

Modelling of machining parameters for MRR in EDM using response surface methodology

Mohan Kumar Pradhan¹ and Chandan Kumar Biswas²

¹Research Scholar, ²Assistant Professor,
Department of Mechanical Engineering, National Institute of Technology,
Rourkela-769 008, India
mohanrkl@gmail.com (Corresponding author)

Abstract

In the present study, Response surface methodology was used to investigate the relationships and parametric interactions between the three controllable variables on the material removal rate (MRR). Experiments are conducted on AISI D2 tool steel with copper electrode and three process variables (factors) as discharge current, pulse duration, and pulse off time. To study the proposed second-order polynomial mode for MRR, we used the central composite experimental design to estimation the model coefficients of the three factors, which are believed to influence the MRR in EDM process. The response was modeled using a response surface model based on experimental results. The significant coefficients were obtained by performing analysis of variance (ANOVA) at 5% level of significance. It was found that discharge current, pulse duration, and pulse off time significant effect on the MRR. This methodology is very effectual, needs only 20 experiments to assess the conditions, and model sufficiency was very satisfactory as the coefficient of determination was 0.962.

Keywords: Electrical discharge machining (EDM), Material Removal Rate (MRR), Response Surface Methodology (RSM), ANOVA, Central composite design (CCD)

1. Introduction

There is a heavy demand of the advanced materials with high strength, high hardness, temperature resistance and high strength to weight ratio in the present day technologically advanced industries like, an automobile, aeronautics, nuclear, mould tools and die making industries etc. This necessity leads to evolution of advance materials like high strength alloys, ceramics, fiber-reinforced composites etc. In machining of these materials, conventional manufacturing processes are increasingly being replaced by more advanced techniques, which use different fashion of energy to remove the material because these advance materials are difficult to machine by the conventional machining processes, and it is difficult to attain good surface finish and close tolerance. With the advancement of automation technology manufacturers are more fascinated in the processing and miniaturization of components made by these costly and hard materials. Electrical discharge machining (EDM) has grown over the last few decades from a novelty to a mainstream manufacturing process. It is most widely and successfully applied for the machining of various workpiece materials in the said advance industry [1]. It is a thermal process with a complex metal removal mechanism, involving the formation of a plasma channel between the tool and work piece electrodes, the repetitive spark instigate melting and even evaporating the electrodes. In the recent years, EDM is firmly established for the production of tool to produce die-castings, plastics a moulding, forging dies etc. The advantage of EDM process is its capability to machine difficult to machine materials with desired shape and size with a required dimensional accuracy and productivity. Due to this benefit EDM is an illustrious technique used in modern manufacturing industry to produce high-precision machining of all types of conductive materials, alloy's and even ceramic materials, of any hardness and shape, which would have been difficult to

manufacture by conventional machining. However, the efficiency of machining is low as compared to conventional machining. Though EDM process is very demanding but the mechanism of process is complex and far from completely understood. Therefore, it is troublesome to establish a model that can accurately predict the performance by correlating the process parameter. The optimum processing parameters are very much essential to establish to boost up the production rate to a large extent and shrink the machining time, since these materials, which are processed by EDM and even the costly process is very costly [2].

Quite a lot of research attempts have been made for modelling of EDM process and investigation of the process performance to recuperate MRR [2]-[11]. Improving the MRR and surface quality are still challenging problems that restrict the expanded application of the technology [3]. Semi-empirical models of MRR for various work piece and tool electrode combinations have been presented by Wang and Tsai [4]. Luis et al. [5] have studied the influence of pulse current, pulse time, duty cycle, open-circuit voltage and dielectric flushing pressure, over the MRR and other response variable on tungsten carbide. To attain high removal rate in EDM, a stable machining process is required, which is partly influenced by the contamination of the gap between the workpiece (hardened steel 210CR12) and the electrode, and it also depends on the size of the eroding surface at the given machining regime [6]. Palanikumarin, in his work using Response Surface Method (RSM) modeled the surface roughness in machining of glass fiber reinforced plastic (GFRP) composite materials [7]. He employed four factors five level central composite, rotatable design matrix for experimental investigation and for validation of the model; he used ANOVA.

