Elucidating the effect of electrical discharge machining parameters on the surface roughness of AISI D6 tool steel using response surface method

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In this investigation, response surface method was used to predict and optimize the surface roughness during electrical discharge machining of AISI D6 tool steel. Pulse on time, pulse current and voltage were considered as input process parameters. Also, the analysis of variance was employed for checking the developed model results. The results showed that the developed model predicted the roughness values, accurately. Also, the pulse on time was the most effective parameter influencing the roughness. Moreover, it was found that the higher values of pulse on time and pulse current and lower values of input voltage caused to in higher amounts of surface roughness. Moreover, the optimal condition to obtain a minimum of surface roughness was 10.22μ s, 8.02 A and 174.74 V, respectively for the pulse on time, pulse current and input voltage.

Keywords: Electrical discharge machining, AISI D6 tool steel, Response surface method, Surface roughness

There is an ever need of advanced technology to manufacture and machining of materials through excessive strength and stability, thus, the modern processes of machining is replacing the traditional process. Electrical discharge machining (EDM) is one of the most crucial and most useful of these processes. In this process, the material removal and a machining can be made by applying a voltage pulse between the tool and the work-piece, which produces a dielectric fluid and spark between them per pulse. Because the EDM process does not engage mechanical energy, the material removal rate is not affected by the material features like hardness, strength, toughness, etc. Therefore, materials with poor machinability such as tool steels can also be machined without much difficulty by the EDM¹⁻³.

The surface roughness of electrical discharge machined metals has an important role in industrial performances. Furthermore, the surface roughness is generally influenced by EDM parameters such as pulse on time, pulse current and voltage, which should be optimized to reach the best conditions^{3,4}. Response surface methodology (RSM) was invented by Box and Wilson in 1951, and it has been used to model and

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optimize the various processes^{5,6}. The RSM has two main aims. The first one is optimizing the responses which are a function of various input parameters. The second one is predicting the mathematical relationships between the process parameters and the measured responses⁷. The RSM would include following steps for EDM process: identifying the EDM effective parameters; considering a reasonable limits of the identified parameters; developing a desired experimental design; performing the tests according to the developed experimental design; measuring the responses; establishing the mathematical models; controlling the model adequacy using analysis of variance (ANOVA), and exploring the influence of the parameters on responses and optimizing them.

Recently some investigators have tried to model and optimize the EDM process of different metals and alloys⁸⁻¹⁵. For instance, Gopalakannan *et al.*⁸ have studied the EDM process of the Al-SiC metal matrix nanocomposites by developing mathematical models using RSM in conjunction with a centered central composite design. They showed that the main significant factors that influences the material removal rate (MRR) are pulse current, pulse on time, and pulse off time whereas voltage remains insignificant. Also, the pulse current and pulse on time have statistical significance on both tool wear ratio (TWR) and surface

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roughness (R_a). Also, Dewangan *et al.*⁴ suggested an optimal setting of EDM process factors with an aim to improve surface integrity aspects after EDM of AISI P20 tool steel using RSM. They have recommended an optimal condition of process factors of pulse current (= 1 A), pulse-on time $(= 10 \text{ } \mu\text{s})$, tool work time (= 0.2 s) and tool lift time (= 1.5 s). Furthermore, Nikalje et al.¹² have studied the effect of the process factors and optimization of MDN 300 steel during EDM by using Taguchi method. They revealed that discharge current, pulse on time, and pulse off time have important role in EDM procedures. Also, they revealed that the discharge current is more significant than pulse on time for MRR and TWR; whereas pulse on time is more significant than discharge current for TWR and R_a . In addition, BagherianAzhiri *et al.*¹⁵ have explored the EDM process of the Al-SiC metal matrix composites by application of Taguchi, ANFIS and grey relational analysis. They found that pulse on time and discharge current are the most significant parameters rather than the others, and wire tension was the most insignificant parameter based on its percentage of contribution. Additionally, they confirmed that the setting of 126 µs pulse on time, 40 µs pulse off time, 20 V gap voltage, 230 A discharge current, 12 mm/min wire feed and 4 gr wire tension lead to higher cutting velocity and lower surface roughness.

Even though the prior investigators explored mathematical models in the case of some alloys, a research into the establishing mathematical relationships between the input parameters and surface roughness during EDM of AISI D6 tool steel is lacking. Therefore, the aim of this study was to apply RSM in conjunction with full factorial design, to establish the functional relationships for EDM of parameters, i.e., pulse on time, pulse current and voltage, and response of AISI D6 tool steel, i.e., surface roughness.

