

**INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH  
TECHNOLOGY****SURFACE ROUGHNESS PREDICTION MODEL FOR ELECTRO CHEMICAL  
MACHINING OF SS-304 STEEL USING RESPONSE SURFACE METHODOLOGY****Vivek Kumar**

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**ABSTRACT**

In this article an attempt has been made to develop a surface roughness prediction model in electrochemical machining of SS-304 using response surface methodology. The relationship between surface roughness and input factors has been developed in the form of cubic polynomial in terms of type of electrolyte, voltage and current using response surface methodology (RSM) based on face centered center composite rotatable design (CCRD). The model thus obtained is improved using Box-Cox transformation. An attempt has also been made to investigate the influence of different electro chemical machining parameters on surface roughness. The result shows that the electrolyte is the main parameter that affects the surface roughness while the voltage and flow rate also affect the surface roughness to some extent.

**KEYWORDS:** MRR, Response surface methodology, Box COX transformation**I. INTRODUCTION**

Electrochemical machining (ECM) is among an important machining process in machining difficult-to-cut materials and shaping complicated contours and profiles at high MRR with good surface finish [1]. In this machining process tool doesn't wear out and the process does not induce residual stress in the workpiece as there is no physical contact between the tool and the workpiece. In this machining process the workpiece is made anode and tool is made cathode and controlled anodic dissolution takes place at the workpiece in the presence of an electrolyte. The process is just the reverse of electrolysis and is based on Faraday's laws of electrolysis. In this process, a low voltage (8-30V) is given between electrodes and a small gap of the order of 0.1 to 1 mm is maintained between tool and workpiece creating a high current density and a metal removing rate of the order of 6-600 mm/hr.

In the last few decades, number of attempts have been made to formulate mathematical relationship to predict the effect of different parameters on surface roughness and material removal rate etc. Neto et al. have studied the effect of the intervening variables in electrochemical machining with two different electrolytes. They found feed rate as the main parameter influencing the MRR [2]. A software has been developed by Bortels et al. to solve the ECM problem through boundary element method (BEM) [3]. Abuzied et. al. have presented artificial neural networks to predict output response like surface roughness and material removal rate based on variation of variation of input variables like applied voltage, feed rate and electrolyte flow rate [4]. Kozak et al. have proposed a concept based on computer aided engineering to select optimal input parameters [5]. Kao et al. have optimized electrochemical polishing of stainless steel by applying grey relational approach [6]. Acharya et al. have developed an empirical relationship to predict material removal rate and surface roughness in ECM of super alloys using RSM [7]. Goswami et. al. have optimized MRR and surface roughness in electrochemical machining of aluminum and MS through Taguchi methodology [8]. Basak and Ghosh [9] have established a simple mathematical model to predict Material removal rate during ECDM operation on glass materials. Chakradhar et al. [10] have studied the effect of process parameters in electrochemical machining of EN 31 using grey relation analysis.

The present work deals with the investigation of effect of process parameters on surface roughness in electrochemical machining of SS-304 stainless steel. The response surface methodology based on face centered central composite design has been utilized to develop cubic model for surface roughness prediction in order to identify the critical parameters affecting the material removal rate most. The Box Cox power transformation was employed further to increase the accuracy of the developed model.

## II. MATERIALS AND METHODS

To achieve the objective of this research study electro chemical machining of SS304 has been done by using cylindrical copper electrode. The parameters used in the process were voltage, type of electrolyte and electrolyte flow rate. The experimental design matrix obtained through response surface methodology has been utilized to study the effect of three independent parameters on surface roughness. Out of these parameters flow rate and voltage are numeric factor whereas electrolyte type is a categoric factor. The input parameters and their levels are presented in Table 1. The surface roughness is measured as average CLA value using Taylor Hobson surface roughness tester

**Table 1: Factors and their levels as per face centered central composite design**

Process Parameters	Type	Levels		
Voltage(V)	Numeric	10	14	18
Electrolyte flow rate (lit/min)	Numeric	4	6	8
Electrolyte	Categoric	Nacl	NaNO <sub>3</sub>	-

In present work, a total of 26 experiments have been conducted (13 sets each for NaCl and NaNO<sub>3</sub>) based on face centered central composite design of RSM. The design matrix along with surface roughness values is shown in Table 2.

