Using Design of Experiments Approach and Simulated Annealing Algorithm for Modeling and Optimization of EDM Process Parameters

Meysam Beytolamani, Farhad Kolahan, Masoud Azadi Moghaddam*

Ferdowsi University of Mashhad, 91775-1111, Mashhad, Iran.

ARTICLE INFO

Article history:

Received 21 September 2017
Accepted 20 October 2018
Available online 5 November 2018

Keywords:

Electrical discharge machining (EDM)
Inconel 718 super alloy
Optimization
Simulated annealing (SA) algorithm
Analysis of variance (ANOVA)
Design of experiments (DOE)

ABSTRACT

Electrical Discharge Machining (EDM) is one of the popular processes for producing electrically hard to machine conductive parts. In this technique, the tool has no mechanical contact with the workpiece therefore, the hardness of workpiece has no effect on the machining pace. Hence, this technique could be used for machining such materials such as hot worked steels and super alloys. Inconel 718 super alloy is a nickel based alloy that is frequently used in various applications, especially in aerospace, oil and gas industries and power stations. In EDM, like other machining processes, the machining cost and the surface quality of final product are affected by the proper selection of parameters levels. Therefore, the main objectives of this research are, to assess the effects of process parameters and to determine their optimal machining levels of Inconel 718 super alloy. Gap voltage, current, time of machining and duty factor are tuning parameters considered to be studied as process input parameters. Furthermore, two important process output characteristic have been evaluated in this research are material removal rate and surface roughness. Determination of a combination of process parameters to minimize surface roughness and maximize material removal rate is the objective of this study. In order to gather required experimental data, D-optimal based design of experiments (DOE) technique has been used. Then, statistical analyses and validation experiments have been carried out to select the best and the most fitted regression models. In the last section of this research, simulated annealing (SA) algorithm has been employed for optimization of performance characteristics of EDM process. A set of verification tests is also performed to confirm the accuracy of the proposed optimization procedure in determining the optimal levels of machining parameters. The results indicate that the proposed modeling technique and SA algorithm are quite efficient in modeling and optimization of EDM process parameters.

1-Introduction

Inconel-based super alloys are used in aerospace, chemical, medical, and nuclear industries due to their excellent mechanical properties comprising excellent corrosion, resistance to fatigue, and creep at high temperatures. Recently, many machining processes have been developed or modified to cope with such materials [1]. Electrical discharge machining (EDM) is one of the suitable non-conventional material removal processes used for machining these alloys. EDM

* Corresponding author:
E-mail address: masoudazadi888@gmail.com

is a process in which material is removed from work piece by erosion effect of series of sparks (electric discharges) between tool and specimen immersed in a dielectric liquid (Fig.1) [2].

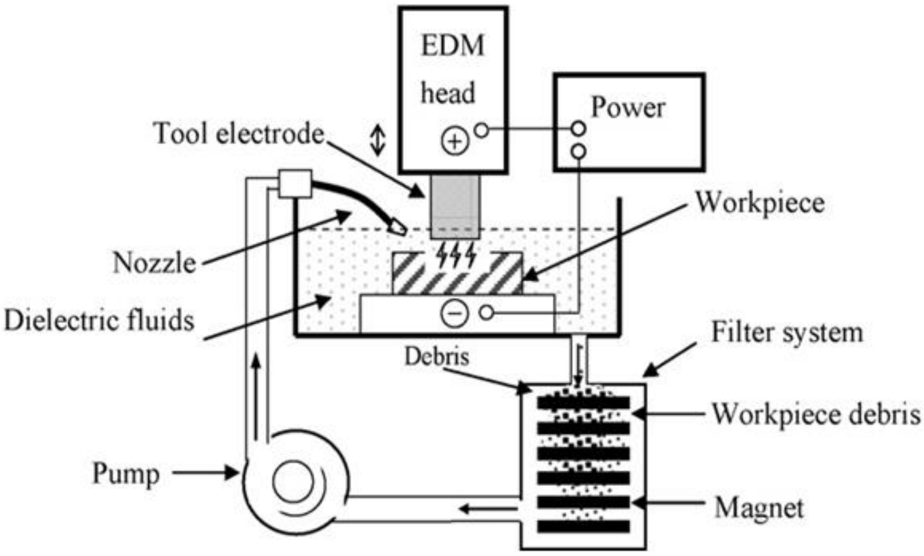


Fig. 1. Schematic illustration of EDM process [2].

