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Mathematical Model for Wear Rate of Negative Graphite Electrode in Electrical Discharge Machining on Ti-5A1-2.5Sn

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Graphical abstract

Abstract

There are several electrical and non-electrical factors having the significant effect on tool wear in electrical discharge machining (EDM). It is very difficult to select the parameters correctly. Likewise, the tool wear rate is changed dramatically with workpiece material and electrode material. Until now no attempt is appeared that yields the tool wear characteristics in EDM on Ti-5Al-2.5Sn retaining Graphite as electrode. Thus, in this study a mathematical model is developed to predict the tool wear rate which will provide the opportunity of proper selection of the EDM parameters and make the EDM cost effective. To model both the linear and non-linear equation is applied using the experimental data which are obtained performing the experimentation as design of experiment. The developed model has been verified through analysis of variance (ANOVA). The second-order non-linear model is found as appropriate as compared with a linear model. It is evidenced that the proposed model can effectively predict the tool wear rate (TWR) and adequately explains the variation in the machining parameters on TWR.

Keywords: Model; TWR; RSM; ANOVA; Ti-5Al-2.5Sn; graphite

Abstrak

Terdapat beberapa faktor elektrik dan bukan elektrik yang mempunyai kesan yang signifikan kepada penggunaan alat dalam pemesinan nyahcas elektrik (EDM). Amat sukar untuk memilih parameter yang betul. Begitu juga, kadar alat haus berubah dengan dramatik dengan bahan kerja dan bahan elektrod. Sehingga kini tiada usaha diambil penggunaan alat EDM pada Grafit Ti-5Al-2.5Sn mengekalkan sebagai elektrod. Oleh itu, dalam kajian ini satu model matematik dibangunkan untuk meramalkan kadar haus alat yan memberi peluang kepada pemilihan parameter EDM dan mengurangkan kos. Untuk menghasilkan kedua-dua persamaan lelurus dan bukan linear, data eksperimen digunakan. Model yang dibangunkan telah disahkan melalui analisis varians (ANOVA). Model bukan linear tertib kedua yang didapati sesuai berbanding dengan model linear. Ia terbukti bahawa model yang dicadangkan boleh meramalkan kadar alat haus (TWR) dan menerangkan perubahan dalam parameter pemesinan ke atas TWR.

Kata kunci: Model; kadar alat haus; RSM; ANOVA; Ti-5Al-2.5Sn; grafit

1.0 INTRODUCTION

EDM is an expertise-demanding process, which is used widely in machining hard metals and alloys in aerospace, automotive and dies industries [1]. During machining, the discharge energy produces very high temperatures at the point of the spark on the surface of the workpiece removing the material by melting and vaporization. The spark occurring during an EDM operation melts and vaporizes a small area on the electrode surface [2]. At the end of the pulse-on time, a small amount of molten material is ejected from the surface and the remaining liquid re-solidifies. In addition to the molten workpiece surface, electrode wear occurs in the EDM process, facilitating to a lack of machining accuracy in the geometry of workpiece [3]. Both electrodes, tool and work piece, suffer a surface modification during the electrical discharge machining process [4]. The mechanism of metal erosion during sparking is not entirely understood due to the complex thermal conduction behaviors in the machining vicinity [5]. Selection of parameters is an eminent problem in EDM. Modelling of the process is an effective way of solving the critical problem of relating the process parameters to the performance measure.

