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An empirical study on statistical analysis and optimization of EDM process parameters for inconel 718 super alloy using D-optimal approach and genetic algorithm

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Abstract

Among the several non-conventional processes, electrical discharge machining (EDM) is the most widely and successfully applied for the machining of conductive parts. In this technique, the tool has no mechanical contact with the work piece and also the hardness of work piece has no effect on the machining pace. Hence, 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 to determine 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).*

1. 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 alloy, which is used in the field of gas turbine

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components, jet engines, cryogenic storage tanks, pump bodies and parts, rocket motors and thrust reversers, hot extrusion tooling, high strength bolting, and down hole shafting.

The associated manufacturing cost is high because of low material removal rates and rapid tool wear rate [1]. 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 (Figure 1) [2].

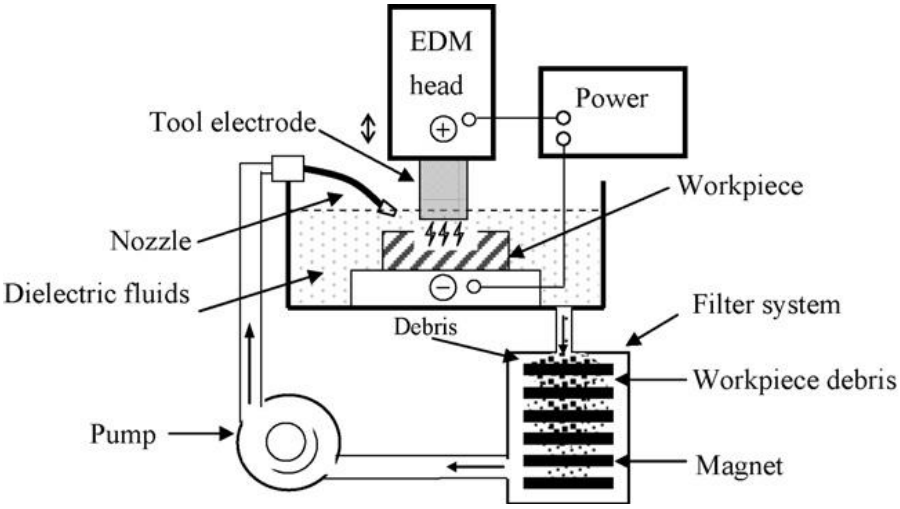

Fig. 1. Schematic illustration of electrical discharge machining [2]

In EDM process, the material erosion mechanism primarily makes use of electrical energy and turns it into thermal energy through a series of discrete electrical discharges occurring between the electrode and workpiece submerged in dielectric. The electrical energy discharges generates a channel of plasma between the workpiece electrode and the tool electrode resulting a substantial amount of heat that, in turn, melts and evaporates the material at the surface of workpiece. When the pulsating current supply is turned off, the plasma channel breaks down causing a sudden reduction in the temperature and allowing the dielectric fluid to implore the plasma channel and flush the molten material from the electrodes surfaces in the form of microscopic debris (chips). This process of melting and evaporating of the workpiece surface is in complete contrast to the conventional machining processes, as chips are not mechanically produced. This unique feature of using thermal energy to machine electrically conductive parts is its distinctive advantage in the manufacturing of molds, dies, aerospace and surgical components [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 [3, 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.

2. Literature review

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].

Manikandan and Venkatesan [3], investigated the optimization of machining parameters for machining in micro EDM for Inconel 718 super alloy. The overcut, MRR and TWR were targeted. The Taguchi method was used to formulate the experiment layout, to study the effect of each parameter on the machining characteristics and to predict the optimal choice for each EDM parameters like discharge current, pulse on time and pulse off time. It has been found that peak current and pulse on time have a significant influence on the machining characteristics.