In EDM process, a pulsed voltage different between a tool electrode and a conductive specimen initiates sparks which erode the specimen material. Removing material in this way is often advantageous when the specimen material would be hard to machine with conventional machining processes due to high strength, hardness and toughness. It is known that the EDM process has a detrimental impact on the surface integrity of machined surfaces. Each spark melts a small portion of the specimen. A portion of this molten material is then flushed away by the liquid used as die electric fluid. As chips are not mechanically produced, this process of melting and evaporating of the specimen surface is in complete contrast to the conventional machining processes. This exclusive feature of using thermal energy to machine electrically conductive hard to machine parts is its distinctive merits in the manufacturing of molds, dies, aerospace and surgical components [2].

The most important process variables in EDM, considered in different papers are peak current (I), voltage (V), time of machining (T), and duty factor (η) [3-6]. These variables, in turn, determine the process output characteristics, among which material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR) are the most important ones [2]. Therefore, finding an accurate relation between process tuning parameters and its output responses is essential.

2-Literature review

Review of the relevant studies reveals that a great deal of studies 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].

Optimization of EDM machining parameters in micro EDM for Inconel 718 super alloy has been investigated by Manikandan and Venkatesan [3]. In this study, MRR and TWR have been considered as the process output characteristics. The Taguchi based design of experiments technique has been used to formulate the experiment layout. The effect of each parameter on the machining characteristics has been investigated. Moreover, EDM parameters like discharge current, time of machining and pulse off time has been optimized in order to get the desired outputs. Results has shown peak current and time of machining are the most significant parameters affecting the process.

The effect of process parameters during EDM of Inconel 718 super alloy based on experimental investigation using Taguchi experimental design have been carried out by Harshit et al [4]. The experimental model has been developed using regression modeling and analysis. Furthermore, analysis of the results has been carried out using signal to noise (S/N) ratio technique and analysis of variance (ANOVA) to identify the significant parameters and their percent contribution in the process measures. The corresponding results illustrated that time of machining has a significant influence on the EDM machining characteristics.

The performance of copper electrode at higher peak current and pulse duration for Inconel 718 has been studied [5]. Moreover, their influence on MRR, TWR, and SR were investigated. Experimental results have shown that machining at a highest peak current (40A) and the lowest pulse duration (200µs) yields the highest MRR (34.94 mm^3/min), whereas machining at a peak current of 20A and pulse duration of 400µs results in the lowest TWR (0.0101 mm^3/min). At a lowest peak current (20A) and pulse duration (200µs), the lowest SR (8.53µm) is achieved.

Multiple characteristic optimizing of EDM for Inconel 718 super alloy using electrodes having different shapes via Taguchi methode-based grey analysis has been investigated by Dehanabalam et al [6]. The ANOVA method has been used to evaluate the significance of the process parameters on the overall quality characteristics of the EDM process. Optimum results were confirmed through additional experimental tests. The results displayed that multiple characteristic of process improved using the proposed technique.

To the best of our knowledge, there is no published works to statistically model and optimize the machining parameters of EDM process including peak current, voltage, time of machining, and duty factor on the output characteristics namely, MRR and SR for machining of Inconel 718 super alloy using D-optimal based design of experiments approach and a heuristic algorithm (simulated annealing). Therefore, the present study has two objectives. 1. To establish the relationship between the input variables and output characteristics of EDM process. 2. To derive the optimal parameter levels in order to achieve maximum MRR and minimum SR using statistical analysis of the experimental data and SA algorithm. Finally, the article concludes with the verification of the proposed approach and a summary of the major findings.

3-Equipment used and experimental set up

Inconel 718 super alloy parts with diameter of 50 mm and thickness of 4mm have been used in this study. This alloy is one of the hard to machine alloys and widely used in various applications, especially in oil and gas, power stations and aerospace industries. Moreover, copper electrodes (99% purity and 8.98 g/cm^3 density) were used as tools to carry out the experiments. Furthermore, the electrodes were replaced after each experiment. The machining time for each test was 1 hour. The tool electrode and the specimen are shown in Fig. 2.

An Azerakhsh-304H die-sinking machine has been used to carry out the experiments. The dielectric for all experiments was pure kerosene. During the experiments specimen and electrode were immersed in the dielectric used.

Table 1 lists the process input parameters and their corresponding levels based on the literature survey and preliminary experimental tests. Peak current (I), voltage (V), time of machining (T), and duty factor (η) were chosen as the independent process input parameters. Therefore, this study has been undertaken to investigate the effects of input parameters on process characteristics such as material removal rate (MRR) and surface roughness (SR). In order to measure the SR and MRR, a surface roughness tester and electronic balance have been used (Fig. 2). Besides, the experiments have been done in random order to increase accuracy.

