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Regression Analysis and Optimization of Material Removal Rate on Electric Discharge Machine for EN-19 alloy steel

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Abstract: In this paper illustration of the influence of input machining parameters on the material removal rate are determined along with performance measurement analysis. Experimentation was conducted on EN-19 alloy steel with Tungsten Copper as tool electrode. The data collected during experimentation has been used to yield responses in respect of material removal rate (MRR). The objective of this paper is to study the influence of operating input parameters of copper electrode on material removal rate of EN-19 material followed by optimization. The effectiveness of EDM process with tungsten copper electrode is evaluated in terms of the material removal rate. In this work the parameters such peak current, voltage gap, pulse on time, duty cycle and flushing pressure were selected. Analysis is carried using the response surface method and Anova analysis.

Index Terms- Central Composite Design, Material Removal Rate, Regression Analysis

1. INTRODUCTION

Electric discharge machining has extensive applications for manufacturing dies and tools to produce mouldings, die casting, and sheet metal dies etc[1][2].Implementation of EDM process will awaken manufacturing engineers, product designers, tool engineer and metallurgical engineers about unique capabilities and benefits of this process[3].EDM can be used for machining of high precision of all type of conductive material (metals, alloys, graphite, ceramics etc.) of any hardness. In EDM process [4], material removal from work piece is done by means of a series of electrical discharges. This paper presents work on machining by EDM for EN-19 alloy steel. Certain parameters in EDM process directly influence the process outputs. Setting appropriate values for such parameters requires the implementation of many machining trials. This leads to time consuming and expensive experimental work. Response Surface Methodology (RSM) has been used for modelling EDM machining of rectangular slot size 15 mm x 20 mm on EN-19 material using copper electrode tool [5, 6-9]. Response surface method is employed to signify relationships between inputs and significant outputs based on minimum number of experiments. This paper presents a mathematical modelling of EDM machining process on EN-19 alloy steel using RSM approach.

2. EXPERIMENTAL WORK

The material used for this work is EN-19 alloy steel square plate of size 100mm x 100mm x 20mm with density 7.85 g/cm^3.The specimen is machined on conventional milling at depth of cut 0.25 mm to produce a plane surface. Tungsten Copper electrodes (99.97% pure, density 13.80 g/cm^3, rectangular shaped 20mm x 15mm 100mm is used in the experiment. The machine used is ENC EDM Microcut make with NC control in Z-direction with EDM oil as dielectric medium.

3. EXPERIMENTAL PLAN

Experiments are planned on the basis of RSM technique used in experimental design. The codes are calculated as functions of the range of interest of each factor as shown in Table 1. A central composite design with five input variables having five levels between ±2 coded values and 32 experimental runs were performed. Different variables represented by x_1, x_2, x_3, x_4, x_5 and their levels are given in Table 2.The coded numbers for the variables used in tables are obtained from the following relationship[10] :

Code	Actual Value of variable
$-\beta$	x_{min}
-1	$[(x_{max} + x_{min})/2] – [(x_{max} – x_{min})/2\alpha]$
0	$[(x_{max} + x_{min})/2$
+1	$[(x_{max} + x_{min})/2] + [(x_{max} – x_{min})/2\alpha]$
$-\beta$	x_{max}

Table 1: Relationship between coded & actual values of variables [10]

The numbers of test required are chosen with the standard 2^k full factorial central composite design. CCRd provides as much as information as a five level factorial, requires many fewer tests and has been shown to be sufficient to describe the majority of process responses [11, 12, 13].Each experiment is performed using copper electrode, with a particular set of input parameters chosen randomly from the planned set of experiments. The polarity of the electrode is set as negative. The depth of machining is set at 2mm for all sets of experiments.

Factor	Level				
	-2	-1	0	1	2
x_1	10	30	50	70	90
x_2	6	9	12	15	18
x_3	3	4	5	6	7
x_4	5	15	25	35	45
x_5	0.1	0.2	0.3	0.4	0.5

Table 2: Coded levels

4. ANOVA and REGRESSION ANALYSIS

According to the experimental plan a total of 12 experiments are conducted, each having the combination of various values of process variables *X*1, *X*2 and *X*3. Each of the responses is fitted into a linear equation represented by:

$$Y\ (MRR) = \beta 0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 \text{----------------------} (1)$$

Where, **Y** is the response and x_1, x_2, x_3, x_4, x_5 are coded levels of the variables. The coefficients β0, β_1, β_2, β_3, β_4, β_5 can be calculated by solving the following equation:

$$\beta = (x^T x)^{-1} x^T Y \text{--------------------} (2)$$

where, *β* is the matrix of parameter estimates, *x* is the matrix of independent variables, x^T is the transpose of *X* matrix and *Y* is the matrix of measured responses. Table 3 gives the design matrix and the responses. Analysis of variance (ANOVA) is performed to test the adequacy of the proposed models. The variance ratio denoted by F in ANOVA tables, is the ratio of the mean square due to a factor and the error means square. In this robust design F ratio can be used for qualitative understanding of the relative factor effects.

