Optimization of Electric Discharge Machining Process Parameters Using Genetic Algorithm

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Abstract: Proper selection of manufacturing conditions is one of the most important aspects in the Electrical Discharge Machining process, as these conditions determine important characteristics such as Material Removal Rate and Tool Wear Rate. In this work, mathematical models have been developed for relating the Material Removal Rate and Tool Wear Rate to machining parameters like discharge current, pulse-on time and pulse-off time. The developed models predict the machining conditions from rough machining region to finish conditions within the experimental domain. Response Surface Methodology has been applied for developing the models using the techniques of Design of Experiments and Central composite rotatable design was used to plan the experiments. Response surface Quadratic models were found to be the most suitable in the present work. A Quadratic equation is found from the Design Experiment.This equation is used in a GA Tool as a fitness function and optimizes the process parameter of EDM.

Keywords: Electric Discharge Machining, Material Removal Rate, Tool Wear Rate, Design Expert Software,Response Surface Methodology,Genetic Algorithm.

1. INTRODUCTION

Electrical discharge machining (EDM) is one of the most extensively used nonconventional manufacturing processes used for hard materials which are very difficult to machine with conventional techniques. EDM is sometimes referred to as spark machining, spark eroding, burning, die sinking or wire erosion. This is a manufacturing process whereby a desired shape is obtained using electrical discharges (sparks). English chemist Joseph Priestly laid the foundation for EDM by discovering the erosive effect of electrical discharges or sparks in 1770. However EDM was discovered in 1943 by two Russian scientists B. R. Lazarenkoand N. I. Lazarenko when they explored the destructive properties of electrical discharges for constructivepurpose. They developed a controlled process for machining difficult-to-cut materials. They invented and applied resistance capacitance (RC) relaxation circuit inEDM that was widely used till 1950s and after that several developments andadvancements were made by different researchers in the field of EDM. Electrical Discharge Machining (EDM) is a non conventional machining process, where electrically conductive materials is machined by using precisely controlled sparks that occur between an electrode and a workpiece in the presence of a dielectric fluid[1].
It uses thermoelectric energy sources for machining extremely low machinability materials; complicated intrinsic-extrinsicshaped jobs regardless of hardness have been its distinguishing characteristics.

EDM founds its wide applicability in manufacturing of plastic moulds, forging dies, press tools, die castings, automotive, aerospace and surgical components. As EDM does not make direct contact (an inter electrode gap is maintained throughout the process) between the electrode and the workpiece it’s eradicate mechanical stresses, chatter and vibration problems during machining [2].Various types of EDM process are available, but here the concern is about die- Sinking (also known as ram) type EDM machines which require the electrode to bemachined in the exact opposite shape as the one in the workpiece [1].

