Evaluating the optimum level of Electrical Discharge Machining parameters regarding decreasing electrode wear ratio by using response surface method

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Abstract

The effect of Electrical Discharge Machining (EDM) parameters (i.e., Voltage, Peak current, Pulse on time and Pulse off time) was investigated in order to minimize the electrode wear ratio. Effects of selected parameters on process variable, electrode wear ratio was investigated by developing the mathematical model using response surface method (RSM). Optimal combination of these parameters was obtained for achieving controlled machining of the work-pieces.

Keywords: Electrical discharge machining, Response surface method, Electrode wear ratio, Mathematical Model.

Introduction

Electrical discharge machining (EDM) is one of the interested used non-traditional machining processes in industries. It is based on removing conductive material specially metals with any soft or hard material, the machining process is due to heat generated of an electric arc between electrode and work-piece in the presence of dielectric fluid [1].

Literature review

To find an optimized level of input parameters for reaching suitable outputs has always been a challenge and a tedious task for researchers for many years. For modelling the mathematical relationship between machining responses and process parameters, there have been different techniques that have been used by different researchers [2] and [3]. However Artificial Neural Network (ANN) model is simple for applying, there is some error of estimation value in this technique when outcomes are nonlinear [4] and [5], adaptive neuro-fuzzy interference have also been used by researchers in the past [6].

Lin et al., used Grey-Taguchi method to achieve multiple performance characteristics like high MRR, low working gap and low electrode wear when machining with Inconel 718 alloy [7]. In the same way, Aliakbari and Baseri optimized machining parameters in the rotary EDM process with the help of the Taguchi technique [8].

Material and Methods

In this work, conductive metal mild steel was selected as the work-piece material. The present experiments have been performed using copper electrode with negative polarity. The electrode used is 10 mm in diameter and 40 mm in height. Commercial Vitol-2 dielectric fluid was used during executing experiments. The weight reduction of tool should be taken before and after each experiment, the digital scale machine was used to measure the weight of work-piece and tool.

Electrode wear ratio (EWR) is defined as ratios of electrode wear weighting under mass loss in the work-piece removal, which are shown in following formula:

$$\mathrm{EWR}(\%) = \frac{\mathrm{EWL(g)}}{T(\min) * \rho_e(\frac{\mathrm{g}}{mm^3})} \times 100 \quad \left(\frac{mm^3}{min}\right) \qquad (1)$$

Where EWR is electrode wear ratio in mm3/min, EWL is the electrode weight loss in grams, ρ_e is the electrode material density in g/mm^3 and T is the machining time in min. To get good results in the empirical setup, the average was calculated from three-time reading of each experiment. In order to get the solution, matrix has been performed by using Minitab 15.

Theory of Experimental Design

In this experimental setup, significant effective factors such as pulse on time (T_{ON}), Discharge peak current (I_P), servo voltage (SV) and pulse off time (T_{OFF}) are selected to examine electrode wear rate. The smallest possible number of experiments (N) can be calculated from the subsequent equation:

$$N = n_c + n_a + n_o \qquad (2)$$

Where n_c defines as factorial points number or corner points of the cube at [-1, 1], n_a defines as axial points number or star points along the outside of the cube at [-2, 2] and n_o defines as a number of center points at the zero level [9].

The design includes 31 numbers of trials, with 8 axial points ($\propto = k^{1/2}$) from the center point of the design, k=4 and thus the $\propto = \mp 2$ and 7 number of center points. Each factor coded in 5 level as shown in Table 1.

The coded value matching to the actual value for each process variable is resulting using the following formula:

$$\text{Coded value} = \frac{\text{actual value} - \text{mean test value}}{\text{range of test conditions}} \tag{3}$$

The coded numbers are thus obtained from the following transformation equations:

$$x_1 = \frac{I_p - I_{p0}}{\Delta I_p} \tag{4}$$

$$x_2 = \frac{SV - SV_0}{\Delta SV} \tag{5}$$

$$x_3 = \frac{T_{ON} - T_{ON0}}{\Delta T_{ON}} \tag{6}$$

$$x_4 = \frac{T_{OFF} - T_{OFF0}}{\Delta T_{OFF}} \tag{7}$$

Table 1. Coded values of process variable

Level	Ip (ampere)	SV (voltage)	TON (μs)	TOFF (μs)
-2	*3	10	*10	10
-1	10	30	50	30
0	20	50	100	50
1	30	70	150	70
2	40	90	200	90

*Even though by using equations (4) and (6) the coded values are ‘0’, the minimum available value of ‘3 and 10’ are sufficient.