Materials and Methods

Design of experiments

In this investigation, full factorial design including 32 runs, three EDM parameters including pulse on time (at four levels), pulse current (at four levels) and voltage (at two levels) was employed to design of experiments. The levels and actual values of EDM parameters are shown in Table 1. In addition, the evaluated and measured response was the surface roughness (R_a). Moreover, Design-Expert Version 8.0 software was used for preparing the experimental design which is presented in Table 2.

EDM process and experimental details

The experiments were carried out according to the design matrix (Table 2) on a spark system which is shown in Fig. 1, and performed for 20 min to obtain more precise results. The AISI D6 tool steels with 20 mm diameter and 20 mm thick were used as work-pieces. Also, circular electrolytic copper with 18 mm diameter were utilized as electrodes. The work-pieces before EDM, electrodes and final productions in this study are illustrated in Fig. 2. Commercial kerosene was used as the dielectric fluid and impulse jet flushing system was employed to remove the eroded materials from the sparking area. The surface roughness of the electrical discharge machined samples was measured using a KosakaSurfcoder SE 1200.

Establishing mathematical model

The mathematical models were established using a second order polynomial regression model including the main and interaction influences of the EDM parameters. If the measured response (*Y*), i.e., R_a is a function of EDM parameters, i.e., pulse on time (*A*), pulse current (*B*) and voltage (*C*), the response surface can be explored as Eq. (1). As well, the employed regression equation in this study is presented as Eq. (2):

$$Y = f(A, B, C) \qquad \dots (1)$$

$$Y = b_0 + \sum_{i=1}^k b_i k_i + \sum_{i=1}^k b_{ii} X_i^2 + \sum_{i < j} b_{ij} X_i X_j \qquad \dots (2)$$

In Eqs (1) and (2), *Y* is the measured responses, X_i and X_j are the independent variables, b_0 stand for the mean value of responses and b_i , b_{ii} and b_{ij} are linear, quadratic and interaction constant coefficients, correspondingly. In addition, the coefficients of the Eq. (2) can be computed using the Eqs (3-6)^{16,17}:

$$b_0 = 0.142857(\sum Y) - 0.035714\sum \sum (X_{ii}Y) \qquad \dots (3)$$

$$b_i = 0.041667(\sum X_i Y)$$
 ... (4)

$$b_{ii} = 0.03125\sum(X_{ii}Y) + 0.00372\sum(X_{ii}Y) - 0.035714(\sum Y)$$
... (5)

$$b_{ij} = 0.0625 \sum (X_{ij}Y)$$
 ... (6)

Table 1 — Coded and actual values of EDM parameters							
Parameters	Symbol	Unit	Levels				
			1	2	3	4	
Pulse on time	A	μs	10	20	30	40	
Pulse current	В	Α	8	10	12	14	
Input voltage	С	V	150	250	-	-	

Table 2 — Design layout including experimental and predicted values							
Standard	Run	Coded values of parameters		R_{a} (µm)			
run no.		A	В	С	Experimental	Predicted	Error %
1	16	10	8	150	3.43	3.12	-9.04
2	23	20	8	150	4.01	4.39	9.48
3	24	30	8	150	4.92	5.33	8.33
4	8	40	8	150	5.91	5.95	0.68
5	15	10	10	150	3.17	3.47	9.46
6	18	20	10	150	4.5	4.7	4.44
7	20	30	10	150	5.84	5.61	-3.94
8	6	40	10	150	7.05	6.19	-12.2
9	31	10	12	150	4.01	3.7	-7.73
10	7	20	12	150	4.92	4.9	-0.41
11	17	30	12	150	6.18	5.77	-6.63
12	32	40	12	150	5.95	6.31	6.05
13	10	10	14	150	3.81	3.82	0.26
14	26	20	14	150	5.06	4.98	-1.58
15	22	30	14	150	5.65	5.82	3.01
16	27	40	14	150	5.99	6.33	5.68
17	29	10	8	250	3.24	3.11	4.01
18	25	20	8	250	3.89	4.01	3.08
19	9	30	8	250	5.34	4.89	-8.43
20	13	40	8	250	5.15	5.44	5.63
21	30	10	10	250	3.24	3.26	0.62
22	11	20	10	250	4.08	4.43	8.58
23	2	30	10	250	5.19	5.27	1.54
24	5	40	10	250	5.8	5.79	-0.17
25	21	10	12	250	3.09	3.3	-6.79
26	12	20	12	250	4.77	4.73	-0.84
27	4	30	12	250	5.61	5.53	-1.43
28	3	40	12	250	5.87	6.01	2.39
29	28	10	14	250	3.74	3.82	2.14
30	19	20	14	250	5.43	4.91	-9.58
31	1	30	14	250	5.57	5.68	1.97
32	14	40	14	250	6.29	6.12	-2.7



