Improvement of Process Quality Characteristics of Electrical Discharge Machining Based on DOE Approach and Heuristic Algorithms

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Abstract

Electrical discharge machining (EDM) is the most widely and successfully applied process for machining of hard to machine conductive parts. In this study the effect of input EDM process parameters on AISI H13, is modeled and optimized. The process input parameters considered here include voltage (V), peak current (I), pulse on time (T_{on}) and duty factor (η). The process quality measures are surface roughness (SR) and material removal rate (MRR). The objective is to determine a combination of process parameters to minimize SR and maximize MRR. The experimental data are gathered based on design of experiments (D-optimal) approach. Then, analyses of variance (ANOVA) and validation experiments have been carried out to select the best and most fitted regression models. In the last section of this research, simulated annealing (SA) and particle swarm optimization (PSO) algorithms have been employed and compared for optimization of the performance characteristics. A set of verification tests is also performed to verify the accuracy of optimization procedure in determining the optimal levels of machining parameters. The results indicate that the proposed modeling technique and SA and PSO algorithms are quite efficient in modeling and optimization of EDM process parameters.

Keywords: Electrical discharge machining (EDM), simulated annealing (SA) algorithm, particle swarm optimization (PSO) algorithms, Analysis of Variance (ANOVA).

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I. INTRODUCTION

Electrical discharge machining (EDM) is one of the most suitable non-conventional material removal processes to machine hard to machine materials. EDM is a thermo-electric process in which material is removed from work piece by erosion effect of series of electric discharges (sparks) between tool and work piece immersed in a dielectric liquid (Figure 1) [1, 2].

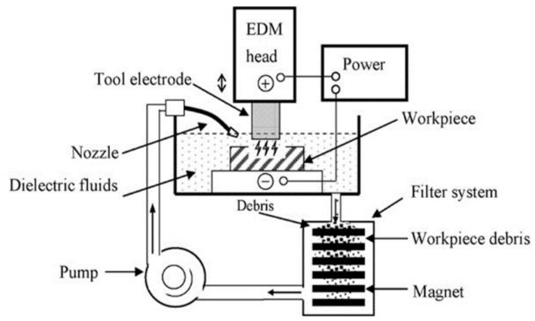

Fig. 1. Schematic illustration of electrical discharge machining [2]

The most influential process parameters of EDM process are discharge voltage, peak current, pulse duration, duty factor, polarity, type of dielectric flushing, spark gap, pulse frequency and corresponding performance measures are material removal rate (MRR), tool wear rate (TWR), surface roughness (SR), total machining time and etc.,. However, optimizing any of these measures alone have a limited value in real practice, due to the complex nature of the process where several different and sometimes contradictory objectives must be simultaneously considered [2-4].

The most important process parameters in EDM, considered in different papers in this regard are peak current (I), voltage (V), pulse on time (T_{on}), pulse off time (T_{off}), and duty factor (η) [1-6]. These parameters, in turn, determine the process output characteristics, among which MRR, TWR and SR are the most important ones [2]. It is essential, therefore, to find an accurate relation between process tuning parameters and its output responses. As a result, a comprehensive study of the effects of EDM parameters on the machining characteristics is of great significance.

Review of the research work reveals that much work has been done on various aspects of EDM process. These studies have mostly emphasized on the modeling and optimization of the process parameters [2-7].

To the best of our knowledge, there is no published works to statistically study and optimize the effect of machining parameters of EDM process on the most important output characteristics namely, MRR and SR for machining of AISI H13 using D-optimal approach for designing experimental matrix, regression approach for modeling and simulated annealing (SA) particle swarm optimization (PSO) algorithms for optimization. Therefore the present study has two objectives. 1. To establish the relationship between the input and output parameters (MRR and SR) of EDM process. 2. To derive the optimal parameter levels for maximum MRR and minimum SR using statistical analysis of the experimental data and SA and PSO algorithms. Finally, the article concludes with the verification of the proposed approach and a summary of the major findings.

II. EXPERIMENTAL SET UP AND EQUIPMENT USED

The experiments were carried out on AISI H13 alloy with 50×4mm dimensions for diameter and thickness respectively. This alloy has very high mechanical properties and is widely used in various applications, especially in oil and gas, power stations and aerospace industries. Based on these facts and the literature survey conducted, copper electrodes, with 99% purity and 8.98 g/cm3 density, were used as tools in our experiments. A total of 26 cylindrical shape electrodes were used as tools. The electrodes were replaced after each experiment. The machining time for each test was 1 hour. The tool electrode and the work piece are shown in Figure 3. An Azerakhsh-304H die-sinking machine, shown in Figure 2, has been employed to carry out the experiments. The dielectric for all experiments was pure kerosene. During the experiments work piece and electrode were immersed in the dielectric used.

