MODELING AND PARAMETER OPTIMIZATION IN ELECTROCHEMICAL MACHINING PROCESS: APPLICATION OF DUAL RESPONSE SURFACE-DESIRABILITY APPROACH

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***Abstract*— Selection of appropriate machining parameters which result in desired outcomes plays a key role in effective utilization of the electrochemical machining (ECM) process. In this paper, in order to correlate between ECM process parameters and cost functions, comprehensive mathematical models were first determined based on response surface methodology (RSM). Voltage, tool feed rate, electrolyte flow rate and concentration of $NaNO_3$ solution were considered as the machining parameters while material removal rate (MRR) and surface roughness (R_a) were considered as cost functions. To do this, three scenarios of machining performances, $R_a \leq 0.9\mu m$, $0.9\mu m \leq R_a \leq 1.8\mu m$, and $1.8\mu m \leq R_a \leq 2.7\mu m$, were considered for optimization search based on desirability functions. The goal is to find the optimum set of machining parameters in order to maximize the MRR while keeping R_a in specified ranges simultaneously. The results show that the errors between experimental and anticipated optimal values are less than 8.16% and hence confirm the effectiveness of the proposed approach.**

***Keywords*— Desirability function, electrochemical machining, modeling, optimization, response surface methodology**

I. INTRODUCTION

Electrochemical machining (ECM) is a non-traditional machining, which has significant applications in various industries from consumer products to more sophisticated, high-tech applications such as micro to macro scale products.

Moreover, ECM has advantages over other machining processes. for instance, conductive materials, regardless of their hardness and toughness, can be machined with a tool, which is not harder than the workpiece and without tool wear (Rumyantsev and Davydov, 1989).

However, the ECM involves several physical and chemical phenomena and a number of process parameters that make it difficult to model (Hinduja and Kunieda, 2013). As a result, experimental investigations, design of experiments (DOE), statistical and optimization approaches play a vital part in the selection of the proper set of parameter (Rao and Kalyankar, 2014; Yusup *et al*., 2012).

There are researches that had investigated this process experimentally and offered some excellent results; still, more experimental studies is required to cover a wide range of materials and methods for the optimization and improvement of the machining performances (Rao and Kalyankar, 2014). Thus, implementation of design-of-experiments (DOE) method has increased in various manufacturing processes (Montgomery, 2009; Singh *et al.* 2010).

Response surface methodology (RSM), a DOE method, is capable of resolving curvature in the output associated with each input, detecting interactions' effects and establishing mathematical models with suitable sets of experiments (Sivaprakasam *et al*., 2013; Assarzadeh and Ghoreishi, 2013).

There are some researches in the ECM processes for single objective optimization (Munda *et al*., 2007; Bähre *et al*., 2013). In addition, advanced optimization techniques have been used so that the optimal conditions of ECM processed can be sought and proposed (Asokan *et al*., 2008; Senthilkumar *et al.*, 2010; Samanta and Chakraborty, 2011; Mukherjee and Chakraborty, 2013).

According to the number of researches conducted on the optimization of machining processes, it is concluded that fewer works dealt with the ECM process than other machining processes (Rao and Kalyankar, 2014). On the other hand, most of the studies conducted for the optimization of the ECM process, are based on single objective optimization (Rao and Kalyankar, 2014). However, it is of desire to have a method that leads to obtain the comprehensive global set of optimal parameters.

The purpose of this research is to propose a reliable approach for process optimization and modeling of the ECM process, therefore a dual response surface-desirability approach has been applied for process optimization. To do this, mathematical models were first established based on response surface methodology (RSM). Then, desirability function is applied as a search optimization procedure.

The goal is to maximize material removal rate (MRR) while keeping the surface roughness (R_a) to its minimum amount within a predefined range. These responses would not be optimized in the same manner and have conflicting behaviors, so a single combination of machining parameters cannot be determined as the only optimal solution. As a result, three scenarios of machining performance, according to the predefined surface roughness, are considered, and the responses have been optimized simultaneously. Finally, the obtained optimal sets of parameters were verified experimentally, and their results approve the effectiveness and feasibility of the proposed approach.

