MODELING AND OPTIMIZATION OF ELECROCHEMICAL MACHINING OF 321-STAINLESS STEEL USING RESPONSE SURFACE METHODOLOGY

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Abstract: *This paper demonstrates a systematic approach for achieving comprehensive mathematical models for electrochemical machining (ECM) of 321-stainless steel based on the response surface methodology (RSM). Machining voltage, tool feed rate, electrolyte flow rate and concentration of NaNO3 solution were considered as the machining parameters while material removal rate (MRR) and surface roughness (Ra) were considered as the process responses. Experimental plan was performed by a central composite design (CCD). The proposed mathematical models statistically have been evaluated by analysis of variance (ANOVA). Analysis shows that the RSM method has been appointed properly as the design of experiments (DOE) method for resolving curvature in ECM process responses. Also, the optimal machining parameter for single optimization of MRR and Ra is determined by desirability function. The results showed that the proposed approach is an effective and suitable way for modeling and optimization of the ECM machining process.*

Keywords: ELCTROCHEMICAL MACHINING, MODELING, OPTIMIZATION, RESPONSE SURFACE METHODOLOGY, DESIRABILITY FUNCTION

1. Introduction

ECM is a modern and non-traditional machining contributing significantly in various industries from consumer product to more sophisticated, high-tech applications and to produce micro to macro scale products. Moreover, ECM gives advantages over other conventional and non-conventional machining processes. As a case in point, conductive materials regardless of their hardness and toughness can be machined with a tool which is not harder than workpiece; there is especially no tool wear. In view of the fact that in this cold process there is no contact between cathode and anode, products without any residual stress and heat affected zone (HAZ) can be machined (Rumyantsev and Davydov, 1989; Rajurkar et al., 2006; Huang and Liu, 2014).

Even though traditional methods for conducting experiments such as trial-and-error, best-guest approach and one variable at a time (OVAT) still common (Neto et al., 2006; Bhattacharyya and Munda, 2003), these methods are time consuming and incapable of detecting the interactions between variables (Montgomery, 2009). Thus, implementation of design-of-experiments (DOE) method has increased in various manufacturing processes (El-Taweel 2008; Haridy et al. 2011). Response surface methodology, RMS, is capable of resolving curvature in the output associated with each input, detecting interactions effects and establishing mathematical models with suitable sets of experiments (Bhattacharyya and Sorkhel, 1999; Malapati and Bhattacharyya, 2011; Munda and Bhattacharyya, 2008; Munda et al., 2007).

However, the ECM process involves several physical and chemical phenomena and a number of process parameters that make it difficult to model the process (Hinduja and Kunieda, 2013). Consequently, experimental investigations, DOE, statistical and optimization approaches play a vital part in selection of proper selection of parameters setting which influence the machining performance considerably (Venkata Rao and Kalyankar, 2014).

There are researches that had been investigated this process experimentally and offer some excellent results and approaches for modeling and predicting machining conditions; still, much more experimental studies must be conducted to cover wide range of materials and methods for optimization and improving machining performance. The purpose of this research is mathematically modeling ECM process parameters, i.e. machining voltage (x_1), tool feed rate (x_2), electrolyte flow rate (x_3) and electrolyte concentration (x_4) on machining criteria, i.e. MRR and Ra of 321stainless steel. This kind of steel contains titanium which making it an excellent choice for prolonged high temperature applications such as aircraft exhaust stacks, manifolds, welded equipment, jet engine parts and so on. Response surface methodology (RSM) is also used for correlating and analyzing the various machining parameters on the response; therefore, mathematical models develop through RSM. In addition, the adequacy of the developed mathematical models has also been tested by the analysis of variance (ANOVA). Finally, optimal machining parameters for achieving maximum MRR and minimum Ra are determined.

