



Multiple Polynomial Regression Model for Predicting Surface Roughness of Titanium Alloy in Electrical Discharge Machining

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Abstract

This study investigated the experimental work of titanium alloy in the die-sinking electrical discharge (EDM) machining process to enhance surface integrity (surface roughness) by applying regression-based modeling. Furthermore, a multiple polynomial regression (MPR) model was developed to predict surface roughness responses under optimized conditions. The effects of EDM parameters, such as pulse-on time (ON), pulse-off time (OFF), peak current (IP), and servo voltage (SV), on surface roughness were studied. The experiment was conducted using a two-level full factorial design with four center points. Roughness was measured using a surface roughness tester (Formtracer SJ-301). The significant cutting parameters for surface roughness were determined using analysis of variance (ANOVA). The results showed that increasing the servo voltage significantly reduced the surface roughness by 46.48%. The developed model also predicted surface roughness values lower than those observed in the experimental data, with an R² value of 0.608.

Keywords: Regression; Polynomial Regression; Surface roughness; Electrical discharge machining; titanium alloy.

1. Introduction

Titanium has recently become an important material widely used in the aerospace industry, as well as biomedical and surgical instruments. Titanium alloys have grown in popularity in the aviation industry due to the increased effectiveness and higher working temperature of air gas turbine motors [1]–[3]. Furthermore, the excellent quality weight proportion of titanium composites reduces airplane weight and, as a result, reduces fuel utilization and emissions. Titanium, in general, has a high melting temperature and low thermal conductivity, putting it in the category of difficult-to-cut materials that are not suitable for traditional machining [2], [4]–[7]. Electrical discharge machining (EDM) has been reported as a potential alternative to mechanical surface modification techniques for modifying the surface of biomedical [8], [9], aerospace [3], etc.

EDM has become one of the most popular machining processes due to its capacity to manufacture complex geometry and hard material components with precision and accuracy [10]–[12]. EDM is a manufacturing process that uses electrical discharges to remove material from a workpiece. It is commonly used for machining difficult-to-machine materials like titanium alloy and pre-hardened steel, which are not feasible to manufacture using traditional machining processes [13]–[15]. Additionally, the EDM process can run for long periods without

intervention, making them highly versatile [13], [16]. During the EDM process, material removal rate (MRR) and surface roughness (Ra) are among the key performance indicators that are always a concern. These factors can impact several functional attributes of the machining process, underscoring the need to consider them carefully. Ra in EDM is an indicator directly related to the choice of the further finishing method and its machining cost. Ra affects machine parts' wear resistance, tensile strength, elasticity, and fatigue strength [17], [18]. As a result, a research effort to improve surface roughness in EDM is crucial.

Many researchers have conducted experiments in recent years to optimize and better understand the effects of the numerous EDM parameters on the overall execution of the machining process. Wandra et al. [19] present an experimental investigation on optimizing Ra of β -phase titanium alloy using ball burnishing-assisted electrical discharge cladding. The study aimed to improve the surface quality of the material for implant applications. The authors used a Taguchi L9 orthogonal array to design the experiments and analyzed the effect of EDM parameters on Ra using an analysis of variance (ANOVA). It was reported that the surface roughness increased with the increase in peak current.

Paulson et al. [20] aim to optimize the wire-EDM process of titanium alloy-Grade 5 using Taguchi's method and grey relational analysis (GRA). The authors conducted experiments based on Taguchi's L16 orthogonal array. The study investigated the influence of peak current, pulse on time, and pulse off time on material removal rate (MRR) and Ra by adopting orthogonal arrays and signal-to-noise ratio. The results showed that the most significant factors affecting surface roughness were peak current and pulse-off time, whereby the surface roughness increased with the increase in peak current.