Little research has been reported about EDM on AISI D2 steel yet for the modeling by, surface response methodology. In this paper, surface response approach is used for development of a model and analysis of MRR, with peak current, pulse on time and pulse off time as input parameters. A central composite design (CCD) for combination of variables and response surface method (RSM) have been used to analyse the effect of the three parameters, pulse current (I_p), pulse on time (T_{on}) and pulse off time (T_{off}), on the MRR of EDM process.

2. Experimentation

A number of experiments were conducted to study the effects of various machining parameters on EDM process. These studies have been undertaken to investigate the effects of current (I_p), pulse on time (T_{on}) and pulse off Time (T_{off}) on MRR.



Figure 1. Experimental set up

The selected work piece material for the research work is AISI D2 (DIN 1.2379) tool steel. D2 is selected due to its growing range of applications in the field of manufacturing tools in mould industries. The electrode material for these experiments is copper.

Experiments are conducted on Electronica Electraplus PS 50ZNC Die Sinking Machine. A cylindrical pure copper with a diameter of 30 mm was used as a tool electrode (of positive polarity) and workpiece materials used were AISI D2 steel square plates of surface dimensions $15 \times 15 \text{ mm}^2$ and of thickness 4 mm. Commercial grade EDM oil (specific gravity = 0.763, freezing point = 94°C) was used as dielectric fluid. Lateral flushing with a pressure of 0.3 kgf/cm^2 was used. The test conditions are depicted in the Table 1. To attain a more accurate result, each combination of experiments (20 runs) was replicated three times and every test ran for 15 min.

3. Response surface methodology

Response surface methodology (RSM) is a collection of mathematical and statistical techniques that are useful for modelling and analysis of problems in which output or response influenced by several variables and the goal is to find the correlation between the response and the variables. It can be used for optimising the response [12]. It is an empirical modelization technique devoted to the evaluation of relations existing between a group of controlled experimental factors and the observed results of one or more selected criteria. A prior knowledge of the studied process is thus necessary to achieve a realistic model. We selected only three experimental factors capable of influencing the studied process yield: three factors discharge current (I_p) pulse duration (T_{on}) and pulse off Time (T_{off}).

The first step of RSM is to define the limits of the experimental domain to be explored. These limits are made as wide as possible to obtain a clear response from the model. The Discharge current (A), Pulse on time (B) and Pulse pause Time (C) are the machining variable, selected for our investigation. The different levels retained for this study are depicted in Table 1.

In the next step, the planning to accomplish the experiments by means of response surface methodology (RSM) using a Central Composite Design (CCD) with three variables, eight cube points, four central points, six axial points and two centre point in axial, in total 20 runs. Total numbers of experiments conducted with the combination of machining parameter are presented in Table 2. The central composite design used since it gives a comparatively accurate prediction of all response variable averages related to quantities measured during experimentation [13]. CCD offers the advantage that certain level adjustments are allowed and can be used in two-step chronological response surface methods [14]. In these methods, there is a possibility that the experiments will stop with fairly few runs and decide that the prediction model is satisfactory. Experiments have been carried out on the EDM set up shown in Fig.1, and the data were collected with respect to the influence of the predominant process parameters on MRR. The 20 number of runs was conducted as per the conditions of run are depicted in the Table 2. To obtain a more precise result, each combination of experiments was repeated three times and every test ran for 15 min.

