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OPTIMIZATION AND REGRESSION ANALYSIS OF SURFACE ROUGHNESS FOR ELECTRIC DISCHARGE MACHINING OF EN-19 ALLOY STEEL USING TUNGSTEN COPPER ELECTRODE WITH DESIGN OF EXPERIMENTS

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ABSTRACT

In this paper, machining of EN-19 has been carried out using rectangular shaped tungsten copper electrode to study the influences of EDM input parameters on surface roughness. The selected EDM input variables are input current (5-45 Amperes), pulse time (10-90 sec.), duty cycle (3-7), Gap voltage (6-18) and Flushing pressure (0.1-0.5). 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 surface roughness. A mathematical model was developed using multiple regression method to formulate the gap voltage, pulse on time, pulse off time and flushing pressure to the surface roughness. The developed model showed high prediction accuracy within the experimental region. Design of experiments was used to design the experiments with coded levels of input parameters and optimum responses were determined through response surface methodology.

Keywords: *Design of Experiments, Surface roughness, Regression Analysis*

1. INTRODUCTION

Non-traditional machining processes are progressively used to manufacture high quality industrial components. Amongst the non-traditional processes of machining methods, electrical discharge machining (EDM) has drawn a great attention because of its broad industrial applications [1].Response Surface Methodology (RSM) is a well known approach for constructing models based on either physical experiments, computer experiments (simulations) [2] [3] and experimented observations. RSM, invented by Box and Wilson, is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are prepared in the input variables in order to recognize the reasons for changes in the output response [4]. RSM involves two basic concepts: (a) The choice of the approximate model, and (b) The plan of experiments where the response has to be evaluated. The analysis of variance (ANOVA) is widely used to consider effects of factors on responses. In experimental investigations, ANOVA is often employed prior to other statistical analysis. Then analysis of variance is carried in order to establish a relation between independent variables and dependent variables is widely applied [5].

The desirability function was originally developed by Harrington [6] to simultaneously optimize the multiple responses and was later modified by Derringer and Suich [7] to improve its practicality. The desirability function approach is one of the most frequently used multi-response optimization techniques in practice. The desirability lies between 0 and 1and it represents the closeness of a response to its ideal value. If a response falls within the unacceptable intervals, the desirability is 0, and if a response falls within the ideal intervals or the response reaches its ideal value, the desirability is 1. Meanwhile, when a response falls within the tolerance intervals but not the ideal interval, or when it fails to reach its ideal value, the desirability lies between 0 and 1. The more closely the response approaches the ideal intervals or ideal values, the closer the desirability is to 1. According to the objective properties of a desirability function, the desirability function can be categorized into the nominal-the best (NB) response, the larger-the-better (LB) response and the smaller-the-better (SB) response. Interested persons can follow the expressed relevant desirability functions in [101].The proposed desirability function transforms each response to a corresponding desirability value between 0 and 1. All the desirability can be combined to form a composite desirability function which converts a multi-response problem into a single-response one. The desirability function is a scale invariant index which enables quality characteristics to be compared to various units. In such method the plant manager can easily determine the optimal parameters among a group of solutions.Kun-Lin Hsieh et al. [8] believed that when desirability values lies more close to 0 or 1 may lead to a bad model's additive.

2. Experimental Method

2.1 Work piece material

Carbon	***Manganese***	***Chromium***	***Molybdenum***
0.37%	0.77%	0.98%	0.21%

Table 1. Chemical composition of EN-19

- Hardness 54 HB
- Thermal conductivity 29W/mK

EN-19 steel grade has been selected as the work piece for this experiment, which means that it has composition of great technological importance. Nickel chromium molybdenum steel with high strength and toughness is used for gears axles and high strength studs.EN-19 is available mostly in rolled, annealed and hardened and tempered form as black round or square bar and bright round or square, and hexagons.

The work piece size prepared on conventional milling was 100 mm **x** 100 mm **x** 20 mm.