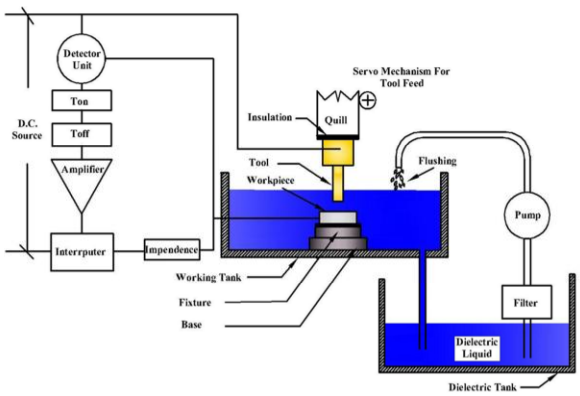

Figure 1.1: Layout of Electric Discharge Machining

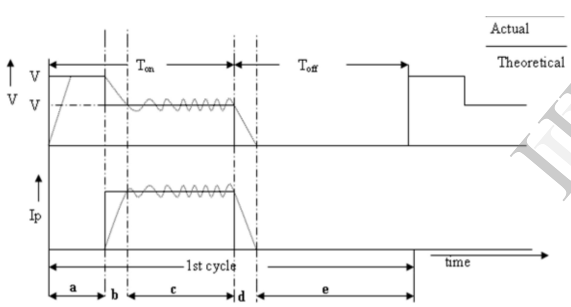

Figure 1.2: Variation of Ip and V in different phases of a spark

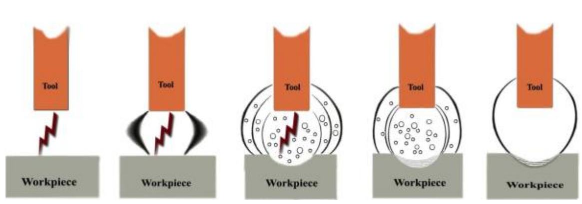

Fig1.3 (a)Fig1.3 (b)Fig1.3 (c)Fig1.3 (d)(e)Fig1.3

Figure 1.3:(a) Pre-breakdown phase (b) Breakdown phase (c) Discharge phase (d) End of the discharge and (e) Post-discharge phase

2. EXPERIMENTATION

In the present study, material removal rate and absolute tool wear rate has been considered for evaluating the machining performance. All these performance characteristics are correlated with machining parameters such as discharge current, pulse-on time and pulse-off time. Proper selection of machining parameters can result in desirable material removal rate and tool wear rate. Experiments were conducted covering wide range of current settings, pulse-on time and pulse-off time. The machining conditions used during experimentation have been shown in Table 1. Work piece material was cut into rectangular cross section and top and bottom faces of the work piece were ground to make flat and good surface finish prior to experimentation. The copper electrode was having rectangular cross section of 20x10mm. The electrode was polished and buffed prior to every experimental run. Machining depth was kept constant at 0.5mm for every experimental run and correspondingly ma-chining time was measured with an accuracy of 1 second. After every run, the work piece and tool were detached from the machine, cleaned, dried and weighed before and after machining.

3. DESIGN OF EXPERIMENTS

The design factors, response variable as well as the methodology employed for the experimentation is described below.

3.1 Design factors

The design factors considered in the present work were discharge current (I), pulse-on time (Ton) and pulse-off time (Toff). The selection of these three factors have been made because they are the most important and widely used by re-searchers in the die sinking EDM field [3].

3.2 Response variables

The selected response variables MRR, TWR and SR are defined as follows:

• Material Removal Rate

MRR is calculated by using the volume loss from the workpiece divided by the time of machining. The calculated weight loss is converted to volumetric loss in mm^3/min as per Equation 1.

$$MRR = \Delta V_w / t = \Delta W_w / \rho_w t \quad (1)$$

Where ΔV_w is the volume loss from the workpiece, ΔW_w is the weight loss from the workpiece, t is the duration of the machining process, and $\rho_w = 7700$ kg/m^3 the density of the workpiece.

• Tool Wear Rate

TWR is expressed as the volumetric loss of tool per unit time, expressed as

$$TWR = \Delta V_t / t = \Delta W_t / \rho_t t \quad (2)$$

Where ΔV_t is the volume loss from the electrode, ΔW_t is the weight loss from the electrode, t is the duration of the machining process, and $\rho_t = 8960$ kg/m^3 the density of the electrode.

TABLE 1

MACHINING CONDITIONS USED DURING EXPERIMENTATION[7]

Electrode	Work-piece	Dielectric fluid	Flushing type
Copper (electrolytic grade)	EN8 Steel	EDM oil	Submerged in
Rectangular: 20mm X 10mm	Rectangular: 40 mm X 50 mm	(Grade30)	dielectric

TABLE 2

MACHINING PARAMETERS AND THEIR CORRESPONDING VARIATION LEVELS[7]

Symbols	machining parameter	units	levels				
A	Discharge current (I)	A	3	6	12	18	21
B	Pulse-on time(Ton)	µs	10	200	500	750	1000
C	Pulse-off time (Toff)	µs	10	200	500	750	1000

3.3Factorial design employed

So, the case of the second order model turned out to be made up of a total of 20 experiments, the previous 14 from the first order model plus the six star points. Based on the Central Composite Design (CCD), experiments were conducted to develop empirical models for MRR and TWR in terms of the three input variables: discharge current, pulse-on time and pulse-off time. Each input variable (factor) was varied over five levels: ±1, 0 and ±α. Table 2 shows the relationship between the ma-chining parameters and their corresponding selected variation levels, taking into account the entire range of machine parameter.