Fig. 1 — The used spark system in this study

The selected polynomials considering the three EDM parameters (A, B and C) will be presented as Eq. (7). Furthermore, the Design-Expert software at 95% confidence level was employed in order to compute the coefficients of the models. Moreover, the sufficiency of the models was confirmed using ANOVA, and models were illustrated by contour and 3D plots.

$$Y = b_0 + b_1(A) + b_2(B) + b_3(C) + b_{11}(A^2) + b_{22}(B^2) + b_{33}(C^2)$$

$$+b_{12}(AB) + b_{13}(AC) + b_{23}(BC)$$

Results and Discussion

Numerical relationships and ANOVA analysis

The FDS (fraction of design space) graph is illustrated in Fig. 3. This graph is a line graph showing the relationship between the volume of the design space (area of interest) and amount of prediction error. The curve indicates what fraction (percentage) of the design space has a given prediction error or lower. In general, a lower (approximately 1.0 or lower) and flatter FDS curve is better, and lower is more important than flatter. Moreover, the Std Err (standard error) of design graph is depicted in Fig. 4. This graph is a contour (Fig. 4a) or 3D (Fig. 4b) plot showing the standard error of prediction for areas in the design space. By default, these values are reflective of the design only, not of the response data.



Fig. 2 - (a) The work-pieces before EDM, (b) copper electrodes and (c) final productions



Fig. 3 — The FDS graph of the developed design matrix

Generally, it is better this graph to have relatively low standard error across the region of interest. Low is approximately 1.0 or lower.



Fig. 4 — The Std Err of design graph: (a) contour plot and (b) 3D plot

The numerical relationships between the EDM parameters and the response R_a has been achieved as follows:

$$Ra(\mu m) = 5.17 + 1.28A + 0.35B - 0.13C - 0.083AB$$
$$-0.049AC + 0.076BC - 0.37A^{2} - 0.13B^{2}$$
$$\dots (8)$$

Equation (8) predicts the R_a for the EDM of the AISI D6 tool steels. The normal plot of residuals, the predicted versus actual response plot, the residuals versus the predicted response plot, and the residuals versus the experimental run plot are respectively illustrated in Fig. 5, for R_a . The normal probability plot indicates whether the residuals follow a normal distribution, in which case the points will follow a straight line. Figure 5a demonstrates that errors are extended normally because the residuals follow a straight line. Figure 5b reveals that the predicted responses values are in good agreement with the actual ones within the ranges of the EDM process parameters, because the data points are split evenly by 45°. Figures 5c and 5d reveal that numerical models predict the responses adequately due to randomly scattered residuals.



Fig. 5 — (a) Normal probability plot of residuals, (b) predicted versus actual response plot, (c) residuals versus the predicted response plot, and (d) residuals versus the experimental run plot for R_a

Table 3 — ANOVA table for response R_a						
Source	Sum of squares	Degree of freedom	Mean square	F-Value	P-Value	
Model	33.13811	8	4.142264	30.82063	< 0.0001	significant
A	29.30944	1	29.30944	218.0777	< 0.0001	
В	2.13444	1	2.13444	15.88136	0.0006	
С	0.525313	1	0.525313	3.908603	0.0601	
AB	0.067344	1	0.067344	0.501079	0.4861	
AC	0.04225	1	0.04225	0.314362	0.5804	
BC	0.10201	1	0.10201	0.759008	0.3926	
A^2	0.851512	1	0.851512	6.335704	0.0193	
B^2	0.1058	1	0.1058	0.787208	0.3841	
C^2	0	0				
Residual	3.091178	23	0.134399			
R^2	0.9147					
Adjusted R ²	0.8850					

The ANOVA analysis results for the response R_a is summarized in Table 3. The *F*-value, *P*-value, R^2 and adjusted R^2 are used for identifying the more significant model and coefficients. Larger *F*-value, R^2 and adjusted R^2 , and smaller *P*-value reveal that the model or a coefficient is significant. According to the Table 3, the *F*-value, *P*-value, R^2 and adjusted R^2 for the predicted R_a model are 30.82, <0.0001, 0.9147, 0.8850. Therefore, the predicted models are adequate and significant. Additionally, *P*-values < 0.05 verify that the coefficients are significant and *P*-values > 0.1 mean that the coefficients are not significant. Thus, according to the *P*-values, *A*, *B*, and A^2 are significant terms for predicted R_a model. After reduction of the models by considering only the significant terms, the following mathematical models are achieved:

$$Ra(\mu m) = 5.10 + 1.28A + 0.35B - 0.37A^2 \qquad \dots (9)$$

Furthermore, the *F*-values prove that the order of the more significant terms in R_a is as follows: $A > B > A^2 > .$