Response Surface Model

The first order model is not enough where there is a curvature on the response surface. In this case second order models are suitable to approximate a part of real response surface with parabolic curvature. The second order modeling contains all terms of first order with some extra terms such as quadratic terms are correspond to $\beta_{11}x_{1i}^2$ and all cross-product terms that corresponding to $\beta_{13}x_{1i}x_{3j}$. The general formulations of the second order models were expressed in equations 8 [10].

$$y = \beta_0 x_0 + \sum_{j=1}^{q} \beta_j x_j + \sum_{j=1}^{q} \beta_{jj} x_j^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{8}$$

In the present study, second order mathematical model is developed for the prediction of EDM die sinking performance as a function of discharge current (amp), servo voltage (volt), pulse off duration (μs) and pulse on time (μs).

If all of these variables are assumed to be measurable, the functional relationship between response (electrode wear ratio) and independent variables (discharge current, servo voltage, pulse off time, and pulse on time) can be expressed as follow:

$$\begin{aligned} y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_{11} x_1^2 \\ + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{44} x_4^2 + \beta_{12} x_1 x_2 \\ + \beta_{13} x_1 x_3 + \beta_{14} x_1 x_4 + \beta_{23} x_2 x_3 \\ + \beta_{24} x_2 x_4 + \beta_{34} x_3 x_4 \end{aligned}$$

Where y is the true modeled response on a logarithmic scale, $x_0 = 1$ (a dummy variable), x_1, x_2, x_3 and x_4 are the logarithmic transformation of discharge current, servo voltage, pulse on time and pulse off time. While $\beta_0, \beta_1, \beta_2, \beta_3$ and β_4 are the parameters to be estimated. The experimental error can be predicted by transforming as:

$$\begin{aligned} \hat{y} = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_5 x_1^2 \\ + b_6 x_2^2 + b_7 x_3^2 + b_8 x_4^2 + b_9 x_1 x_2 \\ + b_{10} x_1 x_3 + b_{11} x_1 x_4 + b_{12} x_2 x_3 \\ + b_{13} x_2 x_4 + b_{14} x_3 x_4 \end{aligned}$$

Where $\hat{y}$ is the estimated and y is the measured value on a logarithmic scale, ε is the experimental random error and b values are the estimates of the β parameters.

The normal equation to estimate the b values can be expressed as:

$$(X^T X) b = X^T y \qquad \text{And thus,} \qquad b = (X^T X)^{-1} X^T y \tag{9}$$

Mathematical Model

The combinatorial model based on Eq. (8), has been developed to correlate the effects of the mentioned process parameters on the EDM characteristics by computing the estimated regression coefficient of Eq. (8) using a statistical computer software ‘‘Minitab version 15” and using the pertinent data from Table 2. The initial regression equation is:

$$\begin{aligned} &EWR = 1.84 + 0.91x_1 - 0.17x_2 - 0.75x_3 - 0.08x_4 \\ &+0.29{x_1}^2 + 0.07{x_2}^2 - 0.44{x_3}^2 + 0.08{x_4}^2 - 0.04x_1.x_2 \\ &-0.36x_1.x_3 - 0.01x_1.x_4 + 0.36x_2.x_3 + 0.02x_2.x_4 \\ &+0.19x_3.x_4 \end{aligned} \tag{10}$$

Analysis of Variance

The analysis of variance was employed for fitting the data to the second-order model of EWR. ANOVA compute the sufficiency of the second order model for response as shown in Table 3.