4-Design of experiments approach

D-optimal design matrix is an important form of design of experiments (DOE) provided by a computer algorithm. Greater flexibility in selecting model types is the most important reason for using D-optimal design instead of central composite and Box-Behnken designs [7]. In practical terms, D-optimal experiments can reduce the costs of experimentation. The details of design of experiments and D-optimal approach are well documented in Refs [7, 8].

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

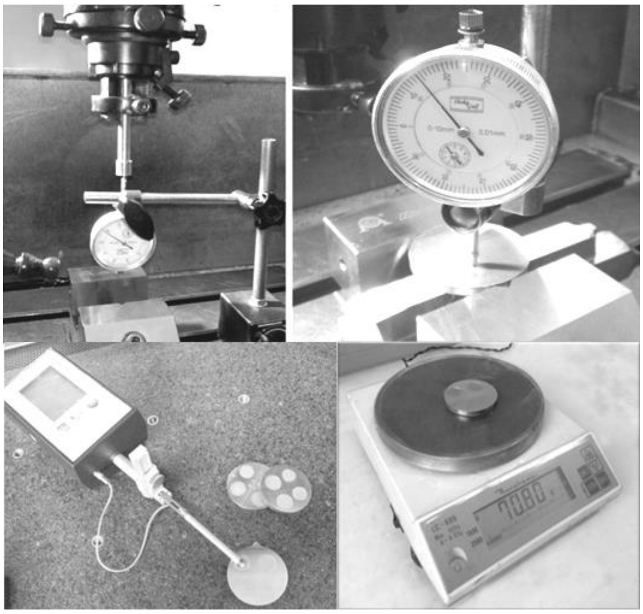


Fig.2. Specimens, copper electrode, digital surface roughness tester and electronic balance used.

Table 1. Process variables and their corresponding levels.

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

5-Measuring the process output characteristics

To evaluate EDM machining process of Inconel 718 super alloy, MRR and SR are considered. These measures are calculated as follows [9]:

MRR is a measure of machining speed and is expressed as the specimen removal weight (SRW) in a predetermined machining time (MT) in hour.

$$\mathrm{MRR} = \frac{SRW}{\mathrm{MT}} \tag{1}$$

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

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

Where, Ra is the mathematics average deviation from the mean line, L is the length being measured, and A (x) is the ordinate of the profile curve. After machining, the surface finish of each sample was measured with an automatic digital surface roughness tester (Fig. 2).

Table 2 illustrates the proposed D-optimal design and their corresponding outputs.

6-Mathematical modeling

Mathematical relations between process output characteristics and variables can be described by regression modeling [10, 11]. The last two columns of Table 2 are the corresponding outputs for each test setting. These data can be used to develop mathematical models.

Table 2. The process input parameters setting their resultant output based on D-optimal experiments matrix.

No	T (μs)	I (A)	η (s)	V (v)	SR (μm)	MRR (mg/hr)
1	200	3	0.4	80	7.98	2.48
2	35	5	0.4	200	6.31	2.47
3	100	5	0.4	80	8.42	2.80
4	200	1	1	80	2.52	2.00
5	200	5	1	200	12.68	24.57
6	100	1	1.8	80	2.38	1.10
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
21	200	1	0.4	200	3.23	0.22
22	200	3	1.8	200	7.98	9.78
23	100	5	1	200	9.05	9.33
24	35	3	1.8	80	5.73	2.46
25	35	5	1.8	200	6.03	4.44
26	100	3	0.4	200	6.44	1.89

Any of the process output characteristic is a function of process input parameters which are expressed by linear, curvilinear or logarithmic functions; as stated in Equations 3 to 5 respectively.

$$Y_1 = \alpha_0 + \alpha_1 A + \alpha_2 B + \alpha_3 C + \alpha_4 D \quad (3)$$

$$Y_2 = \alpha_0 + \alpha_1 A + \alpha_2 B + \alpha_3 C + \alpha_4 D + \alpha_{11} AA + \alpha_{22} BB + \alpha_{33} CC + \alpha_{44} DD + \alpha_{12} AB + \alpha_{13} AC + \alpha_{14} AD + \alpha_{23} BC + \alpha_{24} BD + \alpha_{34} CD \quad (4)$$

$$Y_3 = \alpha_0 A^{\alpha 1} B^{\alpha 2} C^{\alpha 3} D^{\alpha 4} \quad (5)$$

In the above equations A, B, C, D are the process variables and the regression coefficients to be estimated expressed as α_0, α_1, α_3 and α_4. In this study, the regression model is developed using MINITAB software. The choice of the model depends on the nature of initial data and the required accuracy. Three types of mathematical functions include: linear, modified curvilinear (with elimination of insignificant parameters) and logarithmic models have been fitted to the experimental values [12, 13]. Equations 6 to 11 represent the relationship between process parameters and output characteristics. To modify the initial proposed models, stepwise elimination process was used. For instance, as can be seen in Equation 9, independent variable η was eliminated because of its unimportant effect on SR in the curvilinear model.

