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OPTIMIZATION OF MRR OF D-2 STEEL IN WEDM PROCESS

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ABSTRACT *: In the present study, Response surface methodology was used to investigate the effect of four controllable variables on the material removal rate(MRR).The work piece material is D-2 tool steel and the four process variables are pulse on time, pulse off time, peak current and servo voltage. These parameters are varied to study their effect on the MRR of D-2 steel. The response surface methodology (RSM) in conjunction with central composite design has been used to develop the empirical models for response characteristics. Desirability functions have been used for simultaneous optimization of performance measures.It was found that the material removal rate (MRR) directly increases with increase in pulse on time and peak current.*

Keywords:Pulse On Time(Ton),Pulse Off Time(Toff),Material Removal Rate(MRR),Servo Voltage(SV),Response Surface Methodology(RSM),Peak Current(IP),Central Composite Design(CCD).

Introduction

Wire Electric Discharge Machining (WEDM) is a non-traditional process of material removal from electrically conductive materials to produce parts with intricate shapes and profiles. This process is done by using a series of spark erosion. These sparks are produced between the work piece and a wire electrode (usually less than 0.30 mm diameter) separated by a dielectric fluid and erodes the work piece to produce complex two and three dimensional shapes according to a numerically controlled pre-programmed path. The sparks produce heating and melt work piece surface to form debris which is then flushed away by dielectric pressure. During the cutting process there is no direct contact between the work piece and the wire electrode.The wire electrical discharge machining (WEDM) has become an important non-traditional machining process because it can machine the difficult-to-machine materials like titanium alloys and zirconium which cannot be machined by conventional machining processes.

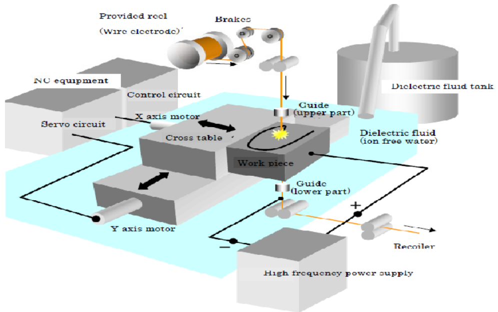

Fig. 1.1 Schematic representation of WEDM cutting process.

Though EDM process is very demanding but the mechanism of process is very complex,therefore,it is troublesome to establish a model that can accurately predict the performance by co-relating the process parameters.The optimum processing parameters are very essenstial to establish to boost up the production rate to a large extent.

Literature review

Saha et al**. [1]** analyzed the wire electrical discharge machining of tungsten carbide cobalt composite.A second order multi-variable regression model and a feed-forward back-propagation neural network model have been developed to correlate the input process parameters such as pulse-on time, pulse-off time, peak current and capacitance with the process performance namely cutting speed and surface roughness.Rao et al.**[2]** discussed influence of parameters such as discharge current, voltage, wire speed, tension on WEDM machining of Brass for optimization of cutting speed, MRR and spark gap using four wires of different Cu percentage. It was observed that cutting speed decreases as thickness of work piece increases due to larger material need to be removed at larger thickness. With increase in current, there is an upward trend in the spark gap, MRR increases with an increase in discharge current. S. Sarkar et al. **[3]** discussed the modeling and optimization of wire electrical discharge machining of γ-TiAl in trim cutting operation. A second-order mathematical model, in terms of machining parameters, was developed for surface roughness, dimensional shift and cutting speed using RSM.The trim cutting operation was optimized for a given machining condition by desirability function approach and pareto optimization algorithm. It was observed that performance of the developed pareto optimization algorithm is superior compared to desirability function approach. Romlay and Mokhtar **[4]** presented an optimization of the WEDM cutting parameter at welding joint area. The experiment was conducted during a gear shape optimization process by reducing the gear material and weight. Some area of the gear is welded for material joining process.The parameters of cutting process such as wire speeds, wire tensions and wire voltage was considered to be optimized. The cutting condition at the single and double materials area has been compared. The result of the experiment shows that the cutting speed of the wire-EDM has been affected by changing cutting parameters. The material properties also give a big impact to the cutting process methodology.Parashar et al. **[5]** reported the statistical and regression analysis of kerf width using design of experiments have been proposed for WEDM operations. Each experiment has been performed under different cutting conditions of gap voltage, pulse ON time, pulse OFF time, wire feed and dielectric flushing pressure. From experimental results, the kerf width was determined for each machining performance criteria. Results showed that, pulse on time and dielectric flushing pressure are the most significant factors, while gap voltage, pulse off time and wire feed are the less significant factor to the kerf width of wire EDMed SS304L.Datta and Mahapatra **[6]** presented the quadratic mathematical models to represent the process behavior of WEDM operation. Experiments have been conducted with six process parameters: discharge current, pulse duration, pulse frequency, wire speed, wire tension and dielectric flow rate; to be varied in three different levels. . Liu et al. **[7]** studied the behavior of wire electrochemical discharge machining of Al_2O_3 particle reinforced aluminum alloy 6061.The effect of machining voltage, current, pulse duration, and electrolyte concentration, on material removal rate were evaluated in the light of the contribution of the wire electrical discharge machining and electrochemical machining actions. The results suggested that for achieving the highest MRR, the applied current is the most influentialparameter. Shah et al. **[8]** investigated the seven different machining parameters in addition to varying the material thickness on the machining responses such as material removal rate, kerf, and surface roughness of tungsten carbide samples machined by WEDM.