II. EXPERIMENTAL WORK

A. Set-up and machine

The experiments were carried out on a home-developed machine (Fig. 1). The tool is moved forward and backward using the AC servo motor through a ground precision ballscrew with a pitch of 2.5 mm and two precision linear guides. Machining place, built by Plexiglas with a door, provides more convenience for changing the workpiece. Figure 2 displays the workpiece and the tool with their fixtures in the machining place. All used connectors, valves and hoses are made of 316 stainless steel, PVC and polyethylene; thus, the electrolyte composition does not change while flowing through these parts. The main pump supplied with 3-ph AC motor and an inverter provide the capability to set the electrolyte flow rate with the help of ultrasonic flowmeter. Output of power supply is 30 V and 100 A DC current.

B. Materials and measurements

Thirty-one 321-stainless steel bars 8 mm in diameter were used as the workpiece. Commercially available cylindrical copper with the same diameter as workpiece was also used as the tool. Whereas the experiments must be conducted in stable conditions with uniform initial gap distance, workpiece and tool were grinded and deburred to remove any possible surface irregularities to guarantee even and parallel surfaces. The experiments were carried out in $NaNO_3$ electrolyte solution with various concentrations. The electrolyte flow system was used in cross and planning method to ensure an effective flushing during machining. The weight of the workpiece was measured before and after machining by a precise weighing machine (0.0001g) to calculate the material removal rate (MRR). The arithmetic mean roughness (R_a) was employed to evaluate the surface roughness of the specimens. This measurement was performed through using surface tester SJ-210-MITUTOYO. The cut-off length and measuring speed were set at 0.8 mm and 0.5mm/s, respectively.

Fig. 1. The ECM machine.

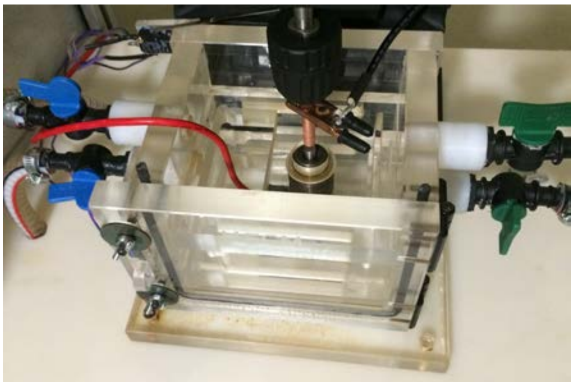

Fig. 2. Machining place with workpiece and tool.

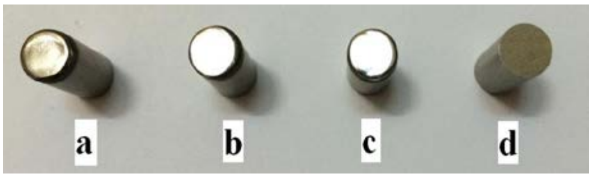

Fig. 3. Workpiece after machining: (a). run 10; (b). run 13; (c). run 18; (d). before machining

Table 1. The independent ECM process factors and their levels.

Factors	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
flow rate (x_3, l/min)	5	6	7	8	9
Concentration (x_4, g/l)	50	100	150	200	250

C. Experimental plan and conditions

The machining was carried out for a fixed time interval of 2 min; the initial gap distance was set at 0.6 mm. In the present study, the experimentation strategy was considered based on the central composite second order rotatable design (CCD) so 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 1. Therefore, the design consists of 31 runs, in which 16 factorial points, 8 axial points, and 7 center points for estimating the experimental error. The central composite parameter α was considered 2 to ensure a rotatable design.

Table 2 presents the values of machining responses, i.e. MRR and R_a according to experimentation plan. Fig. 3 shows the sample workpieces before and after machining.