A large value of F means that the effect of that factor is large compared to the error variance. So the larger value of F, the more important that factor is in influencing the response [14]. In this work from Table 4, Anova table shows the most important factor is input current with 202.41 F ratio and voltage gap with F=18.24. F ratio of other factors is not significant and has minimum effect.

Run	x_1	x_2	x_3	x_4	x_5	MRR
1	0	0	0	0	0	60.00
2	-1	-1	1	-1	-1	72.00
3	-1	1	-1	-1	-1	82.56
4	-1	-1	-1	-1	1	23.95
5	0	0	0	0	0	54.54
6	0	0	0	-2	0	75.00
7	1	1	-1	1	-1	120.00
8	1	-1	-1	1	1	46.15
9	-1	-1	1	1	1	48.98
10	1	1	1	-1	-1	79.00
11	2	0	0	0	0	65.00
12	0	0	0	2	0	78.00
13	0	0	2	0	0	55.00
14	0	0	0	0	0	98.00
15	0	0	0	0	-2	89.00
16	-1	1	1	-1	1	92.00
17	-1	1	1	1	-1	100.00
18	-1	1	-1	1	1	75.00
19	0	0	0	0	2	55.78
20	0	0	0	0	0	60.00
21	1	1	1	1	1	72.00
22	-2	0	0	0	0	87.00
23	1	-1	-1	-1	-1	102.56

24	1	-1	1	1	-1	120.00
25	0	-2	0	0	0	78.00
26	-1	-1	-1	1	-1	84.00
27	1	1	-1	-1	1	118.89
28	0	0	0	0	0	98.97
29	1	-1	1	-1	1	40.00
30	0	0	0	0	0	125.00
31	0	2	0	0	0	63.00
32	0	0	-2	0	0	86.00

Table 3. Design matrix and Response

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Ton	1	13.8	13.8	13.8	0.18	0.673
Vgap	1	1386.7	1386.7	1386.7	18.24	0.000
DC	1	2.1	2.1	2.1	0.03	0.870
Ip	1	15383.9	15383.9	15383.9	202.41	0.000
Fp	1	17.4	17.4	17.4	0.23	0.636
Error	26	1976.1	1976.1	76.0		
Total	31	18780.1				

Table 4. Anova of MRR

Empirical models are fitted for the stated responses material removal rate. Analysis of variance is carried out on all the fitted models for a confidence level of 95%. The fitted model of material removal rate is given by Eq. (3) and its analysis of variance is in Table 4.

Y (MRR) = - 14.6 - 0.0379 Ton + 2.53 Vgap - 0.29 DC + 2.53 Ip + 8.5 Fp ---------------- (3)

From Equation 3, the factors gap voltage, input current, duty cycle, pulse on time have an additive effect on the material removal rate where as flushing pressure has minimum impact on MRR. Analysis of the residuals of the model shown in Equation 3 is performed to test assumptions of normality, independence and constant variance figure 1 of residuals. The quantitative test methods mentioned earlier are employed again, and none of the assumptions are violated.

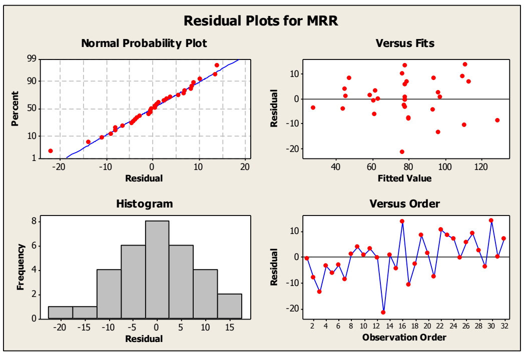

Figure 1. Residual plots for MRR

Regression analysis is carried out to ensure a least squared fitting to error surface in Minitab 15 environment. Regression analysis has been performed to find out the relationship between input factors and MRR. During regression analysis it is assumed that the factors and the response are linearly related to each other. The general first order model is proposed to predict the surface roughness over the experimental region can be expressed as Equation 1.