2. Experimental procedure and details

2.1. Set-up and machine

The experiments were carried out on home-developed machine. This machine was set up in this investigation shows in Fig. 1 consists of four well-designed units, i.e. machine, electrolyte, control and power supply unit. The tool feeds forwards and backwards using the AC servo motor through a ground precision ballscrew with pitch of 2.5 mm and precision linear guides. Machining place was built by Plexiglas with a door provided more convenience for changing the workpiece. All used connectors, valves and hose made of 316 stainless steel, PVC and polyethylene; thus, the electrolyte composition does not change moving through these parts. Two PVC tanks have duty for supplying and storing electrolyte. Main pump with 3-ph AC motor and inverter provide setting electrolyte flow rate with help of ultrasonic flowmeter. Another magnetic pump used for draining electrolyte form storing tank to main supplying tank through filters. Output of power supply is 30 volt and 100 ampere.

Fig. 1 *The ECM machine.*

2.2. Materials and measurements

Fig. 2 displays workpiece and tool with their fixtures in the machining chamber. Thirty-one 321stainless steel bars 8 mm in diameter specimens were used as workpiece for runs and Table 1 presents the weight percentage of chemical composition for the workpiece material. Commercial cylindrical copper with the same diameter as workpiece were also employed as tool. As long as experiments conducted in stable conditions and with uniform initial gap distance, workpiece and tool were grinded and deburred to remove any possible surface irregularities to guarantee an even and parallel surfaces.

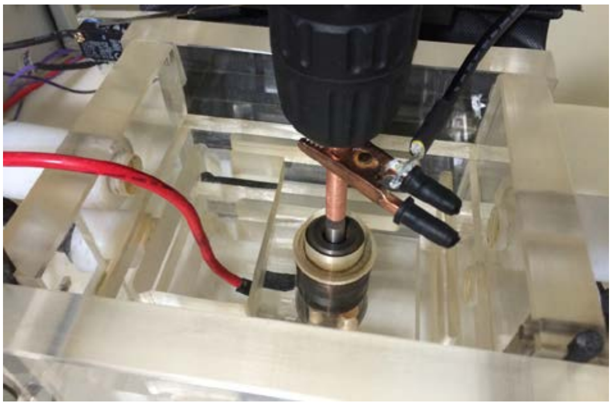

***Fig. 2** machining chamber with workpiece and tool.*

The experiments were carried out in NaNO3 solution electrolyte with various concentrations. The electrolyte flow system used in cross and planning method to ensure an effective flushing during machining. The weight of workpiece was measured before and after machining by a precision weighing machine (0.0001g) for calculating the material removal rate (MRR). The arithmetic mean roughness (Ra) was employed to evaluate surface roughness of specimens. This measurement was performed with the help of surface tester SJ-210-MITUTOYO. The cut-off length and measuring speed were set as 0.8 mm and 0.5mm/s respectively.

***Table 1:** Chemical composition (%wt) of the 321 stainless steel*

Fe	C	Mn	Si	S	P
Rem	0.045	1.66	0.479	0.014	0.034
Cr	**Ni**	**Cu**	**Mo**	**Co**	**Ti**
18.05	8.81	0.59	0.64	0.169	0.227

3. Design of experiments (DOE)

3.1. Experimental plan and conditions

The machining was carried out for a fixed time interval of 2 min and an initial gap distance was 0.6 mm. In the present study, the experimentation strategy was considered based on central composite second order rotatable design (CCD) for the purpose that the higher-order input parameters effects and their interactions on machining responses were determined. The values of four process inputs and their levels are shown in Table 2. Therefore, the design consists of 31 runs, in which 16 factorial points, 8 axial points, 7 center points for estimating the experimental error and the central composite parameter α was considered 2 to ensure a rotatable design Table 3 presents the values of machining responses, i.e. MRR and Ra according to experimentation plan with various sets of machining parameters, i.e. voltage (x1), tool feed rate (x2), electrolyte flow rate (x3) and electrolyte concentration (x4).

