

Metaheuristic Approach of Multi-Objective Optimization during EDM Process

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Abstract

In modern-day manufacturing Electric Discharge Machining (EDM) process has successfully placed itself in the domain of precision machining and generating complex geometries where secondary machining processes are eliminated. In this research paper, a die sinking EDM is applied to machine mild steel in order to measure the different multi-objective results like Material Removal Rate (MRR) and Over Cut (OC). This contradictory objective is accomplished by using the control parameters like a pulse on time, duty factor, gap current and spark gap employing copper tool with lateral flushing. Here the individual objective function of the responses is created through regression analysis. Primarily the contradictory objectives are optimized by employing Taguchi Methodology, then Regression analysis is done on the test results. Additionally, the experimental results are optimized using Response Surface Methodology (RSM). It is followed by a multi-objective optimization through Overlaid contour plots and Desirability functions to ascertain the best parametric combination amongst the set of feasible alternatives.

Keywords- Mild Steel, Regression, Response surface methodology, Overlaid control plot, Desirability function, MRR, Overcut.

1. Introduction

As the modern day looks for advance and superior material to survive in the adverse working environment, they call for hard and high-temperature resistive material; which are very difficult to machine by the traditional machining process. To sustain this challenging situation non-traditional machining is essential. Electrical Discharge Machining (EDM) is a non-conventional machining process that can remove the conductive material by control erosion. In this process, the cathode tool and the anode work piece are separated by a small spark gap and both the tool and the work piece are submerged in the dielectric fluid. When the current passes through, then a high number of electrons from the tool starts to flow towards the work piece like a plasma channel, and as a result, the work piece instantaneously melts and vaporize. The removed material is then flashed always by the continuously flowing dielectric fluid. As the tool and the work piece does not come in direct contact during machining, so the hardness of the work piece is not a factor in this machining process. This process can develop work piece having a complicated shape and profile. The major factors which can influence this process are like work piece material, pulse on time, flushing pressure of the dielectric fluid, duty factor, spark gap, the voltage applied, gap current, retract distance etc. (Kiyak and Cakir, 2007). Finest machining parameters are attained by a thorough analysis of all the control parameters which have the significant effect on the process. In this research work Design of Experiment (DOE) is used, which is a very promising method to find out the optimal machining condition in various manufacturing processes (Varun et al., 2012). The following Fig. 1 illustrated the setup of the EDM process.



Fig. 1. Illustration of EDM setup

A brief detail of the past research work on EDM is presented here. Meena and Nagahanumaiah (2006) as optimized the EDM process parameters while machining EN24 steel using direct metal laser sintering electrodes and find out that the current is the most affecting parameter for machining and porosity is the main cause of electrode wear. Nadpara and Choudhary (2014) Find out that the important parameter to increase the Material Removal Rate (MRR) during machining of D3 steel is peak current and they also concluded that this peak current has also the most effect on the tool wear. Aliakbari and Baseri (2012) has studied the rotary EDM process and optimized the machining parameter taking the rotary speed as one of the machining control parameters. Nipanikar (2012) has optimized the EDM parameters for machining of D3 Steel and also find out the tool wear during machining. Vinoth and Pradeep (2014) has investigated on the cryogenic cooling of liquified Cu (copper) tool used in EDM process and optimized various process parameters. Sharma et al. (2014) have used hybrid EDM process to increase the MRR as well as to reduce the tool wear rate and taper angle at the same time by using a copper tool and brass tool and they find out that the copper tool gives a more optimized result. Vishwakarma et al. (2012) have employed regression equation to find out the most significant process parameter during machining of EN 19 Steel in EDM process. Krishna and Xavier (2015) have employed response surface methodology optimization process on machining of industrial grade material and find out optimal machining configuration for end milling process. Pandey et al. (2014) have optimized different process parameters individually for the micro-EDM process by genetic algorithm and then used response surface methodology to find out the interrelationship in between input parameters and responses. Lin et al. (2012) used the micro-EDM process to machining SK3 carbon tool steel and find out that peak current is the most affecting parameter for this machining process.

It is found out from the past research study that there is no substantial work has done on EDM process by considering four parameters such as Pulse on Time, Duty Factor, Gap current, and Spark Gap to evaluate the effect on different responses which are contradictory in nature like material removal rate and overcut. This research work aimed to achieve an optimal solution to obtain two contradictory objectives simultaneously while machining by using a cylindrical shaped copper (Cu) tool. Response surface methodology is employed to obtain high MRR and low Over Cut (OC). The control plots demonstrate the feasible region to obtain those objectives simultaneously within the range of control parameters.

