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# MRR Prediction Model for Electrical Discharge Machining of INCONEL X750 by Response Surface Methodology Using MINITAB Software

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**ABSTRACT**

*This paper describes the development of a response model for electrical discharge machining inconel X750 utilizing response surface methodology. The metal removal rate (MRR), models are developed in terms of Pulse peak current (Ip), Pulse on time (Ton), Gap voltage (V).The contours have been generated from these model equations and are shown of different plots. The model generated shows that the metal removal rate increases with an increase of pulse on time, and relatively with gap voltage. Metal removal rate decreases when pulse peak current increases.The second order is more accurate based on the variance analysis and the predicted value is closer to the experimental result.*

**Key words:** Bras, Metal removal rate, Response Surface methodology, EDM

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## INTRODUCTION

In order to get the adequate model that related to the metal removal rate and the machining parameters (Pulse peak current, Pulse on time, Gap voltage), a large number of experiments needed, that is different tests for each and every combination of electrode and work-piece material. In this paper, several of Pulse peak current, Pulse on time, Gap voltage been takes into account to predict the metal removal rate. In this work, experimental results were used for modelling using response surface methodology (RSM). The RSM is practical, economical and relatively easy to use and it was used by a lot of researchers for modelling machining processes [1-2]. [3] and [4] reviewed the earliest work on response surface methodology. Response surface methodology (RSM) is a combination of experimental and regression analysis and statistical inferences. The concept of a response surface involves a dependent variable y called the response variable and several independent variables $x_1$, $x_2$,. . .,$x_k$[5,10].

## RESPONSE MODEL

If all of these variables are assumed to be measured, the response surface can be expressed as:

$$y = f(x_1, x_2, \ldots, x_k) \qquad (1)$$

The goal is to optimize the response variable y. It is assumed that the independent variables are continuous and controllable by the experimenter with negligible error. The response or the dependent variable is assumed to be a random variable. Say in an electric discharge machining, it is necessary to find a suitable combination of Pulse peak current (x1=ln Ip), Pulse on time (x2 = ln Ton), Gap voltage (x3 = ln Vg) that optimize metal removal rate (y = ln MRR). The observed response y as a function of the peak current, Pulse on time, Gap voltage can be written as

$$y = f(x_1, x_2, \ldots, x_k) + \varepsilon \qquad (2)$$

Usually a low order polynomial (first-order and second-order) in some regions of the independent variables is employed. The first-order model,

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon \qquad (3)$$

and the second –order model,

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X^2_i + \sum_i \sum_j \beta_{ij} X_i X_j + \varepsilon \qquad (4)$$

For i<j, are generally utilized in RSM problems. The β parameters of the polynomials are estimated by the method of least squares. The proposed relationship between the machining responses and machining independent variables can be represented by the following:

MRR= C (Ipm Tonn Vgy) ε' (5)

Where MRR is the metal removal rate in mm3/min, Ip , Ton, Vg are the Pulse peak current (amps), Pulse on time (µs) and gap voltage (Vg). C, m, and y are the constants. Equation (1) can be written in the following logarithmic form:

1nF= 1nC + m1nIp + n1nIon + y1nVg + 1nε' (6)

Equation (2) can be written as a linear form:

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \quad (7)$$

Where, y is the MRR, x0 = 1(dummy variables), x1= ln Ip, x2 = ln Ion , x3 = ln Vg and ε = lnε,where ε is assumed to be normally-distributed uncorrelated random error with zero mean and constant variance, β0 =ln C and β1, β2, β3 and β4 are the model parameters. The second model can be expressed as:

$$y" = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x^2_1 + \beta_{22} x^2_2 + \beta_{33} x^2_3 + \beta_{11} x_1 x_2 + \beta_{12} x_1 x_3 + \beta_{13} x_2 x_3 \quad (8)$$

The values of β1, β2, β3 and β4 are to be estimated by the method of least squares. The basic formula is:

$$(X^T X)\beta = X^T y \ \beta = (X^T X)^{-1} X^T y \quad (9)$$

where, xT is the transpose of the matrix x and (xTx)-1 is the inverse of the matrix (xTx). The details of the solution by this matrix approach are explained in [6]. The parameters have been estimated by the method of least-square using minitab software.