The mathematical model is then developed that illustrate the relationship between the process variable and response. The behavior of the system is explained by the following empirical second-order polynomial model.

$$Y = \beta_0 + \sum_{i=1}^k \beta_i X_i + \sum_{i=1}^k \beta_{ii} X_i^2 + \sum_{i=1}^{k-1} \sum_{j=2}^k \beta_{ij} X_i X_j \quad (1)$$

Analysis of variance (ANOVA) for the adequacy of the model is then performed in the subsequent step. The F ratio is calculated for 95% level of confidence. The value which are less than 0.05 are considered significant and the values greater than 0.05 are not significant and the model is adequate to represent the relationship between machining response and the machining parameters. Since the EDM process is non-linear in nature [8] the linear polynomial will be not able to predict the response accurately therefore the Second-order model (quadratic model) is

used. It is observed from the adequacy test by ANOVA that linear terms I_p , T_{on} , T_{off} , interaction term I_p with T_{on} and T_{on} with T_{off} and square terms I_p^2 and T_{on}^2 are significant. The levels of significant are depicted in the Table 3. The fit summary recommended that the quadratic model is statistically significant for analysis of MRR. For the appropriate fitting of MRR, the non-significant terms (p-value is greater than 0.05) are eliminated by backward the elimination process. The ANOVA Table for the curtailed quadratic model for MRR is shown in Table 5, the reduced model results indicate that the model is significant (R^2 and adjusted R^2 are 97.6% and 96.2%, respectively), and lack of fit is non significant (p-value is less than 0.05). After eliminating the non-significant terms, the final response equation for MRR is given as follows.

$$\begin{aligned} \text{MRR} = & -10.8997 + 1.3627 \times I_p + 0.2623 \times T_{on} - 0.0006 \times T_{off} - 0.0355 \times I_p^2 \\ & - 0.0004 \times T_{on}^2 + 0.0093 \times I_p \times T_{on} - 0.0001 \times T_{on} \times T_{off} \end{aligned} \quad (2)$$

The final model tested for variance analysis (F-test) indicates that the adequacy of the test is established. The computed values of response parameters, model graphs are generated for the further analysis in the next section.

Table 1. Different variables used in the experiment and their levels

Variable	Coding	level		
		1	2	3
Discharge current (I_p) in A	A	10	20	30
Pulse on time (T_{on}) in μs	B	50	100	200
Pulse off Time (T_{off}) in μs	C	1500	2000	2500

Table 2 - Planning matrix of the experiments with the optimal model data.

Run Order	A (I_p in A)	B (T_{on} in μs)	C (T_{off} in μs)	MRR (mm ³ /min)
1	30	200	2500	45.81
2	20	125	2000	31.14
3	10	50	2500	4.73
4	10	200	2500	18.54
5	10	200	1500	24.45
6	10	50	1500	6.41
7	30	50	1500	14.01
8	20	125	2000	31.15
9	20	125	2000	31.15
10	30	50	2500	11.77
11	30	200	1500	67.49
12	20	125	2000	31.15
13	20	125	2000	31.14
14	20	3	2000	4.90
15	4	125	2000	4.62
16	20	125	2000	31.15
17	36.	125	2000	42.51
18	20	125	2817	20.83
19	20	248	2000	49.42
20	20	125	1184	39.67

Table 3. ANOVA table for MRR (before elimination) Estimated Regression Coefficients for MRR

Term	Coef	SE Coef	T	P	
Constant	31.5533	1.2028	26.233	0.000	(most significant)
Block	-1.0486	0.6708	-1.563	0.152	(not significant)
Ip	11.0118	0.8049	13.68	0.000	(most significant)
Ton	14.4053	0.8049	17.896	0.000	(most significant)
Toff	-5.2096	0.8049	-6.472	0.000	(most significant)
Ip×Ip	-3.5703	0.8088	-4.414	0.002	(significant)
Ton×Ton	-2.2222	0.8088	-2.748	0.023	(significant)
Toff×Toff	-0.2384	0.8088	-0.295	0.775	(non significant)
Ip×Ton	6.9587	1.0392	6.697	0.000	(most significant)
Ip×Toff	-2.0412	1.0392	-1.964	0.081	(non significant)
Ton×Toff	-2.9587	1.0392	-2.847	0.019	(significant)
S = 2.939 R-Sq = 98.6% R-Sq (adj) = 97.0%					

Table 4. ANOVA table for MRR (after backward elimination)