Phan et al. [21] conducted an experiment of titanium alloy Ti-6Al-4V in the EDM process to investigate the effect of peak current, pulse on time, and voltage, which significantly affected surface texture quality. All experiments were systematically conducted with four levels based on the Taguchi method. They observed that peak current and voltage are the EDM parameters that could strongly affect the surface quality with 94.5% and 4.4%, respectively. Goyal et al. [22] present an investigation of the Ra for Inconel 625 using wire electrical discharge machining (WEDM). The authors conducted experiments using a Taguchi design to study the effects of various process parameters such as tool electrode, current, pulse on time, pulse off time, wire feed, and wire tension on the Ra. The study revealed that the pulse-on time has the most significant influence on surface roughness, followed by current, pulse-off time, tool electrode, wire tension, and wire feed. It is seen that current (31.92%), pulse on time (25.46%), and pulse off time (21.54%) have a large impact on the response at a 95% confidence interval level since the p-value is less than 0.05.

Bhowmick et al. [23] attempted a comparative study on the machining properties and surface characteristics of Inconel 625 during powder-mixed electric discharge machining (PMEDM). The study investigated the impact of different process parameters such as powder concentration, pulse current, gap voltage, pulse on time, and pulse off time. The effects of the input parameters were investigated on the MRR and Ra. The results showed that powder concentration, pulse current, gap voltage, and pulse on time are the significant input parameters for MRR and Ra. Ra increased as the current and pulse-on time were increased, whereas Ra decreased as the powder concentration and gap voltage were increased.

Shirguppikar et al. [14] conducted an experimental study investigating the effects of uncoated and coated electrodes on MRR and Ra in EDM of Ti-6Al-4V titanium alloy. The study evaluated the effects of electrode type (uncoated and coated), pulse on current, and pulse on response variables such as MRR, tool MRR, tool wear rate (TWR), and Ra. The study results showed that using a coated electrode (specifically, a tungsten carbide-coated copper electrode) resulted in higher material removal rates and lower tool wear rates than using an uncoated electrode. Additionally, the study found that pulse on time and pulse on current significantly affected MRR, although the pulse on current had a greater impact. In contrast, the increase of mean Ra with respect to the increase in pulse-on time is almost linear, having an approximately 23% rise between 25 and 200 μ s.

In summary, recent experimental investigations have focused on understanding the effect of various EDM parameters on Ra. The results of these studies have shown that machining parameters such as peak current, pulse on time, pulse off time, and voltage can significantly impact Ra. These findings guide the selection of EDM parameters for achieving the desired Ra and further optimize the EDM process.

2. Material and methods

The specimens used for this study were a commercial Ti-6Al-4V titanium alloy (100mm \times 60mm \times 5mm). The mechanical properties and chemical composition of the Ti-6Al-4V are illustrated in Table 1. Copper tungsten was used as the electrode with positive polarity. The experiments were carried out using an AG40L Sodick electrical discharge machine, and oil was used as dielectric fluid. The workpiece was EDMed at a 1.5mm depth of the hole. The experimental setup is shown in Figure 1. Pulse on time (ON), pulse off time (OFF), peak current (IP), and servo voltage (SV) were considered EDM machining parameters. Table 2 shows the machining parameters along with their levels.

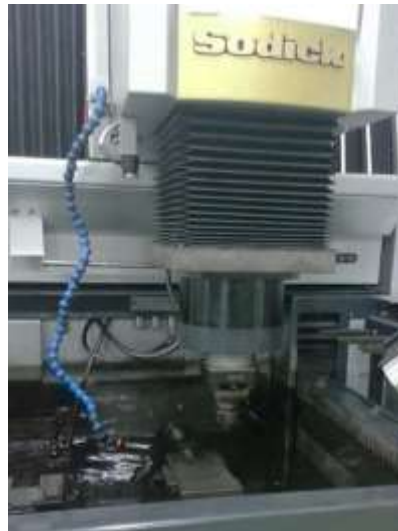


Figure 1: Experimental setup of EDM

Table 1. Chemical composition and mechanical properties of Ti-6Al-4V

Mechanical composition		Mechanical properties	
Al	6.37	Tensile strength (MPa)	960–1270
V	3.89	Yield strength (MPa)	820
Fe	0.16	Elongation 5D (%)	≥8
C	0.002	Reduction in the area (%)	≥25
Mo	<0.01	Density (g/cm ³)	4.42
Mn	<0.01	Modulus of elasticity tension (GPa)	100–130
Si	<0.01	Hardness (Hv)	330–370
Ti	Balance	Thermal conductivity (W/mK)	7