Harshit et al [4] have carried out experimental investigation based on Taguchi experimental design to study the effect of orbital parameters during EDM of nickel based Inconel 718 super alloy. The empirical model has been developed using linear regression analysis by applying logarithmic data transformation of non linear equation. Further, analysis of the results has been carried out using signal to noise analysis and ANOVA to identify the significant parameters and their degree of contribution in the process output. The corresponding results illustrated that pulse on time has a significant influence on the machining characteristics.

Ahmad and Lajis [5] investigated the performance of copper electrode when EDM Inconel 718 at higher peak current and pulse duration. In addition, their influence on MRR, TWR, and SR were experimentally investigated. Experimental results have shown that machining at a highest peak current used of 40A and the lowest pulse duration of 200μs used for the experiment yields the highest MRR with value 34.94 mm^3/min, whereas machining at a peak current of 20A and pulse duration of 400μs yields the lowest TWR with value of -0.0101 mm^3/min. The lowest SR was 8.53μm achieved at a lowest peak current used of 20A and pulse duration of 200μs.

Dehanabalam et al [6] investigated the effectivenees of optimizing multiple characteristic of EDM of Inconel 718 using copper electrodes having different shapes via Taguchi methode-based grey analysis. The significance of the process parameters on the overall quality characteristics of the EDM process was also evaluated quantitatively using the analysis of variance (ANOVA) method. Optimal results were verified through additional experiments. The results showed that multiple charactristice of process improved using the proposed technique.

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.

3. 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.

Various materials such as brass, copper and tungsten alloys as well as graphite may be used as tool electrode in EDM process. The applications of brass and tungsten is limited to certain materials. Graphite and copper are commonly used as electrode in EDM. The wear rate of graphite is less than that of copper due to its extremely high melting point. On the contrary, copper electrode can produce very fine surfaces because of its structural integrity. Moreover, the machinability of copper is much better than that of graphite [6]. Therefore 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. 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. In this machine the Z-axis is servo controlled and X and Y axis are manually controlled. Table 1 illustrates the technical specification of the EDM machine tool used for conduction 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 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 2). 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.

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

Table 1. The detailed technical specifications of the machine tool used

Specification	Size
Work Table Size	500×300 mm
Cross Travel Y	250 mm
Spindle Travel & Head Stock Travel	180+200 mm
Maximum Electrode weight	50 kg
Loading Capacity of Table	500 kg

Table 2. 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 3 illustrates the proposed design for the process characteristics and their corresponding output.

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

4. Evaluation of peformance measures

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

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

Table 3. 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
4	1	200	80	1	2.00	2.52
5	5	200	200	1	24.57	12.68
6	1	100	80	1.8	1.10	2.38
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
21	1	200	200	0.4	0.22	3.23
22	3	200	200	1.8	9.78	7.98
23	5	100	200	1	9.33	9.05
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

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).

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

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 (Fig. 2).

5. Mathematical modeling

Regression models can be used to predict the behavior of input variables (independent variables) and values associated with each test response results [11, 12].

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 3, 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 [12-15].

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 4 and 5 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

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

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

Curvilinear Model

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

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

Logarithmic Model

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

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

Table 4. 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 5. 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							

6. Analysis of variance

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 [11-15]. 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 6 and 7.

To confirm the validation tests in the preceding step analysis of variance (ANOVA) technique within the confidence limit of 95% was performed [16, 17]. Given the correlation factor (R^2) and the adjusted correlation factor (R^2-adj) for these models, it is evidence that curvilinear model is superior to other two for SR, and logarithmic model for MRR, thus these models are considered as the best representative of the authentic EDM process throughout in this paper.

According to the detailed ANOVA results for the most fitted and selected models (Tables 6 and 7), large F–value indicates that the variation of the process parameter makes a big change on the performance characteristics. In this study, a confidence level of 95% is selected to evaluate parameters significances [15].

Table 6. Result of ANOVA for MRR

Machining parameters	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 7. 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 [15-18].

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) [18].

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

In the above formula according to the ANOVA results (Table 6), 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 [17, 18]. 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.

7. 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 [19]. 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 [20, 23].