4. RESPONSE SURFACE METHODOLOGY

Response surface methodology is a collection of mathematical and statistical technique that is useful for modeling and analysis of problems in which a response of interest is influence by several variables and the objective is to optimize the response [3], [4]. In order to study the effect of EDM process parameters on the volumetric Material Removal Rateand Tool Wear Rate a second order polynomial response was fitted into the following equation-

$$Y = \beta 0 + \beta 1X + \beta 2\Phi + \beta 3\ \Psi + \beta 12X\Phi + \beta 13X\ \Psi + \beta 23\Phi\Psi + \beta 11X2 + \beta 22\Phi 2 + \beta 33\ \Psi 2 \quad (3)$$

Where Y is the response and X, Φ, Ψ are the quantitative variables. β1, β2 and β3 represent the linear effect of X, Φ, and Ψ respectively. β11, β22 and β33 represent the quadratic effect of X, Φ and Ψ, whereas β12, β13 and β23 represents the linear by linear interaction between ―X and Φ‖, ―X and Ψ‖, ―Φ and Ψ‖ respectively. These quadratic models work quite well over the entire factor space and the regression coefficients were computed according to Least-square procedures.

5. EXPERIMENTAL RESULTS

Table 3 shows the design matrix developed for the proposed model as well as the machining characteristics value obtained in the experiments for MRR and TWR.

6. MODELING RESPONSE VARIABLES

Equation (4) and (5) presents the prediction models for MRR and TWR respectively.

$$MRR= +2.36771 + 1.06292*I + 0.010620*Ton–0.029306*Toff+0.031945*I^2-3.02001E-5*Ton^2+1.65488E-5*Toff^2+7.22470E-4*I*Ton-6.94470E-4*I*Toff^2+2.72328E-5*Ton*Toff \quad (4)$$

$$TWR = - 0.023232+0.082162*I-1.11420E-3*Ton-9.08270E-5*Toff-1.54239E-3*I^2+1.25744E-6*Ton^2+4.04197E-8*Toff^2-5.91828E-5*I*Ton+2.07481E-6*I*Toff+7.51014E-8*Ton*Toff(5)$$

Where, the values of the variables have been specified according to their original units.

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TABLE 3

DESIGN OF EXPERIMENT MATRIX AND MACHINING CHARACTERISTICS[7]

Std No.	Expt. run	I (A)	Ton (μs)	Toff (μs)	MRR (mm^3/min)	TWR (mm^3/min)
6 1	12.0	50050015.476	0.1167			
13	2	12.0	1000	5008.4353	0.0671	
11312.0	500	1022.437	0.1742			
54	6.0	750	7501.5535	0.0248		
95	3.0	500	5000.3095	0.01		
196	12.0	500	50013.436	0.1256		
207	18.0	200	20032.03	0.5348		
18	6.0	200	7502.9114	0.0401		
179	18.0	200	75018.604	0.5131		
810	12.0	500	50014.258	0.1206		
1511	6.0	200	2005.703	0.0292		
1412	12.0	500	100012.805	0.1450		
313	18.0	750	75028.555	0.200		
414	18.0	750	20027.794	0.1067		
215	21.0	500	50029.802	0.0472		
716 12.0	500	50013.254	0.1186			
1617	12.0	10	5002.2583	0.8764		
1018	6.0	750	2002.6596	0.027		
1219	12.0	500	500	13.825	0.1266	
1820	12.0	500	500	13.554	0.1373	

6.1Model Adequacy Test for MRR

A pre-ANOVA model statistics, the ANOVA results and the post-ANOVA model adequacy for the developed model of MRR are shown in Table 4, 5 and 6 respectively. Least SD and PRESS of quadratic model confirm that quadratic model is most suitable.

TABLE 4

MODEL SUMMARY STATISTICS FOR MRR

Source	SD	R2	Adj. R2	Pred.R^2	PRESS
Linear	4.14	0.8544	0.8271	0.7295	510.49
2FI	4.10	0.8839	0.8304	0.670621.08	
*Quadratic2.49	0.9672	0.9377	0.7422	486.45	
**Cubic	0.78	0.9984	0.9939	-	-

*=Suggested, ****=**Aliased, SD=Std. Dev.