2.2 Machine, electrode and dielectric

The Experiments were carried out using ENC EDM machine. Tungsten Copper was selected as tool electrode material with density 13.80 g/cm^3. The electrode dimensions taken were 112 mm **x** 20 mm **x** 15 mm for experimental work. And the dielectric fluid used is EDM oil.

2.3 Surface Roughness test machine

The surface roughness of the machined surface was measured by using Taylor Hobson Surtonic 3+ surface test equipment shown in figure2.The surface roughness, measured is central line average (*R*a) was employed to assess the quality of the machined surface quantitatively. Each surface roughness value was obtained by averaging three measurements at various positions of work piece. The cut-off length was set as 0.80 mm. The evaluation length was selected as 4.0 mm. Stylus type was diamond with diamond tip radius 5μm, Traverse Length (Max) 25.4mm.

3. Experimental Methodology and analysis

The response surface methodology (RSM) is a combination of statistical and mathematical techniques to analyze, model, and optimize processes. The purpose of this method is to establish the unknown relationship between the independent variables (input factors) and the process responses. Surface experiments are performed to fit either a first order model (linear function). The CCD deploys a 2*k* factorial design with centre runs to fit a first order model and perform the lack of fit test, while the additional runs (axial points) are utilized to determine the incorporation of second-order (quadratic) terms. One of the most important characteristics of CCD is the spherical or rotatability property (variance of predicted responses is the same at all points that are the same distance from the design center), since all axial and factorial design points are on the surface of a sphere of radius, which allows accurate predictions throughout the region of interest at extreme levels, CCD is an appropriate choice of design in this study

[9]. In the present work, a 2^n full factorial design in accordance with Central composite design method was selected for the design of experiments as shown below table 1. A total 32 different combinations runs were carried out as per central composite design $2^5=2^n$ (n is number of factors). The runs are executed in random order according to a CCD configuration for five factors. The coded values of independent variables are found and tabulated in table 2.

Factor	Level				
	-2	-1	0	1	2
T_{on}(μs)	10	30	50	70	90
V_{gap}(V)	6	9	12	15	18
Duty Cycle$_\tau$	3	4	5	6	7
I_p(Amp)	5	15	25	35	45
F_p(kgf/cm^2)	0.1	0.2	0.3	0.4	0.5

Table 2. Coded levels

In accordance with central composite design five independent variables namely current (I_p), voltage (V_{gap}), Pulse on time (T_{on}), Duty cycle (DC) and flushing pressure (F_p) are selected for experimental analysis. Response analysis is statistical and mathematical methods useful for development, improvement and optimizing the processes. The three stages are design and experiments, surface modelling and optimization. Each independent variable had 5 levels which are (–2,-1, 0, 1, 2).Surface roughness of EDMed surface depended on gap voltage, pulse on time, pulse off time and flushing pressure [10].

3.1 Anova for Surface roughness

Anova for surface roughness is carried out to study the effect on of the EDM machining process variables and also used to examine the null hypothesis with respect to the data obtained through experiments. Through null hypothesis it is assumed that there is no difference in treatment way.

($H_0 : \mu_1 = \mu_2 = \ldots.. = \mu_a$) -------------------- (1)

Table 4 is Anova table for surface roughness. Before any presumption is made through analysis of variance table, the assumptions used through Anova process have to be checked. The assumptions underlying the Anova tell the residuals are determined by evaluating the following equation [11].

$$E_{ij} = y_{ij} - \hat{y}_{ij} \text{ ------------------ (2)}$$

Where E_{ij} is the residual, y_{ij} is the corresponding observation of the experimental runs, $\hat{y}_{ij}$ is the fitted value. A check of the normality assumption may be made by constructing the normal probability plot of the residuals. Figure 3 depicts normal plot of residuals which is used to test the normal distribution of errors. If the underlying error distribution is normal, this plot will resemble a straight line [12].