Several studies have been carried out on performance characteristics especially electrode wear in EDM process. Chen *et al*. revealed that the work piece elements migrate to the tool surface when high and low current intensities are used [6]. Electrode wear (EW) were analysed and modelled executing machining on cemented carbide as 94WC–6Co [7]. The electrode used was made of electrolytic copper in machining the composite material. Luis *et al*. carried out the modelling of electrode wear of copper electrode in electrical discharge machining on silicon carbide (SiSiC) [8]. They conducted experiment and modelled the electrode wear through design of experiment (DOE) and multiple regression analysis. A second order, non-linear mathematical model was developed for establishing the relationship between the input parameters and tool wear rate of brass electrode. [9]. The experimental trials were executed in EDM of Al–4Cu–6Si alloy–10 wt.% SiCP composites. Electrode wear was modelled through response surface methodology in EDM process on Ti-6Al-4V using graphite electrode [1]. During machining BS 4695 D2 material, Marafona observed that a black layer mainly carbon and iron formed on the tool surface (W/Cu) and lower the electrode wear [4]. Regression equation for tool wear was derived in die-sinking EDM of DIN 1.2714 tool steel using statistical analysis technique [10]. EDM characteristics were analysed and modelled by Chiang for Al2O3+TiC mixed ceramic using response surface methodology (RSM) [11]. Rahman *et al*. [12] conducted the research work to model as well as to investigate the effects of the EDM parameters on tool wear rate of titanium alloy, Ti-6Al-4V employing RSM.

To the best of the knowledge of the authors, there is no published data on machinability of titanium alloy Ti-5Al-2.5Sn with negative graphite electrode although quantitative studies were made on electrode wear. The selection of this material was made taking into account its wide range of applications in airframes, jet engines, steam turbine blades, aircraft engine, compressor blades, missile fuel tanks and structural parts, etc. [13]. Titanium alloys have enormous uses yet it accrued a key problem in machining using conventional techniques [14]. The proper selection of the various machining parameters is crucial in obtaining effective machining of Ti-5Al-2.5Sn. Thus, this paper aims to model regression equation in order to establish the relation between the EDM parameters and response as tool wear rate. For this purpose response surface methodology is used and the experiments are performed according to DOE. Analysis of variance is used to check the adequacy of the fitted model.

2.0 EXPERIMENTAL SET UP

2.1 Materials and Methods

Experimentation was accomplished according to the central composite design of response surface methodology. Accordance with the literature consulted, past experimentation as well as preliminary experiments four factors peak current (1-29 A), pulse-on time (10-350 µs), pulse-off time (60-300 µs) and servo-voltage (75-115 V) are studied. The job material was titanium alloy Ti-5Al-2.5Sn with following composition: 0.02% C, 0.15% Fe, 2.6% Sn, 5.1% Al and rest Ti. Graphite (ISEM-3) was used as electrode (tool). A new set of workpiece and electrode (tool) were applied for every run. In the present experimental studies, cylindrical graphite (ϕ20 mm× 50 mm) was considered as electrode material maintaining negative polarity whilst Kerosene was used as dielectric. The experimental set up is shown in Figure 1. The levels of peak current were set at 1, 8, 15, 22 and 29 A, while that of pulse-on time were set at 10, 95, 180, 265 and 350 µs, that of pulse-off time were set at 60, 120, 180, 240 and 300 µs and the level of servo-voltage were set at 75, 85, 95 and 115 V. The experiment was conducted according to the design obtained through central composite design as shown in Table 1. Each test run was repeated three times to obtain more accurate results. Then, the mean values of the response measurement (TWR) were used as the output for each set of parameters. Every test run was conducted for a fixed time 40 minutes. During experiments the remaining machining parameters were kept constant.

The electrodes were weighed before and after machining using a digital single pan balance (maximum capacity=210 gm, precision=0.1 mg) and are reported in units of g/min. Tool wear rate is calculated for each cutting condition; by measuring the average amount of electrode eroded and the machining time as follows [15]:

$$\text{Tool wear rate} = \frac{\text{Reduction in wieght of electrode (g)}}{\text{Machining time (min)}} \tag{1}$$

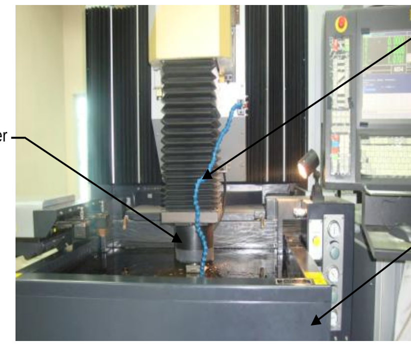

Figure 1 Experimental setup during machining Ti-5Al-2.5Sn

2.2 Response Surface Modelling

Response surface methodology is an assortment of mathematical and statistical techniques that are useful for the modeling and analysis of problems [16]. A model of the response to some independent input variables can be acquired by applying regression analysis and RSM. In RSM, the independent process parameters can be represented in quantitative form as:

$$Y = f(X_1, X_2, X_3, \ldots X_n) \pm \varepsilon \tag{2}$$

where, Y is the response, f is the response function, ε is the experimental error, and X_1, X_2, X_3, . . ., X_n are independent variables.