**Table 2: Design matrix as per face centered central composite design of RSM along with surface roughness**

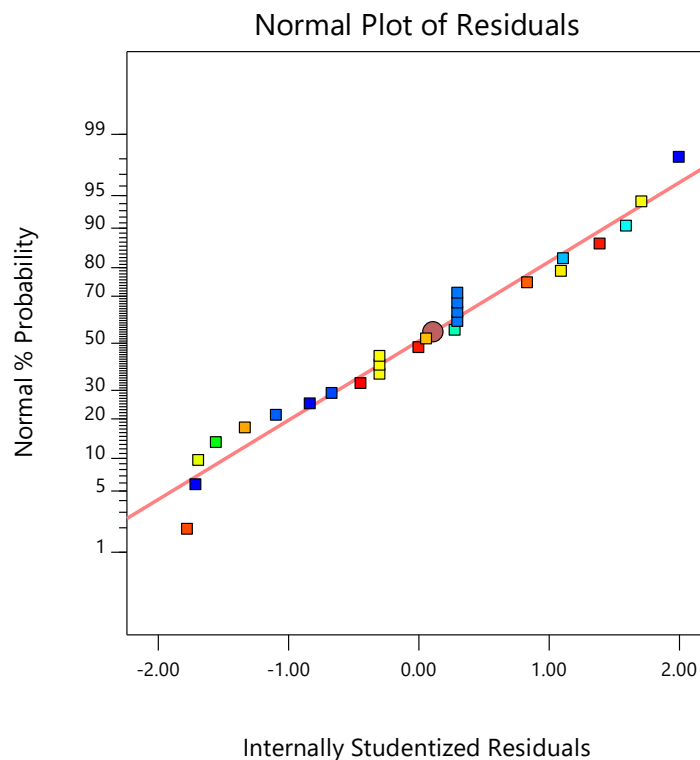
Standard Order	Run Order	Independent Process Parameters			Surface Roughness, R <sub>a</sub> (μm)
		A: Voltage (V)	B: Electrolyte Flow Rate (ltr/min)	C: Type of Electrolyte	
9	1	14	7	NaCl	3.9
4	2	18	8	NaCl	4.7
21	3	14	8	NaNO <sub>3</sub>	0.7
6	4	18	7	NaCl	3.9
7	5	14	6	NaCl	4.6
19	6	18	7	NaNO <sub>3</sub>	0.7
2	7	18	6	NaCl	4.3
15	8	18	6	NaNO <sub>3</sub>	1.5
10	9	14	7	NaCl	3.9
22	10	14	7	NaNO <sub>3</sub>	1.2
25	11	14	7	NaNO <sub>3</sub>	1.2
24	12	14	7	NaNO <sub>3</sub>	1.1
1	13	10	6	NaCl	4.9
16	14	10	8	NaNO <sub>3</sub>	1
14	15	10	6	NaNO <sub>3</sub>	2.8
13	16	14	7	NaCl	3.8
18	17	10	7	NaNO <sub>3</sub>	1.8
8	18	14	8	NaCl	4.9
26	19	14	7	NaNO <sub>3</sub>	1.2
3	20	10	8	NaCl	5
17	21	18	8	NaNO <sub>3</sub>	0.7
5	22	10	7	NaCl	4.2
20	23	14	6	NaNO <sub>3</sub>	2.1
23	24	14	7	NaNO <sub>3</sub>	1.2
12	25	14	7	NaCl	4
11	26	14	7	NaCl	3.9

### III. ANALYSIS OF VARIANCE

The results of experiments done as per the design matrix is given in Table 2. Further analysis of the results is performed through design expert software. ANOVA (analysis of variance) analysis is performed normally to test the significance of model, individual terms and to test the lack of fit of the proposed model. The normal probability plot of the residuals is presented in Figure 1 to test the feasibility of ANNOVA assumptions. The normal probability is generally used as indicator to predict whether the residual follows normal distribution or not. Lying of maximum no. of points falls on the straight line indicates the normal distribution of the residuals. Figure 1 is indicating normal distribution of the residuals except few points which are not falling on straight line, and thus the residuals are not completely follow the normal distribution. Table 3 presents the ANOVA table for reduced cubic model for surface roughness using backward elimination to remove insignificant terms of the model. The analysis has been performed for confidence interval of 95%. The table indicates that p-value for the model is less than 0.0001 (less than 0.05) and thus satisfying the condition of significant model. The cubic regression model for surface roughness in terms of coded factors is given by Eq. 1