In design of experiments (DOE), the number of required experiments (and hence the experiment cost) increases as the number of parameters and/or their corresponding levels increase. That is why it is recommended that the parameters with less likely pronounced effects on the process outputs be evaluated at fewer levels.

At first, some preliminary tests were carried out, to determine the stable domain of the machine parameters and also the different ranges of process variables. Based on literature reviews, preliminary test results and working characteristics of the EDM machine, peak current (I), voltage (V), pulse on time (T_{on}), and duty factor (η) were chosen as the independent input parameters.

Table 1 shows the input parameters and their corresponding levels.

Fig. 2. Die-sinking EDM machine, Digital surface roughness tester and electronic balance used

TABLE I. PROCESS VARIABLES AND THEIR CORRESPONDING LEVELS

No	Symbol	Factor	Unit	Range	L_1	L_2	L_3
1	A	T_{on}	µS	35-200	35	100	200
2	B	I	A	1-5	1	3	5
3	C	η	S	0.4-1.8	0.4	1	1.8
4	D	V	V	80-200	80	200	-

D-optimal designs are one form of design provided by a computer algorithm. These types of computer-aided designs are particularly useful when classical designs do not apply. D-optimal design matrices are usually not orthogonal and effect estimated is correlated. The reasons for using D-optimal designs instead of central composite and Box-Behnken designs generally due to it is much greater flexibility in selecting response surface model types [7]. It also allows parameters to be estimated without bias and with minimum-variance. In practical terms, D-optimal experiments can reduce the costs of experimentation [8].

Table 2 illustrates the proposed design for the process characteristics and their corresponding output.

In this study the Design Expert software have been used to prepare the design matrix needed for formulating the input parameters in order to do the experiments

TABLE II. THE PROCESS CHARACTERISTICS AND THEIR CORRESPONDING OUTPUT

No	I (A)	T_{on} (µs)	V (v)	η (s)	MRR (mgr/hr)	SR (µm)
1	3	200	80	0.4	2.48	7.98
2	5	35	200	0.4	2.47	6.31
3	5	100	80	0.4	2.80	8.42
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
24	3	35	80	1.8	2.46	5.73
25	5	35	200	1.8	4.44	6.03
26	3	100	200	0.4	1.89	6.44

III. Evaluation of Performance Measures

In this study MRR and SR are used to evaluate EDM machining process of Inconel 718 super alloy. These measures of performance are calculated as follows [10]:

MRR is a measure of machining speed and is expressed as the work piece removal weight (WRW) in a predetermined machining time (MT) in minute.

$$\text{MRR} = \frac{\text{WRW}}{\text{MT}} \tag{1}$$

In machining processes, surface quality is usually measured in terms of surface roughness (SR). The average roughness (Ra) is the area between the roughness profile and its mean line, which is defined by Equation (2).

$$\text{Ra} = \frac{1}{\text{L}} \int_0^{\text{L}} \left| \text{Z}(\text{x}) \right| \, \text{dx} \tag{2}$$

In the above, Ra is the arithmetic average deviation from the mean line, L the sampling length, and Z(x) is the ordinate of the profile curve. After machining, the surface finish of each sample was measured with an automatic digital Surtronic (3+) SR tester (Figure 2).

IV. Regression Modeling and Analysis of Variance

Regression models can be used to predict the behavior of input variables (independent variables) and values associated with each test response results [10].

The last two columns of Table 3 are the corresponding outputs for each test setting. These data can be used to develop mathematical models. Any of the process characteristic is a function of process parameters which are expressed by linear, curvilinear or logarithmic functions; as stated in Equations 3 to 5 respectively.

$$Y_1 = b_0 + b_1 A + b_2 B + b_3 C + b_4 D \tag{3}$$

$$Y_2 = b_0 + b_1 A + b_2 B + b_3 C + b_4 D + b_{11} AA + b_{22} BB + b_{33} CC + b_{44} DD + b_{12} AB + b_{13} AC + b_{14} AD + b_{23} BC + b_{24} BD + b_{34} CD \tag{4}$$

$$Y_3 = b_0 A^{b1} B^{b2} C^{b3} D^{b4} \tag{5}$$

Models representing the relationship between process parameters and output characteristics can be stated in equations 6 to 11. Stepwise elimination process was used to modify the initial proposed models. For instance, as can be seen in Equation 9, independent variable V was eliminated because of its improper effect on SR in the curvilinear model. Adequacies of models were checked by validation experiments. Table 3 and 4 illustrate the mean error of the 9 new experiments for the output characteristics. According to the results (the lowest error and the highest R^2-adj) the curvilinear and logarithmic models are the best models among the proposed models for the SR and MRR respectively.