Validation experiments has been used to evaluate the adequacies of models. Table 3 illustrate the mean error of the 9 new experiments for the output characteristics. The curvilinear and logarithmic models are the best models among the proposed models for the SR and MRR respectively based on the new experimental results (the lowest error and the highest R^2-adj).

Linear Model

MRR

$$-6.591 + 0.00886 \times V + 1.30719 \times I + 0.0250265 \times T + 2.11614 \times \eta \quad (6)$$

SR

$$0.393848 + 0.0003583 \times V + 1.34205 \times I + 0.0128686 \times T + 0.161359 \times \eta \quad (7)$$

Curvilinear Model

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

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

Logarithmic Model

MRR

$$0.008324 \times V^{0.0172653} \times I^{1.798} \times T^{0.880033} \times \eta^{0.943937} \quad (10)$$

SR

$$1.226 \times V^{0.0110355} \times I^{0.634706} \times T^{0.200333} \times \eta^{0.0119906} \quad (11)$$

Table 3. Model validation through using new sets of experiments variables.

model	V (v)	I (A)	T (μs)	η (s)	Predicted value	Experimental value	Error
Linear Models							
	80	1	100	1	3.21	2.83	11.8
SR	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							
	80	5	100	1.8	6.97	6.12	12.21
MRR	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 Models							
	80	1	100	1	2.94	2.92	0.74
SR	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							
	80	5	100	1.8	17.16	15.04	12.37
MRR	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 Models							
	80	1	100	1	3.23	2.92	9.80
SR	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							
	80	5	100	1.8	16.25	15. 45	4.94
MRR	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							

Given the correlation factor (R^2) and the adjusted correlation factor (R^2-adj) for these models, it is evident 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.

7-Model adequacy using analysis of variance

Analysis of variance (ANOVA) is used to analyze the experimental results and identify the factors which have an important effect on the machining output characteristics. Based on the ANOVA results, the level of significance of each factor is shown using the p-values or probability values. Lower p-values indicate that the factor values have higher probability of falling within the ranges which impact the outcome of the experiment. 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 [9-13].

ANOVA has been performed on the selected models to evaluate their adequacy, within 95% confidence limit. ANOVA results indicate that the model is adequate within the specified confidence limit. Results of ANOVA are shown in Tables 4 and 5.

According to the detailed ANOVA results for the most fitted and selected models (Tables 4 and 5), 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 the significance of the parameters [9]. 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 4 and 5 [9-11].

8-Process parameters interaction

Fig. 3, illustrates the interaction effect of EDM process parameters for SR. As illustrated by b, d and f), increasing time of machining results in increasing Ra. Similarly, by increasing time of machining (as shown by a, d and e), Ra increases. Similarly, by increasing current (as shown by a, d and e) MRR increases.

By the same token, Fig 4, shows the interaction effect of EDM process parameters for MRR. As illustrated by b, d and f, increasing time of machining ends in increasing the MRR.

Table 4. Result of ANOVA for SR.

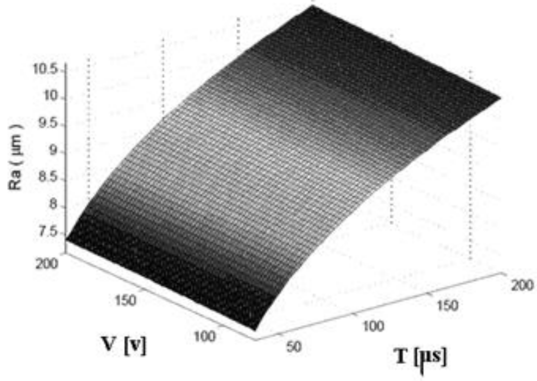
Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (MS_j)	F-Value	P
Regression	5	135.50	27.10	824.26	0.00
I	1	9.17	9.17	279.14*	0.00
V × T	1	0.83	0.83	25.47*	0.00
I × I	1	5.88	5.88	178.81*	0.00
I × T	1	19.00	19.00	577.77*	0.00
T × T	1	2.93	2.93	89.27*	0.00
Error	18	0.52	0.03	-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

