning Inconel 718. There results indicated that feed rate (70.35%) is the most significant factor influencing on the surface roughness. Other parameters have less influenced on the surface roughness are cutting speed (16.12%), tool wear (9.8%), vibrations (3.4%) and temperature (0.4%) [10].

In this paper, response surface methodology had been used to analyze and plan the experiment. A collection of statistical and mathematical techniques was used to analyze and modeling of problems when a response of interest is influenced by large variables and to get optimization the response. It was considered a sequential experimentation strategy for an empirical model to build and optimize, by conducting experiments and apply regression analysis. Depend on the model of the response, an optimal of the near point can then be concluded.

2. Response surface methodology

The RSM (Response surface methodology) is a model used to determine the relationship between responses and various processes with the factors various desired criteria and search the affect of these process factors on the couple responses [11]. It's a strategy of sequential experimentation for building and optimizes the empirical model. Therefore, response surface methodology is a collection of statistical and mathematical procedures, which were useful for analysis and modeling the problem. This process is done when the response of demand is affected by a number of variables and the objective is to optimize the response [12]. Generally, a mathematical second order polynomial response surface model was used, which analyzed the parametric influence on the various response criteria. This model can be described as follows:

$$Y_u = b_\circ + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x^2{}_i + \sum_{j>1}^{k} b_{ij} x_i x_j \qquad (1)$$

Where Xi (1,2, …, k) are code of value, k quantitative variables and Yu is response. The b_0 is the constant value; the bi, bii, and bij are interaction terms, the linear, and quadratic and to prediction equation, a package program MINITAB17 was used to calculate the coefficients of equation depend on the regression of (RSM).

3. Experimental procedure

In the beginning of the experiment, the initial weight of specimens is measured using a precision electronic balance, Electrochemical machine had been used to analyze the effected of predominant machining factors input voltage, electrolyte concentration, inter-electrode gap and feed used during ECM operation on desired machining quality characteristic, surface roughness and metal removal rate of machined product. The ECM is shown in Figure 1.

The material used in these experiments was stainless steel 304. This alloy has high wear resistance, good strength-to-weight ratio, high corrosion resistance, this alloy widely used in automobiles and the aerospace applications. In this work, copper was as tool electrode material as cathode as shown in Figure 2. Its design as circular shape so as to cutting the cavity in work piece in the same profile shape.

Fig. 1: Electrochemical Machine.

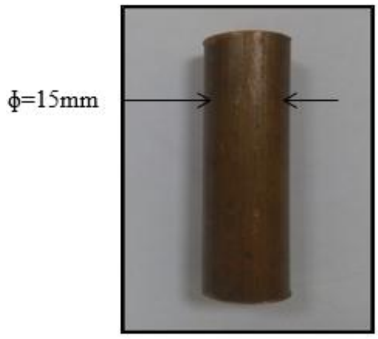

Fig. 2: Tool Used in Experimental Work.

The chemical compositions of workpiece material and tool are presented in Table1 and Table2, which were the test in Central Organization for Standardization and Quality Control. Three independent variables were selected in this work, as shown in table 3.

The electrolytes used for experiment were a fresh solution of sodium nitrate (NaCl) with varying electrolyte concentration. The experiments are conducted by used different factors, and the result was recorded. The surface roughness was measured after every test to comparing the results. The complete working environments of the experiments are shown in Table.3.

Table 1: Material of Workpiece Composition (Stainless Steel 304)

Elements	C %	Si %	Mn%	Cr %	P %	Mo%	S %	Ni %	Al %	Fe %
Carbon steel (1020)	0.615	0.245	0.441	0.907	0.015	0.018	0.005	0.031	0.003	remain

Table 2: Material of Tool Composition (Copper)

Elements	Zn %	P %	Pb %	Sn %	As %	Si %	S %	Cd %	Ag %	Bi %	Sb %	Cu %
Weight %	0.003	0.005	0.004	0.010	0.008	0.013	0.004	0.001	0.002	0.006	0.009	remain

Table 3: Input Parameters of ECM

Parameter	Current (Amp), A	Electrolyte concentration (g/l), B	Inter-electrode gap(mm), C
1	50	25	0.5
2	100	50	1
3	150	75	1.5

4. Results and discussion

12 specimens are being done, and the surface roughness in the design matrix listed in Table 4. For analyzing the data, the goodness of fit for the model and including the test for the effect of the regression model, test for lack of fit and test for significance on model coefficients. Analysis of variance is performed.

