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Multi Objective Optimization of EDM Parameters for 40CrMnMoS86 Hot Worked Steel Using Grey Relational Analysis and Genetic Algorithm

F. Kolahan[1*], M. Azadi Moghaddam[1] and R. Golmezerji[1]
[1] *Department of Mechanical Engineering, College of Engineering, Ferdowsi University of Mashhad, Mashhad, Iran*

Abstract 2722

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Keywords: *Analysis of Variance (ANOVA); Electrical Discharge Machining (EDM); Grey Relational Analysis (GRA); Genetic Algorithm (GA); Multi objective optimization.*

*Corresponding author. Tel.: +98 9153114112, Fax. +98 511-8763304
E-mail address: kolahan@um.ac.ir
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1. Introduction

Electrical Discharge Machining (EDM) has become one of the most extensively used non-traditional material removal process. Its unique feature of using thermal energy to machine hard to machine electrically conductive materials is its distinctive advantage in the manufacturing of moulds, dies, aerospace and surgical components [1, 2].

However, EDM is a costly process and hence proper selection of its process parameters is essential to increase production rate and improve product quality. As a result, a comprehensive study of the effects of EDM parameters on the machining characteristics such as Tool Wear Rate (TWR), Material Removal Rate (MRR) and Surface Roughness (SR) is of great significance.

EDM technique is especially useful when the work piece is hard, brittle and requires high surface finish. Therefore, the virtues of the EDM technique become most apparent when machining such hard material with high wear resistance as 40CrMnMoS86 hot worked steel parts. In addition, mechanical and physical properties of hot worked steel such as hardness, toughness and high wear resistance has made it an important material for engineering components particularly in making moulds and dies [3]. EDM does not make direct contact between the electrode and the work piece where it can eliminate mechanical stresses, chatter and vibration problems during machining process [4].

*Corresponding author. Tel.: +98 9153114112, Fax. +98 511-8763304
E-mail address: kolahan@um.ac.ir
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In EDM process, it is important to select machining parameters to achieve optimal machining performance. Important process parameters in EDM are peak current (I), voltage (V), pulse on time (T_{on}), pulse off time (T_{off}) and duty factor (η) [3-5]. These parameters, in turn, determine the process output characteristics, among which Surface Roughness (SR), Tool Wear Rate (TWR) and Material Removal Rate (MRR) are the most important ones. Usually, the desired machining parameters are determined based on experience or handbook values.

It is well known that modeling the relationships between the input and output variables for non-linear, multi-variable systems are very difficult via traditional modeling methods [7].

In recent years, statistical analysis and Design of Experiments (DOE) technique have increasingly been employed to establish the relationships between various process parameters and the process outputs in variety of manufacturing industries [6-8].

In this study the effects of EDM parameter levels on 40CrMnMoS86 hot worked steel have been investigated. As mentioned earlier, SR, TWR and MRR are the most important performance characteristics in EDM. In turn, these output characteristics are determined by the process parameter settings, such as peak current (I), pulse on time (T_{on}), pulse off time (T_{off}), duty factor (η) and voltage (V).

The proposed procedure is based on statistical analysis of the experimental data. Finally, verification of the proposed approach and summary of the major findings are presented. A schematic illustration of EDM process is given in Fig 1.

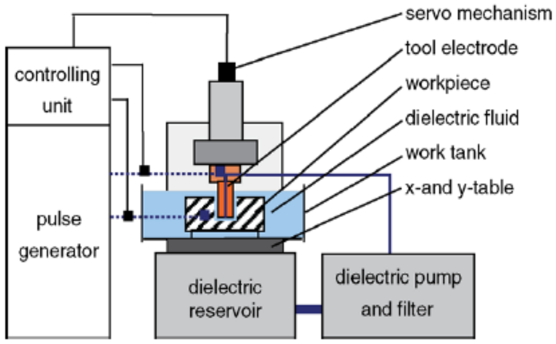

Fig.1 Schematic illustration of Electrical Discharge Machining

2. Test equipment and design of experiments

In this study, an EDM machine (Azarakhsh-304H) was used to perform the experiments (Fig. 2). Cylindrical pure copper (99.8% purity and 8.98 g/cm^3 density) with 16mm diameters were used as electrodes. The work pieces are of 40CrMnMoS86 hot worked steel with 60mm×20mm×10mm dimensions. Pure kerosene was used as the dielectric fluid in all experiments.