2. Experimental Setup

In this machining process “ELECTRONICA- S50 CNC” type EDM is used. This die-sinking servo-head machine maintains a constant gap between the tool and the work-piece. Paraffin oil (specific gravity of 0.850 at 25°C) is used as dielectric fluid with lateral flushing of pressure 0.2 kgf/cm². Cu tool of a length of 16.2 mm with a diameter of 26.1 mm is used to remove the work-piece material which is made of Mild Steel with a dimension of 12x12x12 mm³. A servo control unit is installed in the machine to maintain the pre-defined gap between the tool and the work-piece. It maintains the gap by measuring the gap voltage and current and then regulates the gap distance. This machining setup also consists of X-Y axis moveable working table, working tank with job holding device, a tool holder, a feed pump etc.

The process control parameters are altered within the maximum and minimum range as presented in Table 1. The volumetric material removal rate is expressed as the ratio total volume removed from the work-piece to the machining time. So, the unit of MRR is mg/sec. The overcut is expressed as the difference between the tool diameter and the diameter of the cavity formed in the work-piece. In this purpose Toolmaker’s microscope is used. The unit of the OC is expressed as mm².

Table 1. Control parameters and levels

Cutting Parameters	Symbol	Units	Levels	
			Upper	Lower
Pulse on time	POT	(μ S)	3000	1500
Duty Factor	DF		32	20
Gap current	GI	(Amp)	30	20
Spark gap	SG	(mm)	0.36	0.20

While experimenting, the control parameters are varied all together to save the time and the cost of experimentation. It also helps to find out the interaction in between the different parameters. Depending on the previous research work the main four control parameters chosen are Pulse On Time (POT), Duty Factor (DF), Gap current (GI) and Spark Gap (SG). The parameters are varied in three different level. However other parameters like tool material and the work piece, flushing pressure kept constant during the experiment.

3. Regression Analysis

The regression model contains a subset of two available conflicting regression, like (Montgomery, 2003):

- A regression model needs to contain as many as a possible regressor to make the final resultant equation to evaluate the outcomes.
- A regression model needs to contain as few as a possible regressor to reduce the cost of the model.

In this present experimentation, backward elimination method is applied having L₉ Orthogonal Array (OA). Three graphs generated from the regression calculation, namely histogram of residual, normal probability plot and residual versus fits plot.

Histogram of residuals is an exploratory tool to explain general features of the data which incorporates typical values, dispersion, shape and also abnormal values in the data. Normal Probability Plot can predict the fit of a distribution for a given set of data. It also estimates percentiles, and compare different sample distributions. Residuals versus fits graph show an arbitrary distribution of residuals on either side of zero “0”. Fitted line plots graphically represent the fitted values for all x-values in the region of significance. These plots are a convenient way to compare fitted values to actual data values in order to assess model fit.

3.1 Analysis of the Material Removal Rate (MRR)

The experimental model for Material Removal Rate from L₉ OA is shown in equation 1 below:
 The estimated regression model equation for Material Removal Rate is:

$$\text{MRR (gm/sec)} = 0.0046 + 0.000008 \text{ POT} - 0.000142 \text{ DF} - 0.000875 \text{ I} + 0.00466 \text{ SG} - 0.000000 \text{ POT} * \text{ DF} + 0.000000 \text{ POT} * \text{ I} + 0.000036 \text{ DF} * \text{ I} \quad (1)$$

The result analysis from the experimental model is illustrated in the following Table 2. As the statistical T-value of POT is larger than the other three process control parameter like DF, I and SG, so POT is the most significant parameter for MRR. Also, the value of R-square is 93.42%, it signifies that the data are very close to the mean.

Table 2. Estimated regression coefficient for MRR

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.0046	0.0261	0.18	0.888	
POT	0.000008	0.000006	1.44	0.386	71.73
DF	-0.000142	0.000834	-0.17	0.893	100.34
I	-0.000875	0.000910	-0.96	0.512	82.81
SG	0.00466	0.00668	0.70	0.613	1.07
POT*DF	-0.000000	0.000000	-2.07	0.287	64.19
POT*I	0.000000	0.000000	0.14	0.912	79.10
DF*I	0.000036	0.000025	1.42	0.391	102.76
S=0.0012241; R-sq=93.42%; R-sq(adj)= 47.35%; R-sq(pred)= 0%					

Fig. 2, Fig. 3 and Fig. 4 represent the histogram of residual, normal probably plot and residual versus fits plot for MRR respectively. From Fig. 2 Histogram for MRR shows a truncated distribution from right to left. From Fig. 3 the normal probability plot illustrates all the sample test are distributed near the mean line. All the points in this plot look a straight line for all the output responses, as the residuals are normally distributed. As in the Residuals versus fits plot of MRR i.e. Fig. 4 has a recognizable pattern, so these examples have room for enhancement.

