Study of microEDM parameters of Stainless Steel 316L: Material Removal Rate Optimization using Genetic Algorithm

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Abstract—Material Removal Rate (MRR) is the most significant factor in the finished product during machining in Micro Electro Discharge Machining (microEDM). In the present research, the investigation of MRR of Stainless Steel 316L which is widely used in the Medical, Marine, Architectural and food processing industries is studied. The current, pulse on time and pulse off time are the input parameters selected for machining using 300μm tungsten electrode to obtain the maximum MRR. By using Response Surface Methodology (RSM) the mathematical model of MRR is obtained by correlating the input parameters. The Genetic Algorithm (GA) is applied to model obtained to arrive the optimal input parameters to achieve the maximum MRR. Experiments are conducted for validating the GA results, which shows that the average percentage of error is 3.65%. Hence, the developed model gives more reliability for the manufacturers to select the optimal input parameters to achieve good quality finished product.

Keywords-Response Surface Methodology, Stainless Steel 316L, Material Removal Rate, ANOVA, Genetic Algorithm.

I. INTRODUCTION

EDM (Electrical Discharge Machining) is a non-conventional process used in conductive and semi-conductive materials for manufacturing of complex shapes. Since miniaturizations of the components are increased, the demand for micro holes and micro features has also increased. As a result, the need for a more precise and most economical process like microEDM has been developed. In this process the removed metal is carried away by the dielectric fluid circulated around it as shown in Fig 1 [1], [2].

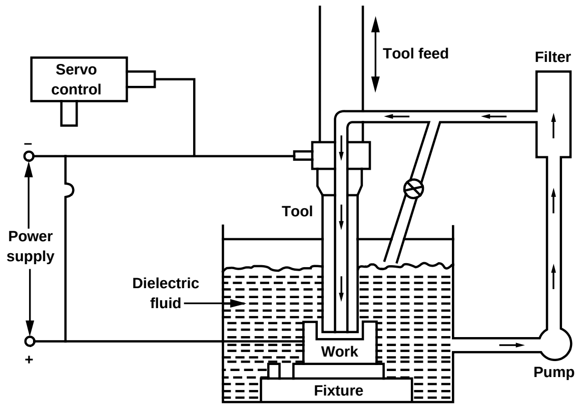

Fig. 1 Layout of microEDM

In micro-EDM, MRR is the most important influencing factor. During the drilling of deep micro holes by Tungsten carbide with low frequency, the vibration assisted work piece results in a significant increase in MRR[3]. In the machining of SS 316 material with Titanium and brass grade electrode, there is a marginal increase in MRR with Titanium grade electrode [4]. The response surface methodology (RSM) is used to analyze the experiments in terms of MRR and EWR. The aluminum powder mixed with dielectric fluid increases the MRR and reduces the EWR [5]. Genetic Algorithms (GA) are widely used for optimization problems. VijayKumar et al [7] have studied the surface roughness of the ball nose end milling of LM6 Al alloy using the GA and concluded that the model developed using RSM helps the manufacturers to achieve the desired roughness. Kannan et al [8] have also used the GA to predict the MRR and surface roughness and resolved that the RSM model is well suited to improve the productivity and product quality.

From the review, the regression GA-based optimization is not widely used by investigators in microEDM process to obtain better MRR for machining of Stainless Steel 316L. In the present work, GA is used for the optimization to determine the optimal machining conditions for maximizing the MRR. The mathematical model for MRR is established using the RSM. The GA is then applied to obtain the optimal process parameters.

II. RESPONSE SURFACE METHODOLOGY (RSM)

A second-order mathematical model can significantly improve the optimization process. The process parameters like current (I) in ampere, pulse on time (T_{on}) in µs and pulse off time (T_{off}) in µs are selected to obtain the mathematical model for MRR. A general form of second-order mathematical model is defined as

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_{ii} x_i^{\,2} + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i<j}}^{n} a_{ij} x_i x_j \qquad \text{….(1)}$$

where x_i and x_j are the design variables and ‘a’ are the tuning parameters.