Linear Model

$$\text{MRR} \quad -6.591 + 0.00886 \times V + 1.30719 \times I + 0.0250265 \times T + 2.11614 \times \eta \tag{6}$$

$$\text{SR} \quad 0.393848 + 0.0003583 \times V + 1.34205 \times I + 0.0128686 \times T + 0.161359 \times \eta \tag{7}$$

Curvilinear Model

$$\text{MRR} \quad 4.81568 + 0.0340054 \times V - 5.9293 \times I - 0.067071 \times T - 0.0312296 \times (V \times \eta) + 0.597425 \times (I \times I) + 0.0305473 \times (I \times T) + 1.7115 \times (I \times \eta) + 0.0270553 \times (T \times \eta) \tag{8}$$

$$\text{SR} \quad 0.521697 + 2.22346 \times I - 0.281034 \times (I \times I) + 0.00846034 \times (I \times T) + 0.0000273 \times (V \times T) - 0.000054 \times (T \times T) \tag{9}$$

Logarithmic Model

$$\text{MRR} \quad 0.008324 \times V^{0.0172653} \times I^{1.798} \times T^{0.880033} \times \eta^{0.943937} \tag{10}$$

$$\text{SR} \quad 1.226 \times V^{0.0110355} \times I^{0.634706} \times T^{0.200333} \times \eta^{0.0119906} \tag{11}$$

TABLE III. New process variables for model validation and corresponding results of SR

Model	V (v)	I (A)	T_{on} (µs)	η (s)	Predicted value	Experiment value	Error
Linear	80	1	100	1	3.21	2.83	11.8
	80	3	35	0.4	4.96	5.43	9.4
	80	5	100	1.8	8.71	9.54	9.6
R^2 = 82.30, R^2 (adj) =78.76, Mean Error= 10.27							
Curvilinear	80	1	100	1	2.94	2.92	0.74
	80	3	35	0.4	5.39	5.56	3.14
	80	5	100	1.8	8.34	8.75	4.92
R^2 = 99.32, R^2 (adj) =99.13, Mean Error= 2.93							
Logarithmic	80	1	100	1	3.23	2.92	9.80
	80	3	35	0.4	5.21	5.56	6.71
	80	5	100	1.8	9.05	8.75	3.36
R^2 = 93.36, R^2 (adj) =92.04, Mean Error= 6.62							

TABLE IV. New process variables for model validation and corresponding results of MRR

Model	V (v)	I (A)	T_{on} (µs)	η (s)	Predicted value	Experiment value	Error
Linear	80	5	100	1.8	6.97	6.12	12.21
	80	3	35	1.8	2.72	2.35	13.92
	80	4	150	1.8	6.91	6.08	12.01
R^2 = 78.2, R^2 (adj) =73.46, Mean Error= 12.71							
Curvilinear	80	5	100	1.8	17.16	15.04	12.37
	80	3	35	1.8	2.21	2.50	11.44
	80	4	150	1.8	16.77	15.32	8.68
R^2 = 96.19, R^2 (adj) =94.29, Mean Error= 10.83							
Logarithmic	80	5	100	1.8	16.25	15. 45	4.94
	80	3	35	1.8	2.64	2.50	5.36
	80	4	150	1.8	15.54	15.32	1.47
R^2 = 95.36, R^2 (adj) =94.43, Mean Error= 3.92							

The ANOVA is used to investigate the most influential parameters to the process factor-level response. In this investigation, the experimental data are analyzed using the F-test and the contribution rate [10]. ANOVA has been performed on the above model to assess their adequacy, within the confidence limit of 95%. ANOVA results indicate that the model is adequate within the specified confidence limit. Result of ANOVA is shown in Tables 5 and 6.

