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PARAMETRIC OPTIMIZATION AND ANALYSIS OF EDM ON EN-31 STEEL USING POWDER METALLURGY ELECTRODE

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ABSTRACT

Electrical discharge machining (EDM) is a non-conventional machining process majorly used for machining process like complex and hard materials. EDM does not make contact with electrode and work piece.An attempt has done using copper-titanium di boride (Cu-TiB_2) powder metallurgy electrode to test in EDM on EN-31 steel material. During the process a dielectric fluid which helps for metal removing and also acts as coolant. This paper presents a parametric optimization and analysis of EN-31 steel using EDM process. The machining parameters such as peak current, pulse on time and gap voltage are chosen to evaluate the Material Removal Rate (MRR) and Surface Roughness (SR). the output responses such as Material Removal Rate (MRR), Surface Roughness (SR) and Central Composite Design (CCD) are calculate using Design of experiment (DoE). For optimization of each parameters on MRR and SR Analysis of Variance (ANOVA) model is implemented and Regression model has also tested through ANOVA test. At result obtained optimum parameters are used as experimental parameters to get the accuracy level of predicted response parameters.

Keywords: Electrical discharge machining, ANOVA, CCD, Tool Electrode

I. INTRODUCTION

Electrical discharge machining (**EDM**) is a process of manufacturing desired shape of a work piece using electrical discharges. Rapidly recurring current discharges between the tool electrode and work piece material helps to remove material which is separated by a dielectric liquid like EDM oil or kerosene oil., when subjected to an electric voltage. No contact is made between the tool and work piece, on which the process depends upon.

The basic principal followed is that the conversion of electricity into thermal energy through a series of separate electrical discharges occurring between the conductor (tool) and piece of work immersed during a dielectric fluid . Because of the insulating impact of the material that is employed in EDM method is extremely necessary as a result of it avoids electrolysis of the electrodes throughout the EDM method. Spark is initiated once high voltage is applied between the conductor and piece of work at smallest purpose distance.. Metal starts erosion from each the surfaces of piece of work similarly as conductor. At the tip sparks meet the whole piece of work surface results in its erosion, or machining to a form that is reflection of the tool.The dielectric fluid helps discharge energy to concentrate into a channel of very tiny cross-sectional area. It additionally acts as fluid and flushes away the particles of machining from the gap. The electric resistance of the dielectric fluid influences the discharge energy at the time of spark initiation. Early discharge can occur, if the resistance is low.

Fig-1:EDM machine

There was a really high peak in current at the moment of spark initiation, followed by a fast rate of decline. By this high current peak abundant higher spark temperature is made that is way more than that required to get rid of material and resulted in thermal injury to the conductor. With the decrease in peak current and increase in spark length helps to reduce the tool wear and rise in the machining efficiency.

II. MATERIALS

1. TOOL ELECTRODE

COPPER TITANIUM DIBORIDE (Cu-TiB2)

Titanium di-boride has very good hardness and stiffness properties but in contrast to ceramics it has electrical and thermal conductivity and also has low coefficient of thermal expansion (CTE) compared with most of the metals. This combination of high thermal, electrical conductivity with low CTE makes TiB2 a perfect tool electrode material for EDM [3].

Table 1 – Properties of TiB2

Density (gcm^{-3})	4.50
Particle size (µm)	3-5
Aspect ratio	~ 3
Electrical resistivity (10^{-6} Ω cm)	10-30
Thermal conductivity (Wm^{-1} C^{-1})	~ 100
CTE (10^{-6} C^{-1})	8.1
Elastic modulus (GPa)	350-570
Poisson's ratio	0.13-0.19

2. WORK PIECE ELECTRODE

(EUROPEAN NORMS) EN-31 STEEL

EN-31 steel – 25x25x10 (15 pieces)

Table. 2– Composition of EN-31 steel

Work piece material (EN-31)	
Element	Percentage
Carbon(C)	0.285
Silicon(Si)	1.05
Manganese(Mn)	0.47
Phosphorus(P)	0.035
Chromium(Cr)	0.57
Vanadium(V)	0.95
Iron(Fe)	Balance