$$R_a = 2.55 - 0.325 \times A - 0.266667 \times B - 1.37143 \times C + 0.1625 \times AB - 0.125 \times AC - 0.4 \times BC + 0.075 \times A^2 + 0.5 \times B^2 + 0.0875 \times ABC - 0.261905 \times B^2C \quad (1)$$

The result obtained from the above model of Eq. (1) can be improved by using Box Cox transformation. This process involves a family of transformations to make the data normalize by finding an exponent  $\lambda$ . Figure 2 shows the Box Cox plot for power transformation. In this plot the blue line shows the current value of lemdu ( $\lambda$ ) and green line indicates the best recommended value of lemdu ( $\lambda$ ) as 1.2.



*Figure 1: Normal probability plot of residuals for surface roughness*

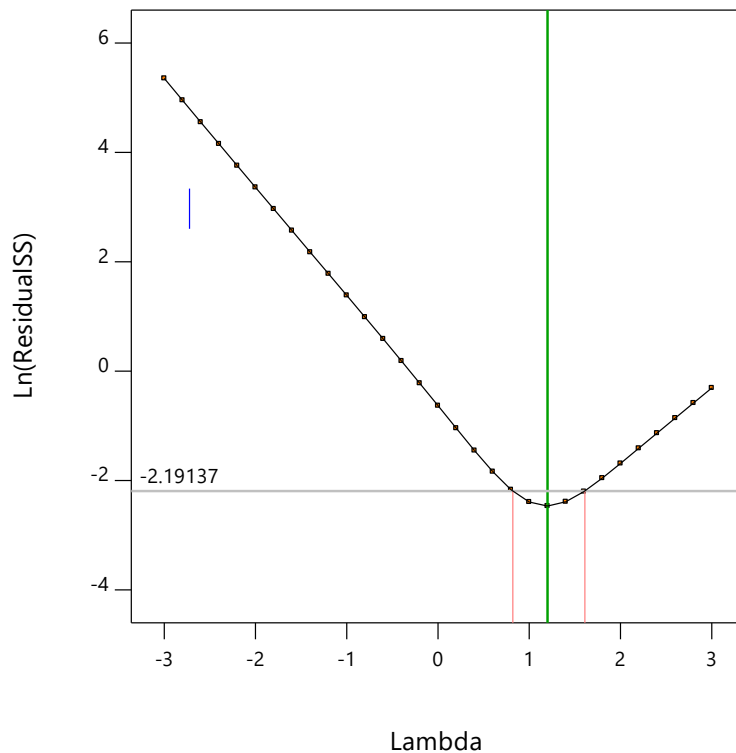
Table 4 Shows the ANNOVA for the reduced cubic model for surface roughness after Box–Cox transformation. The p value for the model is still less than 0.0001 showing that the model is still significant after applying the Box Cox transformation. The lack of fit is also insignificant. The final cubic model after applying Box Cox transformation for surface roughness in terms of coded factors is given in Eq. (2) as

$$R_a^{1,2} = 3.18797 - 0.456767 \times A - 0.324499 \times B - 1.96727 \times C + 0.243567 \times AB - 0.132312 \times AC - 0.542046 \times BC + 0.115448 \times A^2 + 0.783003 \times B^2 + 0.122769 \times ABC - 0.446251 \times B^2C \quad (2)$$

The above equation is useful for examining the relative impact of the parameters by comparing there coefficients.