III. SIGNAL TO NOISE RATIO

The Signal to Noise Ratio for MRR is calculated as given in Equation 2. The Taguchi method is used to analyze the result of response of machining parameter for larger is better criteria.

$$\eta = -10 \log \left[\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right] \qquad \text{….(2)}$$

Where η denotes the S/N ratios calculated from observed values and y_i represents the experimentally observed values.

IV. GA OPTIMIZATION

Genetic Algorithm is one of the main paradigms of evolutionary computing [6]. It is inspired by Darwin’s theory of evolution – the “survival of the fittest”.

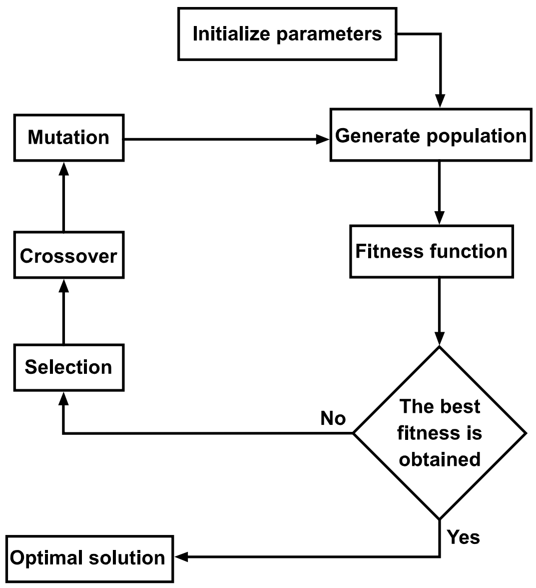

Fig. 2: Basic flow diagram of GA optimization

Fig. 2 shows the basic flow of a GA optimization methodology.

- GA begins with a set of solutions called the population (represented by chromosomes).
- Solutions from one population are taken and used to form a new population. This is motivated by the possibility that the new population will be better than the old one.
- Solutions are selected according to their fitness to form new solutions. More suitable solutions have more chances to reproduce.
- This is repeated until the required condition is satisfied.

In this study, MATLAB GA toolbox is used to find out the optimum process parameters. The mathematical models developed by using RSM have been used as a fitness function for GA.

V. EXPERIMENTATION

5.1 Selection of Material, input Parameters

The work piece is mainly used in food preparation equipment, Pharmaceuticals, Architectural and Marine applications. It is also used for Medical implants, including pins, screws and orthopedic implants like total hip and knee replacements owing to its mechanical properties such as high oxidation resistance, corrosive resistance and hardness. The machining conditions are listed in table I.

TABLE I
Machining Conditions for Experimentation

Work piece	**Electrode**	**Dielectric fluid**
SS 316L, 50mm diameter, 0.5mm thickness	300 µm tungsten	Deionized water

Current (I) in ampere, pulse on time (T_{on}) in µs and pulse off time (T_{off}) in µs were chosen as the input parameters of the current research. The MRR is selected as the objective and generally calculated as;

$$MRR = \frac{\text{weight of material before machining} - \text{after machining}}{\text{Machining time}} \quad \text{.... (3)}$$

5.2 Input parameter levels

Table II gives the input parameter levels taking into account the entire range of the machining capability.

Table II
Machining parameters with levels

Machining parameters	**Units**	**Levels**		
		L1	L2	L3
Current (I)	Ampere	6	9	12
Pulse On time (T_{on})	µs	3	6	9
Pulse off time(T_{off})	µs	3	6	9

5.3 Experimental setup

Experiments have been conducted in Electronica die sinking microEDM machine as shown in Fig. 3 with 300µm diameter tungsten electrode and deionized water as a dielectric fluid for machining the SS 316L.