The form of f is unknown and may be very complex. If the response can be well modeled by a linear function (first-order) of the independent variables, the Equation 2 can be written as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots + \beta_n X_n + \varepsilon \tag{3}$$

However, if the model is not well fitted by the linear function then a higher order polynomial such as the second-order model can be used. In the present study, both the linear and second-order non-linear models are studied. The mathematical models based on a second-order is given as

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \sum_{i,j=1, i\neq j}^{n} \beta_{ij} X_i X_j + \varepsilon \tag{4}$$

where Y is the corresponding response, X_i is the input variables, X_i^2 and X_iX_j are the squares and interaction terms, respectively, of these input variables. β_o, β_i, β_{ij} and β_{ii} are the unknown regression coefficients. In this work, Equation 4 can be rewritten according to the four variables used as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 + \beta_{44} X_4^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{14} X_1 X_4 + \beta_{23} X_2 X_3 + \beta_{24} X_2 X_4 + \beta_{34} X_3 X_4 \quad (5)$$

where X_1, X_2, X_3, and X_4 are four input variables as peak current (I_p), pulse-on time(T_{on}), pulse-off time(T_{off}) and servo-voltage (S_v), respectively.

Table 1 Set of designed experiments

Std Order	Run Order	Peak current (A)	Pulse-on time (μs)	Pulse-off time (μs)	Servo-voltage (V)
29	1	15	180	180	95
7	2	8	265	240	85
18	3	29	180	180	95
28	4	15	180	180	95
23	5	15	180	180	75
31	6	15	180	180	95
1	7	8	95	120	85
8	8	22	265	240	85
15	9	8	265	240	105
30	10	15	180	180	95
13	11	8	95	240	105
21	12	15	180	60	95
3	13	8	265	120	85
10	14	22	95	120	105
14	15	22	95	240	105
9	16	8	95	120	105
16	17	22	265	240	105
4	18	22	265	120	85
17	19	1	180	180	95
25	20	15	180	180	95
22	21	15	180	300	95
26	22	15	180	180	95
6	23	22	95	240	85
12	24	22	265	120	105
2	25	22	95	120	85
24	26	15	180	180	115
11	27	8	265	120	105
19	28	15	10	180	95
5	29	8	95	240	85
20	30	15	350	180	95
27	31	15	180	180	95

3.0 RESULTS AND DISCUSSION

3.1 Modelling

Experiments are carried out using titanium alloy Ti-5Al-2.5Sn as the workpiece material and graphite (ISEM-3) as negative polarity based on Table 1. From experimental data, the tool wear rate is computed by Equation 1. The tool wear rate associated with the set of experiments is tabulated in Table 2. Based on the experimental data gathered, statistical regression analysis has been studied to correlate process parameters with the TWR. The main outputs from ANOVA are the coefficient of determination (R^2), the standard error of the regression (S), P-value, R^2-adjusted, testing for lack-of-fit and prediction sum of squares (PRESS) [16-17]. P-value is used to determine whether a factor is significant. When the P-value is lower than 0.05, the factor is significant; otherwise, it is non-significant. The unknown coefficients of the mathematical model are tabulated in Table 3 based on statistical analysis. The result reveals that all linear terms of the first-order model are significant, as the P-values of these terms are less than α-value (0.05) [17]. In the case of the second-order model, all linear, square, and interaction terms are also significant, since these terms possess P-values less than α-value (0.05). The terms as square of servo-voltage and interaction of pulse-on time and pulse-off time are appeared as non-significant, since these terms possess P-values higher than α-value (0.05). However, sometimes the elimination of the non-significant terms does not enhance the accuracy of the model, and does not produce any significant change in prediction. The effect of the non-significant terms is also related with the number of the non-significant terms. Accordingly, these two terms are retained in the mathematical model.