## EXPERIMENTAL DESIGN

To develop the first-order, a design consisting 15 experiments was conducted. Box-Behnken Design is normally used when performing nonsequential experiments. That is, performing the experiment only once. These designs allow efficient estimation of the first and second –order coefficients. Because Box-Behnken Design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box-Behnken Design does not have axial points, thus can be sure that all design points fall within the safe operating [9]. Box-Behnken Design also ensures that all factors are never set at their highest levels simultaneously .Figure 1 shows the 3 factors Box-Behnken. Preliminary tests were carried out to find the suitable parameters as shown in Table 1.

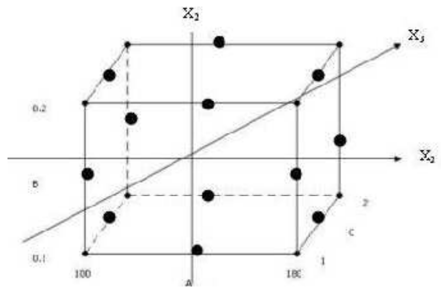

**Fig. 1 3 Factors Box-Behnken**

## EXPERIMENTAL DETAILS

The experiments were conducted in a Smart ZNC Electric discharge machine manufactured by Electronica Machine tools of India. In all experiments, kerosene oil was used as dielectric fluid medium. The dielectric side flushing pressure is maintained as 0.6MPa[7]. The work piece top and bottom surfaces were ground to a surface finish using a surface grinding machine before conducting the experiments. The initial weights of the work piece and electrode were weighed using a electronic balance. A special fixture was used to hold the work plate during machining. In EDM, the work piece is connected to positive terminal whereas the electrode connected with negative terminal of the power supply. Every experiment is conducted for the depth of 2 mm. At the end of each experiment run, the tool and work piece were removed from the machine and dried using the compressor air and weighed using electronic balance. The machine time was noted using a digital stop watch. New brass electrode was used in each experiment. Table I shows the details of the parameters and its three level values.

**Table -1 Parameters with their ranges**

| Parameters | Level 1 | Level 2 | Level 3 |
|---|---|---|---|
| Pulse peak current (Ip) | 3 | 5 | 7 |
| Pulse on time (Ton) | 100 | 300 | 500 |
| Gap voltage (V) | 50 | 60 | 70 |

The work piece material is Inconel X750 with following composition:

| Components | C | Si | Mn | S | Cr | Ni | Al | Co | Cu | Nb | Ti | Fe |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Percentage | 0.045 | 0.23 | 0.7 | 0.006 | 15.28 | 72 | 0.58 | 0.36 | 0.29 | 1.03 | 2.53 | 6.72 |

To develop the relation between various EDM process parameters and electrode wear rate, cylindrical brass electrode of 17mm diameter and 70 mm length was used for machining the work sample. Kerosene was selected as a dielectric because of its high flash point, good dielectric strength, transparent characteristics and low viscosity and specific gravity. The experimental set up is shown in Figure 1. A new set of the brass tool was applied for each run. The full sets of run according to the design of experiment were carried out in the state of positive polarity.

The material removal rate has been defined as the ratio of the wear weight of work piece to machining time [8], Material removal rate (mg/ min) = wear weight of work piece time of machining

$$\text{MRR(mg/ min)} = \frac{\text{WWBM -WWAM}}{\text{T}} \quad (10)$$

Where WWBM is weight of work piece before machining, WWAM is weight of work piece after machining and T is the total time during which machining was performed. After completing of each machining process, the work piece was blown by compressed air using air gun to ensure no debris and dielectrics were present. A precise balance was used to measure the weight of the work piece after machining.