According to the literature survey,it is observed that extensive experimental work is needed to analyze the effect of process parameters on the MRR rate of D-3 steel in WEDM.The present work focuses on the optimization of MRR rate by using response surface methodology.

Material and method

The w/p material is a high carbon,high chromium D-2 steel,with exceelent resistance to wear and abrasion.D-2 steel is choosed due to it's incresing use in the making of press tools,forming rolls,blanking dies,bushes,punches etc.The chemical composition of the material is shown in the table given below.

S.NO	MATERIAL	PERCENTAGE
1.	CARBON	1.50%
2.	SILICON	0.30%
3.	MAGANESE	0.30%
4.	SULPHUR	0.027%
5.	PHOSPHORUS	0.026%
6.	VANADIUM	0.90%
7.	CHROMIUM	11.50%
8.	MOLYBDENUM	0.78%
9.	COPPER	0.009%
10.	IRON	Rest

Table 3.1 Composition of work material.

The experiments were performed on the Sprintcut WEDM machine from Electronica India Pvt Ltd.A brass wire of 0.25 mm was used as a cutting tool.Work pieces are cut into specimens of size 20mmX10mmX10mm.During machining,on the basis of literature review ,the following process parameters have been selected for study in the range shown in table 4.1

S.No.	Input Parameters	Range
1.	Pulse on time (Ton)	112-127 machine units
2.	Pulse off time (Toff)	42-55 machine units

3 .	Peak current (IP)	170-215 Amp
4 .	Servo voltage (SV)	40-60Volts

Table 3.2 Process parameters with their ranges.

Apart from these the following parameters are kept constant during experimentation-

Wire Tension-	4-7-10 unit
Wire feed -	4-7-10m/min
Servo Feed-	2050 unit

Response Surface Methodology

Response surface methodology (RSM) is defined as a collection of mathematical and statistical methods that are used to develop, improve, or optimize a product or process. The independent variables are controlled by the experimenter, in a designed experiment, while the response variable is an observed output of the experiment.Fig. 3.1 illustrates the estimated relationship between a response variable and the two independent variables x_1 and x_2.

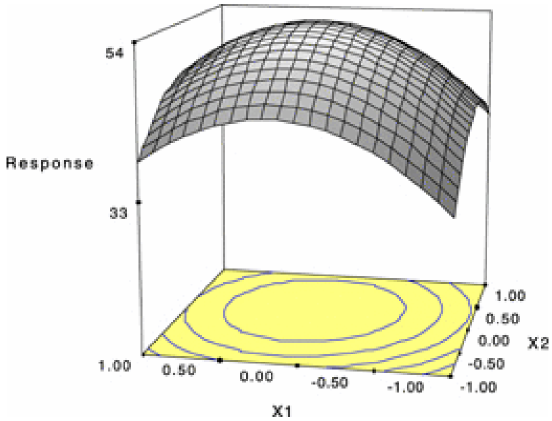

Fig. 4.1 An example of a response surface.