Table 4: ECM Parameters According to RSM

No.	Current (amp)	Electrolyte conc. (g/l)	IEG (mm)	Ra measured (µm)	Ra predicted (µm)
1	50	25	0.5	1.74	1.738
2	50	50	1	1.79	1.823
3	50	75	1.5	1.83	1.856
4	100	25	1.5	1.68	1.701
5	100	50	1	1.89	1.904
6	100	75	0.5	1.76	1.725
7	150	25	1	1.94	1.921
8	150	50	1.5	1.62	1.630
9	150	75	0.5	1.68	1.717
10	50	50	1.5	1.74	1.683
11	100	50	0.5	1.72	1.719
12	150	75	1	1.97	1.941

The recommender is the quadratic model is statistically affect for analyzing Ra. The results have shown the Ra is listed in Table 4. The values of R2, adjust R2 are 92.6% and 59.3%. This means that the regression model gave a good explanation of the relationship between the response (Ra) and the independent variables (factors). The associated p-value for the model is lower than 0.05 (i.e. α=005, or 95% confidence) is indicated that the model is considered to be statistically significant. The levels of significance of machining parameters are concluded from the analysis of variance (ANOVA) as shown in Table 5. It is concluded that the current as value (A) is the most affect factor for minimum Ra, and the electrolyte concentration as value (B) is the next factor for minimum Ra.

Table 5: Analysis of Variance for Ra

Source of variation	DOF	SS	Mean sum of squares	F-value	p-value
Linear	3	0.002470	0.000823	0.17	0.907
Square	3	0.082412	0.027471	5.75	0.152
Interaction	3	0.015913	0.005304	1.11	0.506
Error	2	0.009559	0.004779		
Total	11	0.129200			

A statistical model was created by (RSM) using Minitab package. The surface roughness uses to give the value (β0 & β1,…..etc.) from applied RSM in Minitab package which entered in eq.(3). Using this equation to prediction surface roughness, the functions were deriving to represent the prediction surface roughness:

Ra = 1.297 + 0.00735 X1 - 0.01795 X2 + 1.316 X3 - 0.000026 X1 2 + 0.000120 X2 2 - 0.736 X32 - 0.000002 X1*X2 - 0.00174 X1*X3 + 0.00662 X2*X3 (2)

Where (Ra) is the predicted surface roughness. It was also apparent that Intel electrode gap (x3) was the most significant machining parameter and influence surface roughness (Ra) in equation (2). The relationship between predicted and measured of Ra was shown in Figure 3, this shows that the efficiency response surface method use predicting the variables by multiple regression model. In Figure4, show the normal probability drawing of the residuals response for surface roughness. Checking on this plot in Figure reveal.

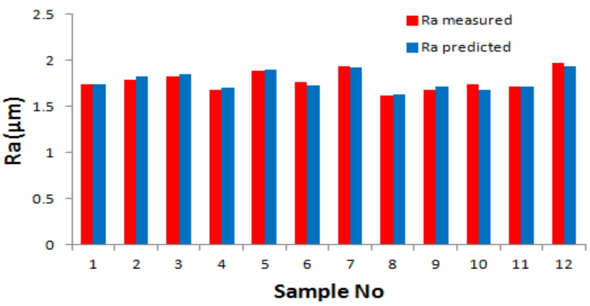

Fig. 3: Bar Chart of the Measured and Predicted Surface Roughness.

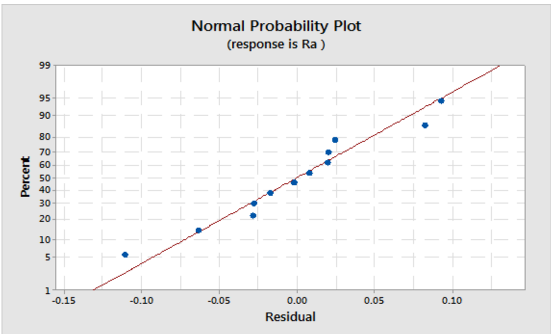

Fig. 4: Normal Probability Using for Response Surface Roughness.

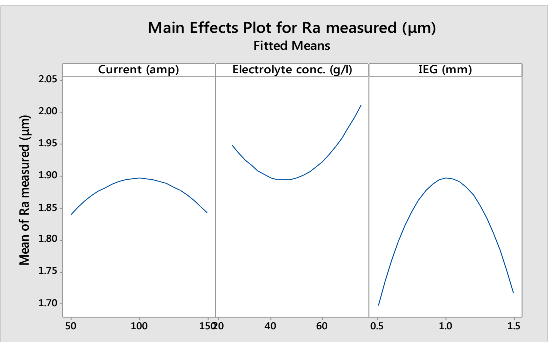

Fig. 5: Main Effects Plot for Measured Surface Roughness.

By using the developed cubic model, the plots between current, electrolyte, IEG and surface roughness have been generated in Figure 5. Influence these parameters on surface roughness with constant other parameters are shown in Figure5. The surface roughness was increasing with increasing current, electrolyte concentration and IEG.

5. Conclusion

1) The surface roughness prediction was effectively method by applying current, concentration, intel electrode gap by using Minitab package.
2) The R2 (ability the input variables to prediction the output variables) of the predictive model is 92.6%.
3) The currents are the most effect factor for minimum Ra, and the electrolyte concentration is the next effect factor for minimum Ra.

The surface roughness of the workpiece is increase with increasing inter-electrode gap.

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