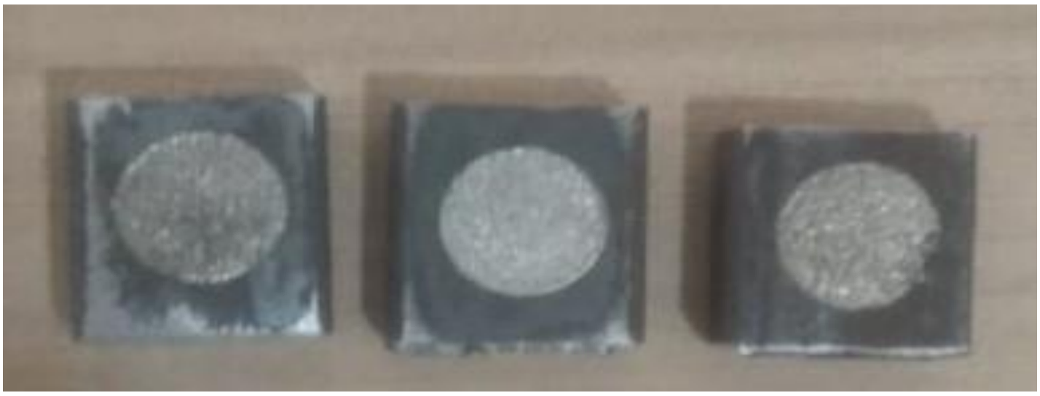

Fig-2: Machined EN-31 steel work piece

III. RESPONSE SURFACE METHODOLOGY

Response surface methodology is used for modeling and analysis of engineering problems. It is a collection of mathematical and statistical methods. In this technique, the main objective is to optimize the response surface that is influenced by various process parameters. The RSM has been applied for modeling and analysis of machining parameters in the WEDM process in order to obtain the relationship between process parameters and response parameters i.e. material removal rate and surface roughness. In the RSM, the quantitative form of relationship between desired response and independent input variables is represented asfollows:

$$Y = f(T_{on}, IP, DV) \pm \varepsilon \qquad (1)$$

Where y is the response (yield), f is the response function, ε is the experimental error, and T_{on}, IP and DV are independent process parameters. A surface known as the response surface is obtained, by plotting the expected response of Y. The form of f is unknown and may be very complicated. Thus, RSM aims to approximate f by a suitable lower ordered polynomial in some region of the independent process variables. If the response can be well modelled by a linear function of the independent variables, the function (equation (2)) can be written as

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots.. + \beta_k x_k + \epsilon \qquad (2)$$

However, if a curvature appears in the system, then a higher order polynomial such as the quadratic model (equation (3)) may be used

$$Y = \beta_0 + \sum_{i=1}^{K} \beta_i X_i + \sum_{i=1}^{K} \beta_{ii} X_{ii}^2 + \sum_{i=1}^{K} \beta_{ij} X_i X_j \qquad (3)$$

If the experimenter has defined factor limits appropriately and/or taken advantage of all the tools available in multiple regression analysis (transformations of responses and factors, for example), then finding an industrial process that requires a third-order model is highly unusual. Therefore, we will only focus on designs that are useful for fitting quadratic models. As we will see, these designs often provide lack of fit detection that will help determine when a higher-order model is needed. The goal of utilizing RSM isn't just to research the reaction over the whole factor space, yet additionally to find the district of intrigue where the reaction arrives at its ideal or close to ideal worth