3.2. Response Surface Methodology (RSM)

In this research, Response Surface Methodology (RSM) was applied, as one of DOE methods, for determining how the machining parameters influence machining responses. RSM is a powerful way for building the relationship between machining parameters and responses that are useful for the modeling and analysis of the problems; accordingly, the relationship mathematically and statistically could be developed by second-order polynomial as follows:

$$y = b_0 + \sum_i^k b_i x_i + \sum_i^k b_{ii} x_i^2 + \sum_i \sum_j b_{ij} x_i x_j + \varepsilon \qquad (1)$$

Where y is the desired response, e.g. MRR and Ra in this paper, xi is the uncoded or coded levels of the independent variables, and ε is the fitting error. Also, the coefficient b0 is the constant value or intercept and the coefficients bi, bii and bij represent the linear, quadratic and interaction terms respectively (Myers and Montgomery, 1995).

***Table 2:** The independent ECM process factors and their levels*

Factors	Symbol	Unit	Levels				
			-2	-1	0	1	2
Voltage	x_1	**V**	**10**	**15**	**20**	**25**	**30**
Tool feed rate	x_2	**mm/min**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**
Electrolyte flow rate	x_3	**l/min**	**5**	**6**	**7**	**8**	**9**
Electrolyte concentration	x_4	**g/l**	**50**	**100**	**150**	**200**	**250**

4. Design of experiments (DOE) Validation and analysis of models

Adequate and suitable measures, tests and analyses were examined the models, so the fitness of the models to the experimental data, significant and insignificant parameters and adequacy of models were analyzed; that is, the analysis of variance (ANOVA) and the F-ratio test have been executed to check the goodness of the mathematically modeled fittings. Moreover, the R-squared (R-Sq) and adjusted R-squared (R-Sq(adj)) is used for assessing the modeling goodness of fit, as more the R2 approaches unity, the better the model fits the experimental data. Indeed, the best condition of analysis of effective models happens as the lack-of-fit is insignificant. Then, a student’s t-test has also been performed for determining the significance of each parameter in the models. Accordingly, insignificant terms have been eliminated from the models, and ANOVA has been done again through the available significant terms. In addition, a complete residual analysis has been done through normal probability plot of residuals, plot of residuals versus fitted values and plot of residuals against the order of experimentations in order that the quality of fit for the responses and adequacy of models have been examined.

5. Results and discussion

5.1. Mathematical modeling of MRR

According to the model explained by Eq. 1, Table 4 details the ANOVA and F-ratio test information about MRR response. On the grounds that the p-value of the quadratic model is greatly less than 0.05, the model is statistically significant in the 95% of confidence interval. Besides, the p-value of the lack-of-fit is more than 0.05, so this term is insignificant which is desired. Through the ANOVA result, the MRR model is developed with coded variables as follows:

$$\begin{aligned} MRR = & -0.3374 + 0.0055x_1 - 0.0496x_2 + 0.0755x_3 + 0.00072x_4 \\ & -1.4494E-05x_1^2 + 0.2275x_2^2 - 0.00551x_3^2 - 2.50494E-06x_4^2 \\ & +0.00049x_1x_2 + 5.875E-05x_1x_3 + 3.4875E-05x_1x_4 + 0.0073x_2x_3 \\ & -2.0875E-04x_2x_4 + 9.125E-06x_3x_4 \end{aligned} \qquad (2)$$

The R2 (R-Sq) and adjusted R2 (R-Sq(adj)) are respectively 99.45% and 99.25% for the above MRR model which ensuring an excellent fitting for the model.