Run	T_{on}	V_{gap}	τ	I_p	F_p	R_a
1	0	0	0	0	0	8.3
2	-1	-1	1	-1	-1	6.0
3	-1	1	-1	-1	-1	4.2
4	-1	-1	-1	-1	1	9.6
5	0	0	0	0	0	8.7
6	0	0	0	-2	0	5.9
7	1	1	-1	1	-1	4.5
8	1	-1	-1	1	1	8.9
9	-1	-1	1	1	1	8.8
10	1	1	1	-1	-1	5.9
11	2	0	0	0	0	8.6
12	0	0	0	2	0	6.1
13	0	0	2	0	0	6.2
14	0	0	0	0	0	4.0
15	0	0	0	0	-2	7.1
16	-1	1	1	-1	1	7.8
17	-1	1	1	1	-1	5.2
18	-1	1	-1	1	1	7.6
19	0	0	0	0	2	8.4
20	0	0	0	0	0	9.6
21	1	1	1	1	1	6.0
22	-2	0	0	0	0	6.1
23	1	-1	-1	-1	-1	4.9
24	1	-1	1	1	-1	4.7
25	0	-2	0	0	0	6.9
26	-1	-1	-1	1	-1	6.9
27	1	1	-1	-1	1	5.1
28	0	0	0	0	0	5.5
29	1	-1	1	-1	1	9.3
30	0	0	0	0	0	6.4
31	0	2	0	0	0	6.8
32	0	0	-2	0	0	6.5

Table 3. Design Matrix

The distribution in figure 3 shows that the error normality assumption is valid. Figure 4 gives the plot of the residuals in time order of data collection. This graph helps to check the independence assumption on the residuals. It is desired that the residual plot should contain no apparent patterns. Figure 4 show the independence assumption on the residuals was fulfilled for the experimentation. Figure 5 and 6 shows residual plot & histogram for residual versus fitted values. The structure less distribution of dots above and below the abscissa (fitted values) shows that the errors are independently distributed and the variance is constant [12].Therefore, it is concluded that the assumption of constant variance of residuals is satisfied. Confidence level is chosen to be 95% in this case. So the p values which are less than 0.05 indicate that null hypothesis should be rejected, and thus the effect of the respective factor is significant. 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 [11]. In this work from table 4, Anova table shows the most important factor are input current with F= 210.19, pulse on time with F=7.27, duty cycle with F=2.39 and voltage gap with F=1.27.Flushing pressure has minimum effect as its f ratio is lower than *p* value.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Ton	1	2.449	2.449	2.449	7.27	0.012
Vgap	1	0.427	0.427	0.427	1.27	0.271
Dutycycle	1	0.807	0.807	0.807	2.39	0.134
Ip	1	70.805	70.805	70.805	210.19	0.000
Fp	1	0.007	0.007	0.007	0.02	0.889
Error	26	8.758	8.758	0.337		
Total	31	83.252				

Table 4. Analysis of Variance for Surface Roughness.

