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Modeling of EDM Process Parameters Based on Design of Experiments and Optimization Using Genetic Algorithm

Hamid Dalir [1], Masoud Azadi Moghaddam [2], Farhad Kolahan [3]

[1] MAPNA, Operation and Maintenance (O&M) Company, Ferdowsi Combined Cyle Power Plant
[2] Department of Mechanical Engineering, Ferdowsi University of Mashhad, MAPNA, Operation and Maintenance (O&M) Company, Ferdowsi Combined Cyle Power Plant, Mashhad, Iran
[3] Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

Abstract
electrical discharge machining (EDM) is the most widely and successfully applied process for machining of conductive parts among the several non-conventional processes. In this process, there is no tool mechanical contact between the work piece and electrode, hence, the hardness of work piece has no effect on the machining speed. Therefore, this technique could be employed to machine hard materials such as super alloys. Inconel 718 super alloy is a nickel based alloy that is mostly used in oil and gas, power stations and aerospace industries. In this study the effect of input EDM process parameters on Inconel 718 super alloy, 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 determining a combination of process parameters to minimize SR and maximize MRR. The experimental data are gathered based on D-optimal design of experiments. Then, statistical analyses and validation experiments have been carried out to select the best and most fitted regression models. In the last section of this research, genetic algorithm (GA) has been employed for optimization of the performance characteristics. Using the proposed optimization procedure, proper levels of input parameters for any desirable group of process outputs can be identified. 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 genetic algorithm are quite efficient in modeling and optimization of EDM process parameters.

Keywords:
Electrical Discharge Machining (EDM), Inconel 718 super alloy, Optimization, Genetic Algorithm (GA), Analysis of Variance (ANOVA).

Introduction

In recent years various machining processes have been developed or modified to cope with high alloy materials. Among these materials, super alloys, such as nickel, iron-nickel, and cobalt based alloys, have high strength at elevated temperatures, show resistance to chemical degradation, and have high wear resistance. Inconel 718 is nickel based super

Electrical discharge machining (EDM) is one of the most suitable non-conventional material removal processes to shape this alloy. 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 [1].

The most infulential process parameters of EDM process are dischrge 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 meaures 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 [1-7].

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].

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 Inconel 718 super alloy using D-optimal approach and genetic algorithm (GA). 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 genetic algorithm. Finally, the article concludes with the verification of the proposed approach and a summary of the major findings.

Experimental set up

The experiments were carried out on Inconel 718 super 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. Inconel 718 super alloy is one of the most difficult-to-cut steel alloys. This calls for more research on employing non-traditional machining for this alloy. based on these facts and the literature survey conducted, copper electrodes, with 99% purity and 8.98 g/cm^3 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. An Azerakhsh-304H die-sinking machine has been employed to carry out the experiments.

At first, some preliminary tests were crried out, to determine the stable domain of the machine parameters and also the different ranges of process variables. Based on literature reviwes, 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.

During these experiments, stable states of the machining conditions have also been specified by altering the values of the input parameters to different levels. Preliminary experiments were conducted for the wide range of pulse-on-time, discharge current and gap voltage. Satisfactory results were obtained for 1-5 A, range of peak current. Below 1 A, MRR was very low and beyond 5 A, MRR was good but SR was vey poor. Similar observations were made for specified range of pulse on, gap voltage and duty factor. The limitations of test equipment may also dictate a certain number of levels for some of the process parameters. In our case, the die-sinking EDM Table machine used for experiments had only two settings for voltage - V (80 and 200 v). Hence,one out of four factors has 2 levels and the rest of the factors have 3 levels each (Table 1). Therefore this study has been undertaken to investigate the effects of peak current (I), voltage (V), pulse on time (T_{on}), and duty factor (η) on material removal rate (MRR) and surface roughness (SR). Furthermore, the experiments have been done in random order to increase accuracy.

Table 1. 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 [7-8].

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 2. The process characteristics an 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

Evaluation of performance measures

Material removal rate (MRR)

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]:

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

$$MRR = \frac{WRW}{MT} \qquad (1)$$

4.2. Surface roughness (SR)

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).

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

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.