**Table 3: ANOVA for reduced cubic model**

Source	Sum Squares	df	Mean Square	F-value	p-value	
<b>Model</b>	64.68	10	6.47	1055.69	< 0.0001	significant
A-Voltage	1.27	1	1.27	206.87	< 0.0001	
B-Electrolyte Flow Rate	0.8533	1	0.8533	139.27	< 0.0001	
C-Type of Electrolyte	26.33	1	26.33	4297.62	< 0.0001	
AB	0.2113	1	0.2113	34.48	< 0.0001	
AC	0.1875	1	0.1875	30.60	< 0.0001	
BC	1.92	1	1.92	313.37	< 0.0001	
A <sup>2</sup>	0.0311	1	0.0311	5.07	0.0397	
B <sup>2</sup>	1.38	1	1.38	225.39	< 0.0001	
ABC	0.0613	1	0.0613	10.00	0.0064	
B <sup>2</sup> C	0.4432	1	0.4432	72.34	< 0.0001	
<b>Residual</b>	0.0919	15	0.0061			
Lack of Fit	0.0639	7	0.0091	2.61	0.1014	not significant
Pure Error	0.0280	8	0.0035			
<b>Cor Total</b>	64.77	25				

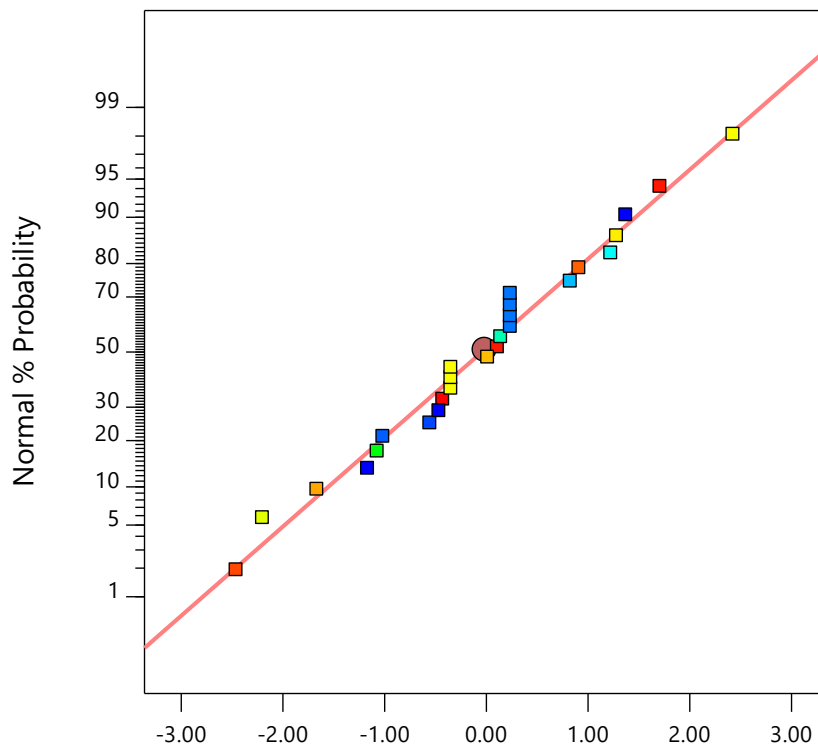


**Figure 2: Box Cox plot for power transformation**

Figure 3 presents the normal distribution plot for residuals for surface roughness with the Box Cox transformation and now one can easily observe that most of the points now fall on the straight line indicating normal distribution of the residuals.

**Table 4: ANNOVA for cubic model with Box Cox transformation**

Source	Sum of Squares	df	Mean Square	F-value	p-value	
<b>Model</b>	136.67	10	13.67	1200.12	< 0.0001	significant
A-Voltage	2.50	1	2.50	219.84	< 0.0001	
B-Electrolyte Flow Rate	1.26	1	1.26	110.95	< 0.0001	
C-Type of Electrolyte	54.18	1	54.18	4757.67	< 0.0001	
AB	0.4746	1	0.4746	41.67	< 0.0001	
AC	0.2101	1	0.2101	18.45	0.0006	
BC	3.53	1	3.53	309.59	< 0.0001	
A <sup>2</sup>	0.0736	1	0.0736	6.46	0.0225	
B <sup>2</sup>	3.39	1	3.39	297.37	< 0.0001	
ABC	0.1206	1	0.1206	10.59	0.0053	
B <sup>2</sup> C	1.29	1	1.29	112.99	< 0.0001	
<b>Residual</b>	0.1708	15	0.0114			
Lack of Fit	0.1090	7	0.0156	2.02	0.1734	not significant
Pure Error	0.0618	8	0.0077			
<b>Cor Total</b>	136.85	25				



Externally Studentized Residuals

**Figure 3: Normal probability plot of residuals for surface roughness with Box Cox transformation**

#### IV. RESULT AND DISCUSSION

To examine the influence of input parameters like voltage, flow rate and type of electrolyte on MRR, the plots between these parameters and surface roughness have been generated using the developed cubic model and are shown in Figures (4). Influence of voltage, flow rate and electrolyte on surface roughness keeping other parameters constant is shown in Figure (4). Keeping other parameters constant, the surface roughness decreases with voltage and first decreases and then increase with flow rate.