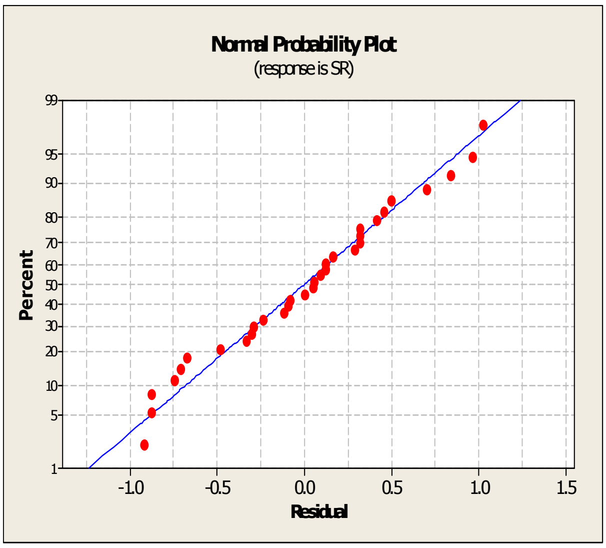

Figure 1. Normal Probability plot for Surface Roughness

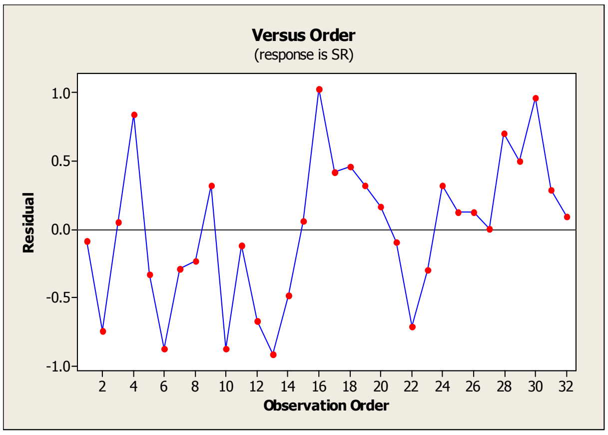

Figure 2. Plot for observation order

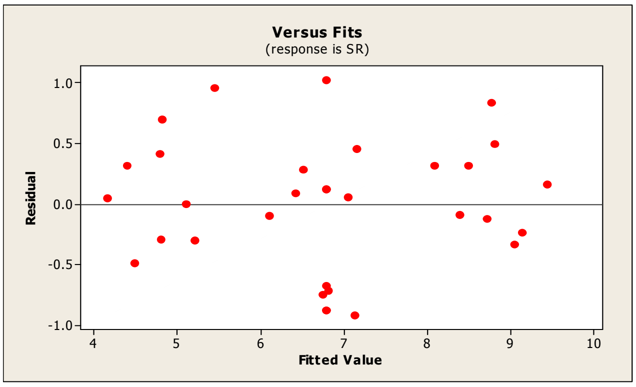

Figure 3. Plot for Residual versus fitted values.

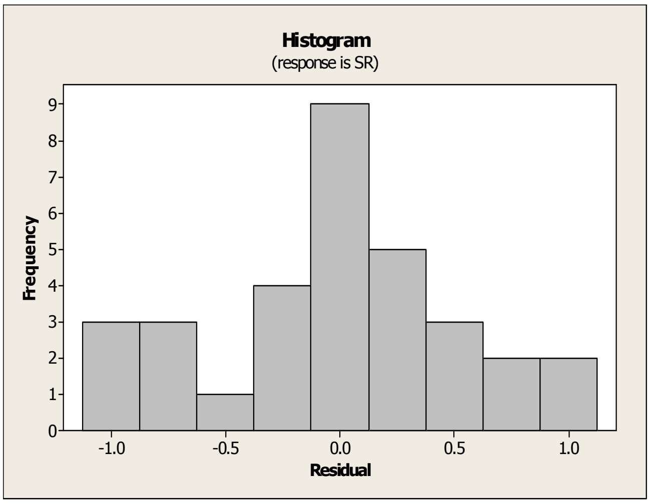

Figure 4. Plot for Residual versus fitted values.

3.2 Results of Anova for Surface Roughness

The analysis carried illustrates that the application of analysis of variance for surface roughness over EN-19 steel in conjunction with central composite design of experiments is effectual, and proficient in developing a robust and versatile EDM process. Results obtained by this investigation are in accord with findings in literature in which surface roughness of EDMed surface depended prominently on input current, voltage gap, pulse on time, duty cycle along with minimum effect of and flushing pressure. Although previous research efforts performed on different materials other than EN-19, the outcomes were in accordance. The parameters affecting the surface roughness were identified using ANOVA technique in Minitab 15 environment. Assumptions of ANOVA were tested using residual analysis. After careful testing, none of the assumptions was violated.