Both linear and non-linear regression models are examined through analysis of variance (ANOVA) as shown in Table 4 and Table 5. The acceptance was based on high to very high coefficients of correlation (R) calculated as well as model adequacy. Normally, the higher the coefficient of determination (R^2), the better the model fits the data. Standard error (S) also called standard deviation represents the standard distance data values fall from the regression line. R^2-adj accounts for the number of predictors in the model describes the significance of the relationship. Predicted R^2 is used in regression analysis to indicate how well the model predicts responses for new observations, whereas R^2 indicates how well the model fits present data. Here, the obtained vale of S (0.228) for quadratic terms is smaller than that of linear terms. On the other hand the value of R^2 (99.84%), R^2-pre (99.21%) and R^2-adj (99.71%) of second-order model are larger than that of linear model. Moreover, the values of S, R^2, R^2-pre and R^2-adj in the case of quadratic model are very satisfactory. Again, during the checking of lack-of-fit the P-value is found as 0.000 and 0.091 for linear and quadratic model, respectively. This means that the lack-of fit of linear model is significant (for α=0.05 and 95% confidence level) that of quadratic model is non-significant as desired. So, the quadratic model is adequate certainly to represent the relationship between process parameters and performance characteristics. Therefore, the regression model with quadratic terms is more significant and can be form as Equation 6 putting the values of the obtained coefficients through ANOVA in the Equation 5.

Table 2 Measured TWR according to the design of experiment

Std Order	Run Order	Peak current (A)	Pulse-on time (µs)	Pulse-off time (µs)	Servo-voltage (V)	TWR (mg/min)
29	1	15	180	180	95	8.5828
7	2	8	265	240	85	6.1885
18	3	29	180	180	95	15.4564
28	4	15	180	180	95	8.7247
23	5	15	180	180	75	11.8579
31	6	15	180	180	95	8.4134
1	7	8	95	120	85	4.1632
8	8	22	265	240	85	15.0421
15	9	8	265	240	105	4.1091
30	10	15	180	180	95	8.6694
13	11	8	95	240	105	2.3970
21	12	15	180	60	95	11.5375
3	13	8	265	120	85	7.3155
10	14	22	95	120	105	8.4093
14	15	22	95	240	105	5.5673
9	16	8	95	120	105	2.8167
16	17	22	265	240	105	10.1128
4	18	22	265	120	85	18.5375
17	19	1	180	180	95	0.8843
25	20	15	180	180	95	8.7972
22	21	15	180	300	95	6.8345
26	22	15	180	180	95	8.5483
6	23	22	95	240	85	8.1891
12	24	22	265	120	105	13.2503
2	25	22	95	120	85	11.7800
24	26	15	180	180	115	5.5058
11	27	8	265	120	105	4.7542
19	28	15	10	180	95	1.0714
5	29	8	95	240	85	3.1317
20	30	15	350	180	95	9.9177
27	31	15	180	180	95	8.8453

$$
\begin{aligned}
TWR = & -5.90490 + 1.40326 I_p + 0.0921633 T_{on} - 0.0294076 T_{off} \\
& + 0.0213449 S_v - 0.00254771 I_p^2 - 1.09867\times10^{-4} T_{on}^2 + \\
& 3.58510\times10^{-5}\, T_{off}^2 + 3.02990\times10^{-5} S_v^2 + 0.00138008 I_p T_{on} \\
& - 0.00146467 I_p T_{off} - 0.00847068 I_p S_v - 6.38359\times10^{-6}\, T_{on} T_{off} - \\
& 4.98788\times10^{-4} T_{on} S_v + 2.29227\times10^{-4}\, T_{off} S_v
\end{aligned}
\tag{6}
$$