Fig 3. Die sinking microEDM Machining Setup

The design of experiments (DOE) has been done using L_{27}orthogonal array Taguchi technique [9] with input parameters I, T_{on} and T_{off} and the objective variable MRR. The table III gives the experiments conducted based on the DOE.

TABLE III
Experimental results using L_{27} Orthogonal Array

Ex. No	I (A)	T_{on} (μs)	T_{off} (μs)	MRR (μg/s)
1	6	3	3	2.6761
2	6	3	6	2.9412
3	6	3	9	2.6357
4	6	6	3	2.7692
5	6	6	6	3.1148
6	6	6	9	4.1121
7	6	9	3	3.0769
8	6	9	6	3.4615
9	6	9	9	4.2194
10	9	3	3	3.2609
11	9	3	6	3.4694
12	9	3	9	3.7109
13	9	6	3	3.4286
14	9	6	6	4.7619
15	9	6	9	4.1463
16	9	9	3	3.4274
17	9	9	6	4.1860
18	9	9	9	5.8824
19	12	3	3	6.5421
20	12	3	6	7.6364
21	12	3	9	7.5862
22	12	6	3	6.8966
23	12	6	6	8.2353
24	12	6	9	8.1818
25	12	9	3	7.4510
26	12	9	6	9.1304
27	12	9	9	10.4762

VI. RESULTS AND DISCUSSION

6.1 Mathematical Modelling

To study the effect of the objective MRR, Design expert 7.0 is used to model input parameters I, T_{on} and T_{off} and the mathematical model is given in the equation 4.

$$\begin{aligned} MRR = {} & 12.6963308 - 2.69508599 * I - 0.35383237 * T_{On} - 0.06668517 * T_{off} \\ & + 0.02581481 * I * T_{On} + 0.02694092 * I * T_{off} + 0.04785933 * T_{on} * T_{off} \qquad \ldots\ldots (4) \\ & + 0.17651315 * I^2 + 0.00294306 * T_{on}^2 - 0.02095109 * T_{off}^2 \end{aligned}$$

6.2 Statistical validation

The Analysis of Variance (ANOVA) of the MRR is given in table IV. At 95% confidence levels of I, T_{on} and T_{off} and the interaction among the parameters indicate that the mathematical model is statistically significant. The multiple regression coefficient R^2 of the developed model MRR is 0.9827 and the adjusted R^2 is found to be 0.9735 which shows that the developed model is statistically significant.

TABLE IV
ANOVA for quadratic model MRR

Source	SS	DF	MS	F Value	*p*-value
Model	136.071	9	15.119	107.312	< 0.0001*
I	103.339	1	103.339	733.485	< 0.0001*
T_{on}	6.543	1	6.543	46.443	< 0.0001*
T_{off}	7.248	1	7.248	51.448	< 0.0001*
I T_{on}	0.648	1	0.648	4.598	0.0468*
I T_{off}	0.705	1	0.705	5.007	0.0389*
$T_{on}T_{off}$	2.226	1	2.226	15.802	0.0010*
I^2	15.142	1	15.142	107.477	< 0.0001*
$T_{on}{}^2$	0.004	1	0.004	0.030	0.8648
$T_{off}{}^2$	0.213	1	0.213	1.514	0.2353
Residual	2.395	17	0.141		
TOTAL	138.466	26			

SS – Sum of Squares DF – Degree of Freedom MS – Mean Squares *-Significant terms

6.3 Influences on MRR

The S/N ratio of the MRR is listed in table V. In this case of MRR, it is “Larger is better”, and so from table V it is clearly understood that the parameter ‘I’ is the most influencing parameter than T_{on} and T_{off}. This is also confirmed from the ANOVA table IV.