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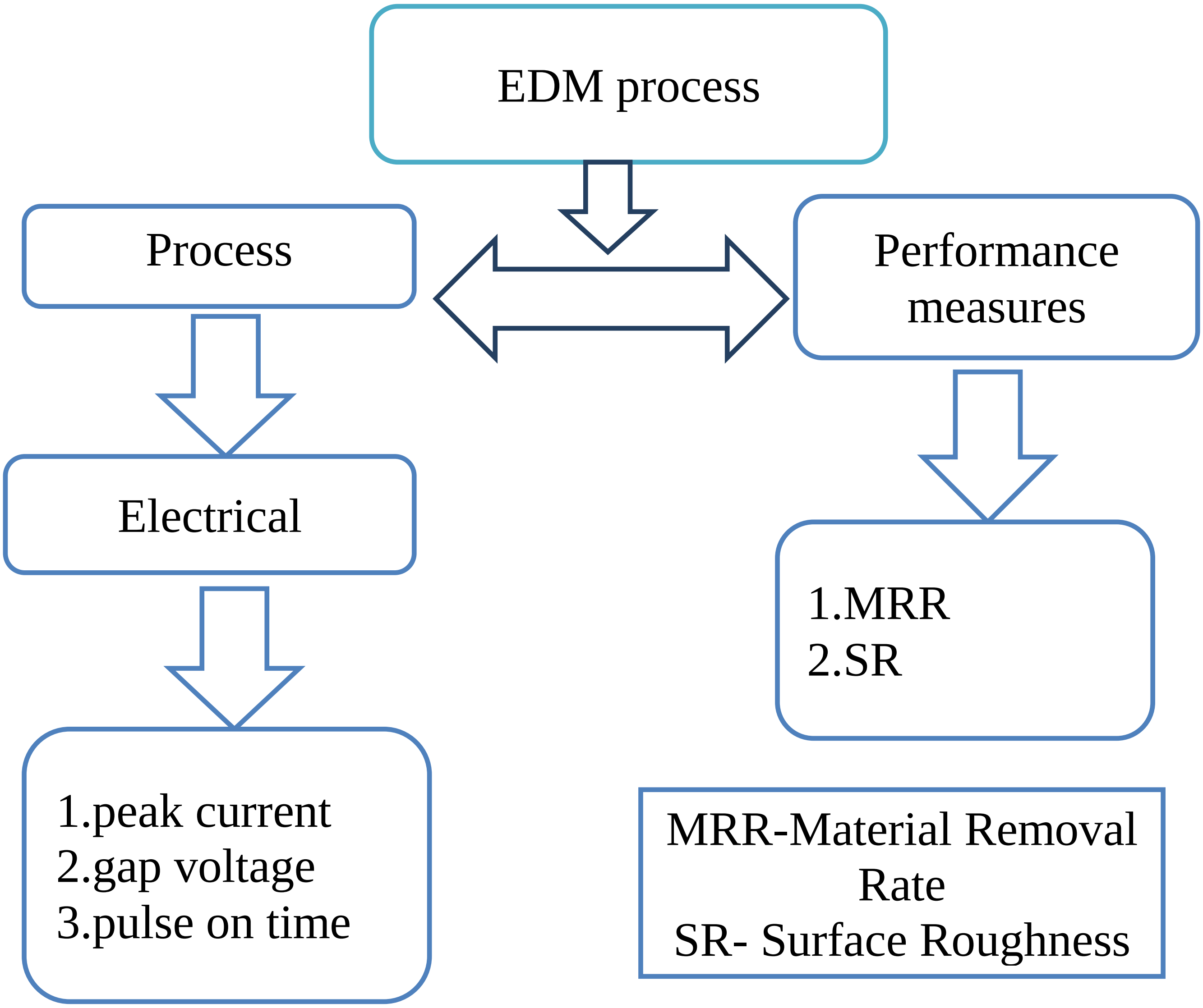

IV. METHODOLOGY PROCEDURE

The modeling is allotted within the following steps [34]

Identifying the necessary method management variables and finding their higher and lower limits.

1. Developing the lookmatrix.
2. Conducting the experiments as per the lookmatrix.
3. Recording the responseparameters.
4. Developing quadratic models and calculative the regressioncoefficients.
5. Checking the adequacy ofmodels.
6. Testing the importance of coefficients and obtained at the finalmodels.
7. Presenting the direct and interaction effects of method parameters on MRR and Ra in graphicaltype.
8. Analysis of results.

V. EXPERIMENTAL DESIGN

1. CENTRAL COMPOSITE DESIGNS (CCD)

BOX-WILSON CENTRAL COMPOSITE DESIGNS

CCD designs start with a factorial or fractional factorial style (with center points) and add "star" points to estimate curvature. A Box-Wilson Central Composite design, usually referred to as 'a central composite design,' contains an imbedded factorial or aliquot factorial design with center points that's augmented with a group of 'star points' that permit estimation of curvature. If the distance from the middle of the design space to a factorial point is ±1 unit for every factor, the distance from the middle of the look space to a star purpose is $|\alpha| > 1$. The precise value of α depends on bound properties desired for the look and on the quantity of thingsconcerned.

Similarly, the quantity of center point runs the design is to contain also depends on certain properties needed for the design.