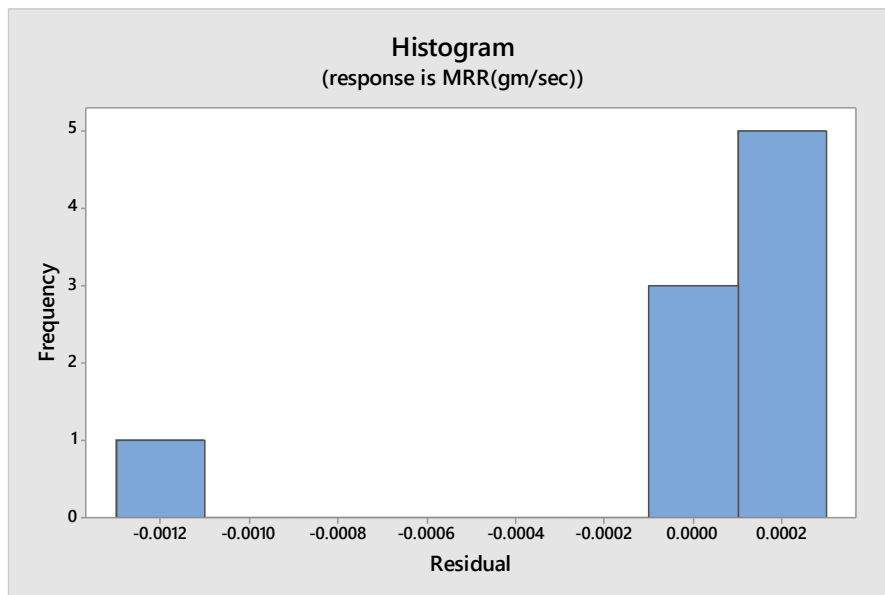


Fig. 2. Histogram for MRR

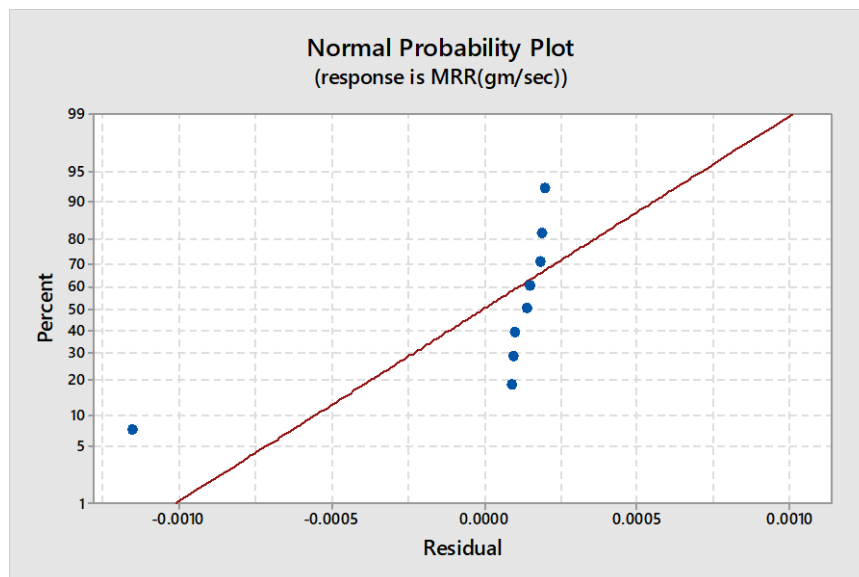


Fig. 3. Normal probability plot for MRR

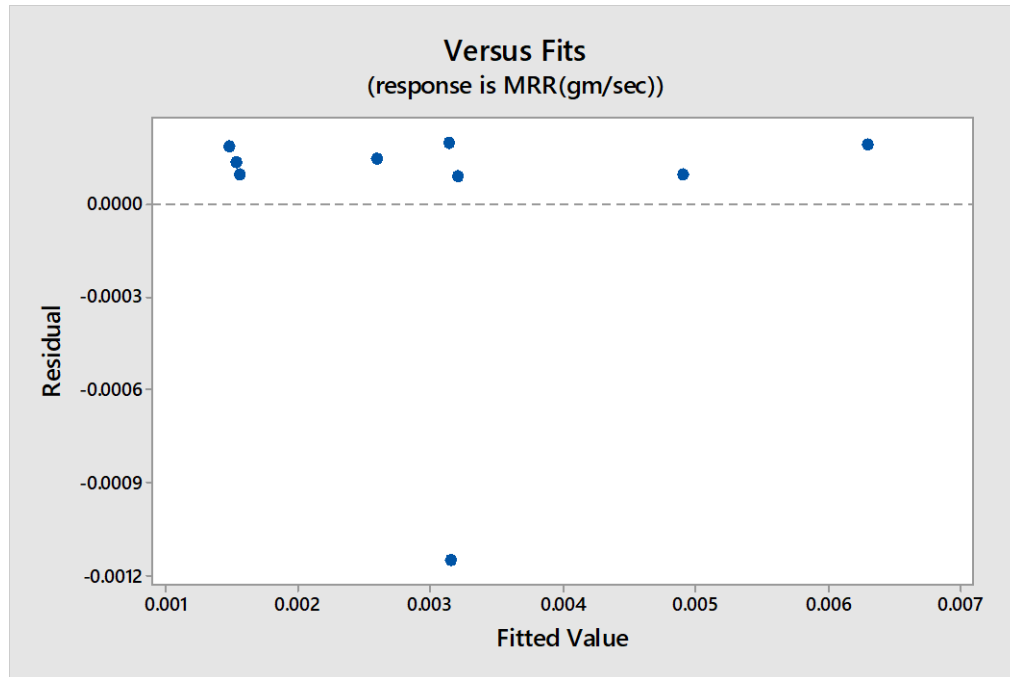


Fig. 4. Residuals versus fits plot for material removal rate

3.2 Analysis of the Over Cut (OC)

The empirical relation for OC from L_9 OA is shown in equation 2 below:

The estimated regression model equation for overcut is:

$$OC(\text{mm}^2) = -622 + 0.102 \text{ POT} + 18.1 \text{ DF} + 25.6 \text{ I} - 71 \text{ SG} - 0.00005 \text{ POT} * \text{ DF} - 0.00465 \text{ POT} * \text{ I} - 0.591 \text{ DF} * \text{ I} \quad (2)$$

The result analysis from the experimental model is illustrated in the following Table 3. As the statistical T-value of I is larger than the other three process control parameter like POT, DF, and SG, so I is the most significant parameter for OC. Also, the value of R-square is 73.97%, it signifies that the data are not very close to the mean. So, it got a room to develop.

Table 3. Estimated regression coefficient for OC

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-622	827	-0.75	0.589	
POT	0.102	0.176	0.58	0.666	71.73
DF	18.1	26.4	0.68	0.618	100.34
I	25.6	28.8	0.89	0.538	82.81
SG	-71	212	-0.33	0.795	1.07
POT*DF	-0.00005	0.00528	-0.01	0.994	64.19
POT*I	-0.00465	0.00635	-0.73	0.598	79.10
DF*I	-0.591	0.803	-0.74	0.596	102.76

S = 38.7860; R-sq = 73.97%, R-sq (adj) = 0.00%, R-sq (pred) = 0.00%

Fig. 5, Fig. 6 and Fig. 7 displays the histogram of residual, normal probably plot and residual versus fits plot for OC respectively. From Fig. 5 Histogram of OC shows a skewed distribution from left to right. From Fig. 6 the normal probability plot illustrates each value with respect to the proportion of the sample values which are quite near to the mean value that means it fitted along the distribution line. As all the residuals are typically spread in this plot, as a result it forms a straight line for all the responses. In Fig. 7 Residuals versus fits plot of OC has a recognizable pattern, so these models have room for improvement.