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The field of response surface methodology consists of the experimental strategy for exploring the space of the process or independent variables, empirical statistical modelling to develop an appropriate approximating relationship between the yield and the process variables, and optimization methods for finding the values of the process variables that produce desirable values of the response.In general, the relationship between the response y and independent variables, $\xi_1, \xi 2, \ldots, \xi_k$

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$$y = f(\xi_1, \xi 2, \ldots, \xi_{k.}) + \varepsilon$$

(4.1)

Usually ε is treated as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2. Then

$$E(y) = \eta = E\,[f(\xi_1, \xi 2, \ldots, \xi_{k.})] + E(\varepsilon) = f(\xi_1, \xi 2, \ldots, \xi_{k.}) \qquad (4.2)$$

The variables $\xi_1, \xi 2, \ldots, \xi_k$ in Equation (3.2) are usually called the **natural variables**.In much RSM work it is convenient to transform the natural variables to **codedvariables** $X_1, X_2 \ldots X_k$, which are usually defined to be dimensionless with mean zero and the same standard deviation. In terms of the coded variables, the response function (3.2) will be written as

$$\eta = f(X_1, X_2 \ldots X_k)$$

(4.3)

In many cases, either a **first-order** or a **second order** model is used.For the case of two independent variables, the first-order model in terms of the coded variables is

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 (4.4)$$

The form of the first-order model in Equation (3.4) is sometimes called **main effects model**, because it includes only the main effects of the two variables $X_1$and X_2. If there is an **interaction** between these variables, it can be added to the model easily as follows:

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2$$

(4.5)

This is the first-order model with interaction.Often the curvature in the true response surface is strong enough that the first-order model (even with the interaction term included) is inadequate. A second-order model will likely be required in these situations. For the case of two variables, the second-order model is

$$\eta = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{12} X_1 X_2$$

(4.6)

This model would likely be useful as an approximation to the true response surface in a relatively small region. The second-order model is widely used in response surface methodology.

Design of experiment

The experiments were designed by using Design expert software.Response surface methodology was used and central composite design was applied.Total 30 runs were obtained by applying given procees parameters. The value of input parameters were set according to this design for each run.The value of MRR was calculated for each run.The design is shown in table 3.1 with response MRR

Std	Run	Block	Factor 1 A: Ton Machine unit	Factor 2 B: Toff Machine un	Factor 3 C: SV Volts	Factor 4 D: IP Amp	Response MRR Mm^2/min
14	1	DAY 1	123	44	55	215	22.1
2	2	DAY 1	124	44	45	185	23.6
9	3	DAY 1	116	44	45	200	12.5
5	4	DAY 1	116	44	55	215	12.4
3	5	DAY 1	116	51	45	215	12.1
17	6	DAY 1	120	47	50	185	18.3
8	7	DAY 1	123	51	55	200	21.7
15	8	DAY 1	123	51	55	185	21.5
12	9	DAY 1	120	51	45	215	18.2
18	10	DAY 1	123	47	50	185	21.7
6	11	DAY 2	123	43	55	200	22.1
16	12	DAY 2	120	51	55	185	17.9
20	13	DAY 2	116	47	50	200	12.2
11	14	DAY 2	123	51	45	215	21.9
10	15	DAY 2	123	43	45	185	22.3
4	16	DAY 2	116	51	45	185	12.1
7	17	DAY 2	116	51	55	215	11.9
1	18	DAY 2	116	43	45	215	12.8
13	19	DAY 2	120	43	55	215	18.8
19	20	DAY 2	120	47	50	185	18.8
23	21	DAY 3	119	40	50	200	18.1
29	22	DAY 3	120	47	50	200	18.2
30	23	DAY 3	120	47	50	200	18.6
26	24	DAY 3	119	47	60	200	17.1
24	25	DAY 3	120	55	50	230	17.8
28	26	DAY 3	120	47	50	200	18.3
27	27	DAY 3	119	47	50	170	16.9
25	28	DAY 3	127	47	40	200	25
22	29	DAY 3	120	47	50	200	18.2
21	30	DAY 3	112	47	50	200	6.8

Table3.1:Experimental design with response data(MRR)

Result and disscussion-

In this study models as well as experimental results of the responses have been analyzed.Model analysis was made by using Design-Expert version 8.0.3 while the analysis of MRR is done in line with the behaviour of machining parameters on the responses.