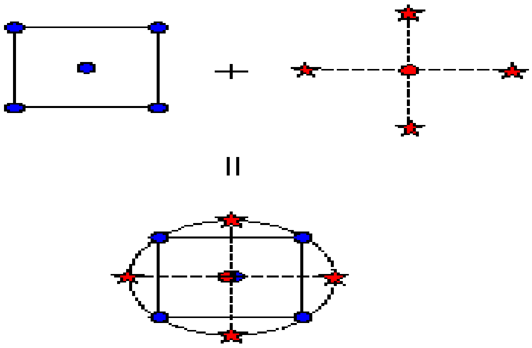

Fig-3: Generation of a Central Composite Design for Two Factors

DETERMINING α IN CENTRAL COMPOSITE DESIGNS

To maintain rotatability, the value of α depends on the number of experimental runs in the factorial portion of the central composite design:

$$\alpha = [\text{number of factorial runs}]^{1/4}$$

If the factorial is a full factorial, then $\alpha = [2^k]^{1/4}$
However, the factorial portion can also be a fractional factorial design of resolution V. Table 3.23 illustrates some typical values of α as a function of the number of factors.

Table 3 – Determining α for Rotatability

Number of Factors	Factorial Portion	Scaled Value for α Relative to ±1
2	2^2	$2^{2/4} = 1.414$
3	2^3	$2^{3/4} = 1.682$
4	2^4	$2^{4/4} = 2.000$
5	2^{5-1}	$2^{4/4} = 2.000$
5	2^5	$2^{5/4} = 2.378$
6	2^{6-1}	$2^{5/4} = 2.378$
6	2^6	$2^{6/4} = 2.828$

The value of α also depends on whether or not the design is orthogonally blocked. That is, the question is whether or not the design is divided into blocks such that the block effects do not affect the estimates of the coefficients in the second order model.

VI. PROCESS PARAMETERS

The experiments were performed using circumscribed central composite design. The pilot experimentation was in hot water the choice of method parameters levels throughout machining. Table 4.2 shows the method parameters and their levels.

Table 4 – Process parameters and their levels

			Levels		
Parameters	-1.68	-1	0	1	1.68
Pulse Current (I)	12	15	20	25	28
Pulse On Time (T_{on})	12	23	33	43	50
Discharge Voltage (V)	43	50	60	70	76

RESPONSE SURFACE DESIGN

The design matrix to quantify that behavior want solely contains factors with two levels -- low and high. This model could be a assumption of easy two-level factorial and fractional factorial designs. The minimum number of levels needed for a factor to quantify that behavior is 3. One would possibly logically assume that adding center points to a two-level design would satisfy that demand, however the arrangement of the treatments in such a matrix confounds all quadratic effects with each other. whereas a two-level design with center points cannot estimate individual pure quadratic effects, it will find them effectively.

A solution to making a design matrix that allows the estimation of easy curvature would be to use a three-level factorial design. Table 4.3 explores that possibility.

A solution to making a design matrix that allows the estimation of easy quadratic curvature would be to use a three-level factorial design. two-level factorial designs quickly become large for application because the range of factors investigated will increase. This drawback was the motivation for creating 'fractional factorial' styles

Table 5- Three-level Factorial Designs

Number of Factors	Treatment Combinations 3^kFactorial	Number of Coefficients Quadratic Empirical Model
2	9	6
3	27	10
4	81	15
5	243	21
6	729	28

The number of runs required for a 3^kfactorial becomes unacceptable even more quickly than for 2^kdesigns (*k* is the number of factors). The last column in Table 3.21 shows the number of terms present in a quadratic model for each case.

Therefore minimize number of runs, a factional factorial design is considered. A fraction nearer to 3-level is required for the model to fit in quadratic model therefore a factorial of 2.7 is considered.

$$2.7^k = 2.7^3 = 19.6\sim 20 \text{ runs}$$

Therefore the mathematical experimentation model of 20 runs is developed for the further analyses.

VII. EXPERIMENTATION AND MODELING

5.1. MATHEMATICAL MODELING

The 20 experiments according to Central Composite design were conducted.

Table 6– List of experimental results

Runs	**Current (A)**	**Pulse on time (µs)**	**Voltage (v)**	**MRR (mg/min)**	**SR RA (µm)**
1	20	33	60	194.285	7.392
2	20	33	60	184.108	7.315
3	20	33	60	169.984	8.641
4	20	33	60	145.454	9.027
5	15	23	50	131.294	8.536
6	20	33	76	112.158	9.101
7	20	50	60	174.149	11.022
8	20	33	43	299.771	8.46
9	15	43	50	157.046	11.717
10	15	23	70	145.945	7.75
11	28	33	60	253.246	10.506
12	25	23	70	237.5	7.056
13	25	43	50	252.033	8.813
14	12	33	60	206.552	12.228
15	20	12	60	121.311	7.281
16	20	33	60	194.117	8.85
17	25	23	50	239.544	9.56
18	20	33	60	217.391	8.759
19	25	43	70	207.936	9.02
20	15	43	70	130.306	9.754