Table 1 lists the ranges of machining parameters used in experiments. As illustrated, pulse off time is considered at two levels, while all other process variables have three levels. The experiments were performed based on L_{36} Taguchi matrix (Table 2). This results in 36 sets of data needed for modeling.

Table 1 Process parameters and their levels

No.	Symbols	Parameters	Units	levels		
				1	2	3
1	A	Pulse off time	µs	10	75	-
2	B	Pulse on time	µs	25	100	200
3	C	Peak current	A	2.5	5	7.5
4	D	Voltage	V	50	55	60
5	E	Duty factor	S	0.4	1	1.6

Material removal rate (MRR) is expressed as the work piece removal weight (WRW) under a period of machining time in minute (T), as given by Eq. (1). Tool wear rate (TWR), usually expressed as a percentage, is defined by Eq. (2) and is the ratio of the tool wear weight (TWW) to the work piece removal weight (WRW).

$$MRR\ (gr/\min) = \frac{WRW}{T} \tag{1}$$

$$TWR(\%) = \frac{TWW}{WRW} \times 100 \tag{2}$$

To measure the MRR and EWR an A&D electronic weighing scale with 0.01gr accuracy has been used. After machining, the surface finish of each specimen was measured with an automatic digital Surtronic (3+) surface roughness tester with 0.1µm accuracy. Fig. 3 illustrates the digital surface roughness tester and electronic balance used for measurements.

Fig. 2 Die-sinking EDM machine used for experiments

Table 2 Experimental layout using L_{36}

No.	T_{off}(µs)	T_{on}(µs)	I(A)	η(Sec)	V(V)
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	1	1	1	1
5	1	2	2	2	2
6	1	3	3	3	3
7	1	1	1	2	3
8	1	2	2	3	1
9	1	3	3	1	2
10	1	1	1	3	2
11	1	2	2	1	3
12	1	3	3	2	1
13	1	1	2	3	1
14	1	2	3	1	2
15	1	3	1	2	3
16	1	1	2	3	2
17	1	2	3	1	3
18	1	3	1	2	1
19	2	1	2	1	3
20	2	2	3	2	1
21	2	3	1	3	2
22	2	1	2	2	3
23	2	2	3	3	1
24	2	3	1	1	2
25	2	1	3	2	1
26	2	2	1	3	2
27	2	3	2	1	3
28	2	1	3	2	2
29	2	2	1	3	3
30	2	3	2	1	1
31	2	1	3	3	3
32	2	2	1	1	1
33	2	3	2	2	2
34	2	1	3	1	2
35	2	2	1	2	3
36	2	3	2	3	1

Fig. 3 Digital surface roughness tester and weighing scale

3. Grey Relational Analysis (GRA)

The grey theory, first proposed by "Deng" [8] avoids the inherent defects of conventional statistical methods and only requires a limited set of data to estimate the behavior of an unknown system. In the Grey relational analysis (GRA), data preprocessing is first performed in order to normalize the raw data for analysis. During the past two decades, the grey theory has been successfully applied to research in industry, engineering, social sciences, economy, etc. [8].

Suppose in a system there are *n* series of data (number of run tests) and in each series *m* responses (number of dependent variables measured). Test results are then determined by $y_{i,j}$ (i = 1,2, ..., n and j = 1,2, ..., m). In GRA of such systems the following steps are performed [9, 10]:

a) Normalizing the data for each response to avoid the effect of adopting different units and reduce the variability.

When the higher value of a response is desired, Eq. (3) is used for normalizing which is named "the- higher-the-better" criterion. Thus, Material Removal Rate (MRR) is normalized by this equation. When the lower value of a favorable response is desired, Eq. (4) is used for normalizing, termed "the-lower-the-better" criterion. By the same token, Eq. (4) is used to normalize observed surface roughness (SR) and tool wear rate (TWR).

$$Z_{i,j} = \frac{(y_{i,j} - \min(y_{i,j}, i = 1,2\ldots,n))}{(\max(y_{i,j}, i = 1,2\ldots,n) - \min(y_{i,j}, i = 1,2\ldots,n))} \tag{3}$$

$$Z_{i,j} = \frac{(\max(y_{i,j}, i = 1,2\ldots,n) - y_{i,j})}{(\max(y_{i,j}, i = 1,2\ldots,n) - \min(y_{i,j}, i = 1,2\ldots,n))} \tag{4}$$

b) Calculating the Grey Relational Coefficient (GRC) for the normalized values through the following equation:

$$\gamma(Z_o, Z_{i,j}) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{oj}(k) + \zeta\Delta_{\max}} \tag{5}$$

Where:

ζ is the distinguishing coefficient and $0 \le \zeta \le 1$.