III. RESPONSE SURFACE METHODOLOGY (RSM)

In this research, RSM was applied as a design of experiment (DOE) method to determine how the machining parameters influence the machining responses. RSM is a powerful way for establishing the relationship between input parameters and responses which is useful for the modeling and analysis of the problems; the relationship could be mathematically and statistically developed by second-order polynomial as follows (Myers and Montgomery, 1995):

Table 2. Central composite design plan matrix and results.

Exp. No.	Factors				Responses	
	x_1	x_2	x_3	x_4	MRR (g/min)	R_a (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 3. The T-test for MRR response including all parameters using the Minitab software

Terms	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

$$y = b_0 + \sum_{i}^{k} b_i x_i + \sum_{i}^{k} b_{ii} x_i^2 + \sum_{i} \sum_{j} b_{ij} x_i x_j + \varepsilon \tag{1}$$

where y is the desired response, e.g. MRR and R_a in this paper, x_i is the levels of the independent variables, and ε is the fitting error. Coefficient b_0 is the constant value or intercept and coefficients b_i, b_{ii} and b_{ij} represent the linear, quadratic and interaction terms, respectively (Myers and Montgomery, 1995).

A. Mathematical modeling of MRR

The same procedure has been applied for the modeling of the machining criteria, MRR and R_a, with machining parameters based on the RSM.

Therefore, the analysis of variance (ANOVA) and t-test have been executed to establish model. Also, the fitness of the model to the experimental data, significant and insignificant parameters and adequacy of model were analyzed.

Table 4. The ANOVA results for MRR response without insignificant parameters using the Minitab software

Source of variation	DF	Sum of Squares	Mean Squares	F value	P value
Regression	8	0.103873	0.012980	494.83	0.000
Linear	4	0.100478	0.025120	957.65	0.000
Square	3	0.002142	0.000714	27.23	0.000
Interaction	1	0.001216	0.001216	46.37	0.000
Residual Error	22	0.000577	0.000026		
Lack-of-Fit	16	0.000455	0.000028	1.39	0.359
Pure Error	6	0.000122	0.000020		
Total	30	0.104414			
R-Sq = 99.45%, R-Sq(adj) = 99.25%					

Moreover, the R-squared (R-Sq) and adjusted R-squared (R-Sq.(adj)) are used for assessing the modeling goodness of fit. The more the R^2 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.

Next, insignificant terms have been eliminated from the models, and ANOVA has already been done again through the available significant terms (dual response surface).

In this way, Table 3 shows the t-test results for the MRR regression model. It is concluded that all the linear terms, 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; the ANOVA have again been done to significant terms; the results are shown in Table 4. The p-value of the quadratic model is much less than 0.05, so 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. As a result, the final reduced model of MRR based on significant parameters is developed as follows:

$$\begin{aligned} MRR = &-0.35879 + 0.00549x_1 - 0.02305x_2 + 0.08043x_3 \\ &+ 0.00069x_4 + 0.23137x_2^2 - 0.00547x_3^3 - 2.48952E\text{-}06x_4^4 \\ &+ 3.48750E\text{-}05x_1x_4 \end{aligned} \tag{2}$$

The R^2 (R-Sq) and adjusted R^2 (R-Sq(adj)) are respectively 99.45% and 99.25% for the above MRR model ensuring an excellent fitting for the model. Normal probability plot of residuals in Fig. 4 show that experimental data are located approximately along a straight line; that is, the experimental values correlate closely with the predicted values for the response.

B. Mathematical modeling of R_a

The same procedure is used to deal with the R_a. The student's t-test (Table 5) has also been done for determining the significance of each parameter. Therefore, 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 regarded as insignificant terms.