VIII. ANALYSIS AND DISCUSSION

ANALYSIS FOR MATERIAL REMOVAL RATE(MRR)

Table 6.2 presents the results of the quadratic model for the MRR within the type of multivariate analysis. the worth of P in table 6.2 for this model is less than 0.05 (i.e. $\alpha = 0.05$, or 95th confidence) indicates that the model is taken into account to be statistically vital, that is desirable because it demonstrates that the terms within the model have a significant impact on the response [3

Table 7 - Analysis of Variance for MRR

Source	Sum of Squares	df	Mean Square	F-value	p- value	
Model	41706.09	9	4634.01	4.00	0.0207	significant
A-Pulse Current (A)	17036.38	1	17036.38	14.71	0.0033	
B-Pulse on Time (μs)	123.25	1	123.25	0.1064	0.7510	
C-Discharge Voltage (V)	15968.44	1	15968.44	13.79	0.0040	
AB	374.60	1	374.60	0.3234	0.5821	
AC	145.36	1	145.36	0.1255	0.7305	
BC	34.05	1	34.05	0.0294	0.8673	
A^2	2972.26	1	2972.26	2.57	0.1403	
B^2	1012.73	1	1012.73	0.874	0.3718	
C^2	693.61	1	693.61	0.5988	0.4569	
Residual	11583.62	10	1158.36			
Lack of Fit	8578.59	5	1715.72	2.85	0.1372	not significant
Pure Error	3005.03	5	601.01			
Cor Total	53289.71	19				

Table 8 - Fit statistics for MRR

Std. Dev.	34.03	**R^2**	0.7826
Mean	193.71	**Adjusted R^2**	0.5870
C.V. %	17.57	**Predicted R^2**	-0.3529
		Adeq Precision	6.5019

REGRESSION

MRR = 559.53 – 9.121 I + 5.607 Ton – 11.065 V- 0.128 I * Ton - 0.0852 I * V + 0.021 Ton * V + 0.636 I^2 - 0.0738Ton^2+ 0.0719 V^2