In addition, the main contribution can be referred as significant at an individual level. There are some terms in significant level. All linear terms, constant coefficient, x_1 , x_2 , x_3 and x_4, the quadratic terms, ${x_1}^2, {x_2}^2, {x_3}^2$ and ${x_4}^2$, interaction terms, $x_1 * x_3$, $x_2 * x_3$ and $x_3 * x_4$, significantly contribute to the response model at alpha = 0.05. As a result, the final model for the response variable EWR is concluded as follows:

$$\begin{aligned} &EWR = 1.84 + 0.91x_1 - 0.17x_2 - 0.75x_3 - 0.08x_4 \\ &+0.29{x_1}^2 + 0.07{x_2}^2 - 0.44{x_3}^2 + 0.08{x_4}^2 - 0.36x_1 * x_3 \\ &+0.36x_2 * x_3 + 0.19x_3 * x_4 \end{aligned} \tag{11}$$

Adequacy of the model

The accuracy of prediction models are analyzed by statistical methods. This includes statistical analysis in terms of absolute fraction of variance (R2), root mean square (RMS) and mean absolute percentage error (MAPE). These statistical methods are shown in equations 12-14.

Table 2: Experimental results of die sinking EDM for developing RSM models

Trial no.	Actual value IP	SV	TON	TOFF	Coded value X1	X2	X3	X4	EWR (%)
1	10	30	50	30	-1	-1	-1	-1	2.907
2	30	30	50	30	1	-1	-1	-1	5.608
3	10	70	50	30	-1	1	-1	-1	1.914
4	30	70	50	30	1	1	-1	-1	4.318
5	10	30	150	30	-1	-1	1	-1	1.083
6	30	30	150	30	1	-1	1	-1	2.154
7	10	70	150	30	-1	1	1	-1	1.541
8	30	70	150	30	1	1	1	-1	2.542
9	10	30	50	70	-1	-1	-1	1	2.308
10	30	30	50	70	1	-1	-1	1	4.984
11	10	70	50	70	-1	1	-1	1	1.585
12	30	70	50	70	1	1	-1	1	3.823
13	10	30	150	70	-1	-1	1	1	1.379
14	30	30	150	70	1	-1	1	1	2.385
15	10	70	150	70	-1	1	1	1	1.683
16	30	70	150	70	1	1	1	1	2.815
17	3	50	100	50	-2	0	0	0	1.157
18	40	50	100	50	2	0	0	0	5.014
19	20	10	100	50	0	-2	0	0	2.563
20	20	90	100	50	0	2	0	0	1.841
21	20	50	10	50	0	0	-2	0	5.234
22	20	50	200	50	0	0	2	0	2.129
23	20	50	100	10	0	0	0	-2	2.482
24	20	50	100	90	0	0	0	2	2.023
25	20	50	100	50	0	0	0	0	1.783
26	20	50	100	50	0	0	0	0	1.841
27	20	50	100	50	0	0	0	0	1.968
28	20	50	100	50	0	0	0	0	1.783
29	20	50	100	50	0	0	0	0	1.783
30	20	50	100	50	0	0	0	0	1.968
31	20	50	100	50	0	0	0	0	1.729

Table 3. Analysis of Variance for EWR

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Significance
Regression	14	46.6187	46.6187	3.32991	219.64	0.000	Significant
Linear	4	34.5161	34.5161	8.62902	569.18	0.000	Significant
Square	4	7.3367	7.3367	1.83417	120.98	0.000	Significant
Interaction	6	4.7659	4.7659	0.79432	52.39	0.000	Significant
Residual Error	16	0.2426	0.2426	0.01516			
Lack-of-Fit	10	0.1881	0.1881	0.01881	2.07	0.193	Insignificant
Pure Error	6	0.0545	0.0545	0.00908			
Total	30	46.8613					
Standard deviation = 0.123128				R-Sq = 99.48%			
Mean = 2.527				R-Sq Adjusted = 99.03%			
Predicted residual error of sum of squares (PRESS) = 1.15751				Predicted R-Sq = 97.53%			
				Coefficient of variation= 4.873			

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{N}(E_a - E_p)^2}{\sum_{i=1}^{N}(E_a - E_M)^2}\right] \quad (12)$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{N}(E_a - E_p)^2}{N}} \qquad (13)$$

$$MAEP = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|E_a - E_p|}{E_a} \times 100\right) \qquad (14)$$

Where E_a is the actual result, E_p is the predicted result, E_M is the mean value and N is the number of patterns. A perfect fit would result in R^2 value of 1 and a very good fit near 1. RMS and MAEP should be as close as 0 for excellent accuracy of prediction.