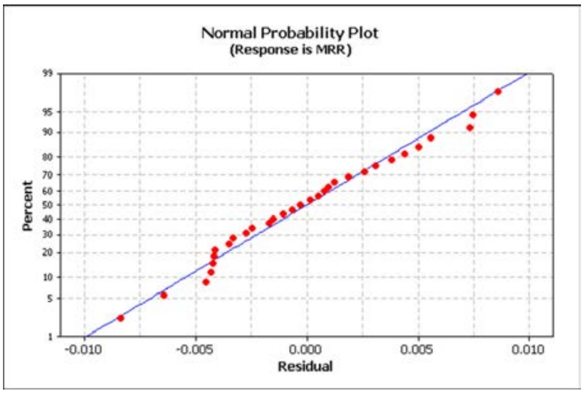

Fig. 4. Normal probability plot of Residuals for MRR

Table 5. The T-test results for R_a response including all parameters using the Minitab software

Terms	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

By removing these insignificant terms and applying the ANOVA, the proper quadratic model for R_a can be developed as follows:

$$\begin{aligned} Ra = {} & 8.61964 - 0.303714x_1 - 6.6753x_2 - 0.87792x_3 - 0.0234x_4 \\ & + 0.0069x_1^2 + 7.74256x_2^2 + 0.05743x_3^2 + 5.79702E\text{-}05x_4^2 \\ & + 0.00338x_1x_3 + 0.00035x_1x_4 + 0.01013x_2x_4 + 0.00051x_3x_4 \end{aligned} \quad (3)$$

The ANOVA details of reduced R_a model are shown in Table 6. Consequently, the model is significant while the lack-of-fit is insignificant. The R^2 and adjusted-R^2 for the R_a trimmed model are respectively 99.80% and 99.67% revealing sufficient adequacy in model predictive capabilities. Like before, normal probability plot of residuals in Fig. 5 are nearly linear.

IV. OPTIMIZATION, RESULTS AND DISCUSSION

A. Desirability approach

This approach developed by Derringer and Suich (1980) 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 y_i is transformed to an individual desirability function (d_i) 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 (Castillo *et al.*, 1996):

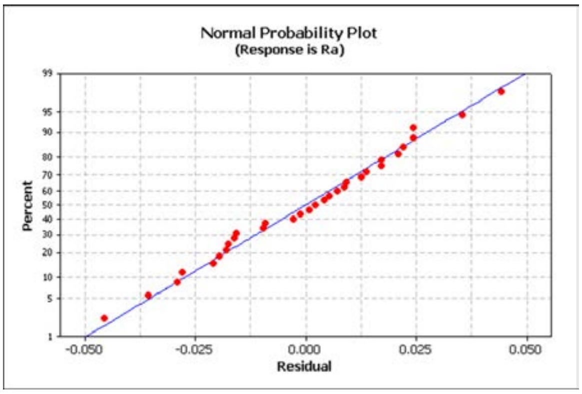

Fig. 5. Normal probability plot of Residuals for Ra

Table 6. The ANOVA results for R_a response without insignificant parameters using the Minitab software

Source of variation	DF	Sum of Squares	Mean Squares	F value	P value
Regression	12	7.73675	0.64473	763.05	0.000
Linear	4	6.16678	1.54170	1824.62	0.000
Square	4	1.39314	0.34828	412.20	0.000
Interaction	4	0.17682	0.04421	52.32	0.000
Residual Error	18	0.01521	0.00084		
Lack-of-Fit	12	0.00844	0.00070	0.62	0.772
Pure Error	6	0.00677	0.00113		
Total	30	7.75195			
R-Sq = 99.80%, R-Sq(adj) = 99.67%					

$$D = (d_1 d_2 \ldots d_n)^{1/n} = \left[\prod_{i=1}^{n} (d_i)\right]^{\frac{1}{n}} \quad (4)$$

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

B. Optimization formulation

The goal of the optimization in the ECM process is to maximize the MRR and minimize the surface roughness (R_a).However, these objectives are conflicting in nature; therefore the determination of the single combination of the machining parameters for response optimization is impossible.