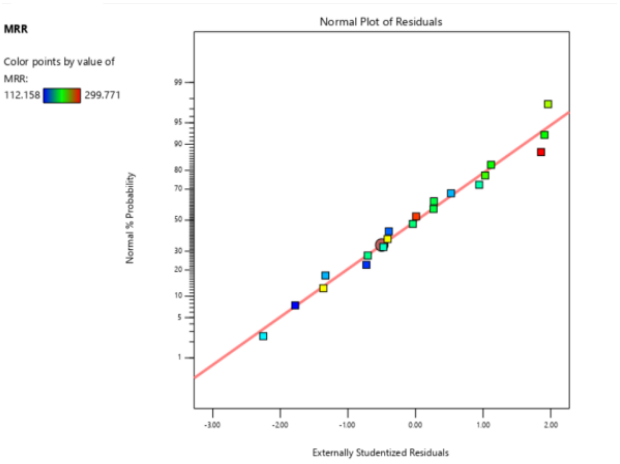

Fig-4: Normal probability plot on MRR

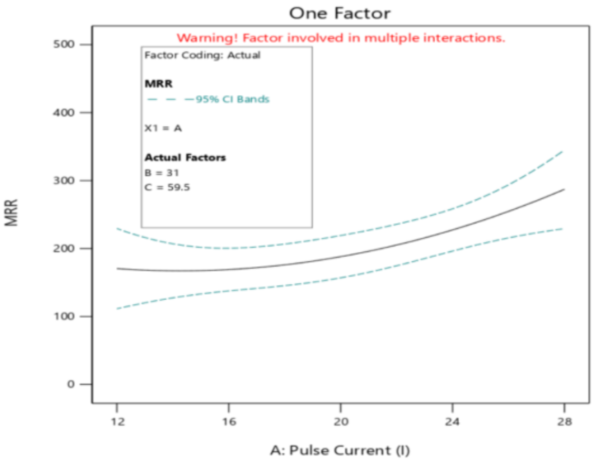

Fig-5: Effect of Pulse Current residuals for MRR

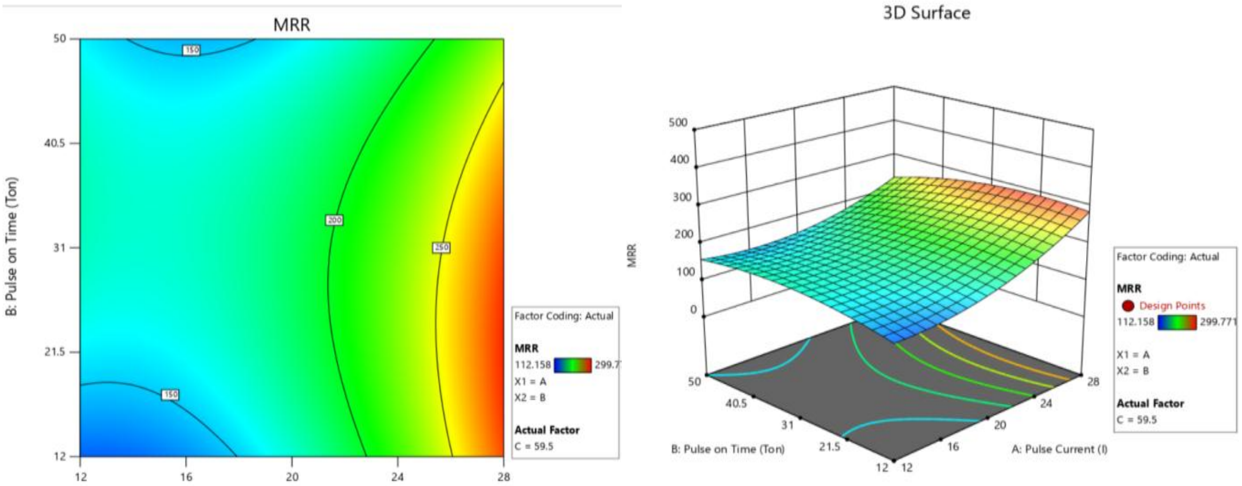

Fig-6: Effect of Pulse Current and Discharge Voltage on MRR

The optimum MRR 307.738 mg/min as shown in figure 6.2 and 6.3 has been obtained at lowest pulse on time and close to high pulse current of 26.64 A once Voltage is at lowest potential. The MRR directly proportional to pulse currentasshowninfigure6.2alsoinfigure6.3itisclearthathigherMRRis attained at lowest discharge voltage and will increase with increase in pulse on time. Short pulse period would cause less surface vaporization, whereas long pulse period might cause the plasma channel to expand and to decrease the energy density for the workplace [12].

ANALYSIS FOR SURFACE ROUGHNESS (SR)

The same procedure is applied to deal with the other response, the surface roughness, and the results are shown in Table 6.5 and Table 6.6. For the surface roughness, the main effect of Pulse on Time (Ton) and second order effect of Pulse Current (I) are more significant. The R^2-value for the surface roughness is 79.09%, which is again more than 75% which is adequate. The Figure 6.6 displays the normal probability plot of the residuals for surface roughness. It can be noticed that the residuals fall on a straight line implying that the errors are normally distributed. The final response equation is given in Eqn.5.

REGRESSION

$$\mathbf{SR = 20.81 - 1.359\ I + 0.122\ Ton - 0.015\ V - 0.01\ I * Ton + 0.001\ I * V + 0.001\ Ton * V + 0.374\ I^2 + 0.0005 Ton^2 - 0.0009\ V^2} \quad \mathbf{(5)}$$

Table 9 - Fit statistics for SR

Std. Dev.	**0.9558**	R^2	**0.7598**
Mean	9.07	**Adjusted R^2**	0.5436
C.V. %	10.54	**Predicted R^2**	-0.6441
		Adeq Precision	6.5499

A negative **Predicted R^2** implies that the overall mean may be a better predictor of the response than the current model. In some cases, a higher order model may also predict better.

Adeq Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 6.726 indicates an adequate signal. This model can be used to navigate the design space.

Table 10 - Analysis of Variance for SR

Source	Sum of Squares	df	Mean Square	F-value	p- value	
Model	28.90	9	3.21	3.51	0.0315	significant
A-Pulse Current (A)	1.88	1	1.88	2.06	0.1819	
B-Pulse on Time (µs)	10.10	1	10.10	11.06	0.0077	
C-Discharge Voltage (V)	1.44	1	1.44	1.58	0.2374	
AB	1.96	1	1.96	2.14	0.1739	
AC	0.0315	1	0.0315	0.0345	0.8564	
BC	0.3136	1	0.3136	0.3433	0.5709	
A^2	10.26	1	10.26	11.23	0.0073	
B^2	0.0663	1	0.0663	0.0726	0.7930	
C^2	0.1057	1	0.1057	0.1157	0.7408	
Residual	9.14	10	0.9136			
Lack of Fit	6.92	5	1.38	3.12	0.1186	not significant
Pure Error	2.22	5	0.4433			
Cor Total	38.03	19				