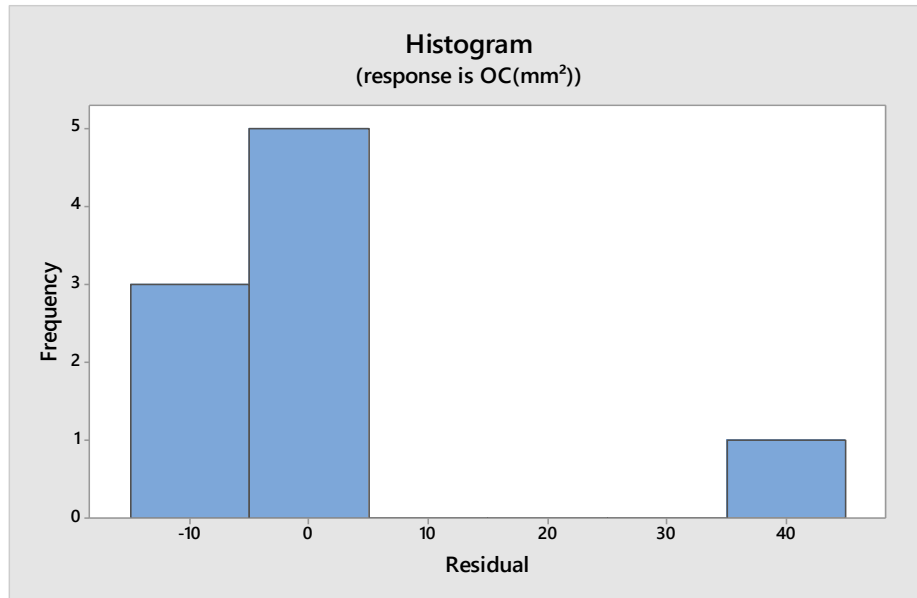


Fig. 5. Histogram for OC

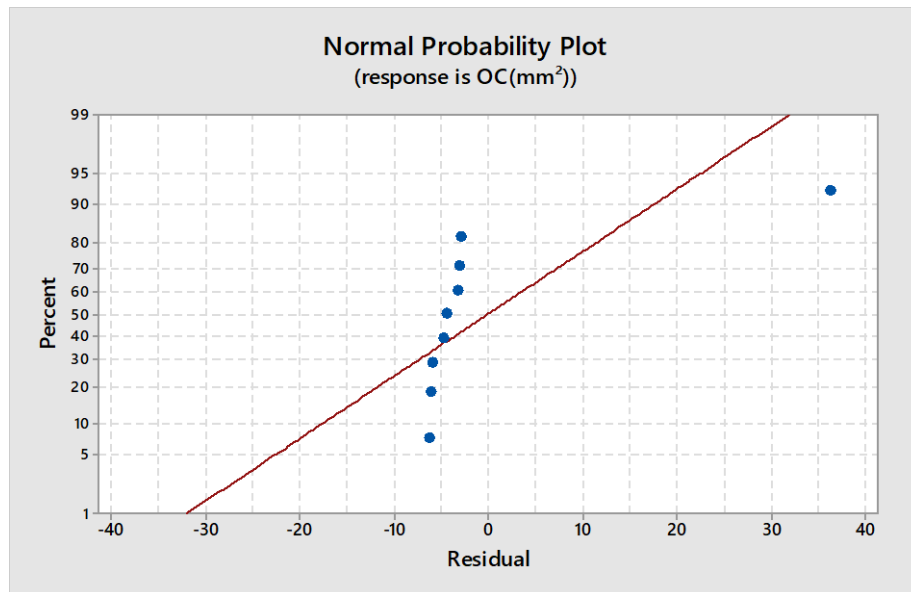


Fig. 6. Normal probability plot for OC

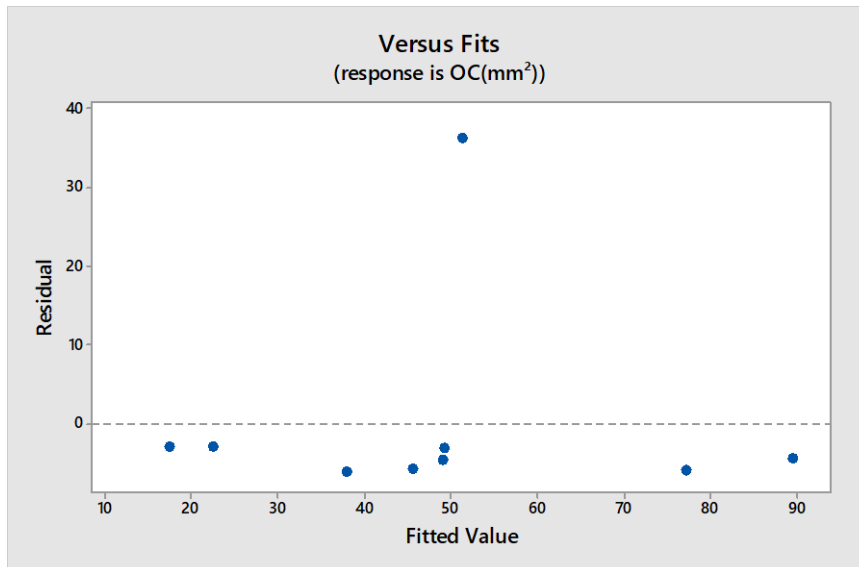


Fig. 7. Residuals versus fits plot for OC

4. Response Surface Methodology (RSM)

Response Surface Methodology (RSM) relates the relation between several process control variables and one or more responses. The RSM is used to obtain responses from a sequence of the designed experimental run. The individual variables are controlled by the experimenter, in a designed research, while the process response is a collected output during experimentation. Fig. 8 illustrates the inscribed type response surface design which has 5 level of factors and over all accuracy is good.