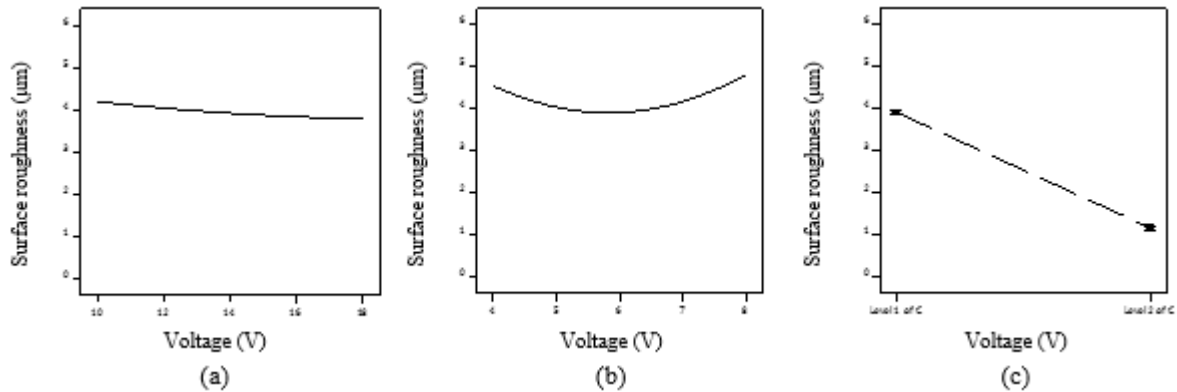


Figure 4: Variation of surface roughness with varying a) Voltage b) Electrolyte flow rate and c) Type of Electrolyte

Figure 5 shows interaction of voltage and electrolyte flow rate with NaCl as electrolyte. Following facts have been observed from this plot: (1) The surface roughness value,  $R_a$  decreases with voltage. The rate with which surface roughness changes, increases with decrease in flow rate. (2) The effect of flow rate on surface roughness is also noticed from the vertical space between curves corresponding to different flow rates, and the maximum effect appears at minimum voltage.

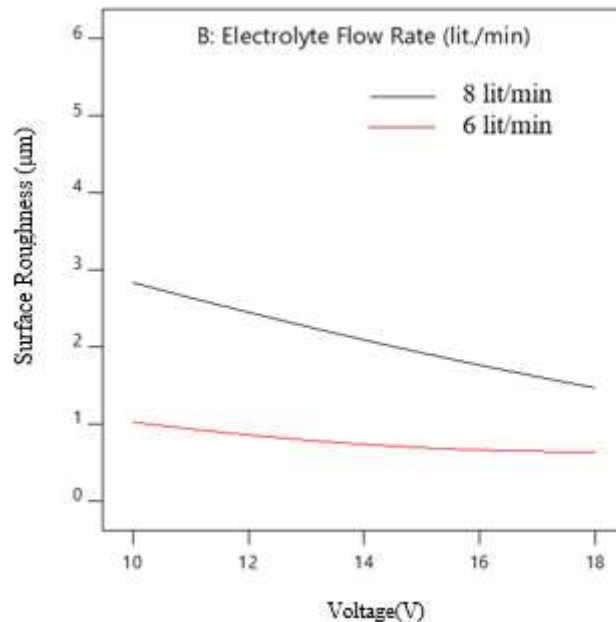


Figure 5: Interaction plot of voltage and electrolyte flow for surface roughness

Figure 6 shows interaction of voltage and electrolyte type and electrolyte flow rate at 6 lit/min. Following facts have been observed from this plot: (1) The surface roughness value decreases with voltage. The rate with which surface roughness changes, decreases with decrease in flow rate.