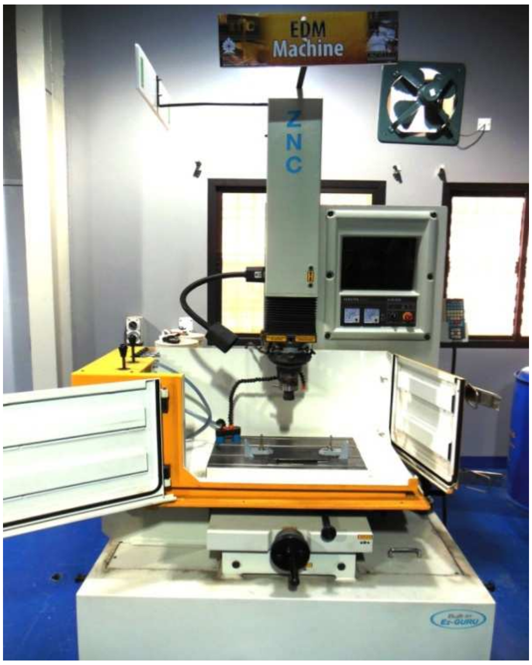


**Fig. 2 Experimental setup**

## MATHEMATICAL MODELLING

Response surface methodology is an assortment of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is biased by several variables and the objective is to optimize this response .It is a sequential experimentation strategy for empirical model building and optimization. A model of the response to some independent input variables can be acquired by carrying out experimentation and applying regression analysis. In RSM, the independent process parameters can be represented in quantitative form as Eq. (2):

$$Y = f(X_1, X_2, X_3 \ldots X_n) \pm \varepsilon \quad (11)$$

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

On the other hand, the second-order model is normally used when the response function is nonlinear. The experimental values are analyzed and the mathematical model is then developed. The mathematical model based on a second-order polynomial is expressed as Eq. (3):

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \sum_{i,j=1, i \neq j}^{n} \beta_{ij} X_i X_j + \varepsilon \quad (12)$$

where $Y$ is the corresponding response, $X_i$ is the input variables, $X_i^2$ and $X_i X_j$ are the squares and interaction terms, respectively, of these input variables. $\beta_o$, $\beta_i$, $\beta_{ij}$ and $\beta_{ii}$ are the unknown regression coefficients.

## RESULTS AND DISCUSSION

The MRR second order model is

$$y" = 0.75265x_0 - 0.00813_1 x_1 + 0.00068x_2 - 0.00518x_3 + 0.0007x^2_1 + 0x^2_2 + 0.0003x^2_3 - 0.00001x_1x_2 + 0x_1x_3 + 0.00004x_2x_3 \quad (13)$$

Table 2 shows the results obtained using ANOVA. The coefficient of determination is the ratio of the sum of squares of the predicted responses (corrected for the mean) to the sum of squares of the observed responses .The value of $R^2$ and adjusted $R^2$ is over 98%. This means that mathematical model provides an excellent explanation of the relationship between the independent variables and the response (MRR). The obtained values of standard deviation and $R^2$- predicted evidence that the proposed model is adequate to predict the response. The associated *p*-value for the model is lower than 0.05 (i.e. $\alpha$ = 0.05, or 95% confidence) indicates that the model is considered to be statistically significant.

**Table - 2 Analysis of Variance for MRR**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| Regression | 3 | 0.169216 | 0.169216 | 0.056405 | 241. | 0.0000 |
| Linear | 3 | 0.169216 | 0.169216 | 0.056405 | 241. | 0.000 |
| Residual Error | 11 | 0.002565 | 0.002565 | 0.000233 | | |
| Lack-of-Fit | 9 | 0.002506 | 0.002506 | 0.000278 | 9.48 | 0.099 |
| Pure Error | 2 | 0.000059 | 0.000059 | 0.000029 | | |

When the p-value is less than the α-level, evidence exists that the model does not accurately fit the data. The p-value for the lack-of-fit is 0.099, which is larger than 0.05 (95% confidence) and the F statistics is 9.480. Hence, the lack-of-fit term is insignificant as it is desired. The fit summary recommended that the quadratic model is statistically significant for analysis of MRR. Figure 3 indicates the residual plots for material removal rate.