3.3 Regression analysis for Surface Roughness

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 surface roughness. During regression analysis it is assumed that the factors and the response are linearly related to each other. In common, the units of process parameters differ from each other. Even, if some of the factors have the same units, not all of these factors are tested over the same range. Since factors gap voltage, pulse on time, duty cycle, flushing pressure, input current have different units and different ranges in the experiment data set, regression analysis is not performed on the raw or natural factors. The normalized factors are called coded factors are hereby used in accordance to central composite design. In this study, coded factors of gap voltage, pulse on time, duty cycle, input current and flushing pressure are used as the independent factors in the regression analysis. A coded factor must be defined for each of the actual factor. The general first order model is proposed to predict the surface roughness over the experimental region can be expressed as equation 3.

$$Y\ (SR) = \beta 0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \quad (3)$$

Where Y is the response (surface roughness) and X_1, X_2, X_3, X_4, X_5 are the coded factors respectively. βs are regression coefficients. The derived regression equation is as follows:

$$SR(Y) = 9.48 + 0.0171\ T_{on} + 0.0444\ V_{gap} + 0.183\ DC + 0.198\ I_p - 0.17\ F_p \quad (4)$$

From equation 4, the factors gap voltage and input current have an additive effect on the surface roughness and duty cycle, pulse on time, flushing pressure have negative impact on surface roughness. Analysis of the residuals of the model shown in equation 4 is performed to test assumptions of normality, independence and constant variance Figure 8 of residuals. The quantitative test methods mentioned earlier are employed again, and none of the assumptions are violated.

Analysis of variance is derived to inspect the null hypothesis for the regression model that is presented in Table 6. The results indicate that the estimated linear model by the regression procedure is significant at the α–level of confidence (0.05). R-squared (R^2) amount is calculated to check the goodness of the fit. R^2 is a measure of the amount of reduction in the variability of response obtained by using the regressor variables in the model. As R^2 always increases, as we add terms to the model, some model builders prefer to use an adjusted R^2 statistic.

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 [24]. For this experiment the R^2 value indicates that the predictors explain 85.27 % of the response variation. Adjusted R^2 for the number of predictors in the model is 87.46 % both values shows that the data are fitted well. The prediction model was then validated with another set of data. *Table 5* 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 these performances.

In Table 5 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 12.7 % and the average percentage error of this method validation was about 6.4%. As a result, the prediction accuracy of the model appeared satisfactory.

According to the regression analysis shown in Table 5.The model is built for 95% confidence level. As the probability values (*p*) for the linear term were found to be <0.05, which states that it has significant contributions towards the response output: Surface roughness. In the Table 5 Degree of freedom (DF) is the rank of a quadratic form. As in this case there are 32 observations for one response surface roughness to be estimated. As per Anova it needs total *(n-1) =31* DF for estimating variability. The sequential sums of squares (Seq SS) measures the reduction in the residual sums of squares provide by each term in the model. The adjusted sums of squares (Adj SS) measures the reduction in the residual sums of squares provided by each term relatively to a model containing all the other terms. The sequential and adjusted sums of squares will be the similar for all terms, if the design matrix is orthogonal.

T_{on}	V_{gap}	DC	Ip	Fp	Predicted SR(µm)	Experimental SR µm)	% (Error)
30	15	4	15	0.2	8.87	8.3	6.8
50	12	5	25	0.3	6.70	5.9	1.3
30	9	6	15	0.2	8.49	8.8	3.5
50	12	5	25	0.3	6.7	6.1	9.8
30	15	6	35	0.2	4.79	5.2	7.8
50	12	5	25	0.1	6.8	6.1	11.4
70	15	4	35	0.2	5.11	5.1	0.19
70	9	4	15	0.2	8.81	9.3	5.2
50	6	5	25	0.3	5.66	6.8	12.7
50	12	3	25	0.3	6.41	6.5	1.3

Table 5. Percentage Error

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	74.494	74.494	14.8987	44.23	0.000
Linear	5	74.494	74.494	14.8987	44.23	0.000
Residual Error	26	8.758	8.758	0.3369		
Lack-of-Fit	21	5.910	5.910	0.2814	0.49	0.883
Pure Error	5	2.848	2.848	0.5697		
Total	31	83.252				