TABLE V
SN ratio response table

Level	Material removal rate		
	I	$\mathbf{T_{on}}$	$\mathbf{T_{off}}$
1	10.04	12.26	12.15
2	11.96	13.44	13.56
3	18.00	14.29	14.29
Delta	7.95	2.03	2.14
Rank	1	3	2

During the process of machining, the influence of various machining parameter like I, T_{on} and T_{off} has significant effect on MRR, as shown in the main effect plot for S/N ratio of MRR in Fig 4a. The current (I) is directly proportional to MRR in the range of 9 to 12A. This is because an increase in current produces solid spark, which yields the higher temperature, causing more material to melt and erode from the work piece. Moreover, it is clearly evident that the other factor does not influence much as compared to current I.

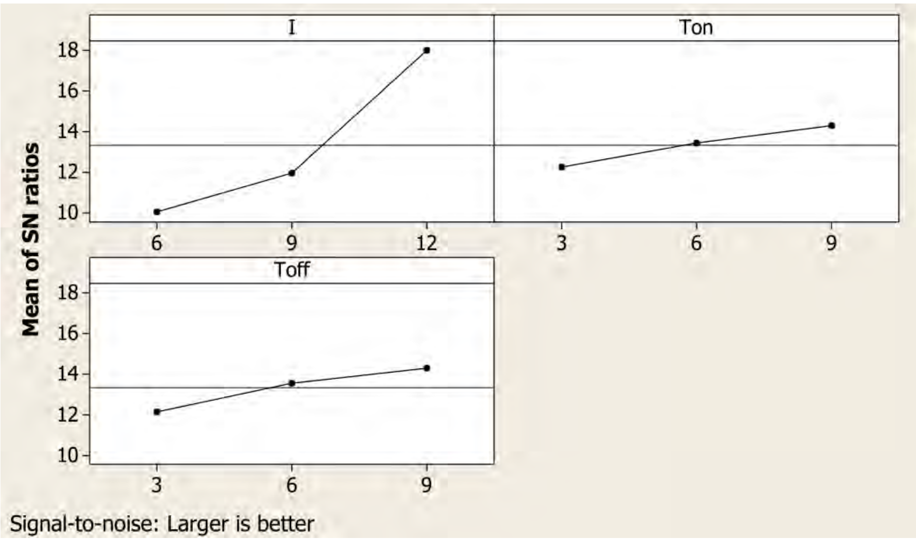

Fig 4a. Main Effects Plot for S/N ratios

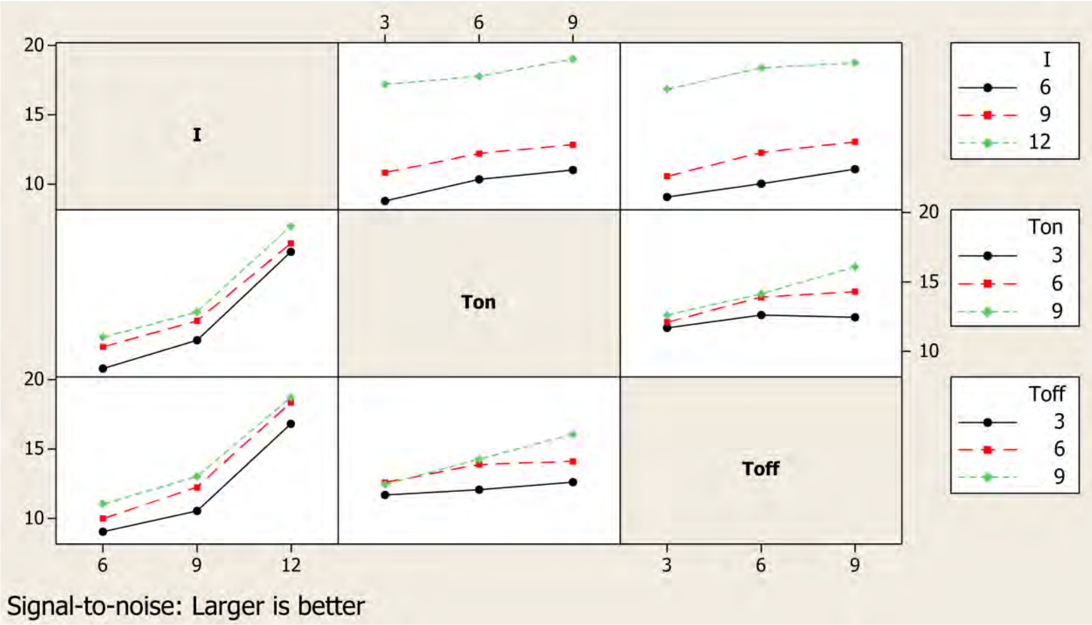

Fig 4b. Interaction Plot for S/N ratios

The interaction plot of MRR is shown in Fig 4b, where each plot displays the interaction between parameters I, T_{on} and T_{off}. This implies that the effect of one factor is dependent upon another factor. It is also confirmed by the ANOVA table IV.

VII. OPTIMIZATION

The main objective of this study is to find out the optimum process parameter that maximizes the Material removal rate. In this study, MATLAB GA toolbox is used to find out the optimum process parameters. The mathematical models developed by using RSM have been used as a fitness function for GA. The limitations for the optimization are given as

$$6 \le I \ge 12, \quad 3 \le T_{on} \ge 9, \quad 3 \le T_{off} \ge 19$$