In general, the R^2 **adj** statistic will not always increase as variables are added to the model. In fact, if unnecessary terms are added, the value of R^2 **adj** will often decrease. When R^2 and R^2 adj differ dramatically, there is a good chance that no significant terms have been included in the model [15]**.**

For this experiment the R^2 value indicates that the predictors explain 83.44% of the response variation. Adjusted R^2 for the number of predictors in the model 87.45% values shows that the data are fitted well. The prediction model was then validated with another set of data. Table 6 shows verification of the tests results for surface roughness. The predicted machining parameters performance is compared with the actual machining performance and a good agreement is observed between this performances. In Table ***6*** process factors are given in terms of natural factors and their corresponding coded factors. In order to assess the accuracy of the prediction model, percentage error and average percentage error were recorded. Percentage of prediction errors is shown in the last column of Table 5. The maximum prediction error was 11.62 % and the average percentage error of this method validation was about 7.29%. As a result, the prediction accuracy of the model appeared satisfactory.

The verification of the tests results for material removal rate is shown in Table 5. The predicted machining parameters performance is compared with the actual machining performance and a good agreement is observed between these performances. In Table 5 process factors are given in terms of natural factors and their corresponding coded factors. In order to assess the accuracy of the prediction model, percentage error and average percentage error were recorded. Percentage of prediction errors is shown in the last column of Table 5. The maximum prediction error was 17.38 % and the average percentage error of this method validation was about 6.87%. As a result, the prediction accuracy of the model appeared satisfactory.

Run	x_1	x_2	x_3	x_4	x_5	Predicted MRR	Exp MRR	Error (%)
1	30	15	4	15	0.2	60.70	60.00	1.66
2	50	12	5	25	0.5	79.92	72.00	11
5	70	15	4	15	0.4	60.88	54.54	11.62
9	30	9	6	15	0.2	44.94	48.98	8.2
12	50	12	5	25	0.3	78.22	78.00	0.28
17	30	15	6	35	0.2	110.72	100.00	10.72
21	10	12	5	25	0.3	79.73	72.00	10.73
25	50	12	5	25	0.3	78.22	78.00	0.28
29	70	9	4	15	0.2	44.01	40.00	10.02
32	50	12	3	25	0.3	78.79	86.00	8.38

Table 5. Error Prediction

Factor	Level				
	-2	-1	0	1	2
x_1	10	30	50	70	90
x_2	6	9	12	15	18
x_3	3	4	5	6	7
x_4	5	15	25	35	45
x_5	0.1	0.2	0.3	0.4	0.5

Table 2. Coded levels

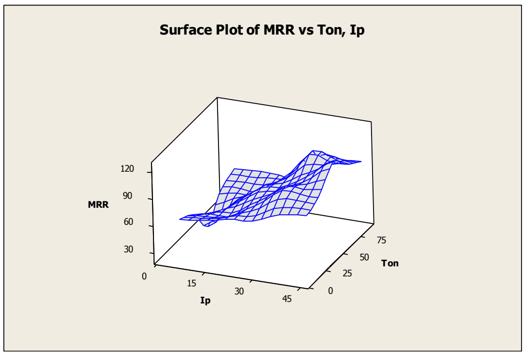

Figure 2. Surface Plot for MRR Vs Ton & Ip

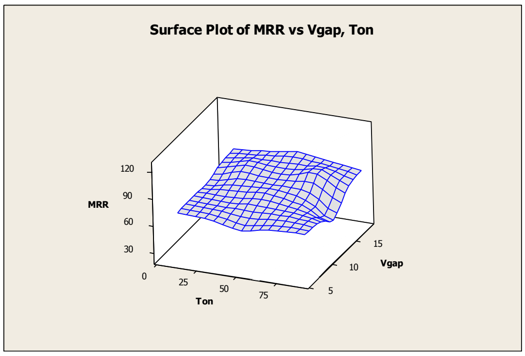

Figure 3. Surface Plot for MRR Vs Ton & Vgap

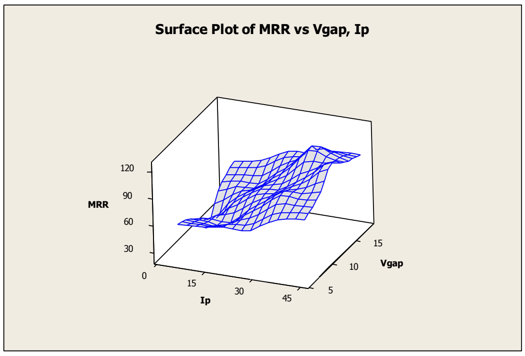

Figure 4. Surface Plot for MRR Vs Vgap & Ip

Figure 2 shows that material removal rate increases with the increase in input current and is low at high T_{on}. Though, there is low MRR at the low I_p which gives linear relation but there after it is increased with rise in current. Figure 3 show similar relationships between MRR versus T_{on} and V_{gap} in which it shows that there at high peaks of $V_{gap\ high}$ MRR is achieved. The influence of F_p is minimum on material removal rate. And figure 4 show the relation between I_p and Vgap. In this graph the high peaks show that the there is increase in MRR with increase in I_p and V_{gap}.