Table 2: Factor and level for EDM parameters of titanium alloy

Symbol	Name	Units	Level	
			Low (-1)	High (+1)
ON	Pulse on time	μs	150	230
OFF	Pulse off time	μs	60	90
IP	Peak current	Ampere	10	12
SV	Servo voltage	Volt	30	60

In addition, the experiments were performed using a full factorial design approach involving two levels of machining parameters, with the addition of four center points. This experiment consisted of a total of 20 runs, which included 16 regular runs and four center-point runs. The Design Expert software was utilized to obtain the fractional combinations of machining parameters. The experimental parameters were coded in terms of low level (-), center point (cp), and high level (+), as shown in Table 3.

Table 3: A two level full factorial with four factors and four center points

Run	ON (μs)	OFF (μs)	IP (A)	SV (Volt)
1	-	-	-	-
2	+	-	-	-
3	-	+	-	-
4	+	+	-	-
5	-	-	+	-
6	+	-	+	-
7	-	+	+	-
8	+	+	+	-

9	-	-	-	+
10	+	-	-	+
11	-	+	-	+
12	+	+	-	+
13	-	-	+	+
14	+	-	+	+
15	-	+	+	+
16	+	+	+	+
17	cp	cp	cp	cp
18	cp	cp	cp	cp
19	cp	cp	cp	cp
20	cp	cp	cp	cp

2.1 Data

Regression analysis is a statistical method to establish a relationship between a dependent variable and one or more independent variables. It predicts the dependent variable's value based on the independent variables' values [11]. The relationship is derived from an equation that connects the dependent variable and one or more independent variables [11]. Regression analysis is widely used in various fields, such as economics, psychology, biology, engineering, and machining. One of the main advantages of regression analysis is that it allows researchers to identify the relationship between variables and make predictions based on that relationship.

The regression analysis has various types, including simple linear regression, multiple linear regression, logistic regression, and polynomial regression. The type of regression used depends on the nature of the data and the research question being investigated. When a linear line cannot adequately explain the data, this may indicate that the model is under-fitted. To address this issue, the model's complexity needs to be increased, which could generate a quadratic equation [24]. Polynomial regression is a second-order regression model that uses five regression terms from two predictors (X, Y, X-squared, XY interaction, and Y-squared) to predict an outcome variable [25]. Polynomial regression, or multiple regression with polynomial terms, is a regression analysis technique that involves fitting a polynomial equation to a dataset with multiple independent variables. Polynomial regression is an extension of linear regression, which involves fitting a linear equation to a dataset with one independent variable. The polynomial model defines the relationship between the response variable y and the independent variable x , denoted as an n th degree of x . The polynomial equation is expressed as in (1):

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3^2 + b_4x_4^3 + \dots + b_kx_k^p \quad (1)$$

Where y is the dependent variable, b_0 is the intercept, b_1 to b_k is the regression coefficients, x_1 to x_k are the independent variables, and p is the degree of the polynomial term for each independent variable.

3. Result and Discussion

The machining experiments were performed to investigate the effects of different EDM parameters more accurately and cost-effectively. The Ra values calculated using the surface roughness tester model Formtracer SJ-301 for all trials are shown in Table 4.

Table 4: Two-level full factorial experiemnts with actual values

Run	ON (μ s)	OFF (μ s)	IP (A)	SV (Volt)	Ra (μ m)
1	150	60	10	30	2.6106
2	230	60	10	30	3.7860
3	150	90	10	30	2.6137
4	230	90	10	30	3.5734
5	150	60	12	30	3.4860
6	230	60	12	30	3.4398
7	150	90	12	30	2.5694
8	230	90	12	30	2.9312
9	150	60	10	60	2.4475
10	230	60	10	60	2.3038
11	150	90	10	60	2.2949
12	230	90	10	60	2.4646