Material Removal Rate(MRR) model-

The regression equation for MRR as a function of four input process variables- Pulse on time (Ton), Pulse off time (Toff), Servo voltage (SV), peak current (IP) was developed using experimental data and is given below.

Final Equation in Terms of Coded Factors-

$$MRR=+17.70+5.00*A-0.33*B+0.055*C-0.41*A^{2}-0.14*C^{2}$$

Final Equation in Terms of Actual Factors-

$$MRR=-571.92416+8.36169*ton-0.087745*toff+0.5708*sv-0.029410*ton^{2}-5.59881E-003*sv^{2}$$

Effect of process parameters on MRR-

The figure 6.1 shows the effect of input parameters Pulse on time (Ton), Pulse off time (Toff), Servo voltage (SV) and peak current (IP) on the MRR.The

MRR increased with Pulse on time,and decreased with Pulse off time and servo voltage.The peak current has a very small influence on the MRR,But the Ton is the most influential parameter among them.In this process spark energy affects the MRR.And it is a function of Pulse on time and peak current.In The view point of industrial economy it is desirable to obtain higher value of MRR.

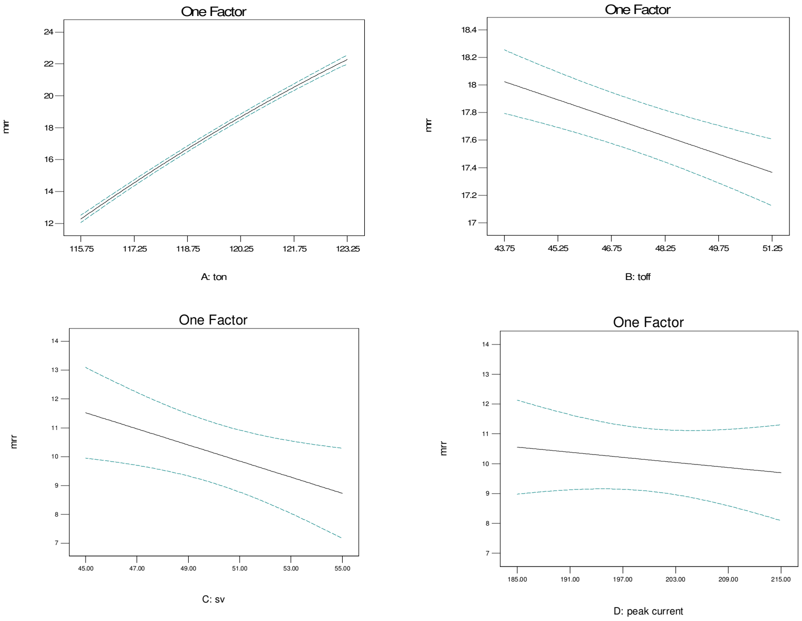


Fig 6.1 Showing the effect of Ton,Toff,S.V,Peak current on the M.R.R

The effects of process parameters are taken two at a time on MRR is shown in the Fig 6.2-6.5.Fig 6.2 shows the combined effect of Ton and Toff on MRR.Fig 6.3 shows the combined effect of SV and Toff.Fig 6.3 shows the combined effect of peak current and SV on MRR.Fig 6.4 shows the combined effect of Ton and peak current on MRR.

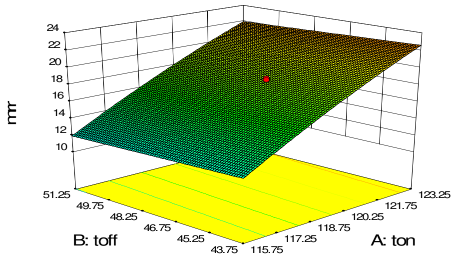


Fig 6.2 3-D graph of Effects of Ton and Toff on MRR

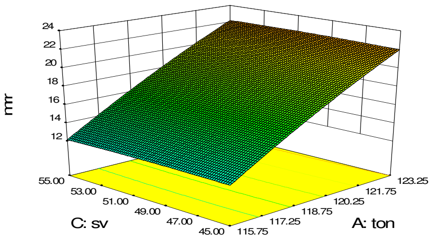
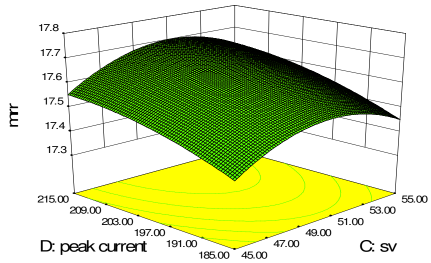


