# Optimization of the Process Parameters in Micro-Electric Discharge Machining Using Response Surface Methodology and Genetic Algorithm

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***Abstract-*** Micro Electric Discharge Machining is a non-traditional machining process which can be used for drilling micro holes in high strength to weight ratio materials. This present research study deals with the single optimization of micro EDM process using Genetic Algorithm. Mathematical models using Response Surface Methodology (RSM) is used to correlate the response and the parameters. The desired responses are minimum tool wear rate. The control parameters considered are pulse on time, peak current and flushing pressure on micro EDM of AISI stainless steel 304. The process control parameters of the machine have to be set at an optimal setting in order to achieve the desired responses.

***Index Terms-*** Micro electric discharge machining (micro EDM), Response surface methodology (RSM), Genetic Algorithm (GA), TWR.

## I. Introduction

Micro-EDM is a recently developed process which is used to produce micro-parts in the range of 50µm -100µm. In this process, metal is removed from the work piece by melting and vaporization due to pulse discharges that occur in a small gap between the work piece and the electrode. It is a novel machining process used for fabrication of a micro-metal hole and can be used to machine hard electrically conductive materials. The characteristic of non-contact between the tool and the work piece in this process eliminates the chance of stress being developed on the work piece by the cutting tool force.

However, to achieve the desired responses, the independent control parameters which affect the responses are to be set at an optimal value. Such problems can be solved by first developing mathematical models correlating the responses and the parameters. The second step is to choose a suitable optimization technique to search for correct parameter values for the desired responses.

Mukherjee and Ray [1] presented a generic framework for parameter optimization in metal cutting processes for selection of an appropriate approach. In practice, a robust optimization technique which is immune with respect to production tolerances is desirable [2]. Hung et al. [3] while using a helical micro-tool electrode with Micro-EDM combined with ultrasonic vibration found that it can substantially reduce the EDM gap, variation between entrance and exit and machining time, especially during deep micro-hole drilling. Jeong et al. [4] proposed a geometric simulation model of EDM drilling process with cylindrical tool to predict the geometries of tool and drilled hole matrix. The developed model can be used in offline compensation of tool wear in the fabrication of a blind hole.. Karthikeyan et al. [5] conducted general factorial experiments to provide an exhaustive study of parameters on material removal rate (MRR) and tool wear rate (TWR) while investigating performance of micro electric discharge milling process. Taguchi method is used for experiment design to optimize the cutting parameters [6]. Experimental methods increase the cost of investigation and at times are not feasible to perform all the experiments specially when the number of parameters and their levels are more. RSM is employed to design the experiments with a reduced number of experimental runs to achieve optimum responses [7]. Lalwani et al. [8] applied RSM to investigate the effect of cutting parameters on surface roughness in finish hard turning of MDN250 steel using coated ceramic tool. Yildiz [9] compared state-of-the-art optimization techniques to solve multi-pass turning optimization problems. The results show the superiority of the hybrid approach over the other techniques in terms of convergence speed and efficiency. Yusup et al. [10] discussed evolutionary techniques and basic methodology of each technique in optimizing machining process parameters for both traditional and modern machining. Application of evolutionary techniques in optimizing machining process parameters positively gives good results as observed in the literature. Samanta and Chakraborty [11] proved the applicability and suitability of evolutionary algorithm in enhancing the performance measures of non-traditional machining processes. Jain et al. [12] used GA for optimization of process parameters of mechanical type advanced machining processes. Traditional optimization methods are not suitable to solve problems where the formulated objective functions and constraints are very complicated and implicit functions of the decision variables.

## II. RSM Modeling

Table 1 lists the values for process control parameters of pulse on time, peak current and flushing pressures with five levels for each parameter. A sum of twenty experimental runs is designed using Centre composite design. The combinatorial effects of process control parameter at different levels on the measured response are listed in Table 2.