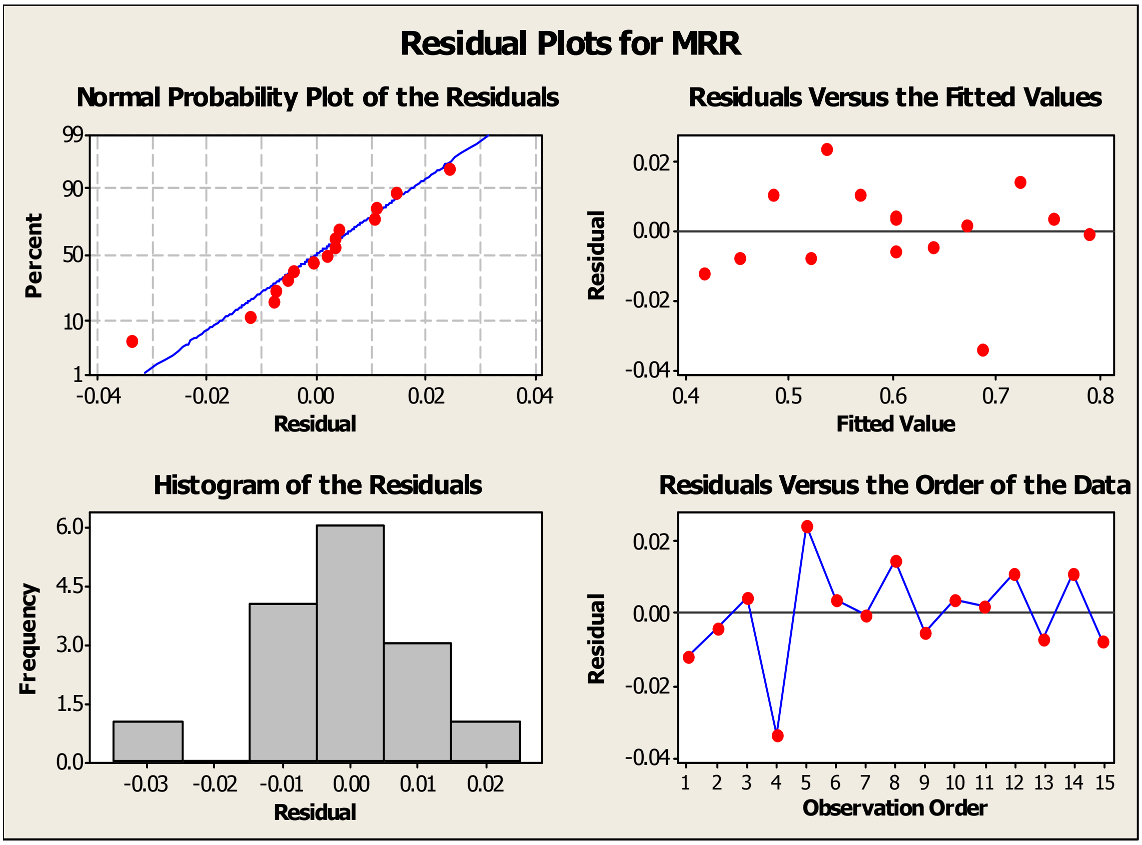


**Fig.3. Residual plots for MRR**

Equation 13 is helpful to develop the MRR graphs with selected parameters. Figure 4 to 6 shows the MRR with selected pulse peak current, pulse on time and gap voltage. These graphs help to predict the MRR at any point. Figure 6 represents a three dimensional surface plot of the data for pulse peak current and gap voltage with hold values of pulse on time (Ton) 300 µs. It is observed that the effect of the interaction between pulse peak current (Ip) and gap voltage (V) in the data is twist planes that there is curvature in the response function to the material removal rate.