Fig 6.3 3-D graph of effects of SV and Toff on MRR



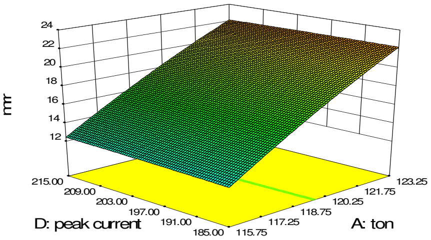


Fig 6.4 3-D graph of Effects of peak current and SV current on MRRon MRR

Residual Analysis-

The residual analysis as a primary diagnostic tool is also done. Normal probability plot of residuals has been drawn (Figure 6.6). All the data points are following the straight line. Thus the data is normally distributed. It can be seen from Figure 6.3 that all the actual values are following the predicted values and thus declaring model assumptions are correct

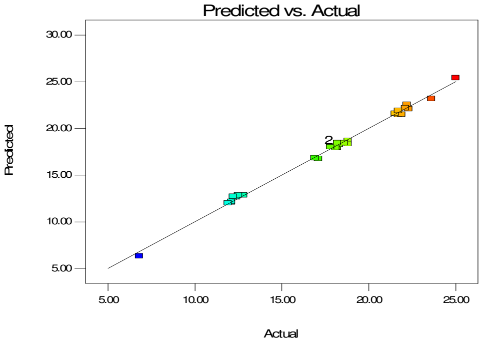


Fig 6.5 3-D graph of Effects of Ton and peak

Analysis of variance-

In order to statistically analyze the results, ANOVA was performed. Process variables having p-value<0.05 are considered significant terms for the requisite response characteristics. The insignificant parameters were pooled using backward elimination.

Source	**Sum Of Squares**	**Df**	**Mean Square**	**F-Value**	**p-Value Prob>f**	
Block	9.13	2	4.56			
Model	531.58	5	106.32	873.12	<0.0001	Significant
A-ton	467.42	1	467.42	3838.71	<0.0001	
B-toff	2.60	1	2.60	21.31	0.0001	
C-sv	0.060	1	0.060	0.49	0.4895	
A^2	3.48	1	3.48	28.62	<0.0001	
C^2	0.42	1	0.42	3.47	0.0759	
Residual	2.68	22	0.12			
Lack of Fit	2.57	20	0.13	2.41	0.3339	Not-significant
Pure Error	0.11	2	0.053			
Cor Total	543.49	29				

1.The Model F-value of 873.12 implies the model is significant.There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise.

2 Values of "Prob > F" less than 0.0500 indicate model terms are significant.

3. In this case A, B,A^2 are significant model terms.

4. Values greater than 0.1000 indicate the model terms are not significant.

5. If there are many insignificant model terms (not counting those required to support hierachy model reduction may improve our model.

6. The "Lack of Fit F-value" of 2.41 implies the Lack of Fit is not significant relative to the pure error.There is a 33.39% chance that a "Lack of Fit F-value" this large could occur due to noise.Non-significant lack of fit is good.We want the model to fit.