TABLE V. RESULT OF ANOVA FOR MRR

Machining parameters	Degree of freedom (Dof)	Sum of square (SSj)	Adjusted (MSj)	F-Value	P
Regression	4	54.96	13.74	102.74	0.00
V	1	0.05	0.00	0.01	0.00
I	1	37.76	34.98	261.54*	0.00
Ton	1	8.95	10.95	75.47*	0.00
η	1	8.20	8.20	61.32*	0.00
Error	20	2.68	0.13	-	-
Total	24	57.64	-	-	-
*Significant Parameters, $F_{0.05,1,26} = 4.23$					

TABLE VI. RESULT OF ANOVA FOR SR

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (MS_j)	F-Value	P
Regression	5	135.50	27.10	824.26	0.00
I	1	9.17	9.17	279.14*	0.00
V × T	1	0.83	0.83	25.47*	0.00
I × I	1	5.88	5.88	178.81*	0.00
I × T	1	19.00	19.00	577.77*	0.00
T × T	1	2.93	2.93	89.27*	0.00
Error	18	0.52	0.03	-	-
Total	23	136.03	-	-	-
*Significant Parameters, $F_{0.05,1,26} = 4.23$					

Therefore, F–values of machining parameters are compared with the appropriate values from confidence table, $F_{\alpha,v1,v2}$; where α is risk, v_1 and v_2 are degrees of freedom associated with numerator and denominator which illustrated in Tables 5 and 6 [10]

As the F-value of each parameter is greater than the $F_{\alpha,v1,v2}$ observed from the table means the corresponding parameter is influential in the process characteristic. The percent contribution of the parameters can be calculated by using ANOVA result and Equation (12) [10].

$$P_i\,(\%) = \frac{SS_i - (DOF_i \times MS_{error})}{Total\ Sum\ of\ Squre} \tag{12}$$

In the above formula according to the ANOVA results (Table 5), P_i is Contribution percentage, SS_i is sum of square, DOF_i is degree of freedom of i^{th} factor, and MS_{error} is mean sum of square of error [10]. The percent contributions of the EDM parameters on MRR are shown in Figure 3.

According to Figure 3, peak current is the major factor affecting the MRR with 65.3% contribution. It is followed by pulse on time and duty factor with 15.3% and 14.0% respectively. The remaining (4.9%) effects are due to noise factors or uncontrollable parameters.

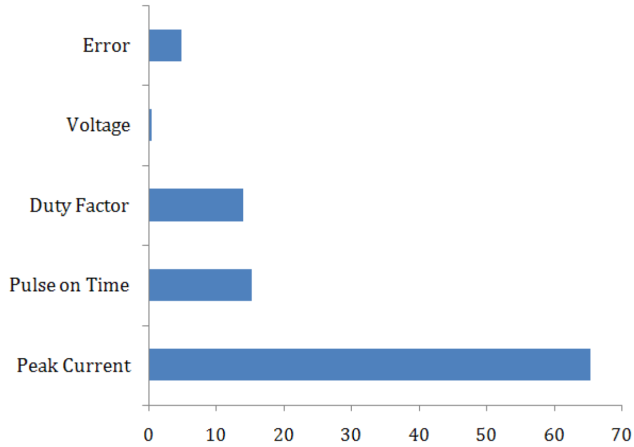

Fig. 3. The effect of machining parameters on the MRR

V. HEURISTIC ALGORITHMS (SA AND PSO)

Simulated annealing (SA) algorithm is an optimization process whose operation is reminiscent of the physical annealing of crystalline compounds such as metals and metallic alloys [11].

A standard SA procedure begins by generating an initial solution at random. At initial stages, a small random change is made in the current solution. Then the objective function value of new solution is calculated and compared with that of current solution. A move is made to the new solution if it has better value or if the probability function implemented in SA has a higher value than a randomly generated number. The probability of accepting a new solution is given as follows:

$$p = \begin{cases} 1 & \text{if } \Delta < 0 \\ e^{-\Delta/t} & \text{if } \Delta \geq 0 \end{cases} \tag{13}$$

The calculation of this probability relies on a temperature parameter, T, which is referred to as temperature, since it plays a similar role as the temperature in the physical annealing process. To avoid getting trapped at a local minimum point, the rate of reduction should be slow. In our problem the following method to reduce the temperature has been used:

$$T_{i+1} = cT_i \qquad i = 0,1,\ldots \quad \text{and} \quad 0.9 \le c < 1 \tag{14}$$

Thus, at the start of SA most worsening moves may be accepted, but at the end only improving ones are likely to be allowed. This can help the procedure jump out of a local minimum. The algorithm may be terminated after a certain volume fraction for the structure has been reached or after a pre-specified run time.