*Significant Parameters, $F_{0.05,1,26} = 4.23$

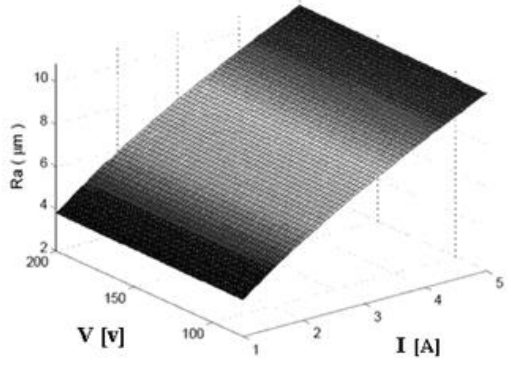
Table 5. Result of ANOVA for MRR.

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
T	1	8.95	10.95	75.47*	0.00
I	1	37.76	34.98	261.54*	0.00
η	1	8.20	8.20	61.32*	0.00
V	1	0.05	0.00	0.01	0.00
Error	20	2.68	0.13	-	-
Total	24	57.64	-	-	-

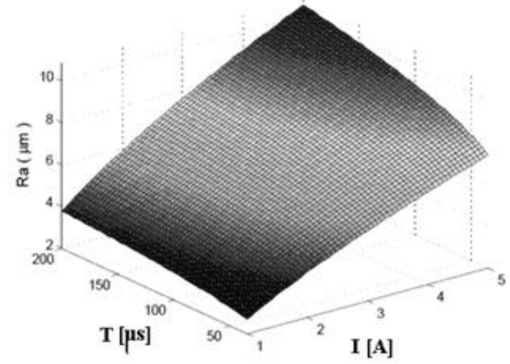
*Significant Parameters, $F_{0.05,1,26} = 4.23$



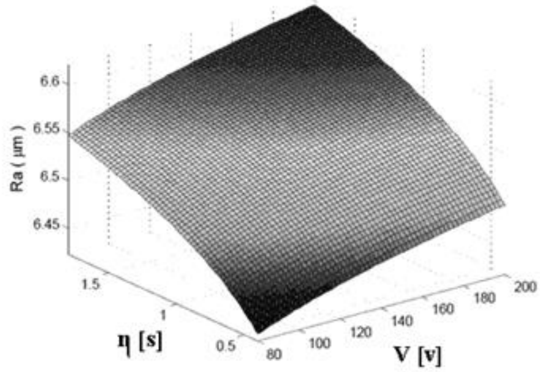
(b)
(I=5 و η=1.8)



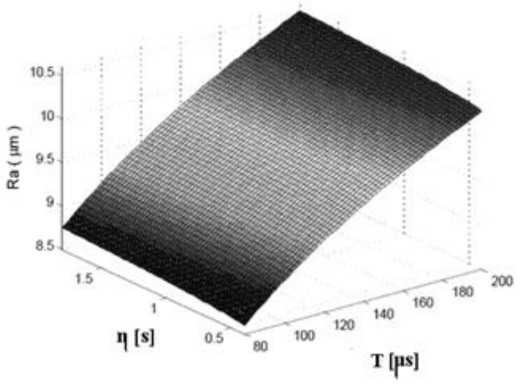
(a)
(T=200 و η=1.8)



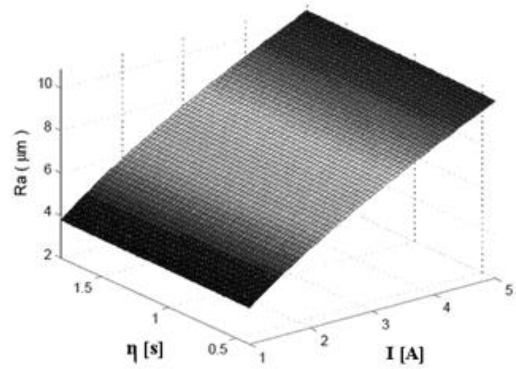
(d)
(V=200 و η=1.8)



(c)
(T=100 و I=3)



(f)
(I=5 و V=200)



(e)
(T=200 و V=200)

Fig. 3. Interaction of EDM process parameters for SR.