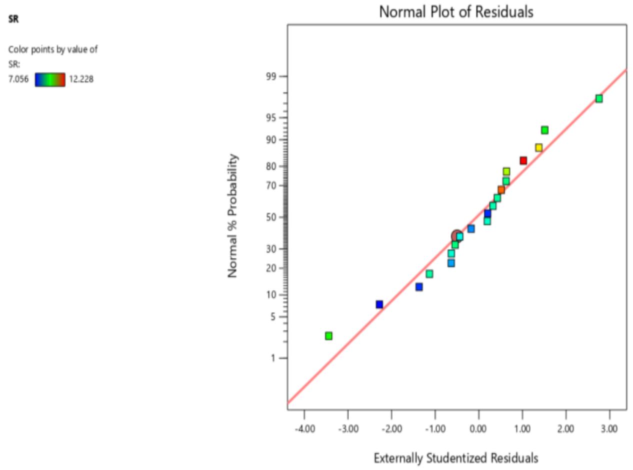

Fig-7: Normal probability plot residuals

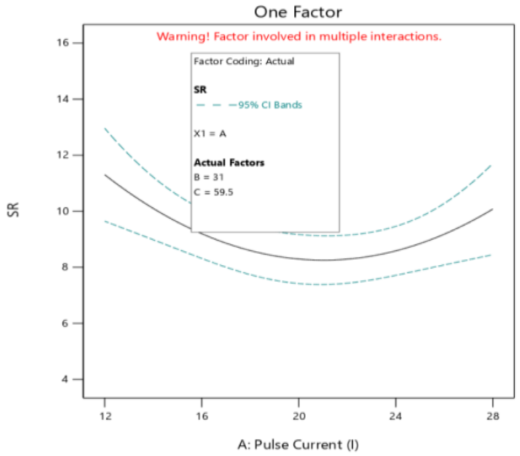

Fig-8: Effect Pulse current on SR

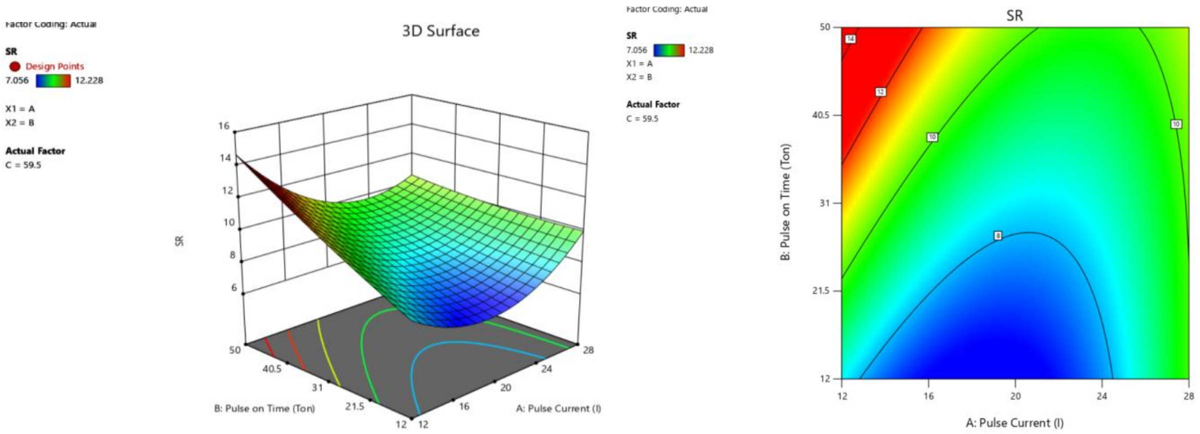

Fig-9: Effect of Pulse Current and Pulse on Time on SR

The possible optimum surface roughness of 6.843 µm can be achieved with desirability of 100% inferred from fig 6.8 with table 12 optimization criteria in the following optimal process parameters: V= 43.411 V, Ton =12 µs and I=22.21 A as shown in figure 6.9**.** Hence these conditions can be considered as the possible optimal solution. It is observed in the numerical optimization in Fig.12 and 13.