**Table 1 Coded and actual control parameter values at different levels**

| Machining parameters | Symbol | Units | Levels | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| Coded Value | | | -1.682 | -1 | 0 | 1 | 1.682 |
| Pulse-on-time | (Ton) | µs | 1 | 5 | 12 | 18 | 22 |
| Current | (Ip) | A | 0.4 | 0.7 | 1.2 | 1.7 | 2.0 |
| Flushing Pressure | (P) | $Kg/cm^2$ | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |

**Table 2 Design of experiments matrix showing coded values and observed response**

| Sl. No. | Coded values of parameters | | | Actual values of response |
|---|---|---|---|---|
| | Pulse-on-time (µs) | Current (A) | Flushing Pressure ($Kg/cm^2$) | Tool Wear Rate (mg/min) |
| 1 | -1 | -1 | -1 | 0.00033 |
| 2 | 1 | -1 | -1 | 0.00040 |
| 3 | -1 | 1 | -1 | 0.00047 |
| 4 | 1 | 1 | -1 | 0.00136 |
| 5 | -1 | -1 | 1 | 0.00149 |
| 6 | 1 | -1 | 1 | 0.00127 |
| 7 | -1 | 1 | 1 | 0.00062 |
| 8 | 1 | 1 | 1 | 0.00123 |
| 9 | -1.682 | 0 | 0 | 0.00062 |
| 10 | 1.682 | 0 | 0 | 0.00112 |
| 11 | 0 | -1.682 | 0 | 0.00066 |
| 12 | 0 | 1.682 | 0 | 0.00089 |
| 13 | 0 | 0 | -1.682 | 0.00060 |
| 14 | 0 | 0 | 1.682 | 0.00150 |
| 15 | 0 | 0 | 0 | 0.00081 |
| 16 | 0 | 0 | 0 | 0.00074 |
| 17 | 0 | 0 | 0 | 0.00077 |
| 18 | 0 | 0 | 0 | 0.00078 |
| 19 | 0 | 0 | 0 | 0.00082 |
| 20 | 0 | 0 | 0 | 0.00078 |

The mathematical model correlating the tool wear rate with the process control parameters is developed as:
Y(TWR)= (0.000708)+((0.000070*x(1))-((0.000058)*x(2))+((0.000296)*x(3))+((0.000011)*x(1)*x(1))-((0.000004)*x(2)*x(2))+((0.000095)*x(3)*x(3))+((0.000112)*x(1)*x(2))-((0.000038)*x(1)*x(3))-((0.000252)*x(2)*x(3)); ..........................................................................(1)

Where,
$X_1$= pulse on time
$X_2$= current
$X_3$= Flushing pressure

## III. OPTIMIZATION USING GA

Genetic algorithm is an evolutionary algorithm which applies the idea of survival of the fittest amongst an interbreeding population to create a robust search strategy. Initially a finite population of solutions to a specified problem is maintained. It then iteratively creates new populations from the old by ranking the solutions according to their fitness values and interbreeding the fittest to create new off-springs which are optimistically closer to the optimum solution to the problem at hand. It uses only the fitness value and no other knowledge is required for its operation. It is a robust search technique different to the problem solving methods used by more traditional algorithms which tend to be more deterministic in nature and get stuck up at local optima. As each generation of solutions is produced, the weaker ones fade away without producing offspring's, while the stronger mate, combining the attributes of both parents, to produce new and perhaps unique offspring's to continue the cycle. Occasionally, mutation is introduced into one of the solution strings to further diversify the population in search for a better solution.

The present research work optimizes the desired response and control parameters by writing the mathematical models as developed in equations 1 as .M-files and then solved by GA using the MATLAB software. The initial population size considered while running the GA is 20. A test of 10 runs has been conducted and the results are listed in Tables 3 for minimum tool wear rate.

The GA predicted value of minimum tool wear rate and the corresponding control parameter values are shown in Figure 1. It is observed from the figure that the best minimum tool wear rate predicted using GA is 0.00082664 mg/min with the corresponding control parameter values of 1µs for pulse on time, 0.4 A for peak current and 0.1 kg/cm2.

The results predicted using GA for minimum tool wear rate is listed in Table 3. Trial and error method for the selection of initial population size found the best result when the initial population size of 20 was chosen.