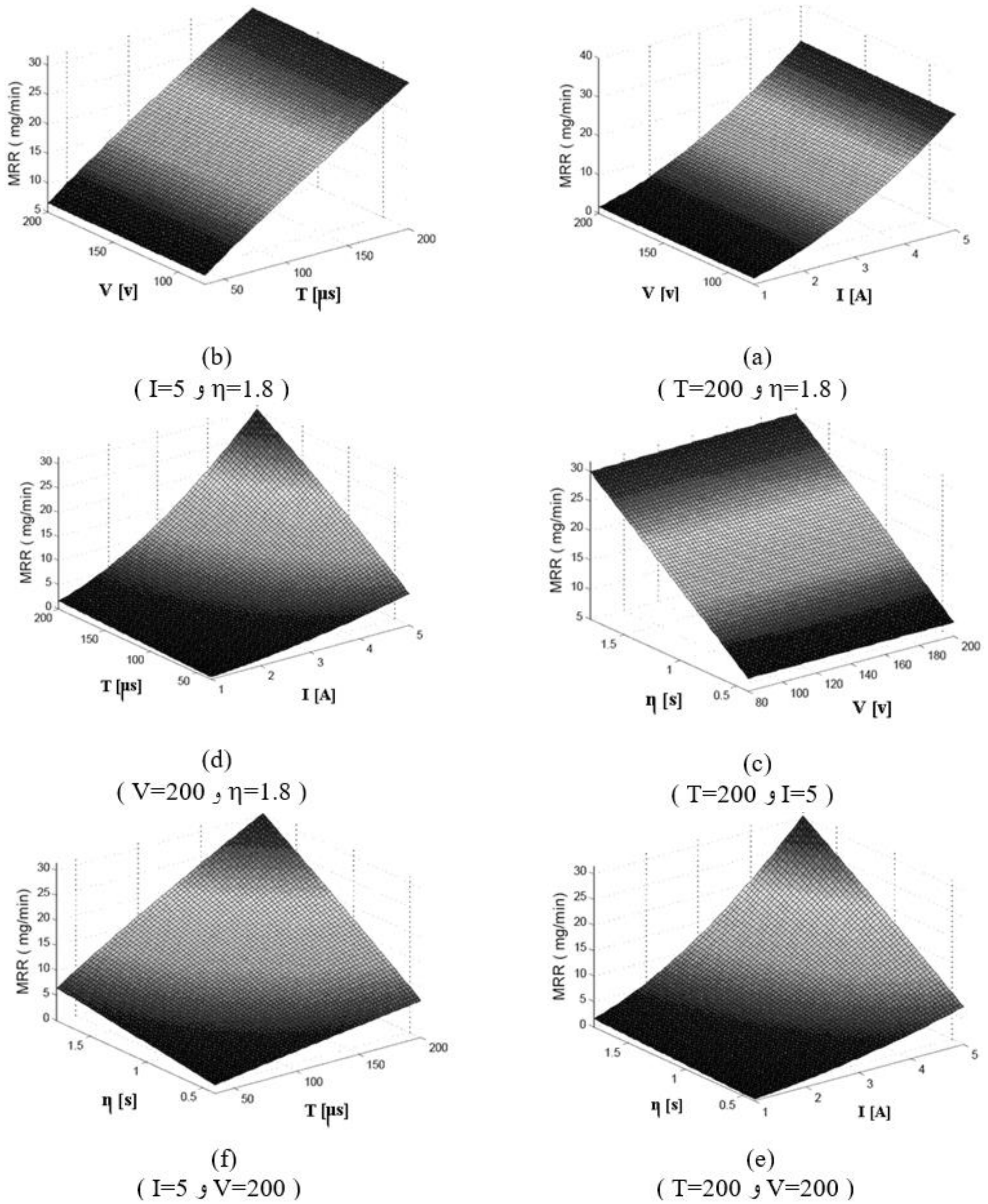


Fig. 4. Interaction of EDM process parameters for MRR.

9-Optimization based on simulated annealing algorithm procedure

Simulated annealing (SA) algorithm is a popular heuristic algorithms, whose procedure is reminiscent of the physical annealing process [14]. Annealing is a physical process used to reconstruct the micro structure of a solid along with a low energy state. Firstly, a solid is heated up above its melting point temperature. At this temperature, all particles are in random motions. Then, the solid is slowly cooled down. Thus, all particles rearrange themselves and a low energy state is achieved. As the cooling of the particles is carried out sufficiently slowly, lower and lower energy state are obtained until the lowest energy state is reached. Likewise, in EDM process an energy function is created which is minimized. While minimizing efforts are made to avoid local minimum and to achieve global minimum. The lowest energy level gives the optimized value of EDM process parameters [15].