5. OPTIMIZATION OF MATERIAL REMOVAL RATE

The designed experiments involve determination of optimal conditions that will produce the "best" or "optimum" value for the response (MRR). Depending on the design type (factorial, response surface, or mixture), the controllable operating conditions may include one or more of the following design variables: factors, components, process variables, or amount variables. Optimal settings of the design variables for one response may be far from optimal or even physically impossible for another response. Response optimization is a method that allows for compromise among the various responses. The optimization is carried by obtaining the individual desirability (d) for each response combining the individual desirability to obtain the combined or composite desirability (D) thereby maximizing or minimizing the composite desirability and identifying the optimal input variable settings. Here in case of surface roughness optimization, it single response optimization where the overall desirability is equal to the individual desirability.

5.1 INDIVIDUAL DESIRABILITY

As in this case of MRR we need to optimize single response, so here individual desirability (d) for material removal rate is obtained using the goals and boundaries for MRR that is given in Minitab session window. There are three optimization goals desired as follows:

- minimize the response (smaller is better)
- target the response (target is best)
- ***maximize the response (larger is better)***

For material removal rate (MRR) it is desirable to obtain maximum value for better surface finish of material. As response MRR is desired to be maximizing for which determination of target value and an allowable maximum response value is provided to response optimizer. The desirability (d=1) is one for MRR response below the target value: above the maximum acceptable value the desirability (d=0) is zero.

In the below Table 6, y is the response value, T and L are the target and lower boundaries (i.e. minimum and maximum acceptable values for the response), respectively, and T is the target. For the MRR(y) to maximize by:

$f_i(y)$ =	**0**	**Y< L**
	y-L/ T-L	**$L \le y \le T$**
	1	**Y > T**

Table 6. Maximization of response by individual desirability[29]

5.2 RESPONSE OPTIMIZATION

Parameters

Goal	Lower	Target	Upper	Weight	Import
MRR Maximum	50	80	80	0.1	1

Table 7. MRR Range

Starting Point : **Ton = 50**; **Vgap = 12; DC = 5; Ip = 25; Fp = 0.3**

Ton = 10
Vgap = 18
DC = 3
Ip = 45
Fp = 0.5

Table 8.Global Solution

Predicted Responses as shown in Minitab session window.

MRR = 147.941 , desirability = 1.000000

Composite Desirability = 1.000000

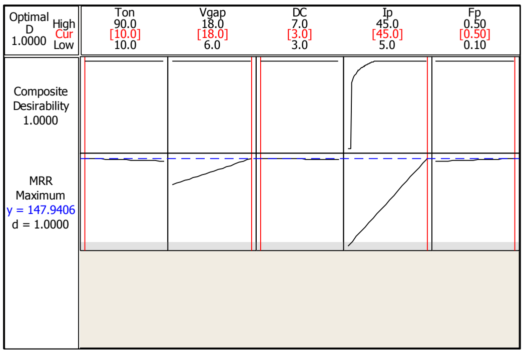

Figure 5.Optimization Plot

Each response in the research work are expressed separately as linear and non linear functions of input variables such as I_p, T_{on}, V_{gap}, DC, F_p. Now, aim is to maximize the response MRR and simultaneously maintain other responses in EDM process. As shown in *table 8* global solution of input parameters is obtained by response optimizer by maximization desirability function. To determine global solution of input variables in order to satisfy the above criteria of MRR maximization, it had been solved by Response optimizer desirability maximization function in Minitab 15 environment.
The individual desirability for MRR material removal rate is 1. To obtain this desirability, the optimum values factor levels can be set as shown under Global Solution in the Minitab Session window in table 8. That is, I_p= 45, Ton=10, V_{gap}=18, DC=3, F_p= 0.5.The optimum predicted value for MRR = 147.941 obtained for 100 % desirability.

6. RESULT AND DISCUSSION

Results show that input current, voltage gap are significant factors for MRR and flushing pressure, duty cycle and pulse on time have minimum effect on the material removal rate of EN-19 alloy steel material. Finally, a mathematical model was developed using multiple regression method to formulate the input current, gap voltage, pulse on time, and flushing pressure to the MRR. The developed model showed high prediction accuracy within the experimental region.

7. CONCLUSIONS

From this analysis we can conclude that the most significant EDM process variable influencing all the stated machinability parameters of EN-19 alloy steel is pulse current. The significance order of other parameters is gap voltage followed by pulse on time and gap voltage. These models can be effectively utilized by the process planners to select the level of parameters to meet any specific EDM machining requirement EN-19 alloy steel within the range of experimentation.

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