Using the MATLAB GA tool box, multiple runs of the algorithm have been carried out at different settings and the optimum results are given in fig 5. The corresponding optimum process parameters are I=12.00, T_{on} = 8.994 and T_{off} =8.995.

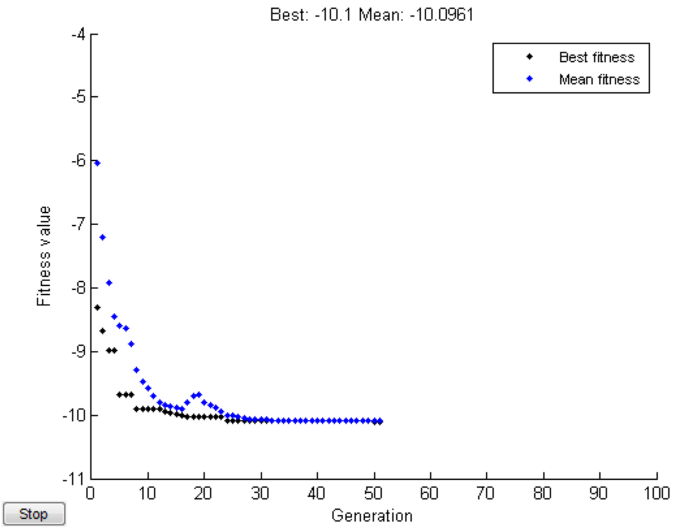

Fig 5. Optimum results from GA tool box

VIII.CONFIRMATION TEST

The confirmatory experiments are conducted for the optimal parameters obtained from the MATLAB GA and listed in table VI.

TABLE VI
Error between optimum values from GA and confirmation test value

Optimum values from GA	
Current (I)	12.00
Pulse on time (T_{on})	8.994
Pulse off time (T_{off})	8.995
MRR	10.10
Confirmation test value	
MRR	10.468
Error	3.65 %

The average prediction error for MRR is 3.65%. Thus, the GA predicted results are within the acceptable limits. Hence, the predicted model is found satisfactory for the microEDM process.

IX. CONCLUSIONS

In the current work, the effect current, pulse on time and pulse off time with three levels are considered to study the material removal rate of Stainless Steel 316 L using a 300µm tungsten electrode in microEDM. The mathematical model is derived from the Response Surface Methodology having the R^2 equal to 0.9827, which shows that the model is statistically significant, and has been used as fitness function to optimization using Genetic Algorithm (GA). The S/N ratio on MRR reveals that the current (I) plays the most significant role in the parameters chosen. The confirmation results prove that the developed mathematical model has deviated 3.65% only from the experimentation. Thus, for the manufacturers, the developed mathematical model is well suited to improve the productivity for selecting the optimal parameters.

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