A standard SA procedure begins by generating an initial solution at random. At initial stages, a small change is made in the current solution randomly. Then the objective function value of new solution is calculated and compared with the current objective function. A move is made to the new solution if it has better objective function or if the probability function implemented in SA has a higher value than a randomly generated number. The accepting probability of a new solution is calculated using Equation (12) [16].

$$p = \begin{cases} 1 & if \ \ \Delta < 0 \\ e^{-\Delta/t} & if \ \ \Delta \geq 0 \end{cases} \tag{12}$$

Where, T, is referred to as temperature parameter and plays a similar role as the temperature in the annealing process. The rate of temperature reduction should be slow to avoid getting trapped at a local minimum point [14]. In our problem for temperature reduction Equation (13) has been used:

$$T_{i+1} = cT_i \qquad i = 0,1,... \ \ and \ \ \ 0.9 \leq c < 1 \tag{13}$$

Thus, at the initial stages of SA algorithm, most worsening moves may be accepted. However, at the final stages only improving ones are likely to be accepted. This can help the process 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.

SA algorithm has diverse applications including improving the performance of other artificial intelligence techniques and determining the optimal set of process parameters [16]. In this study SA algorithm has been used to maximize the MRR and minimize the SR equations.

Fig. 5 displays the convergence curve towards the optimal solution for SR.

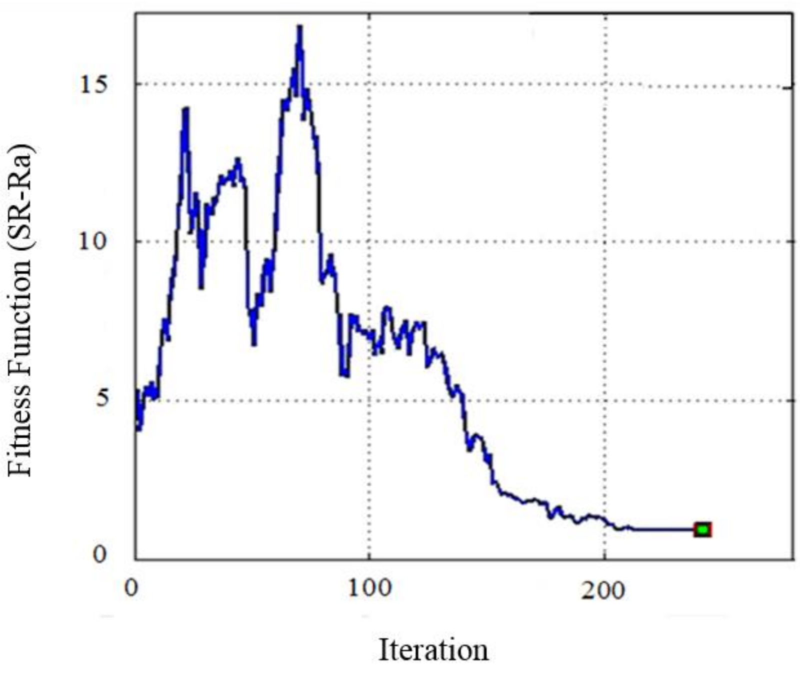


Fig. 5. Simulated annealing algorithm convergence curve for surface roughness.

10-Confirmation of procedure through experimental tests

Table 6, displays the comparison between the predicted and experimental results using optimal process parameters based on the SA algorithm results. As indicated, the differences between predicted and actual process outputs are less than 5%. Given the nature of EDM process and its many variables, these results are quite acceptable.

Table 6. Optimization results of the proposed SA and confirmation experiments.

Process measures	Prediction	Experiment	Difference	Error (%)
MRR	30.39	29.12	1.27	4.2
SR	1.04	1.09	0.09	4.8
Parameter setting for MRR (T =200µs, I =5A, η =1.8 S, V =200V)				
Parameter setting for SR (T =103µs, I =1A, η =0.7S, V = 80 V)				

11-Conclusion

In this study, the effects of EDM process input parameters (time of machining, voltage, current and duty factor) settings on the process output characteristics (material removal rate and surface roughness) for Inconel 718 super alloy have been investigated. The following can be concluded from the present study.

The mathematical models for MRR and SR were developed from the experimental data gathered using D-optimal design of experiments approach. Then, statistical analyses have been carried out to select the best and most fitted models as a representative of the process measures.

Validation of the proposed models via new sets of experiments and the result of ANOVA proved that the curvilinear and logarithmic models are the best and the most fitted models among the proposed models for SR and MRR respectively. Next, the selected models considered as objective functions to optimize the process input parameters using SA algorithm. 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 proved that the differences between predicted and actual process outputs (error) are less than 5%. Given its many variables and the nature of EDM process, these results are quite acceptable.