TABLE 5

ANOVA FOR QUADRATIC MODEL OF MRR

Source	SS	DF	MS	F-value	P-value
Model 1825.20	9	202.80	32.79	<0.0001*	
I	1502.49	1	1502.49	242.92<0.0001*	
Ton 6.92 1	6.921.12 0.3149				
Toff 55.23 1	55.23 8.93 0.0136*				
I^2	13.44 1	13.44 2.17 0.1712			
$Ton^2$95.07	1	95.07	15.37 0.0029*		
$Toff^2$	28.55	1	28.55 4.62 0.0572		
I*Ton	11.40	1	11.40 1.84 0.2044		
I*Toff 10.54	1	10.54 1.700.2211			
Ton*Toff 34.18	1	34.18	5.53 0.0406*		
Residual	61.85 10	6.19	--	--	
Lack of fit	58.83	5	11.77 19.47	0.0027*	
Error	3.02	5	0.60	--	--
Total	1887.05	19			

*significant terms

The model F-value of **32.79** implies the model is significant. There is only a **0.01%** chance that a **"Model F-value"** this large could due to noise. Value of **"Prob>F"** less than **0.0500** indicate model are significant. Values greater than **0.100** indicate the model terms are not significant. The**"Lack of Fit F-**

value"of 19.47 implies the Lack of Fit is significant. There is only 0.27% chance that lack of fit value this large could occur due to noise.

TABLE 6
POST ANOVA MODEL ADEQUACY FOR MRR

R^2	0.9672
Adj.R^2	0.9377
Pred.R^2	0.7422
Adeq.Precisior	18.870

The "Pred R^2" of 0.7422 is in reasonable agreement with the Adj.R^2 of 0.9377.Adeq.Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 18.870 indicates an adequate signal.

6.2 Model Adequacy Test for TWR

The statistical analysis of the model of TWR is presented in Table 7, 8 and 9respectively. Since quadratic model is having least Standard Deviation (0.12) and Predicted Error Sum of Squares (1.07) among the other models, hence suggested.. The results of the statistical analysis show that model can satisfactorily be used in predicting the response of TWR.

TABLE 7
MODEL SUMMARY STATISTICS FOR TWR

Source	SD	R^2	Adj.R^2	Pred.R^2	Press
Linear	0.16	0.5286	0.4402	0.1468	0.77
2FI	0.16	0.6133	0.4349	-0.0089	0.92
*Quadratic	0.12	0.8457	0.7069	-0.1771	1.07
**Cubic	9.063E-3	0.9995	0.9983	--	--

*=Suggested, ****=**Aliased, SD=Std. Dev.

TABLE 8
ANOVA FOR QUADRATIC MODEL OF TWR

Source	SS	DF	MS	F-value	P-value
Model	0.77	9	0.085	6.09	0.0046*
I	0.12	1	0.12	8.39	0.0160*
Ton	0.29	1	0.29	20.43	0.0011*
Toff	1.765E-4	1	1.765E-4	0.013	0.9129
I^2	0.031	1	0.031	2.24	0.1657
Ton^2	0.16	1	0.16	11.76	0.0064*
$Toff^2$	1.703E-4	1	1.703E-4	0.012	0.9144
I*Ton	0.077	1	0.077	5.46	0.0416*
Residual	0.14	10	0.14	--	--
Lack of fit	0.14	5	0.028	340.21	<0.0001*****
Error	4.107E-4	5	8.21E-5	--	--
Total	0.91	19			

*significant terms

The model F-value of **6.09** implies the model is significant. There is only a **0.46%** chance that a **"Model F-value"** this large could due to noise. Value of **"Prob>F"** less than **0.0500** indicate model are significant. Values greater than **0.100** indicate the model terms are not significant. The**"Lack of Fit F-value" of 340.21** implies the Lack of Fit is significant. There is only 0.01% chance that lack of fit value this large could occur due to noise.

TABLE 9
POST ANOVA MODEL ADEQUACY FOR TWR

R^2	0.8457
Adj.R^2	0.7069
Pred.R^2	-0.1771
Adeq.Precisior	9.982

A negative "Pred.R^2" implies that the overall mean is a better predictor of your response than the current model. "Adeq.Precision"measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 9.982 indicates an adequate signal.