13	150	60	12	60	2.5322
14	230	60	12	60	2.5121
15	150	90	12	60	2.5067
16	230	90	12	60	2.5430
17	190	75	11	45	2.3455
18	190	75	11	45	2.6518
19	190	75	11	45	2.5493
20	190	75	11	45	2.4989

3.1 Effect of EDM machining parameters on Ra using analysis on variance (ANOVA)

The analysis of variance (ANOVA) analysis enables the identification of machining parameters that have a statistically significant impact on the machining performances, along with the percentage contribution of each EDM parameter towards Ra values. The analysis is conducted with a significance level of $\alpha=0.05$, corresponding to a confidence level of 95%. According to ANOVA, machining parameters with a "p-value" less than 0.05 are statistically significant, whereas those with a "p-value" greater than 0.05 are considered statistically insignificant. The ANOVA table for Ra is presented in Table 5, revealing that SV is statistically significant in affecting Ra with the P-value of $0.0007 < 0.05$. Conversely, ON, OFF, and IP are deemed insignificant with respective P-values of 0.0706, 0.2250, and 0.7441. Additionally, it indicates that SV contributed the greatest contribution to the Ra, followed by ON, OFF, and IP, with percentage contributions of 46.48%, 9.89%, 4.18%, and 0.29%, respectively.

Table 5: ANOVA table of Ra

Source	Sum of Squares	DF	Mean Square	F-Value	P-value	Contribution (%)
Model	2.3901	4	0.5975	5.8265	0.0049	
ON	0.3884	1	0.3884	3.7875	0.0706	9.89
OFF	0.1642	1	0.1642	1.6016	0.2250	4.18
IP	0.0113	1	0.0113	0.1105	0.7441	0.29
SV	1.8261	1	1.8261	17.8065	0.0007	46.48
Residual	1.5383	15	0.1026			39.16
Lack of Fit	1.4894	12	0.1241	7.6260	0.0603	
Pure Error	0.0488	3	0.0163			
Cor Total	3.9283	19				100

3.2 Analysis of main effect plot for signal-to-noise (S/N) ratios

The main effect plot, on the other hand, employs graphical representations to analyze the effect of EDM machining parameters. Figure 2 illustrates the main effects plot for Ra results, whereas the lowest mean value indicates the most significant level. The excellent machining performance for Ra means "smaller is better" was acquired as 190 μ s of ON, 75 μ s of OFF, 11A of IP, and 60V of SV. From Table 6, the machining parameters exhibiting a low mean quantity are considered appropriate combinations for obtaining minimum surface roughness: ON at level two, OFF at level two, IP at level two, and SV at level one. A rising trend in Ra was noticed as SV decreased. However, the trend of Ra shows a slightly different behavior regarding ON and IP, whereas when the value of ON and IP moves from level 2 to level 3, an increasing trend is recorded in Ra. Conversely, a decreasing trend in Ra is recorded.

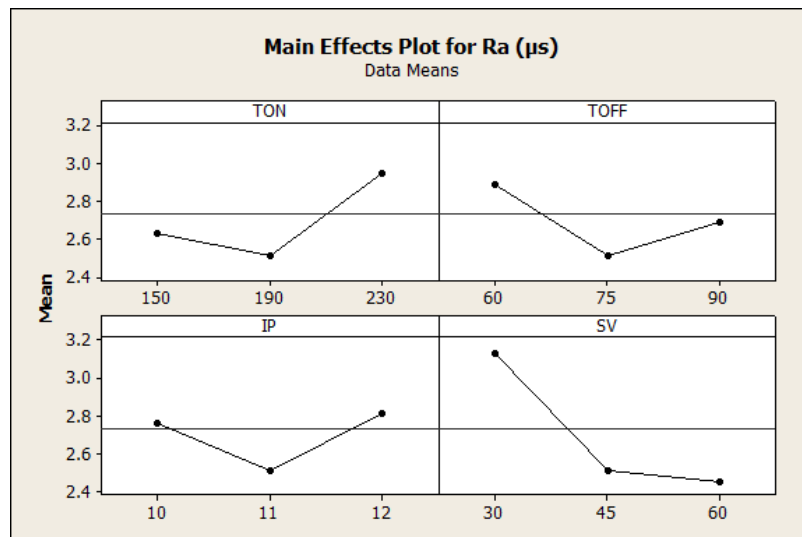


Figure 2: Main effect plot for Ra

3.2 Regression-based modeling for Ra

The multiple polynomial regression (MPR) models of Ra are as follows:

$$Ra = 2.9168 + 0.0000107ON^2 - 0.0000422OFF^2 + 0.00134IP^2 - 0.000242SV^2 \quad (2)$$