Thus, in this paper, three scenarios of surface roughness are considered. The goal is to achieve the highest possible material removal rate (MRR) while keeping the R_a to its minimum possible at each scenario. Hence, the optimization problem of the ECM process is formulated as bellow:

$$\begin{aligned} & Max: G(x) = MRR \\ & Subject\ to: H(x) = Ra \le Ra_{\max} \\ & Side\ \ CONSTRAINTS: \ 10 \le x_1 \le 30 \\ & \qquad\qquad 0.2 \le x_2 \le 0.6 \\ & \qquad\qquad 5 \le x_3 \le 9 \\ & \qquad\qquad 50 \le x_4 \le 250 \end{aligned} \quad (5)$$

C. Optimization of the ECM process and analysis

As previously mentioned, three different values, 0.9, 1.8, and 2.7 µm, have been selected for maximum limits of surface roughness at each scenario, and accordingly maximum MRR have been determined. Consequently, two desirability functions, d_1 and d_2 have been appointed for the MRR and R_a, respectively. The optimization results were obtained by Minitab 16 software. Optimization results for these three described scenarios are shown in Figs. 6-8.

In Figs 6-8, each column of plots represents a process parameter and each row represents the responses, i.e., performance measures. Also, the first row shows the range of input machining parameters and their optimal values located between the upper and lower bounds (red values) of four machining input parameters. Moreover, the first column represents the composite desirability, individual desirability and optimal values of the MRR and R_a responses (blue values). Also, the vertical lines (red lines) inside the cells represent current optimal set of parameters whereas the dotted horizontal lines (blue lines) represent the current response values.

Also in Figs 6-8, each cell in the MRR and the Ra rows illustrates how the response varies with the changes in one machining parameter as the other parameters remain constant. These cells of the figures demonstrate that the MRR increases with an increase in the voltage, tool feed rate and electrolyte concentration. A higher voltage and electrolyte concentration results higher current in machining gap, thus increasing the material dissolutions. Also, the higher tool feed rate creates a smaller inter electrode gap (IEG), so the electrical current increases. Furthermore, for achieving proper flushing along the IEG, the electrolyte flow rate, approximately in the middle level, is the best condition for both responses. On the contrary, below the middle level of voltage, tool feed rate and electrolyte concentration cause more localized dissolution and reduce the height of valleys and peaks in the surface decreasing the surface roughness.

Figure 6 shows the result of optimization in the first scenario. Therefore, the middle level of voltage, tool feed rate and electrolyte flow rate, 20 V, 0.4 mm/min and 7 l/min, respectively and 137.8 g/l electrolyte concentration are the optimal machining input parameters in this scenario. The results of optimal conditions in the second scenario are depicted in Fig. 7. 23.3 V, 0.6 mm/min tool feed rate, 6.5 l/min electrolyte flow rate, and 158 g/l concentration are the optimal machining parameter settings in this scenario. Finally, optimal machining parameters combination, 30 V, 0.5 mm/min tool feed rate, 6.97 g/l electrolyte flow rate, and 175.6 g/l concentration are shown in Fig. 8 for the third scenario.

The overall and individual desirability functions in all of these figures are in the highest values 1, which indicate the existence of global optimum points in each case (Derringer and Suich, 1980).

D. Confirmation experiments

In this section, new experiments were conducted with the optimum machining parameters of these regimes. Table 7 summarizes simulated and actual values of responses. It is observed that the maximum percentage relative errors for MRR and R_a are below 5.86 and 8.16 %, respectively. This confirms excellent predictability and reproducibility of the proposed approach.