7.Genetic Algorithms:History

The idea of evolutionary computing was introduced in 1960 by I.Rechenberg in his work evolutionary strategies. Genetics algorithms are computerized search andoptimization algorithms based on the mechanics of natural genetics and natural selection.Prof. Holland of University of Michigan, Ann Arbor, envisaged the concept of these algorithms in the mid –sixties and published his seminal work (Holland, 1975) [5].

Introduction:

Evolutionary algorithms (EAs) are population-based meta heuristic optimization algorithms that use biology-inspired mechanisms and survival of the fittest theory in order to refine a set of solution iteratively. Genetic algorithms (GAs) are subclass of evolutionary algorithms (EAs) where the elements of the search space are binary strings or arrays of other elementary types. Genetic algorithms (GAs) are computer based search techniques patterned after the genetic mechanisms of biological organisms that have adapted and flourished in changing highly competitive environment. Last decade has witnessed many exciting advances in the use of genetic algorithms (GAs) to solve optimization problems in process control systems. Genetic algorithms (GAs) are the solution for optimization of hard problems quickly, reliably and accurately. As the complexity of the real-time controller increases, the genetic algorithms (GAs) applications have grown in more than equal measure.

Basic Concepts

Genetic algorithms are good at taking larger, potentially huge, search spaces and navigating them looking for optimal combinations of things and solutions which we might not find in a life time[5].

Three most important aspects of using GA are:

1. Definition of objective function
2. Definition and implementation of genetic representation
3. Definition and implementation of genetic operators.

Working Principle of Genetic Algorithms

The workability of genetic algorithms (GAs) is based on Darwinian's theory of survival of the fittest. Genetic algorithms (GAs) may contain a chromosome, a gene, set of population, fitness, fitness function, breeding, mutation and selection. Genetic algorithms (GAs) begin with a set of solutions represented by chromosomes, called population. Solutions from one population are taken and used to form a new population, which is motivated by the possibility that the new population will be better than the old one. Further, solutions are selected according to their fitness to form new solutions, that is, offspring. The above process is repeated until some condition is satisfied. Algorithmically, the basic genetic algorithm (GAs) [6] is outlined as below.

Step I [Start] Generate random population of chromosomes, that is, suitable solutions for the problem.

Step II [Fitness] Evaluate the fitness of each chromosome in the population.

Step III [New population] Create a new population by repeating following steps until the new population is complete.

- **a)** [Selection] Select two parent chromosomes from a population according to their fitness. Better the fitness, the bigger chance to be selected to be the parent.
- **b)** [Crossover] With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover was performed, offspring is the exact copy of parents.
- **c)** [Mutation] With a mutation probability, mutate new offspring at each locus.
- **d)** [Accepting] Place new offspring in the new population.

Step IV [Replace] Use new generated population for a further run of the algorithm.

Step V [Test] If the end condition is satisfied, stop, and return the best solution in current population.

Step VI [Loop] Go to step 2.

Objective Function:

Objective function obtained from design expert software and this function use as a fitness function of GA Tool. This fitness function used to optimization and we get the result.

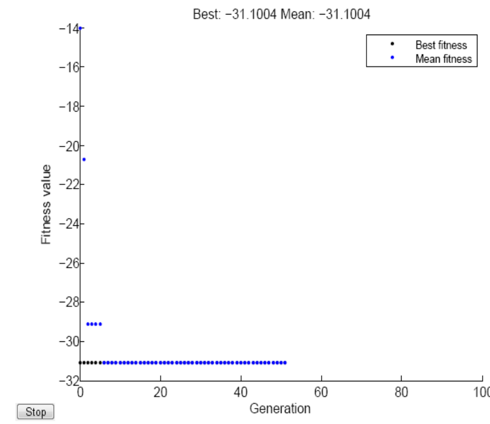
Objective Function For MRR

```
function y=azam(x)
y(1)=-((2.36771)+(1.06292*x(1))+(.010620*x(2))-(.029306*x(3))+(.031945*x(1)^2)-(.0000302001*x(2)^2)+(.0000165488*x(3)^2)+(.000722470*x(1)*x(2))-(.000694470*x(1)*x(3))+(.0000272328*x(2)*x(3)));
```