Table 3: *Central composite design plan matrix and results*

Exp No.	Factors				Responses	
	x_1	x_2	x_3	x_4	MRR (g/min)	Ra(μm)
1	-1	-1	-1	-1	0.1253	0.76
2	1	-1	-1	-1	0.2134	1.08
3	-1	1	-1	-1	0.1547	0.89
4	1	1	-1	-1	0.2361	1.13
5	-1	-1	1	-1	0.1246	0.84
6	1	-1	1	-1	0.2107	1.16
7	-1	1	1	-1	0.1569	0.96
8	1	1	1	-1	0.2525	1.31
9	-1	-1	-1	1	0.1673	1.29
10	1	-1	-1	1	0.2921	1.94
11	-1	1	-1	1	0.1975	1.63
12	1	1	-1	1	0.3218	2.21
13	-1	-1	1	1	0.1779	1.47
14	1	-1	1	1	0.2979	2.15
15	-1	1	1	1	0.2019	1.78
16	1	1	1	1	0.3235	2.49
17	-2	0	0	0	0.1154	1.22
18	2	0	0	0	0.3379	2.17
19	0	-2	0	0	0.1989	1.12
20	0	2	0	0	0.2755	1.51
21	0	0	-2	0	0.1927	1.12
22	0	0	2	0	0.2194	1.35
23	0	0	0	-2	0.1365	0.72
24	0	0	0	2	0.2696	2.45
25	0	0	0	0	0.2351	1.00
26	0	0	0	0	0.2291	0.98
27	0	0	0	0	0.2250	1.02
28	0	0	0	0	0.2238	0.96
29	0	0	0	0	0.2220	1.04
30	0	0	0	0	0.2275	0.95
31	0	0	0	0	0.2232	1.02

Table 4: *The ANOVA results for MRR response using the Minitab software*

Source of variation	DF	Sum of Squares	Mean Squares	F value	P value
Regression	14	0.103873	0.007419	219.16	0.000
Linear	4	0.100478	0.025120	742.00	0.000
Square	4	0.002148	0.000537	15.85	0.000
Interaction	6	0.001216	0.000208	6.14	0.002
Residual Error	16	0.000542	0.000034		
Lack-of-Fit	10	0.000419	0.000042	2.06	0.195
Pure Error	6	0.000122	0.000020		
Total	30	0.104414			
R-Sq = 99.45%, R-Sq(adj) = 99.25%					

A student's t-test has also been performed for determination of significant terms in the model. Based on the t values and their p values shown in Table 5, it is concluded that all the linear terms (input parameters, i.e. x_1: voltage, x_2: feed rate, x_3: flow rate and x_4: electrolyte concentration), quadratic terms of input factors x_2, x_3 and x_4, and interaction effect of factors x_1 and x_4 are significant and other terms are insignificant. The insignificant terms have been eliminated, and the ANOVA has again been done to significant terms. As a result, the final reduced model of MRR based on significant parameters in terms of coded factors is developed as follows:

$$MRR = -0.35879 + 0.00549x_1 - 0.02305x_2 + 0.08043x_3 + 0.00069x_4 + 0.23137x_2^2 - 0.00547x_3^3 - 2.48952E\text{-}06x_4^4 + 3.48750E\text{-}05x_1x_4 \quad (3)$$

Table 5: *The T-test results for MRR response including all parameters using the Minitab software*

All Term	Coefficient	SE coefficient	T value	P-value
x_1	0.053621	0.001188	45.148	0.000
x_2	0.016204	0.001188	13.644	0.000
x_3	0.003796	0.001188	3.196	0.006
x_4	0.032163	0.001188	27.080	0.000
$x_1 * x_1$	-0.000362	0.001188	-0.333	0.743
$x_2 * x_2$	0.002275	0.001188	2.091	0.053
$x_3 * x_3$	-0.005512	0.001188	-5.066	0.000
$x_4 * x_4$	-0.006262	0.001188	-5.755	0.000
$x_1 * x_2$	0.000244	0.001455	0.168	0.869
$x_1 * x_3$	0.000294	0.001455	0.202	0.843
$x_1 * x_4$	0.008719	0.001455	5.994	0.000
$x_2 * x_3$	0.000731	0.001455	0.503	0.622
$x_2 * x_4$	-0.001044	0.001455	-0.718	0.483
$x_3 * x_4$	0.000456	0.001455	0.314	0.758

Next, a complete residual analysis has been performed for evaluating the quality of fit for the yielded MRR response. Normal probability plot of residuals in Fig. 3 shows that experimental data are located approximately along a straight line; that is, the experimental values correlate closely with the predicted values for the response.