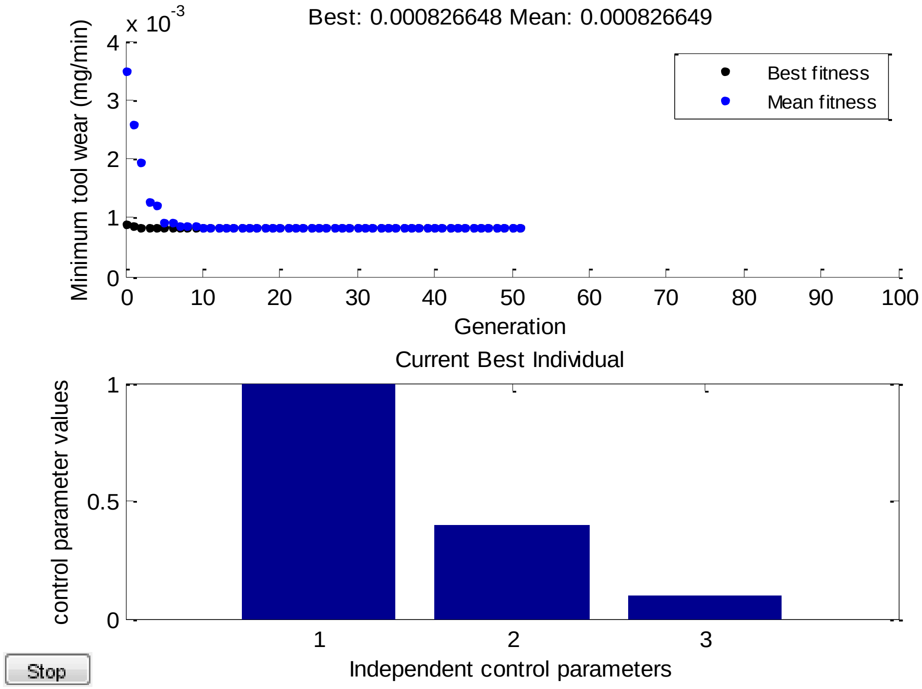


**Fig. 1 GA predicted plot for minimum tool wear rate and the control parameter values**

**Table 3 GA predicted results for minimum tool wear rate**

| Trial number | Control parameters | | | TWR (mg/min) |
|---|---|---|---|---|
| | Pulse on time | current | Flushing pressure | |
| 1 | 18 | 1.7 | 0.4 | 0.00195386 |
| 2 | 18 | 1.7 | 0.4 | 0.00199364 |
| 3 | 18 | 1.7 | 0.4 | 0.00225604 |
| 4 | 12 | 1.2 | 0.3 | 0.00285234 |
| 5 | 12 | 1.2 | 0.3 | 0.00452525 |
| 6 | 12 | 1.2 | 0.3 | 0.00625264 |
| 7 | 5 | 0.7 | 0.2 | 0.00975433 |
| 8 | 5 | 0.7 | 0.2 | 0.00094524 |
| 9 | 1 | 0.4 | 0.1 | 0.00089732 |
| 10 | 1 | 0.4 | 0.1 | 0.00082663 |

## IV. VALIDITY OF GA PREDICTED RESULT

Validation of the simulation results with the experimental results is done in order to conform the simulation results to the actual working conditions and to know how much is it varying with the actual experimental results which is measured by the percentage of prediction error.

The percentage of prediction error is calculated as:

$$\text{Prediction error \%} = \frac{(\text{Experimental result} - \text{GA predicted result})}{(\text{Experimental result})} \times 100$$

In order to validate the test results predicted by GA, five random experimental results are compared with the GA predicted results as shown in Table 4.

**Table 4 Comparison of Experimental and GA predicted results**

| S. No. | Experimental result | GA Predicted result | Prediction error % |
|---|---|---|---|
| 1 | 0.00112 | 0.00109 | 2.678 |
| 2 | 0.00136 | 0.00128 | 5.882 |
| 3 | 0.00089 | 0.00083 | 6.741 |
| 4 | 0.00152 | 0.00148 | 2.631 |
| 5 | 0.00082 | 0.0008264 | 0.762 |
| Average % of error | | | 3.737 |

It is observed from the table that average prediction percentage error is well within acceptable limits thus establishing the results predicted using GA to be valid.

## V. RESULT AND ANALYSIS

While drilling micro holes by micro EDM in AISI SS 304, the objective, tool wear rate is considered to be important as they affect the machining efficiency and the quality of the product. While optimizing the responses individually, the GA predicted value of minimum tool wear rate is 0.00082664 mg/min with the corresponding control parameter values of 1µs for pulse on time, 0.4 A for peak current and 0.1 kg/cm2. It is observed that the all three of the control parameters are to be set at low values in order to obtain minimum tool wear rate.

Also, the average percentage prediction error of GA when compared with the experimental results as shown in Table 4 is 3.737. Thus, the GA predicted results are within acceptable limits establishing the validity of the GA as an appropriate optimization technique for the micro EDM process.

## VI. CONCLUSION

AISI SS 304 has a wide range of applications in engineering due to its characteristic of high strength to weight ratio. Micro EDM offers a suitable process for drilling micro-holes in SS 304 mainly due to its characteristic of non contact between the tool and the work piece. The qualities required during micro hole drilling in SS 304 is to decrease the tool wear rate while drilling a micro-hole. The tool wear rate can be considered as a measure of machining efficiency.

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