Table 6. Anova for Regression of SR

The most common case where this occurs is with factorial and fractional factorial designs, when analyzed in coded units. For 95% confidence level, if the p (probability) value for one or more coefficients is <0.05, then these coefficients can be called statistically significant. The adjusted mean square (Adj MS) values are adjusted sums of squares (Adj SS) divided by the corresponding DF. The F ratio is the statistical test used to decide whether the model altogether has statistically significant predictive capability, i.e., whether the regression SS is big enough, considering the number of variables needed to achieve it. F is the ratio of the model mean square to the error mean square. If for a particular type of terms (say linear), the calculated F value is found to be above the table-calculated value, it will have significant contribution toward the response. The *p* values tell whether a variable has statistically significant predictive capability in the presence of the other variables, i.e., whether it adds something to the equation. In some circumstances, a non-significant *p* value might be used to determine whether to remove a variable from a model without significantly reducing the model’s predictive capability.

4. Optimization of Surface Roughness

The designed experiments involve determination of optimal conditions that will produce the "best" or “optimum” value for the response (SR). 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.

4.1 Individual desirability

As in this case of SR we need to optimize single response , so here individual desirability (d) for surface roughness is obtained using the goals and boundaries for SR that have been 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 surface roughness (SR) it is desirable to obtain *minimum value* for better surface finish of material. As response SR is desired to be minimizing for which determination of target value and an allowable maximum response value is provided to response optimizer. The desirability (d=1) is one for SR response below the target value: above the maximum acceptable value the desirability (d=0) is zero [30].

Individual desirability:

The individual desirability is calculated as follows:

$d_i = f_i(y)^{w_i}$----------------------(5)

Where:

- W_i is the Weight for response i and the function $f_i(y)$

In the below table 7, y is the response value, U and L are the upper and lower boundaries (i.e. minimum and maximum acceptable values for the response), respectively, and T is the target. For the SR(y) to optimize our aim is its minimization then:

$f_i(y)$ =	1	Y<T
	U – y/ U –T	T ≤ y ≤ U
	0	y ≥ U

Table 7. Minimization of response by individual desirability [29]

4.2 Response Optimization

Parameters

	Lower	Target	Upper	Weight	Import
SR Minimum	3	3	6.5	10	1

Table 7. SR Range

Starting Point

T_{on} = 50; V_{gap} = 12; Dutycycle = 5; I_p = 25; F_p = 0.3.

Ton	= 10
Vgap	= 6
Dutycycle	= 3
Ip	= 35
Fp	= 0.5

Table 8. Global Solution

Predicted Responses

SR = 3.44285, desirability = 0.258519

Composite Desirability = 0.258519

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 (Duty cycle), F_p. Now aim is to minimize the response SR and simultaneously maintain other responses in EDM process. As shown Global solution of input parameters is obtained by response optimizer. To determine global solution of input variables in order to satisfy the above criteria of SR minimization, it had been solved by Response optimizer desirability minimization function table 7.The individual desirability for SR surface roughness 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= 35, T_{on}=10, V_{gap}= 6, DC= 3, F_p= 0.5.The optimum predicted value for SR = 3.44285 obtained for 100 % desirability. If it is further desired to improve this initial solution, you can use the plot. Move the red vertical bars to change the factor settings and see how the individual desirability of the responses and the composite desirability change.

5. RESULTS & CONCLUSIONS

Results show that the flushing pressure has minimum effect, while pulse on time, duty cycle, voltage gap and input current are the significant factors for the surface roughness of for EN-19 alloy steel material. Finally, a mathematical model was developed using multiple regression method to formulate the gap voltage, pulse on time, pulse off time and flushing pressure to the surface roughness. The developed model showed high prediction accuracy within the experimental region. The maximum prediction error of the model was 12.7 % and the average percentage error of prediction was 6.4 %.

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