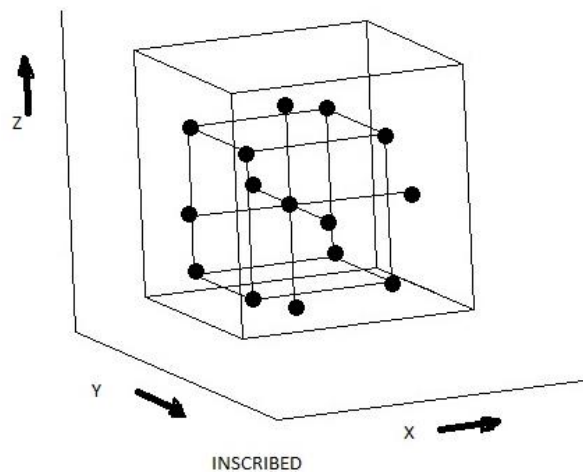


Fig. 8. Inscribed type response surface design

The response surface can be correlated with controllable variables like X_1, X_2, \dots, X_k

$$y = f(X_1, X_2, \dots, X_k) + \varepsilon \quad (3)$$

The second order mathematical equation is established in order to formulate an input-output connection proficiently which takes the general form:

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^k \beta_{ij} x_i x_j + \varepsilon \quad (4)$$

The calculated response for the model is

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^k \hat{\beta}_i x_i + \sum_{i=1}^k \hat{\beta}_{ii} x_i^2 + \sum_{i=1}^k \hat{\beta}_{ij} x_i x_j \quad (5)$$

In the present research work, Box-Behenken Design is used which is based on 2^k ($k = 4$) factorials with incomplete designs and found to be very efficient. The process variables combinations and the corresponding responses are presented in Table 4.

4.1 Analysis of the Test Result for Material Removal Rate

The response surface (RSM) graph of MRR regarding POT, DF, SG and I are exposed in Fig. 9. In these plots, MRR is taken in the z-axis and at the time two control parameters are varied in x-axis and y-axis respectively, while other two parameters are kept constant. It is evident from the graph that the highest points of the control parameters produce an extreme response. Since the response is fully dependent on the variables therefore they cannot have any fixed location which is obvious from this plot.

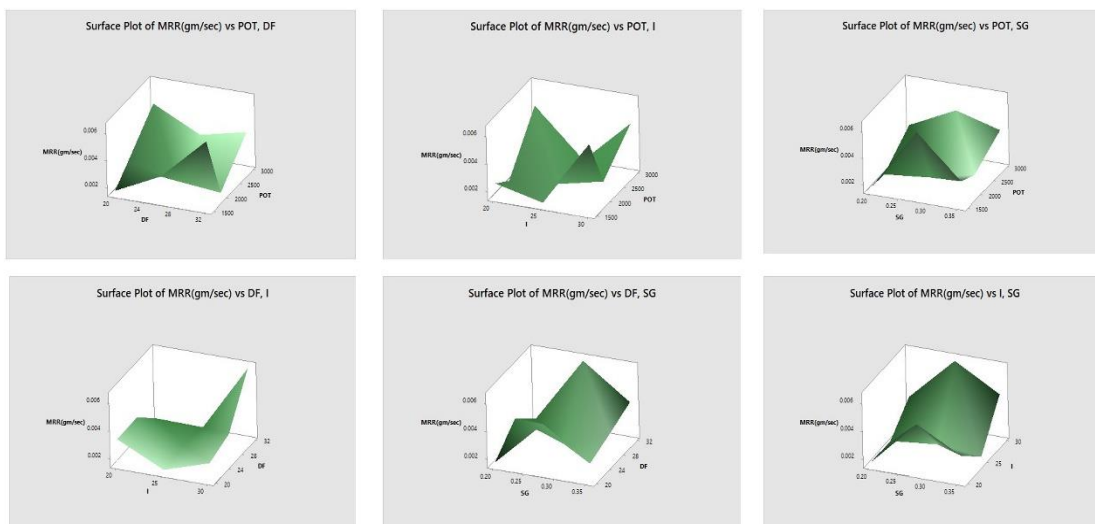


Fig. 9. Surface plot for the results of material removal rate

4.2 Analysis of the Test Result for Over Cut

The response surface (RSM) graph of OC regarding POT, DF, SG and I are shown in Fig. 10. In these plots, the variation of OC is shown in the z-axis and two control parameters are taken in x-axis and y-axis respectively, while other two parameters are kept constant. The graph manifest that the highest levels of the control parameters produce a maximum response. Subsequently the response is supported by the variables therefore they cannot have any fixed location which is obvious from this plot. (Ojha et al., 2012).