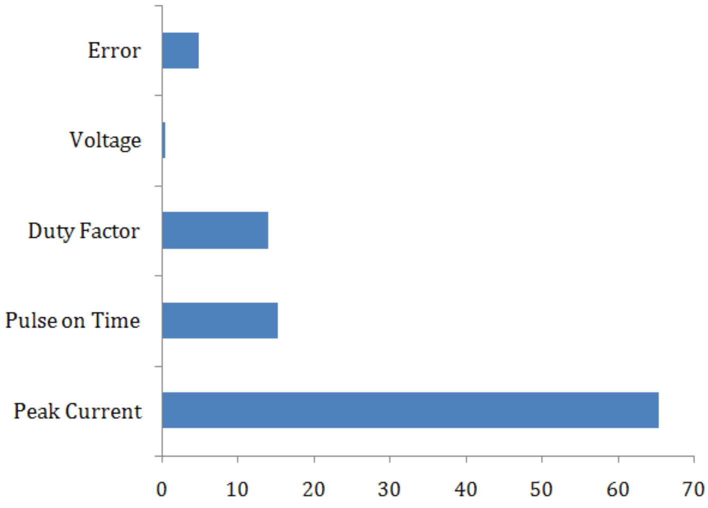

Fig. 3. The effect of machining parameters on MRR

There are three main operators in GA: selection, crossover and mutation. Selection means that two individuals from the whole population of individuals are selected as "parents". Crossover serves to exchange the segments of selected parents between each other according to a certain probability. In other words, it combines two parents to form children for the next generation. The mutation operation randomly alters the value of each element in a given chromosome according to a given mutation probability. Mutation forms new children at random so as to avoid premature convergence. The procedure may be stopped after the terminated condition has been reached. A complete description of this algorithm and some of its applications can be found in [19, 20].

In this section, a genetic algorithm (GA) procedure is employed to determine the optimal machining parameters set in optimization of the chosen models. The, MRR and SR are the target output values for the machining operation .The objective is to set the process parameters at such levels that these process characteristics optimized. In the optimization process, the purpose is to minimize SR and maximize MRR. By doing so, the process parameters are calculated in such way that the EDM parameters approach their optimal values. For this purpose, a GA method is employed to find the best machining variables with respect to process specifications. The best tuning parameters found for the algorithm are found through several test runs (Table 8). Figure 4 shows the convergence curve towards the optimal solution for SR.

8. Running 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 9, 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 8. The best tuning parameters for the GA procedure

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

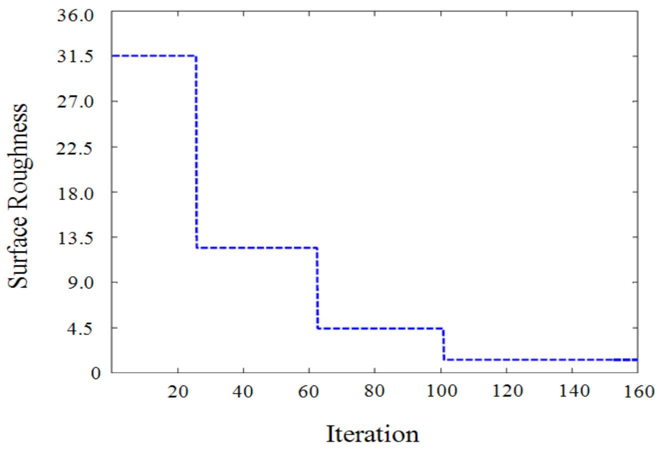

Fig. 4. Genetic algorithm convergence curve for SR

Table 9. 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)				

9. 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.

Validation of the models via new set of experiments and the result of ANOVA illustrated that the curvilinear and logarithmic models are the best and the most fitted models among the proposed models for SR and MRR respectively.

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.

The study can also be extended using other methods like response surface methodology (RSM), artificial neural networks (ANN) and other heuristic algorithms like simulated annealing (SA) algorithm and etc.,

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