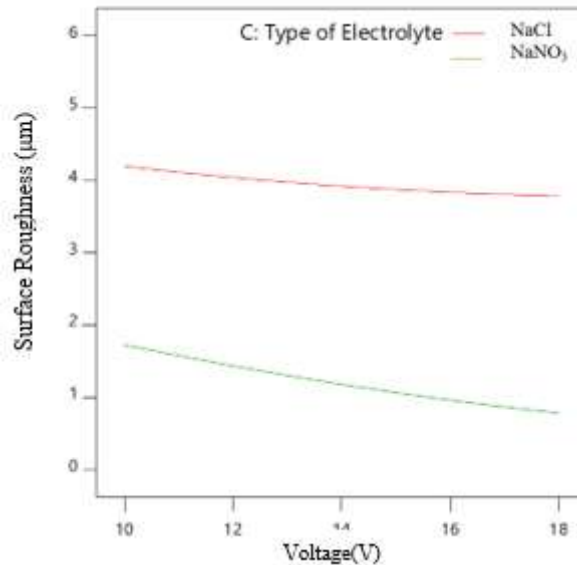


Figure 6: Interaction plot of voltage and electrolyte type for surface roughness

## V. CONCLUSION

The present paper is aimed to investigate the effect of input parameters on surface roughness in electro chemical machining of SS 304 steel. Response surface methodology has been utilized to obtain empirical relationship between ECM parameters and surface roughness. This relationship has been developed in the form of a cubic model in terms of electrolyte, voltage and current using response surface methodology (RSM) based on face centered center composite rotatable design (CCRD) and is improved using Box-Cox power transformation. Following conclusions have been drawn from the present study:

- The electrolyte has been found as the most influencing factor for surface roughness. The surface roughness has been improved with NaNO<sub>3</sub> in comparison to that obtained with NaCl.
- The voltage and electrolyte flow rate have also been observed as the significant parameters and affects the surface roughness up to some extent.
- The results evidently demonstrate surface roughness value increases with increase in flow rate and decreases with increase in voltage.

## VI. REFERENCES

- [1] Kozak, J., & Zybura-Skrabalak, M. (2016). Some problems of surface roughness in electrochemical machining (ECM). *Procedia CIRP*, 42, 101-106.
- [2] Da Silva Neto, J. C., Da Silva, E. M., & Da Silva, M. B. (2006). Intervening variables in electrochemical machining. *Journal of Materials Processing Technology*, 179(1-3), 92-96.
- [3] Bortels, L., Purcar, M., Van den Bossche, B., & Deconinck, J. (2004). A user-friendly simulation software tool for 3D ECM. *Journal of materials processing technology*, 149(1-3), 486-492.
- [4] Abuzied, H. H., Mohamed, A. A., & Hesham, A. S. "Prediction of electrochemical machining process parameters using artificial neural networks." *International Journal on Computer Science and Engineering* 4.1 (2012): 125.
- [5] Kozak, J., Dabrowski, L., Lubkowski, K., Rozenek, M., & Sławiński, R. (2000). CAE-ECM system for electrochemical technology of parts and tools. *Journal of Materials Processing Technology*, 107(1-3), 293-299.
- [6] Kao, P. S., & Hocheng, H. (2003). Optimization of electrochemical polishing of stainless steel by grey relational analysis. *Journal of Materials Processing Technology*, 140(1-3), 255-259.
- [7] Acharya, B. R., Mohanty, C. P., & Mahapatra, S. S. (2013). Multi-objective optimization of electrochemical machining of hardened steel using NSGAI. *procedia Engineering*, 51, 554-560.



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- [8] Goswami, R., Chaturvedi, V., Chouhan, R. (2013). Optimization of Electrochemical Machining Process Parameters Using Taguchi Approach. *International Journal of Engineering Science and Technology* 5, 999-1006.
- [9] Basak, I., & Ghosh, A. (1997). Mechanism of material removal in electrochemical discharge machining: a theoretical model and experimental verification. *Journal of materials processing technology*, 71(3), 350-359.
- [10] Chakradhar, D., & Gopal, A. V. (2011). Multi-objective optimization of electrochemical machining of EN31 steel by grey relational analysis. *International Journal of Modeling and optimization*, 1(2), 113.