Table 3 Coefficients of tool wear rate with negative graphite electrode

Term	Second-order model		First-order model	
	Coefficient	P-value	Coefficient	P-value
Constant	-5.90490	0.000	13.2995	0.000
I_p (A)	1.40326	0.000	0.506886	0.000
T_{on} (µs)	0.0921633	0.000	0.0247786	0.000
T_{off} (µs)	-0.0294076	0.000	-0.0178438	0.001
S_v (V)	0.0213449	0.000	-0.148479	0.000
I_p (A) × I_p (A)	-0.00254771	0.010		
T_{on} (µs) × T_{on} (µs)	-1.0986×10^{-4}	0.000		
T_{off} (µs) × T_{off} (µs)	3.5851×10^{-5}	0.008		
S_v (V) × S_v (V)	3.0299×10^{-5}	0.944		
I_p (A) × T_{on} (µs)	0.00138008	0.000		
I_p (A) × T_{off} (µs)	-0.0014646	0.000		
I_p (A) × S_v (V)	-0.0084706	0.000		
T_{on} (µs) × T_{off} (µs)	-6.3835×10^{-6}	0.577		
T_{on} (µs) × S_v (V)	-4.98788×10^{-4}	0.000		
T_{off} (µs) × S_v (V)	2.29227×10^{-4}	0.029		

Table 4 Analysis of variance for TWR considering linear model

Source	Degree of Freedom	Sum of Squares	Mean Squares	F-ratio	P-value
Regression	4	489.038	122.259	68.95	0.000 (significant)
Linear	4	489.038	122.259	68.95	0.000 (significant)
Residual error	26	46.099	1.773		
Lack-of-Fit	20	45.963	2.298	101.04	0.000 (significant)
Pure Error	6	0.136	0.023		
Total	30	535.137			

S = 1.33156, R-Sq = 91.39%, R-Sq (pred) = 86.83% and R-Sq (adj) = 90.06%

Table 5 Analysis of variance for TWR considering second-order model

Source	Degree of freedom	Sum of squares	Mean squares	F-ratio	P-value
Regression	14	534.301	38.164	730.19	0.000 (significant)
Linear	4	489.038	122.259	2339.15	0.000 (significant)
Square	4	19.599	4.900	93.74	0.000 (significant)
Interaction	6	25.664	4.277	81.84	0.000 (significant)
Residual error	16	0.836	0.052		
Lack-of-Fit	10	0.700	0.070	3.08	0.091 (non-significant)
Pure Error	6	0.136	0.023		
Total	30	535.137			

S = 0.228619, R-Sq = 99.84%, R-Sq (pred) = 99.21%, and R-Sq (adj) = 99.71%

3.2 Confirmation Testing

In the present work some production data are applied to confirm the validity of the established model through confirmation tests as presented in Table 6.

Table 6 Error for predicted values of TWR model

Peak Current (A)	Pulse-on Time (μs)	Pulse-off Time (μs)	Servo-voltage (V)	TWR (mg/min)		Error (%)
				Experimental	Predicted	
29	320	60	75	11.8305	11.4795	2.97
15	250	120	90	0.81503	0.77903	4.42
5	150	150	100	24.7275	25.546	-3.31
					Average	3.56

It is apparent that the error between the observed value and predicted value of TWR is in the range of 2.97-4.42%. However, the average error of the model is found as 3.56%. Accordingly, the developed regression model is demonstrated to be a practical and effective way for the evaluation of tool wear rate in EDM process.

4.0 CONCLUSION

In the present study, the process parameters with significant influence on tool wear rate are determined by using RSM. A second-order model of these parameters are developed and found that factors pulse current, pulse-on time, pulse-off time and servo-voltage have the significant effect. Almost all linear, square, and interaction terms are found as significant in the mathematical model. The lack-of-fit as well as adequacy of the model is verified through ANOVA. According to the result obtained via ANOVA it is observed that the developed model can be used effectively for prediction tool wear rate in EDM of Ti-5Al-2.5Sn material. The confirmation tests showed that the average error between experimental and predicted values of TWR is 3.56% which is acceptable. Thus, the proposed model can predict the TWR of the material considered with the graphite tool successfully and make EDM more effective and economic.

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