The study can also be extended using other methods like response surface methodology (RSM), artificial neural networks (ANNs) and other heuristic algorithms like genetic annealing (GA) and particle swarm optimization (PSO) algorithm.

Reference

[1] Assarzadeh, S. and Ghoreishi, M. “Mathematical modeling and optimization of the Electro-Discharge Machining (EDM) parameters on tungsten carbide composite”, Combining response surface methodology and desirability function technique, Scientia Iranica, Transactions B: Mechanical Engineering, Vol. 22, No. 2, (2015). pp. 539-560.

[2] Lia. L, Guob. Y. B, “Surface integrity characteristics in wire-EDM of inconel 718 at different discharge energy”, Procedia CIRP, Vol. 6, (2013), pp. 220 – 225.

[3] Zohoor, M. and Hosseinali Beigi. A.R. Application of electrical discharge machining for machining of semi-conductor materials, Scientia Iranica, Transactions B: Mechanical Engineering, Vol. 21, No. 4, (2014), pp. 1341-1346.

[4] Harshit, K. Dave, P. and Harit, K. “Modeling and Analysis of Material Removal Rate during Electro Discharge Machining of Inconel 718 under Orbital Tool Movement”. International journal of manufacturing system, Vol. 12, No. 7, (2012), pp.12-20.

[5] Ahmad, S. and Lajis, M. A., “Electrical discharge machining (EDM) of Inconel 718 by using copper electrode at higher peak current and pulse duration”. 2nd International Conference on Mechanical Engineering Research, ICMER, 2013.

[6] Dehanabalam, S. Sivakumar, H. and Sathya, K. “Optimization of process parameters of EDM while machining Inconel 718 for form tolerance and orientation tolerance”. Indian journal of engineering and materials sciences, Vol. 20, No. 7, (2013), pp. 391-397.

[7] Hewidy, M.S. and El-Safty, M.F. "Modeling the machining parameters of wire electrical discharge machining of Inconel 601 using RSM", Journal of Materials Processing Technology,Vol. 169, (2005), pp. 328–336.
[8] Toutenburg, H., "Statistical Analysis of Designed Experiments", Springer-Verlag New York, Second Edition, 2002.
[9] Moghaddam, M.A. and Kolahan, F. "Modeling and Optimization of Surface Roughness of AISI2312 Hot Worked Steel in EDM based on Mathematical Modeling and Genetic Algorithm". International journal of engineering, Vol. 27, No. 3, (2014), pp. 417-424.
[10] Ahmadi, E., and Ebrahimi, A.R. The Effect of Activating Fluxes on 316L Stainless Steel Weld Joint Characteristic in TIG Welding Using the Taguchi Method, Journal of Advanced Materials and Processing, Vol. 1, No. 1, (2013), pp. 55-62
[11] Kolahan, F. Golmezerji, R. and Moghaddam, M.A. "Multi Objective Optimization of Turning Process using Grey Relational Analysis and Simulated Annealing Algorithm", Applied Mechanics and Materials, Vol. 5, No. 12, (2012), pp. 2926-2932.
[12] Vahdatia, M., Mahdavinejada, R. A., Aminib, S. and Moradic, M. Statistical Analysis and Optimization of Factors Affecting the Surface Roughness in the UVaSPIF Process Using Response Surface Methodology, Journal of Advanced Materials and Processing, Vol.3, No. 1, (2015), pp.15-28
[13] Hosseini, A. Farhangdoost, Kh., and Manoochehri, M. "Modelling of extrusion process and application of Taguchi method and ANOVA analysis for optimization the parameters", MECHANIKA, Vol. 18, No. 3, (2012), pp. 301-305.
[14] Kirkpatrick, A. Gelatt, J. and Vecchi, D.D. "Optimization by simulated annealing", Science Vol. 220, No. 671, (1983), pp. 680.
[15] Yang, S.H. Srinivas, J. Mohan, S. Lee, D.M. and Balaji, S. "Optimization of electric discharge machining using simulated annealing", Journal of Materials Processing Technology, Vol (22), (2009), pp.4471-4475.
[16] Jahromi, M. Tavakkoli-Moghaddam, R. Makui, A. and Shamsi, A. "Solving an one-dimensional cutting stock problem by simulated annealing and tabu search", Journal of Industrial Engineering International, Vol (8), (2012), pp. 24-32.