Mathematical modeling

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.

$$Y_1 = b_0 + b_1A + b_2B + b_3C + b_4D \tag{3}$$

$$\begin{aligned} Y_2 = {} & b_0 + b_1A + b_2B + b_3C \\ & + b_4D + b_{11}AA + b_{22}BB + b_{33}CC \\ & + b_{44}DD + b_{12}AB + b_{13}AC + b_{14}AD \\ & + b_{23}BC + b_{24}BD + b_{34}CD \end{aligned} \tag{4}$$

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

In the above formula b_0, b_1, … b_5 are the regression coefficients to be estimated and A, B, C, D are the process variables. In this study, based on the data given in Table 2, the regression model is developed using MINITAB software. The choice of the model depends on the nature of initial data and the required accuracy. Using regression technique, in MINITAB Software, three types of mathematical functions (linear, curvilinear and logarithmic) have been fitted to the experimental data [10].

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

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

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

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

model	V (v)	I (A)	T_{on} (µs)	η (s)	Predicted value	Experimental 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 4. New process variables for model validation and corresponding results of MRR

model	V (v)	I (A)	T_{on} (µs)	η (s)	Predicted value	Experimental 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							

Analysis of variance

The ANOVA is used to investigate the most influential parameters to the process factor-level response (Table 5 , 6) [10].

Table 5. Result of ANOVA for MRR

Machining parameter	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (MS_j)	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
T_{ON}	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 6. 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 6 and 7 [10].

As the F-value of each parameter is greater than the $F_{\alpha,v1,v2}$ observed from the table means th 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].

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

The percent contributions of the EDM parameters on MRR are shown in Figure 1.

According to Figure 1, 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.

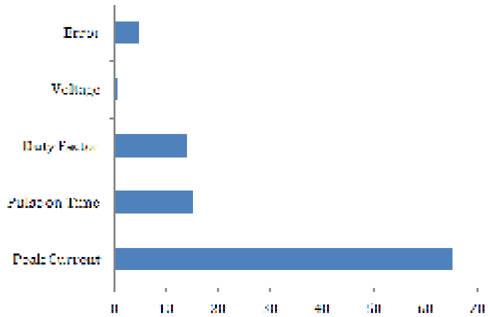

Figure 1. The effect of machining parameters on the MRR

Genetic algorithm

Genetic algorithms (GA) are direct, parallel, stochastic method for global search and optimization, which imitates the evolution of the living beings, described by Charles Darwin [9]. GA is part of the group of evolutionary algorithms (EA). The evolutionary algorithms use the three main principles of the natural evolution: reproduction, natural selection and diversity of the species, maintained by the differences of each generation with the previous. The selection principle is applied by using a criterion, giving an evaluation for th individual with respect to the desired solution. The best suited individuals create the next generation. The large variety of problems in the engineering sphere, as well as in other fields, requires the usage of algorithms from different type, with different characteristics and settings [9]. The best tuning parameters found for the algorithm are found through several test runs (Table 7). Figure 2 shows the convergence curve towards the optimal solution for SR.

Table 7. The best tuning parameters for the GA procedure

No. of Generations	Population size	Crossover rate	Crossover mechanism	Mutation rate
160	30	80%	scatter	1%

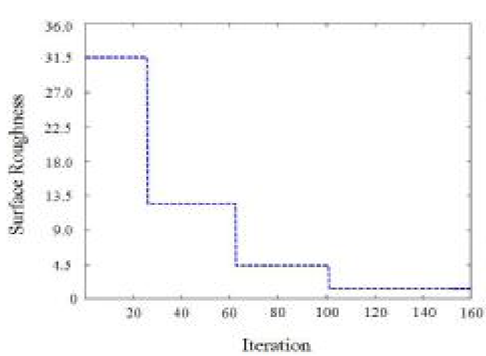

Figure 2. Genetic algorithm convergence curves for SR

Running confirmation experiments

The optimal levels of the process parameters are predicted based on the values given in Table 3. Table 3, 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 3. Optimization results of the proposed GA 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)				

Concluding

The quality of final product in EDM is significantly affected by the choice of process parameters levels. In this study, the effects of EDM process parameters settings on the most important output characteristics for Inconel 718 super alloy have been investigated. The following can be concluded from the present study. The regression models for MRR and SR were developed from the experimental data gathered using D-optimal 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, genetic annealing (GA) has 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%. 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.

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