Term	Coef	SE Coef	T	P	Remark
Constant	31.162	1.1599	26.867	0.000	(most significant)
Ip	11.012	0.9115	12.08	0.000	(most significant)
Ton	14.405	0.9115	15.803	0.000	(most significant)
Toff	-5.21	0.9115	-5.715	0.000	(most significant)
Ip×Ip	-3.553	0.9136	-3.889	0.002	(significant)
Ton×Ton	-2.205	0.9136	-2.414	0.033	(significant)
Ip×Ton	6.959	1.1768	5.913	0.000	(most significant)
Ton×Toff	-2.959	1.1768	-2.514	0.027	(significant)
S = 3.328 R-Sq = 97.6% R-Sq(adj) = 96.2%					

Table 5. Analysis of Variance for MRR

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	7	5422.17	5422.17	774.6	69.92	0.00
Linear	3	4745.5	4745.5	1581.83	142.78	00.00
Square	2	219.25	219.25	109.62	9.89	0.003
Interaction	2	457.43	457.43	228.71	20.64	0.00
Residual Error	12	132.94	132.94	11.08		
Lack-of-Fit	7	132.94	132.94	18.99	*	*
Pure Error	5	0.00	0.00	0.00		
Total	19	5555.12				

The 20 experiments were conducted in duplicate and the average values of MRR with design matrix were tabulated in Table 2. For analysis the data, the checking of goodness of fit of the model is very much required. The model adequacy checking includes the test for significance of the regression model, test for significance on model coefficients, and test for lack of fit. For this purpose, analysis of variance (ANOVA) is performed. The fit summary recommended that the quadratic model is statistically significant for analysis of MRR.

The check of the normality assumptions of the data is then conducted, it can be seen in Figure 2 that all the points on the normal plot come close to forming a straight line. This implies that the data are fairly normal and there is no deviation from the normality. This shows the effectiveness of the developed model. Notice that the residuals are falling on a straight line, which means that the errors are normally distributed. In addition, Fig. 3 illustrate that there is no noticeable pattern and unusual structure. This implies that the proposed model is adequate to illustrate the pattern of MRR.

3. Result and Discussion

The effect of the machining parameters (I_p , T_{on} and T_{off}) on the response variables MRR have been evaluated by conducting experiments as described in Section 2. The results are put into the Minitab software for further analysis following the steps summarized in Sect. 3. The second-order model was proposed in find the correlation between the MRR and the process variables taken into account. The analysis of variance (ANOVA) was used to check the sufficiency of the second-order model. The results obtained from the experiments are compared with the predicted value calculated from the model in fig 4. It can be seen that the regression model is reasonably well fitted with the observed values. The residues, which are, calculated as the difference between the predicted and observed value lies in the range of -5.56 to 4.87.

Figure 5 shows the estimated response surface for MRR in relation to the process parameters of pulse current and pulse on time. It can be seen from the figure, the MRR tends to increase, significantly with increase in peak current for any value of pulse on time. Hence, maximum MRR is obtained at high peak current (30 A) and high pulse on time (200 μ s). This is due to their dominant control over the input energy i.e. with the increase in pulse current generates strong spark which create the higher temperature cause the more material to melt and erode from the workpiece.

The effect of I_p and T_{off} is on the estimated response surface of MRR is depicted in the Figure 6, the T_{on} remains constant in its maximum level of 200 μ s. It can be noted that the MRR increases when the I_p increases, the explanation is same, as stated earlier, however with the increase in T_{off} , MRR decreases, this is because when T_{off} increases, there will be an undesirable heat loss which does not contribute to MRR. This will lead to drop in the temperature of the workpiece before the next spark starts and therefore MRR decreases. The maximum MRR is achieved with

high $I_p = 30$ A and lower $T_{off} = 1200$ μ s for the given range of input parameters. Finally, Fig 8 represents MRR as a function of T_{on} and T_{off} , whereas the I_p remains constant in its higher level of 30 A. It can be seen that the highest MRR values occurred at the higher I_p and T_{on} and at the lower T_{off} . The contours suggest that even higher MRR could be obtained for higher I_p , higher T_{on} , and lower T_{off} . The direction of further improvement is depicted in the counter plots presented as arrow. This is the direction taken in further experimentation. From this observation, it can be concluded that I_p and T_{on} are directly and T_{off} is reciprocally proportional to the MRR for the given range of experiments conducted for our test.