Multi Response Optimization Using Desirability Function-

The goal of optimization is to find a good set of conditions that will meet all the goals. It is not necessary that the desirability value is 1.0 as the value is completely dependent on how closely the lower and upper limits are set relative to the actual optimum. A set of 40 optimal solutions is derived for the specified design space constraints (Table 6.1) for MRR using Design expert statistical software. The set of conditions possessing highest desirability value is selected as optimum condition for the desired responses. Table 6.1 shows the optimal set of condition with higher desirability function required for obtaining desired response characteristics under specified constraints –

Solutions Number	Ton	Toff	Sv	Peak current	mrr	desirability	
1.	123.20	51.25	45.00	215.00	21.6952	0.685	selected
2.	123.23	51.25	45.00	215.00	21.7349	0.685	
3.	123.18	51.22	45.00	215.00	21.6833	0.685	
4.	123.14	51.25	45.00	215.00	21.6294	0.685	
5.	123.18	51.25	45.00	215.00	21.6953	0.685	
6.	123.25	51.24	45.00	215.00	21.7722	0.685	
7.	123.12	51.12	45.00	214.98	21.6259	0.685	
8.	123.25	51.23	45.00	214.67	21.7576	0.685	
9.	123.16	51.25	45.00	214.67	21.6535	0.685	
10.	123.12	50.98	45.00	215.00	21.6307	0.685	
11.	123.07	51.25	45.00	215.00	21.6098	0.685	
12.	123.10	50.88	45.81	215.00	21.6241	0.685	
13.	123.09	51.25	45.92	215.00	21.6676	0.685	
14.	123.13	51.25	45.00	215.00	21.7394	0.684	
15.	122.99	50.39	45.00	215.00	21.5389	0.684	
16.	123.09	51.25	45.00	215.00	21.7321	0.684	
17.	123.14	49.65	45.00	215.00	21.7755	0.683	
18.	123.11	51.25	45.02	213.70	21.7654	0.683	
19.	123.22	51.23	46.21	211.03	21.7253	0.683	
20.	123.05	51.25	45.27	211.06	21.5347	0.683	
21.	123.11	51.25	45.00	215.00	21.7781	0.683	
22.	123.21	49.38	45.00	215.00	21.8706	0.683	
23.	123.25	51.25	45.00	211.37	21.9096	0.682	
24.	123.25	48.70	45.00	213.87	21.9786	0.681	
25.	122.95	51.25	45.00	206.24	21.6176	0.679	
26.	122.87	51.25	45.05	210.79	21.5058	0.679	
27.	122.99	47.73	45.00	213.50	21.7764	0.679	
28.	122.99	50.87	45.00	206.50	21.6149	0.677	
29.	123.17	45.89	45.00	212.31	22.1387	0.671	
30.	122.66	45.54	48.01	215.00	21.5952	0.671	
31.	122.56	44.71	45.00	192.03	21.653	0.667	

Table6.1 Solution according to desirability for MRR

Ramp function and bar function graphs-

The ramp function graphs and bar graphs drawn using Design expert shows the desirability for each factor and each response. The dot on each ramp reflects the factor setting or response prediction for that response characteristic.Bar graphs show the individual/ partial desirability functions (d_i) of each of the responses.

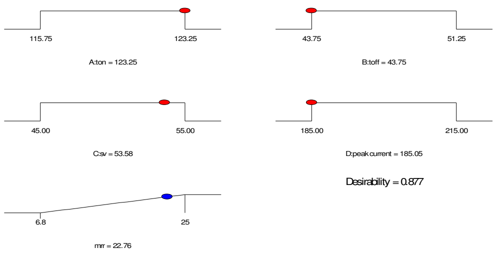


Fig6.7 Ramp Graph showing desirability for MRR

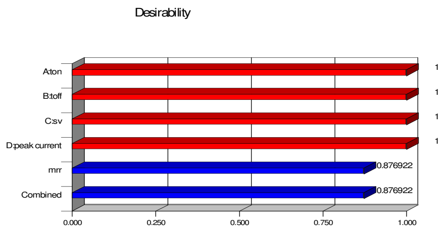


Fig6.8 Bar graph of Desirability for MRR

Conclusion-

In this research an experimental investigation was performed to consider the machining chracteristics of D-2 steel and following results are obtained-

1.Results shows that the Central composite design is a powerful tool for providing experimental diagrams and statstical-mathematical models,to perform the experiments appropriately and economically.

2.The MRR increased with ton and the ton has the maximum influence on the MRR.

3.The peak current has a very less influence on the MRR.

4.The MRR decreased with toff and sv.

5.The methodology adopted establishes the optimization of D-2 steel machining in WEDM.And facilitates the effective use of D-2 steel in industrial applications by reducing the cost of machining.

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