Particle swarm optimization (PSO) algorithm, a population based stochastic optimization algorithm, has been proposed by Eberhart and Kennedy in 1995 [12]. During optimization, after initializing PSO parameters using a group of random particles, optimal solution is achieved through the problem space. Although conventional PSO can rapidly find out good solutions, it may be trapped in local minimum and fails to converge to the best position. To obviate this problem and improve resolving capacity, an improved PSO algorithm with the rule of mutation is proposed. Using both the best and worst particle positions in the improved PSO algorithm accelerate the finding of the optimal solution. The particle positioning is accomplished by modifying the particle parameters including the speed and position (Viand Xi) which are defined in the following expressions.

$$\begin{aligned} X_i(k+1) &= X_i(k) + V_i(k+1) \\ V_i(k+1) &= \gamma.V_i(k) + c_1 r_1 (p_i - x_i(k)) + c_2 r_2 (p_g - x_i(k)) \end{aligned} \tag{15}$$

Where c_1 and c_2 and are acceleration parameters, r1 and r_2 are random numbers ranged between 0 and 1, and γ represents the inertia weight which decreases linearly from 1 to near 0 while convergence of algorithm. p_i and p_g denote the best position of the i^{th} particle and the best position of the colony respectively. Each evolutionary optimization algorithm has its own parameters that affect its performance and the quality of solution. In this study optimal value of parameters involved in algorithm is determined by large numbers of trials are conducted by varying different parameters to obtain the best performance of PSO.

PSO and SA convergence curves for SR have been illustrated in Fig 4.

Based on the Fig 4 shown the PSO and SA algorithms have similar results for optimization of EDM process.

For validation of method used for modeling and optimization, a set of experimental tests has been carried out based on the results gained from PSO and SA algorithms.

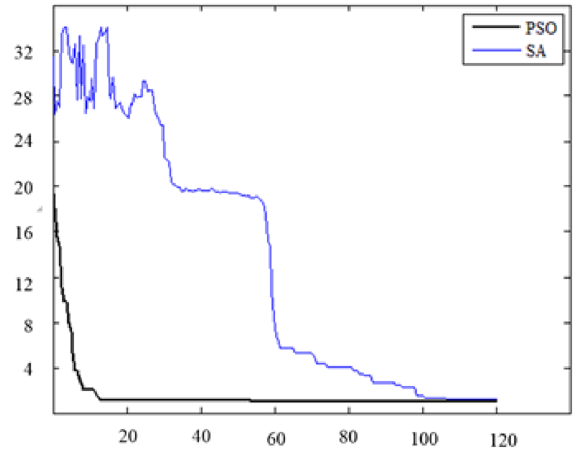

Fig. 4. PSO and SA convergence curves for optimization of SR

VI. CONFIRMATION EXPERIMENTS

To evaluate the adequacy of the proposed approach and statistical analysis, a set of verification test has been carried out based on the predicted values.

The optimal levels of the process parameters are predicted based on the values given in Table 3. Table 8, shows the comparison between the predicted and experimental results using optimal process parameters. As indicated, the differences between predicted and actual process outputs are less than 7%. Given the nature of EDM process and its many variables, these results are quite acceptable and prove that the experimental results are correlated with the estimated values.

TABLE VII. OPTIMIZATION RESULTS OF THE PROPOSED SA AND PSO AND CONFIRMATION EXPERIMENTS

	Prediction	**Experiment**	**Difference**	**Error (%)**
MRR	30.39	29.12	1.27	4.2
SR	1.43	1.52	0.09	6.3
Parameter setting for MRR (T_{on} =200µs, I =5A, η =1.8 S, V =200V)				
Parameter setting for SR (T_{on} =103 µs, I =1 A, η =0.7 S, V = 80 V)				

VII. CONCLUDING

The regression models for MRR and SR were developed from the experimental data gathered using D-optimal approach based on design of experiments approach. Then, statistical analyses have been carried out to select the best and the most fitted models.

The results of ANOVA used to determine the influential parameters and their corresponding percent contribution. For instance peak current followed by pulse on time are the most significant factors affecting the MRR with 65.3% and 15.3% percent contribution respectively.

Next, SA and PSO algorithms have been employed for optimizations of process parameters. The predicted and measured values are fairly close, which indicates that the developed model can be effectively used to predict the MRR and SR for EDM process.

The Confirmation experiments illustrate that the differences between predicted and actual process outputs are less than 7%.

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