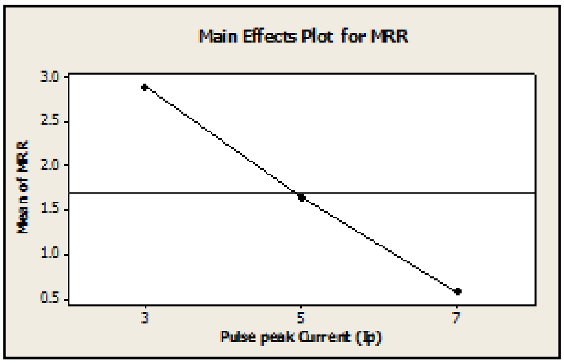


**Fig.4(a) Graph of MRR versus $I_p$**

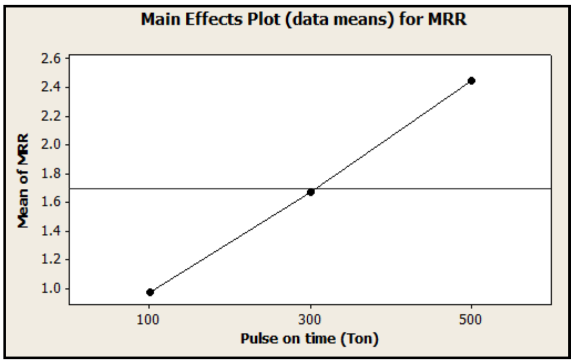


**Fig. 4(b) Graph of MRR versus Ton**

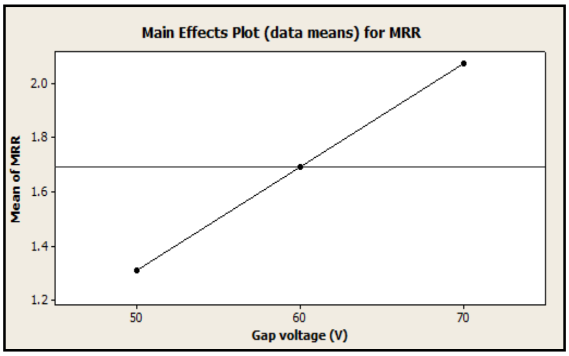


**Fig.5 Graph of MRR Vs**

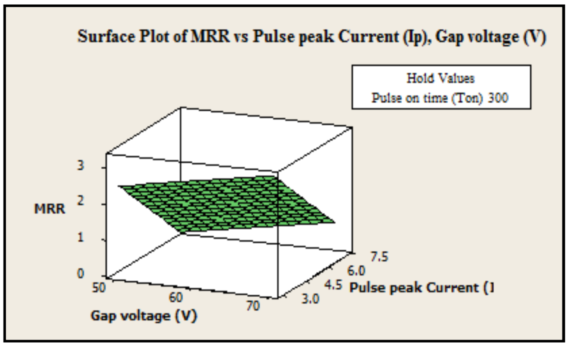


**Fig. 6 3 Dimensional surface plot**

## CONCLUSION

MRR prediction model has been developed and used in machining of Inconel X750 with brass electrode in electric discharge machine. The MRR equation indicates that the process parameters such as pulse peak current, pulse on time and gap voltage play a major role in maximizing the material removal rate. It is observed from the graph that the metal removal rate increases with an increase of pulse on time, and relatively with gap voltage also, MRR decreases with increase of pulse peak current. In order to get the maximum MRR the higher value of gap voltage should be used. Response surface methodology gives more information from the conducted experiments with less runs.

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