Fig. 6 — Perturbation plot illustrating the influence of EDM parameters on the R_a

Effect of EDM parameters on R_a

The perturbation plot for R_a is presented in Fig. 6. Also, Figs 7(a-f) show the contour and 3D surface plots. These plots illustrate the interaction effect of any two EDM parameters on the R_a when the other parameter is on its level zero (center level). Figures 6 and 7(a-f) reveal that increase in pulse on time and pulse current, and decrease in input voltage all cause to higher amounts of R_a . On the surface of the electrical discharge machined materials there are a lot of microscopic craters which are due to random spark discharge between the electrodes. The most effective parameter on the size of these craters is the energy of the discharge. The higher energetic pulses result in higher material removal, and hence a deeper cavity produces. The deeper the cavity



Fig. 7 — Contour and 3D plots for the response R_a

depth, the higher the roughness. The correlation between the three main parameters affecting the EDM discharge energy (W) can be stated as follow¹⁸:

$$W = \int_0^{on} U(T_i) I(T_i) dT_i \qquad \dots (10)$$

Where, U, I and T_i stand for the input voltage (V), the peak current (A) and the pulse-on time (μ s), respectively. In fact, increasing the pulse on time increases the machining time and consequently the work-piece surface temperature; thus, the volume of melt holes increase. Also, with increasing the pulse current, based on the increased current density, cause to faster dielectric fluid ionization, and hence higher material removal and bigger craters on the surfaces.

Based on Eq. (10), by increasing the input voltage the discharge energy rate must have increased, and hence the R_a should be increased, too. But, according to Figs 6 and 7, the R_a decreases as the input voltage increases. Increasing the input voltage to an appropriate level can increase material removal rate, but at low input voltage, the plasma channels generated on compact work-piece surface that is more compact cause the multi sparking phenomenon. Therefore, this speeds up the machining process and increases the material removal rate at lower voltages, which cause to formation of the bigger craters on the machined surfaces.

10.00

A:Pulse on time (ms) = 10.22

Optimization of EDM parameters

In this study, the desirability method was used for optimization of EDM parameters. This method employs an objective function, called the desirability function, and transforms (by desirability function) an estimated response into a scale-free amounts called desirability. The desirability varies between 0 and 1. An amount of 1 signifies the ideal case, where 0 represents that the response is outside its acceptable limits. Combined desirability is the weighted statistical mean of the individual desirability for the all parameters. The parameters settings with highest total desirability are regarded to be the best possible parameter conditions. The optimization process has been conducted using the Design Expert Software in which the R_a was optimized using the established model (Eq. (8)). The optimality solution to calculate the process parameters for minimizing the R_a is illustrated in Figs 8 and 9. The amounts of constraints, optimum amounts of EDM parameters, and the predicted amount of R_a are summarized in Table 4.

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ompact	Table 4 — Constraint of input parameters, and optimum values for parameters and R_a					
ses the	Parameter or response	Goal	Optimum value			
which on the	Pulse on time Pulse current Input voltage <u>Ra</u>	in range in range in range minimize	10.43 μs 8.05 A 242.8 V 2.9 μm			
40.00	B:Pulse current (ar	np) = 8.02 14.00	_			







Fig. 9 — Bar graph showing the maximum desirability of 1 for the combined objective

Conclusions

In this study the effect of EDM input parameters (pulse on time, pulse current and voltage), on the surface roughness in the machining of AISI D6 tool steel has been studied using RSM. The range of EDM parameters for machining the AISI D6 tool steel was achieved. Also, the numerical models were effectively established to predict and optimize the R_a . Furthermore, the ANOVA analysis revealed that the models can be successfully applied for prediction of $R_{\rm a}$. The pulse on time was identified as the most effective parameter influencing the $R_{\rm a}$. Moreover, decreasing the pulse on time and pulse current and increasing the input voltage resulted in lower R_a . Furthermore, the minimum value of 3.07 μ m for the R_a was predicted by the model. Finally, the optimized pulse on time, pulse current and input voltage to get minimum amount of R_a was 10.22 µs, 8.02 A and 174.74 V.

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