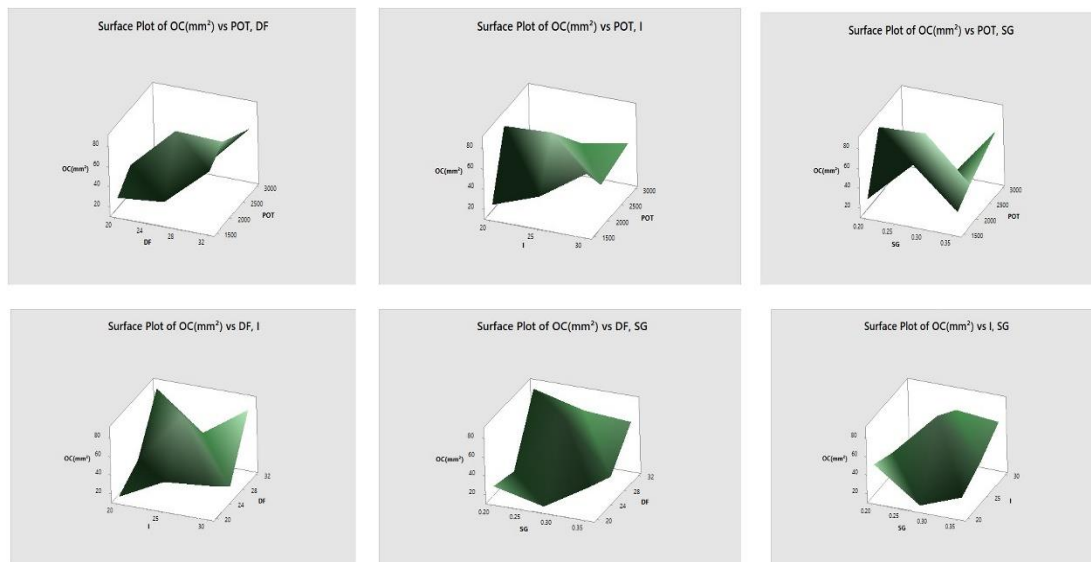


Fig. 10. Surface plot for the results of over cut

5. Simultaneous Optimization of Responses

5.1 Overlaid Contour Plots

High material removal rate and low over cut are the two main contradictory features for optimizing the complex process like EDM process. Both responses are contradictory, so, achieving them instantaneously by a single set of the optimum interchangeable mixture is rather tough. In this research work the multi-response optimization is applied in order to achieve these two conflicting goals concurrently. The levels of operating parameters are reviewed and satisfied those two constrained objectives by overlay control plots.

5.2 Analysis of the Test Result Using Control Plot

The overlaid control plots of responses with respect to control parameters are shown in Fig. 11. In these plots two control parameters are taken in x-axis and y-axis, while other two parameters are kept constant. The continuous line in the plot represents the lower boundary while the dotted line represents the upper boundary of the responses. The white area is the feasible region, where all the responses are optimizing simultaneously.

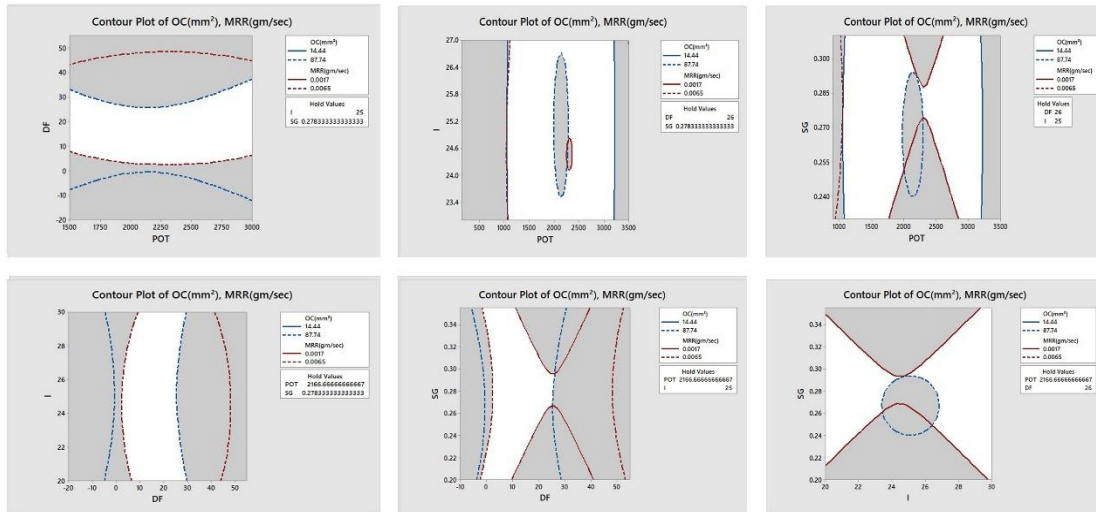


Fig. 11. Control plots of responses

6. Desirability Functions

The response optimizer can recognize the pattern and can help to optimize a single response as well as a set of responses. For a set of responses, the criteria for all the responses are taken care at the same time. (Cho and Park, 2006; Jeong and Kim, 2009). The basic attempt is to initially convert each response into a separate desirability function that differs with in a range (0 to 1) (Salmasnia et al., 2013). Here for over cut the target is set as minimum and for MRR the target is set as maximum. The significant parameter(s) choose how the desirability function can combine in a single composite desirability. Then finally the overall desirability function as well as composite desirability is calculated as per the individual mean of the functions.