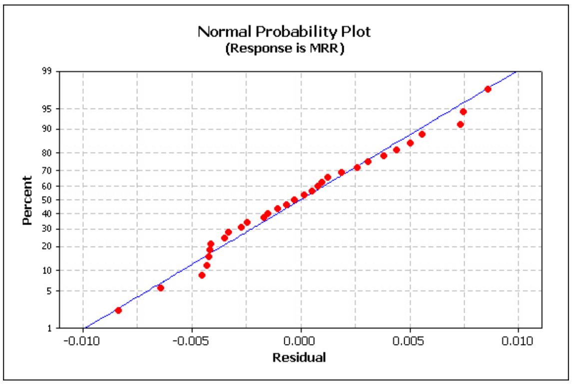

Fig. 3 *Normal probability plot of Residuals for MRR*

The plot of residuals versus fitted values is shown in Fig. 4 indicates that only small variations can be seen. Also, it is clearly observed form the plot of residual versus order of the experimentation, Fig. 5, that residuals are independent of one another and both negative and positive residuals exist in this plot indicate no special tendency. Hence, the presented discussion implies that the above MRR model does not show any inadequacy.

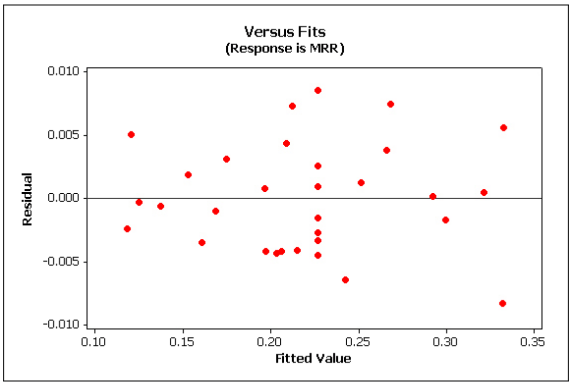

Fig. 4 *Residuals versus Fits for MRR*

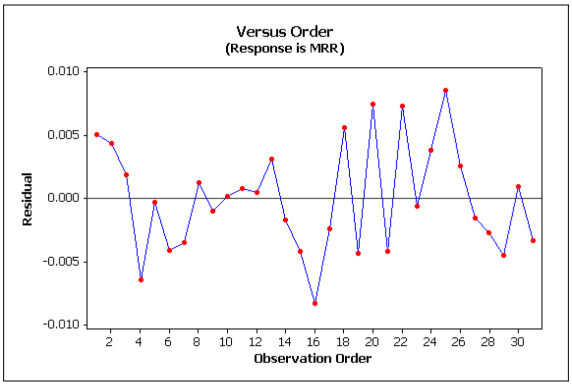

Fig. 5 *Residuals versus Observation Order for MRR*

5.2. Mathematical modeling of Ra

The same procedure is used to deal with the Ra and the ANOVA details of quadratic model are shown in Table 6. The results of the table points out that the model is significant and the lack-of-fit is insignificant according to the p-values. Based on the ANOVA result, the developed mathematical model for Ra with coded variables as follows:

$$
\begin{aligned}
Ra = {} & 8.75714 - 0.29921x_1 - 7.01905x_2 - 0.91042x_3 - 0.0234x_4 \\
& + 0.0069x_1^2 + 7.74256x_2^2 + 0.05743x_3^2 + 5.79702\text{E-}05x_4^2 \\
& - 0.01125x_1x_2 + 0.00338x_1x_3 + 0.00035x_1x_4 + 0.08125x_2x_3 \\
& + 0.01013x_2x_4 + 0.00051x_3x_4 \qquad (4)
\end{aligned}
$$

Table 6: *The ANOVA results for Ra response using the Minitab software*

Source of variation	DF	Sum of Squares	Mean Squares	F value	P Value
Regression	14	7.73831	0.55274	648.07	0.000
Linear	4	6.16678	1.54170	1807.59	0.000
Square	4	1.39314	0.34828	408.35	0.000
Interaction	6	0.17839	0.02973	34.86	0.000
Residual Error	16	0.01365	0.00085		
Lack-of-Fit	10	0.00688	0.00069	0.61	0.767
Pure Error	6	0.00677	0.00113		
Total	30	7.75195			
R-Sq = 99.82%, R-Sq(adj) = 99.67%					

The R2 and adjusted-R2 for the Ra trimmed model are respectively 99.82% and 99.67% revealing sufficient adequacy in model predictive capabilities.