Result and Discussion

Optimal condition of the different process-factors effects with the machining characteristic of EWR values can be evaluated based on the developed mathematical models to reaching controlled electrical discharge machining. The graphical comparison of prediction results of EDM process performance with experimental values are depicted in Figure 1. The prediction result of RSM performance is parallel with experimental results. This indicates the ability of RSM model to predict the performance of EDM process.

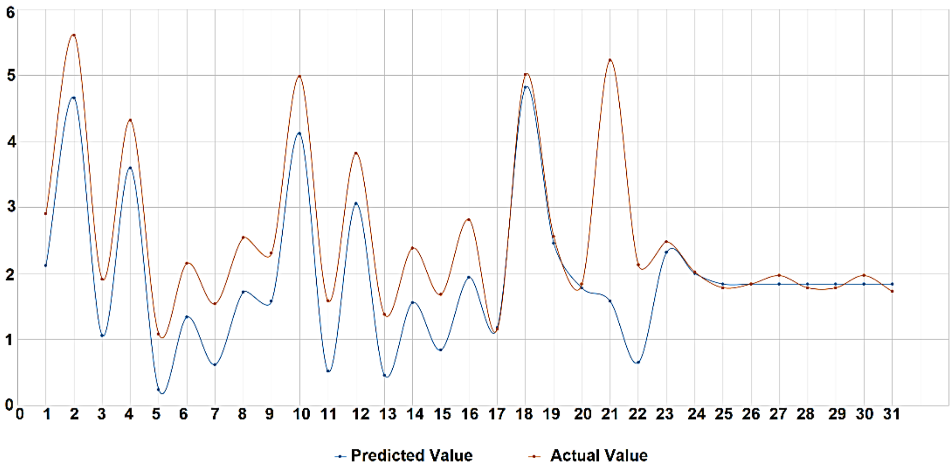

Figure 1. RSM predicted value and experimental value of EWR

Furthermore, Minitab software plots four residual graphs as shown in figure 2. The residual graphs do not show any problems with the model. In the Normal probability plot of residuals the points in this plot are generally form near to the straight line, then the residuals are normally distributed. As shown in figure 2, Residuals versus fitted value plot is used to distinguish outliers, nonlinearity and unequal error variance.

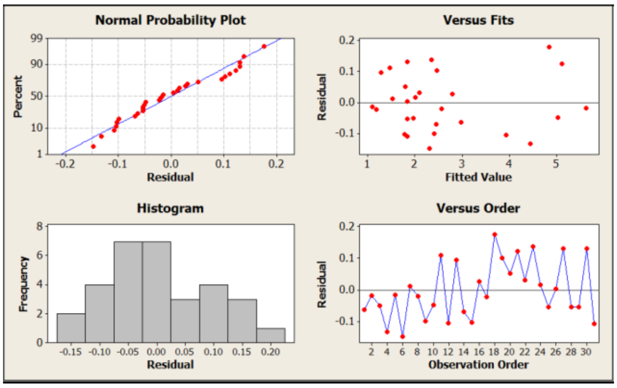

Figure 2. Residual plots

Residual versus order is a plot to show that all residuals are in the order of the collected data and used to detect non-random of error terms which is named serial correlation. A positive correlation and negative correlation are specified by a clustering of residuals with the same sign and quick changes in the signs of consecutive residuals, respectively.

As the response surface is described by the full quadratic EWR model, it is essential to analyze the optimum value of each factor levels setting. The graphical plots are very useful to analyze the result of second-order response surface model. Specially, surface plots are very helpful to illustrate the shape of the surface and determine the near optimum response. The surface plot of interaction of factors in EWR model is shown in Figures 3 and 4.