6.1 Analysis of the Test Result Using Desirability Functions

The response optimization is presented in Table 4 below.

Table 4. Desirability function result

Responses	Goal	Lower boundary	Upper boundary	Weight
MRR	Maximum	0.0017	0.0065	1
OC	Minimum	14.44	87.74	1
Predicted Responses				Global Solution
MRR = 0.0058 gm/sec, desirability = 0.85933 (85.933%) OC = 14.9109 mm ² , desirability = 0.99355 (99.355%)				POT=3000 μS DF=20 I=30 amp SG=0.2894 mm
Composite Desirability = 0.9257 (92.57%)				

Fig. 12 illustrate the optimized graph of the response parameters MRR and OC with the process control variables. The desirable response of MRR becomes 85.933% with the predicted response of 0.0058 gm/sec, similarly the desirability of OC becomes 99.355% having the predicted response 14.911 mm². Hence composite desirability is 92.40% having the paramedic combination of POT=3000 μS, DF=20, I=30 amp and SG=0.2894 mm for a multi objective optimal solution for higher MRR and lower OC.

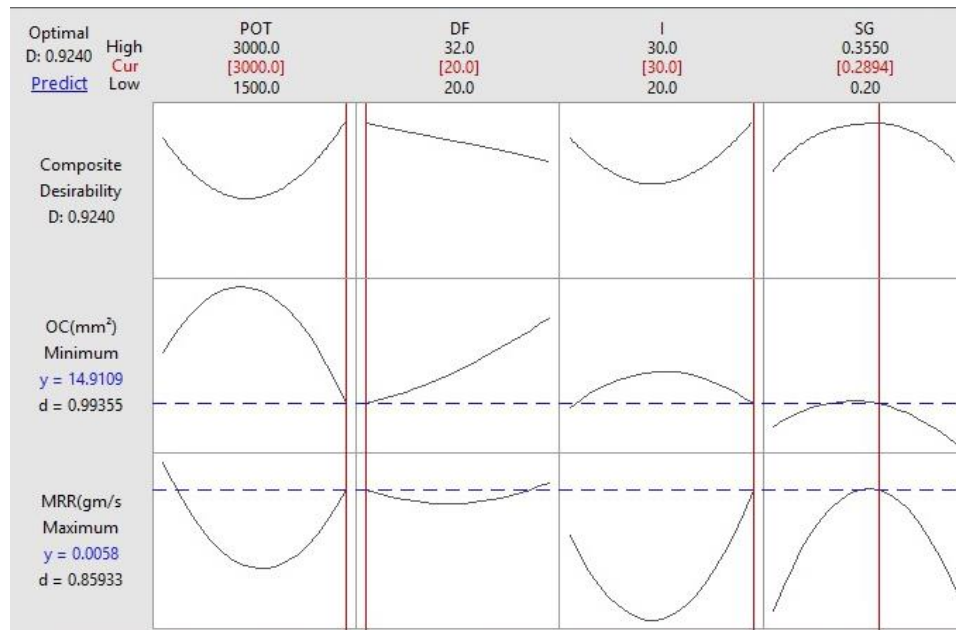


Fig. 12. Plot showing responses parameters versus process variables

7. Conclusion

The present paper attempts to validate and optimize the machining variables while machining of Mild Steel by EDM. The regression models are evaluated to fully clarify input-output correlation with an accurate probability. It is found that the MRR is mostly influenced by POT whereas OC is affected by I. Histogram for MRR shows a truncated distribution from right to left and for OC histogram also shows a skewed distribution from left to right. The points in the normal probability plot form a straight line for all the responses since the residuals are normally distributed. For each residual versus response, plots have a recognizable pattern, so this model has room for improvement. The single response optimization is then found out using response surface methodology which finds the optimal solution. Then the multi-objective optimization is carried out by employing overlaid control plot. The overlaid control plot can recognize a desirable region where the responses can have the best value. The reasonable region is obtained for Material Removal Rate (MRR) which is between 0.0065 gm/sec to 0.0017 gm/sec and for Over Cut (OC) between 87.44 mm² to 14.44 mm². The clarifications obtained from the regression analysis is highlighted with the desirability functions. In order to attain maximum MRR, and minimum OC

the possible parametric combination of the control parameters is POT=3000 μ S, DF=20, I=30 amp and SG=0.2894 mm.

Hence, the analytical findings for evaluating the optimum parametric combination of Electric Discharge Machining of Mild Steel can perform an important role and an efficient guideline for manufacturing of complex products of similar material.

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