The student's t-test has also been done for determining the significance of each parameter. The results in Table 7 indicates that all linear and quadratic terms of parameters and the interaction between x_1 (voltage) and x_3 (flow rate), x_1 and x_4 (concentration), x_2 (tool feed rate) and x_4, and x_3 and x_4 are significant. The other model terms can be regard as insignificant terms. By removing these insignificant terms and applying the ANOVA, the proper quadratic model for Ra can be developed as follows:

$$
\begin{aligned}
Ra = {} & 8.61964 - 0.303714x_1 - 6.6753x_2 - 0.87792x_3 - 0.0234x_4 \\
& + 0.0069x_1^2 + 7.74256x_2^2 + 0.05743x_3^2 + 5.79702\text{E-}05x_4^2 + 0.00338x_1x_3 \\
& + 0.00035x_1x_4 + 0.01013x_2x_4 + 0.00051x_3x_4 \qquad (5)
\end{aligned}
$$

Table 7: *The T-test results for Ra response including all parameters using the Minitab software*

All Term	Coefficient	SE coefficient	T value	P-value
x_1	0.239583	0.005961	40.190	0.000
x_2	0.103750	0.005961	17.404	0.000
x_3	0.070417	0.005961	11.812	0.000
x_4	0.428750	0.005961	71.922	0.000
$x_1 * x_1$	0.172426	0.005461	31.572	0.000
$x_2 * x_2$	0.077426	0.005461	14.177	0.000
$x_3 * x_3$	0.057426	0.005461	10.515	0.000
$x_4 * x_4$	0.144926	0.005461	26.537	0.000
$x_1 * x_2$	-0.005625	0.007301	-0.770	0.452
$x_1 * x_3$	0.016875	0.007301	2.311	0.034
$x_1 * x_4$	0.086875	0.007301	11.899	0.000
$x_2 * x_3$	0.008125	0.007301	1.113	0.282
$x_2 * x_4$	0.050625	0.007301	6.934	0.000
$x_3 * x_4$	0.025625	0.007301	3.510	0.003

Like before, a complete residual analysis has been done presented in the Figs. 6, 7 and 8. Similarly, the Ra model does not show any inadequacy.