IX. RESULT

The objectives of the current work are to identify optimal combination of method parameters which will maximize the MRR and minimize the TWR of the EDM method victimization desirability approach. Because the objectives square measure conflicting in nature, one optimum answer won't fulfill our purpose. During this work, the desirability perform was accustomed remodel the individual responses to the corresponding desirability index [9]. It's an accepted methodology within the industry for the improvement of multiple response issues [11]. The subsequent steps square measure accustomed accomplish the transformation. Step 1: The individual desirability index (yi) for every response has calculated first. The equations used for this calculation are as follows: If the response is needed to be maximized, then the individual desirability index has calculated as:

$y_i = 0 \quad i < S$

$y_i = [(i – S_i) /(H_i – S_i)]^{ri} \quad S_i \leq i \leq H_i$

$y_i = 1 \quad i > H_i$

If the response is required to be minimized, then the individual desirability index has been calculated as:

$y_i = 0 \quad i > Hi$

$y_i = [(H_i - i)/(H_i - S_i)]^{ri} \quad S_i \leq i \leq L_i$

(

7)

$y_i = 1 \quad i < S_i$

If the response is required to achieve a particular target "T_i", then the individual desirability index has been calculated as:

$y_i = 0 \quad i < S$

$y_i = [(i - S_i)/(T_i - S_i)]^{ri} \quad S_i \leq i \leq L_i$

$y_i = [(i - H_i)/(T_i - H_i)]^{ri} \quad T_i \leq i \leq H_i$ (8)

$y_i = 0 \quad i > H_i$

Where i, predicted value of ith response ri, weight exponent Si, smallest acceptable value for ith response Hi, highest acceptable value for ith response, yi, individual desirability for ith response. Step 2: The individual desirability indexes were combined to obtain the global desirability index (D). The equation used for this combination was

$$D = (y_1 \times y_2 \times \ldots\ldots\ldots\ldots \times y_n)^{1/n} = [\pi(y_i^{wi})]^{1/w}$$

9) where n, number of responses Wi, importance of ith response

$$W - \sum Wi$$

Criteria selected for multiple-objective optimization are shown in Table 14. The goal for Pulse on time is set to minimum as it has adverse effect on surface roughness. The composite desirability value of the combination process parameters is shown in Table 15. The composite desirability (D) value has taken as 0.875 which is near to 1. Optimal input parameter values observed from multi response optimization are pulse current of 22.903 A, pulse on time of 12 µs and discharge voltage of 43V.

Table 11- Selected criteria for optimization of MRR and SR

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
Pulse Current (A)	is in range	12	28	1	1	3
Pulse on Time (µs)	minimize	12	50	1	1	3
Discharge Voltage (V)	is in range	43	76	1	1	3
MRR	maximize	112.2	299.771	1	1	3
SR	minimize	7.056	12.228	1	1	3

Finally, improvement in performance is predicted and verified based on optimal setting. Table 16 shows the error percent for experimental validation of the developed models. The error between experimental and predicted values for MRR and SR lies within 3.04% and 5.36%,respectively.

Table 12- Confirmations run with optimal parameter settings

Responses	Predicted	Desirability	Experimental Values	Error%
MRR	215.519	100	209.81	2.72
SR	9.9409	100	9.526	4.35

X. CONCLUSION

Experiments were performed to study the effect of process parameters, i.e., pulse current, pulse on time and discharge voltage on MRR and SR. Experiments were conducted in EDM with copper composite electrode using EN-31 steel work piece. Center composite second-order rotatable design of RSM was used to find the significant factors and their interaction effect. The following conclusions were drawn from the experimental analyses:

[1] It was concluded that the Pulse Current is found to be the most influencing parameter is pulse current among all other parameters which affects MRR, whereas Pulse on Time affects less.
[2] SR is affected mostly by Pulse on Time and Pulse current at all values of Discharge Voltage.
[3] Cu-TiB2 powder metallurgy electrode was more suitable for low voltage setting rather than high voltage setting, as it at low voltages it removes more material and does have any effect on SR. Therefore, it is better set voltage to minimum.
[4] Cu-TiB2 like the entire electrode has adverse effect when pulse on time is set to higher values.
[5] The increase in pulse on time affects SR negatively while MRR is directly proportional to pulse current.
[6] To achieve optimum result without deterioration of the machined surface, it is better to keep pulse on time always minimum.
[7] The optimum setting parameters obtained from desirability multi response optimization were pulse current of 22.903 A, pulse on time of 12 µs and discharge voltage of 43V.

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