TABLE 10

RESULT OBTAINED FROM GENETICALGORITHMS

S.N	Discharge current(A)	Pulse on Time(µs)	Pulse off Time(µs)	MRR (mm3/min)
1	13.789	828.496	356.625	15.7056
2	14.229	456.768	281.964	20.9796
3	20.572	440.38	806.176	28.3981
4	16.057	885.899	10	23.4938
5	20.995	695.869	371.905	35.1015
6	17.667	427.162	204.036	30.1684
7	15.721	318.378	155.562	26.4021
8	18.644	794.677	904.872	28.2584
9	16.172	299.019	101.808	28.7535
10	17.893	460.229	190.2	31.1004



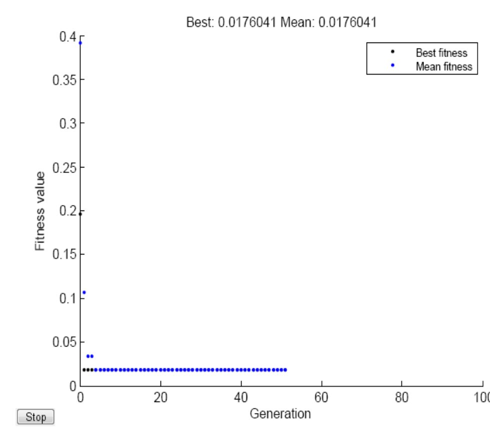
BFST FIT GRAPH FOR MRR

Objective Functionfor TWR

```
function y=azam1(x)
y(1)=(-(.023232)+(.082162*x(1))-(.00111402*x(2))-(.0000908270*x(3))-(.00154239*x(1)^2)+(.00000125744*x(2)^2)+(.0000000404197*x(3)^2)-(.0000591828*x(1)*x(2))+(.00000207481*x(1)*x(3))+(.0000000751014*x(2)*x(3)));
```

TABLE 11
RESULT OBTAINED FROM GENETIC ALGORITHMS

S.N	Discharge current (A)	Pulse on Time (µs)	Pulse off Time(µs)	TWR(mm3/min)
1	13.588	697.997	689.854	0.09432
2	3	10	10	0.19574
3	15.485	723.943	744.37	0.08745
4	3	142.776	776.492	0.01760
5	17.421	790.267	121.978	0.03132
6	16.449	721.13	10.393	0.05944
7	9.868	573.542	576.753	0.07479
8	6.751	776.258	825.934	0.05621
9	7.72	787.01	10	0.06150
10	10.169	844.146	223.589	0.10098



BEST FIT GRAPH FOR TWR

RESULT AND DISCUSSION

Because Original Chromosomes are randomly this may induce getting different solution set, so the procedure was repeated many times. The result shows that although the set are slightly different and we get the maximum MRR and minimum TWR for the corresponding parameters.

Table 10 and table11 shows one group set of solution. Parameter listed in number 5 lead to the optimal solution for MRR but not consider because this MRR out of range of experimental data. So in Table10 S.N.10 optimal solution of MRR values are 31.1004 mm^3**/min**, where current 17.893A, pulse on time 460.229µs and pulse off time190.2µsrespectively. Similarlyin Table 11,S.N. 4 the minimum values of TWR is .01760mm^3/min, wherecurrent 3A, pulse on time 142.776µs and pulse off time776.496µsrespectively. Compare them with maximum MRR and minimum TWRin table 3,it is clear that MRR and TWR is improved using optimized parameters.

CONCLUSION

In this paper optimize EDM process parameters areintroduced, which uses design expert and GA algorithm. Design expert model was set up to represent the relationshipbetween MRR and input parameter similarly as relationship between TWR and input parameters.

GA is used to optimize parameter. MRR and TWR improved**by** using optimized parameter; it is close to experiment result. With the increase of current, MRRcan be improved, similarly with theincrease pulse on time, TWR can be decrease. MRR and TWR can also be improved when we set proper current, proper pulse on time and proper pulse off time.

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