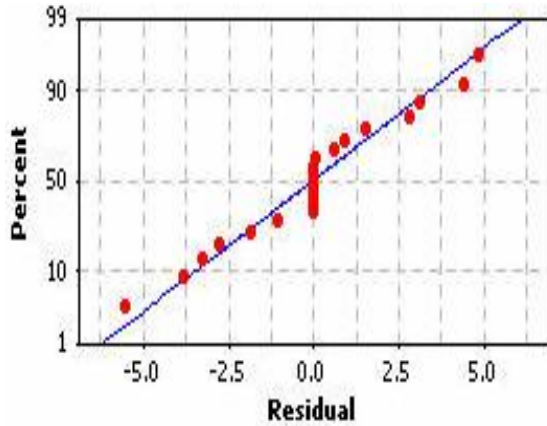


Figure 2. Correlation plot

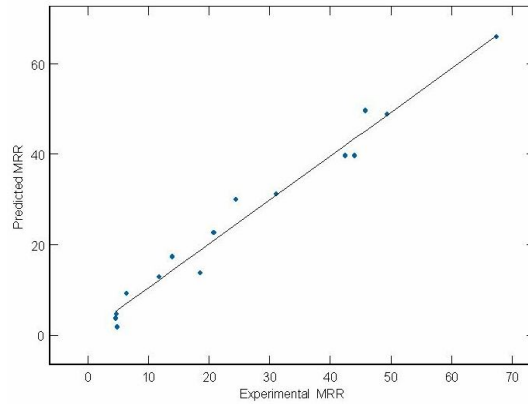


Figure 3. Predicted vs. experimental MRR

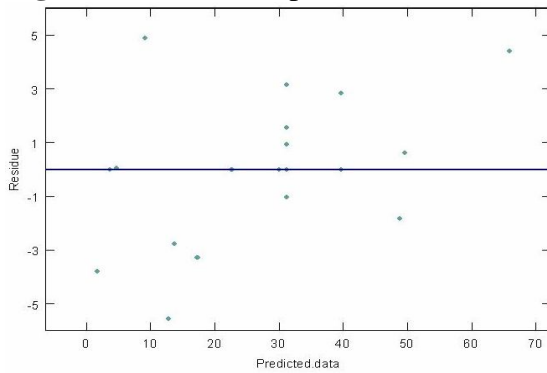


Figure 4. Plot of residuals vs. fitted value

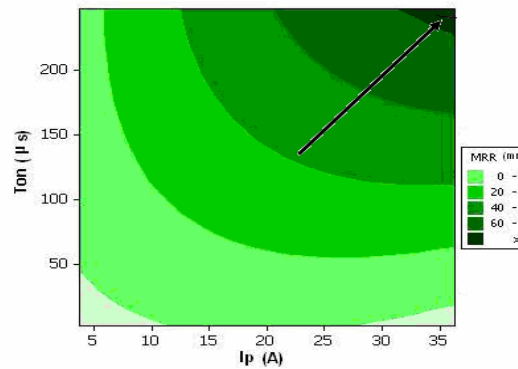


Figure 5. Effect of I_p and T_{on} on MRR

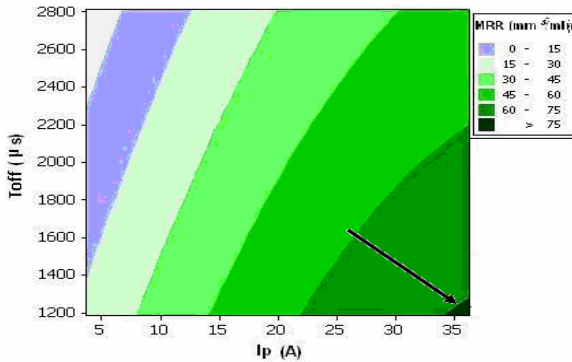


Figure 6. Effect of I_p and T_{off} on MRR

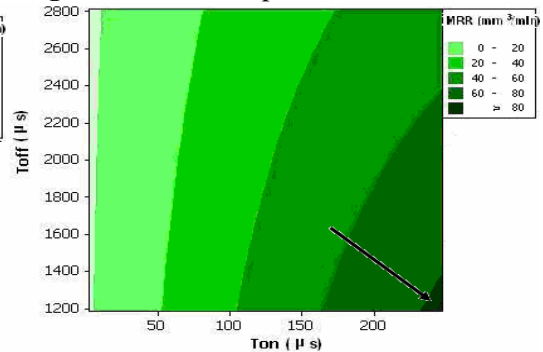


Figure 7. Effect of T_{on} and T_{off} on MRR

4. Conclusions

The present study develops MRR models for three different parameters namely pulse current, discharge time, and pause time for EDM process of AISI D2 steel using response surface method. The second-order response models have been validated with analysis of variance. It is found that all the three machining parameters and some of their interactions have significant effect on MRR considered in the present study. Finally, an attempt has been made to estimate the optimum machining conditions to produce the best possible MRR within the experimental constraints. Optimum machining parameter combinations for different roughness parameters are also tested through confirmation experiments that show reasonably good concurrence with prediction of response surface method.

REFERENCES

1. R. Snoyes, F. Van Dijck, Investigations of EDM operations by means of thermo mathematical models”, *Annals of CIRP* 20 (1), pp.35 , 1971
2. D. Mandal, S.K. Pal, and P. Saha, Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimizations using non-dominating sorting genetic algorithm-II, *Journal of Materials Processing Technology*, Vol. 186, 154-162, 2007.
3. K. Wang , Hirpa L. Gelgele, Yi Wang , Qingfeng Yuan, Minglung Fang., A hybrid intelligent method for modelling the EDM process, *International Journal of Machine Tools & Manufacture* 43, pp.995–999, 2003.