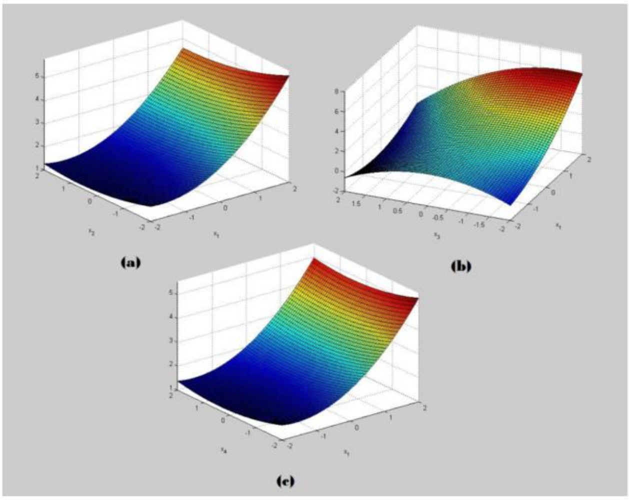

Figure 3. Response surface plot of different interaction: a) X1*X2, b) X1*X3, c) X1*X4

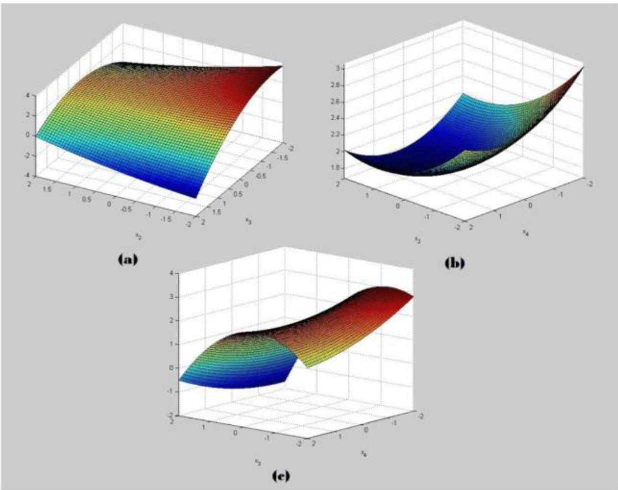

Figure 4. Response surface plot of different interaction: a) X2*X3, b) X2*X4, c) X3*X4

In case of situation that response surface is not a plane; it is more difficult to find the optimum value of each factor‘s levels. To this aim, Minitab software has an option to determine the optimum value in the possible criteria of each factor as shown in figure 5.

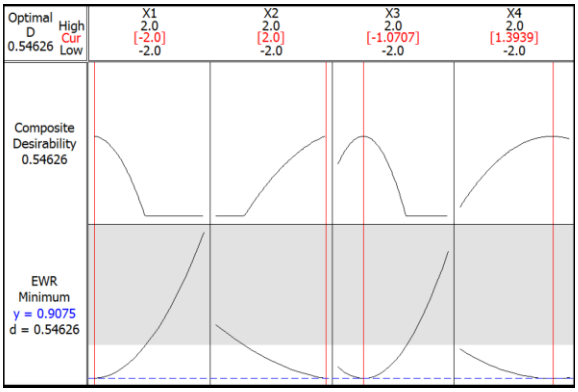

Figure 5. optimum value of each factor‘s levels

The optimum condition was expressed for the many process factors based on minimizing the EWR. The optimum values of parameters as seen in Figure 5 have been found, which are shown in Table 4.

Table 4: Optimal value of EDM parameter

Process parameter	EWR
Peak current	3
Servo voltage	90
Pulse ON time	46.5
Pulse OFF time	77.9

The R2, RMS and MAPE value for RSM model of EDM process performance is shown in Table 5.

Table 5: prediction performance of RSM and ANN models

Prediction parameter	Response Surface Method		
	R^2	RMS	MAPE
EWR	0.995	0.088	3.265

Conclusion

It is observed from response surface model that the effect of discharge current and pulse on time duration were high on EDM performance. On the other hand the servo voltage and pulse off time duration on EDM Performance had less effect on the EWR.

Also this research has investigated the optimization of control parameters in electrical discharge machining on mild steel work-piece with copper tools. Machining performance in the EDM process can be improved effectively by using optimum factors that had been determined.

Additionally, the main benefit of RSM is its ability to display the factor influences from the model of regression coefficients.

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