Where Ra is surface roughness in μm , ON is a pulse on time in μs , OFF is pulse off time in μs , IP is peak current in Ampere, and SV is servo voltage in volt.

The ANOVA results for the Ra model are presented in Table 6, indicating that the developed model is statistically significant, with a P-value of 0.007. Furthermore, the calculated F-value is greater than the tabulated F-value, indicating that the model is significant. Additionally, the mean square value of the Ra model is greater than the mean square value of the residual, which provides further evidence that the model is significant.

Table 6: ANOVA for Ra model

Source	DF	Sum of Square	Mean Square	F-value (calculated)	F-value (tabulated)	P-value
Regression	4	2.2993	0.5748	5.290	2.90	0.007
Residual error	15	1.6290	0.1086			
Total	19	3.9283				

3.2 Confirmation test of Ra model

To evaluate the predicted optimum machining parameters, a confirmation test is carried out to ensure they fall within the allowable range of machining parameters, as indicated in Table 7. Five experiments are chosen randomly, each with a different combination of EDM machining parameters. To estimate the accuracy of the model, the percentage error and average percentage error are computed. Equation 5.13 is then utilized to calculate the prediction error.

$$PE(\%) = \frac{\text{predicted value} - \text{experimental value}}{\text{experimental value}} \times 100 \quad (2)$$

where PE is the prediction error in %, the predicted value is the value obtained from the Ra model developed, and the experimental value is the value obtained from the experiment.

The prediction errors of the Ra model for five different combinations of machining parameters are 13.14%, 5.74%, 2.97%, 1.91%, and 10.83%, as shown in Table 7. Moreover, the maximum error percentage in Ra is 13.14%, and the minimum error percentage is 1.91%. The average prediction error calculated is 6.48%.

Table 7: Percentage error for Ra

Model	Machining parameters				Experimental value (μm)	Predicted value (μm)	Percentage Error (%)
	ON (μs)	OFF (μs)	IP (A)	SV (V)			
MPR	150	60	10	30	2.6106	2.0513	13.14
	150	90	10	30	2.6137	1.6553	5.74
	230	60	12	30	3.4398	3.0553	2.97
	230	90	12	60	2.5430	0.4012	1.91
	190	75	11	45	2.5493	1.6263	8.64
Average percentage error (%)							6.48

The predicted values in Table 7 clearly show that the MPR model of Ra predicted much lower values than the experimental values, which are 2.0513 μm , 1.6553 μm , 3.0553 μm , 0.4012 μm , and 1.6263 μm , respectively. It can be summarized that a regression-based Ra model is considered to give a low prediction error, which also matches the experimental results.

4. Conclusion

The present study evaluated the Ra of the EDM-machined surface using the proposed MPR model. The titanium alloy Ti-6Al-4V was used as the specimen. Four input factors (machining parameters) were incorporated: the pulse-on time, pulse-off time, peak current, and servo voltage. The experiments were performed using a two-level full factorial experiment with four center points. ANOVA main effect plots and confirmation tests were used. The following conclusions were drawn from the results: (i) The minimum Ra value (2.2949 μm) was found at run number 11 with a combination of 150 μs pulse on time, 90 μs pulse off time, 10A peak current, and 60 volts of servo voltage. (ii) Servo is the main effector factor affecting Ra, with 46.48% of the contribution. (iii) The peak current had the least effect on Ra, with 0.29% of the contribution. (iv) The optimal machining parameters for obtaining the minimum Ra are ON at level two, OFF at level two, IP at level two, and SV at level one. Future work will consider improving the MPR using feature importance analysis techniques like recursive feature elimination or correlation analysis.

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