4. Wang P.J.; Tsai K.M, Semi-empirical model on work removal and tool wear in electrical discharge machining, *Journal of Materials Processing Technology*, Volume-114, Issue 1, pp. 1-17, 2001.
5. C.J. Luis, I. Puertas, G. Villa, Material removal rate and electrode wear study on the EDM of silicon carbide, *Journal of Materials Processing Technology* 164–165, pp.889–896, 2005.
6. V. Josko and M. Junkar. “On-line selection of rough machining parameters” *Journal of Materials Processing Technology*, 149:256-262, 2004.
7. K. Palanikumar, “Modeling and analysis for surface roughness in machining glass fiber reinforced plastics using response surface methodology”, *Materials and Design* **28** 2611–2618, 2007.
8. M. K. Pradhan, C K Biswas, “Modeling of Residual Stresses of EDMed AISI 4140 Steel”, *International Conference on Recent Advances in Materials, Processing and Characterization*, V.R.S Engineering College, Vijayawada, A.P, India, pp 49-55, 3-4 July 2008.
9. C.L. Lin, J.L. Lin, T.C. Ko, Optimization of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method, *International Journal Advance Manufacturing. Technology*. 19, pp.271–277, 2002.
10. J. L. Lin, C. L. Lin, The use of grey-fuzzy logic for the optimizations of the manufacturing process, *Journal Advance Manufacturing Technology*.160 9–14, 2005.
11. Guu, Y.H., Hocheng, H., “Effects of workpiece rotation on machinability during electrical discharge machining”. *Material Manufacturing Processes* 16 (1), 91–101. 2001.
12. D. C. Montgomery, *Design and Analysis of Experiments* (second ed.), Wiley, New York, 1990.
13. Theodore T. Allen, *Introduction to Engineering Statistics and Six Sigma*, Springer-Verlag London Limited, 2006
14. Robert L. Mason, Richard F. Gunst, Dallas, Texas, .James L. Hess. *Statistical Design and Analysis of Experiments With Applications to Engineering and Science* (Second Edition), A John Wiley & sons publication, 2003
15. Minitab User Manual Release 14 *MINITAB Inc*, State College, PA, USA, 2003.