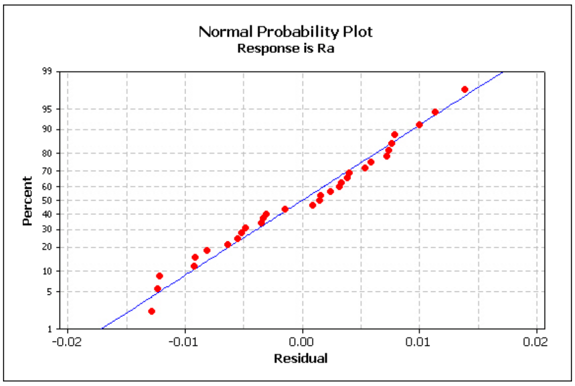

Fig. 6 *Normal probability plot of Residuals for Ra*

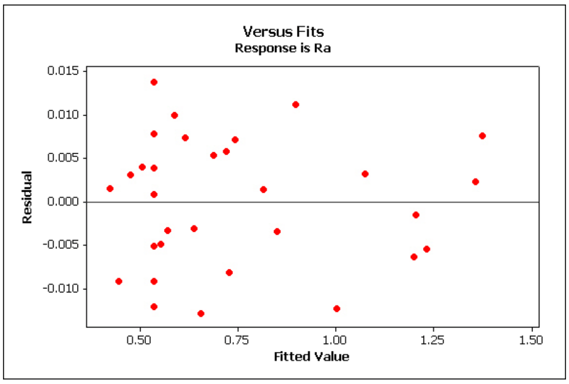

Fig. 7 *Residuals versus Fits for Ra*

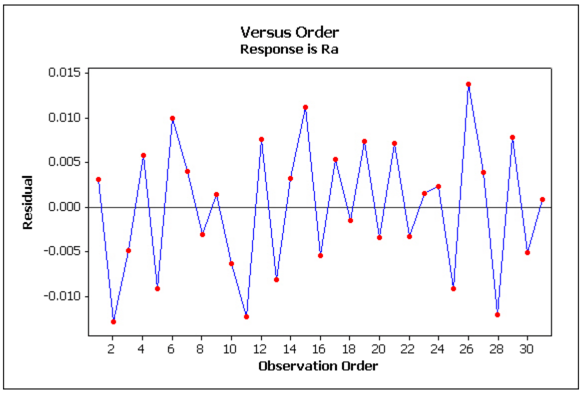

Fig. 8 *Residuals versus Observation Order for Ra*

5.3. Optimization by desirability functions

This desirability function approach developed by Derringer and Suich [16] is an attractive search-based optimization technique used to find the optimal parameters combination globally. This technique uses a desirability function as an objective function in which each response yi is transformed to an individual desirability function (di) between zero and one. That is, one indicates that the response is the completely desirable value (at its target), and zero shows that the response is the least desirable value (outside of its acceptable limits). Thus, the overall (composite) desirability (D) is determined by the geometric mean of the individual desirability functions as follows:

$$D = (d_1 d_2 ... d_n)^{1/n} = \left[\prod_{i=1}^{n} (d_i) \right]^{\frac{1}{n}} \qquad (6)$$

Where n is the number of responses. Also, the individual desirability function di will be defined depending on whether the response yi is to be maximized, minimized, or assigned a target value.

The goal of optimization in this article is to find maximum MRR (productivity) and minimum surface roughness (Ra). The optimization results were obtained by Minitab 16 software. According to the results of optimization, 30 V voltage, 0.6 mm/min tool feed rate, 7.34 l/min electrolyte flow rate, and 250 g/l concentration is the optimal machining parameters setting for achieving maximum MRR. Similarly, 18.28 V voltage, 0.38 mm/min tool feed rate, 6.74 l/min electrolyte flow rate, and 84.34 g/l concentration is the optimal machining parameters combination for achieving minimum Ra.

6. Conclusion

This study highlights that the electrochemical machining of 321 stainless steel criteria, i.e. MRR and Ra are greatly influenced by the different machining parameters. To sum up, the followings can be acquired from this investigation as main findings:

1. For gaining the model that covers all linear, quadratic and interaction terms, the RSM method has been appointed properly as the DOE method for solving curvature in ECM process responses.
2. Mathematical models have been developed through the RSM method for correlation the machining parameters, i.e. voltage, tool feed rate, electrolyte flow rate and concentration on the machining criteria, i.e. MRR and Ra, of 321stainless steel.
3. According to the ANOVA among the process parameters, the machining voltage and electrolyte concentration are the most effective factors on the machining criteria.
4. Increasing voltage and electrolyte concentration lead to increase in the MRR. Also, the proper flushing of electrolyte improves MRR which can be regulated by the electrolyte flow rate.
5. According to the optimization results, 30 V voltage, 0.6 mm/min tool feed rate, 7.34 l/min electrolyte flow rate, and 250 g/l concentration is the optimal machining parameters setting for maximum MRR, and 18.28 V voltage, 0.38 mm/min tool feed rate, 6.74 l/min electrolyte flow rate, and 84.34 g/l concentration is minimum Ra.

7. Acknowledgment

The authors would like to thank the Iran National Science Foundation (INSF) for financial support of this research.

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