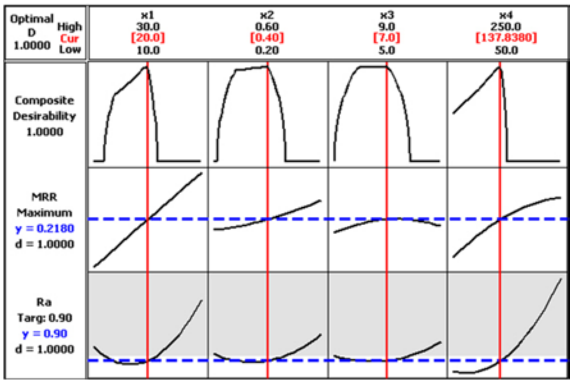

Fig. 6. Optimization results for first regime ($R_a \leq 0.9$)

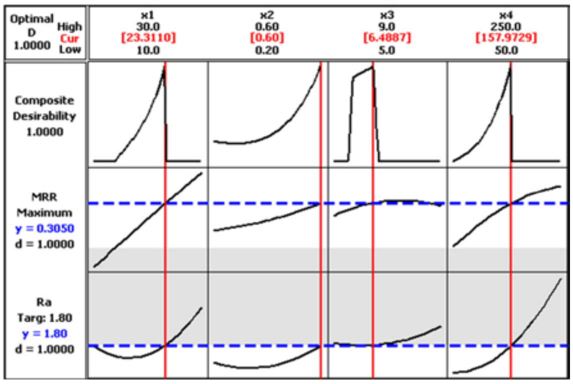

Fig. 7. Optimization results for second regime ($0.9 \leq Ra \leq 1.8$)

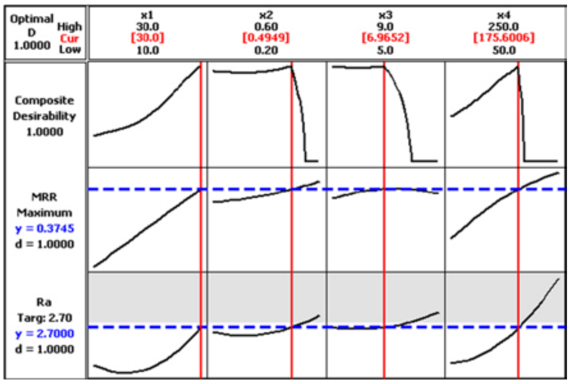

Fig. 8. Optimization results for third regime ($1.8 \leq R_a \leq 2.7$)

Table 7. Results of confirmation experiments

regime	MRR		R_a		error (%)	
	Exp.	Opt.	Exp.	Opt.	MRR	R_a
First regime	0.228	0.218	0.98	0.9	4.39	8.16
Second regime	0.324	0.305	1.93	1.8	5.86	6.74
Third regime	0.386	0.375	2.57	2.7	2.85	5.06

V. CONCLUSIONS

The main contribution of this research is to establish a reliable approach for the process optimization and modeling of the ECM. In brief, a dual response surface-desirability approach was applied for this matter. The main outcomes are as follow:

1. All the linear terms, quadratic terms of tool feed rate, electrolyte flow rate and concentration, and interaction effect of factors voltage and concentration are significant terms in the MRR response. See Section III and Tables 3-4.

2. All linear and quadratic terms of parameters and the interaction between voltage and flow rate, voltage and concentration, tool feed rate and electrolyte flow rate, electrolyte flow rate and concentration are significant terms in the R_a response. See Section III and Tables 5-6.
3. According to the ANOVA and t-test, among the process parameters, the machining voltage and electrolyte concentration are the most effective factors.
4. Increasing voltage, tool feed rate and electrolyte concentration lead to an increase in the MRR. In addition, the proper flushing of electrolyte improves MRR, which can be regulated by the electrolyte flow rate.
5. Below the middle level of the voltage, tool feed rate and electrolyte concentration, causes a decrease in the surface roughness. It means, suitable flushing of electrolyte enhances the surface roughness.
6. The results of verification experiments for each scenario showed 5.86 and 8.16 % as the maximum percentage of relative errors for MRR and R_a, respectively. Thus, the desirability function-based optimization technique proves to be an effective and robust approach in finding optimal parameters related to the predefined desired machining performance.

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