$Z_o\ (k)$ is the reference sequence ($Z_o(k)$=1, k=1, 2... m);

Δ_{oj} is the absolute value of the difference between $Z_o(k)$ and $Z_{i,j}(k)$; $\Delta_{oj} = |\, Z_o(k) - Z_{i,j}\,|$. Δ_{min} and Δ_{max} are the smallest and the largest value of difference between $Z_o(k)$ and $Z_{i,j}(k)$ which are given by:

$$\Delta_{\min} = \min|\, Z_o(k) - Z_{i,j}\,|, \Delta_{\max} = \max|\, Z_o(k) - Z_{i,j}\,|$$

c) Computing Grey Relational Grade (GRG) for any response using Eq. (6):

$$\text{Grade}\,(Z_o, Z_{i,j}) = \sum_{k=1}^{n} \beta_k \gamma(Z_o, Z_{i,j}) \tag{6}$$

Where:

$\sum_{k=1}^{n} \beta_k \gamma(Z_o, Z_{i,j}) = 1$ and β_k is weighting factor of each response [11].

The results for GRA are shown in Table 3. The results of experiments using above mentioned method are used for model development. The weighting of parameters depends on the relative importance of each response. When weighting coefficients of each response are equal, the value of ζ is set to 0.5 [10].

In the Table 3, the last column is the weighted GRG for the three process outputs.

Table 3 Result of Grey Relational Analysis

No.	GRC of MRR	GRC of TWR	GRC of SR	Grade
1	0.334	0.676	0.882	0.631
2	0.404	0.906	0.574	0.628
3	0.566	0.983	0.338	0.629
4	0.333	0.725	1	0.686
5	0.376	0.881	0.586	0.614
6	0.576	0.990	0.356	0.640
7	0.336	0.783	0.897	0.672
8	0.502	0.903	0.502	0.636
9	0.398	0.979	0.361	0.580
10	0.338	0.819	0.814	0.657
11	0.362	0.865	0.544	0.590
12	1	0.981	0.333	0.771
13	0.366	0.396	0.766	0.509
14	0.389	0.762	0.517	0.556
15	0.346	0.961	0.636	0.678
16	0.355	0.396	0.789	0.513
17	0.381	0.783	0.436	0.533
18	0.352	0.972	0.669	0.664
19	0.338	0.402	0.755	0.498
20	0.403	0.684	0.580	0.555
21	0.345	0.960	0.614	0.639
22	0.353	0.375	0.766	0.498
23	0.453	0.752	0.488	0.565
24	0.334	0.903	0.644	0.627
25	0.374	0.336	0.695	0.695
26	0.343	0.955	0.669	0.656
27	0.367	0.984	0.399	0.583
28	0.369	0.345	0.755	0.490
29	0.341	0.947	0.789	0.692
30	0.371	0.986	0.385	0.581
31	0.362	0.359	0.755	0.492
32	0.336	0.9186	0.629	0.628
33	0.447	0.979	0.484	0.636
34	0.345	0.333	0.755	0.478
35	0.340	0.945	0.695	0.660
36	0.483	1	0.443	0.642

4. Multi objective modeling

Many problems in engineering and science involve exploring the relationships between two or more variables. Regression analysis is a statistical technique that is very useful for these types of problems [10]. Regression models can be used to predict the behavior of input variables (independent variables) and output responses. In this paper, the output responses are GRG's associated with experimental tests. In this study, various regression functions have been fitted on the data given in Table 3. Among these models, quadratic regression model was found to be the most appropriate in terms of estimating the real process. Eq. (7) shows the adjusted second order regression model for EDM process:

$$\text{Grade} = 0.823 + 0.001\text{T}_{\text{off}} - 0.009\ \text{I} + 0.006\ \text{I}^2 + 0.001\text{T}_{\text{off}} \times \eta + 0.0002\ \text{T}_{\text{on}} \times \text{I} - 0.006\ \text{I} \times \eta - 0.0002\text{T}_{\text{on}} \times \eta + 0.0001\text{T}_{\text{on}} \times \text{V} \quad (7)$$

Statistical analysis has shown that the coefficient of determination (R^2) for this model is 98.7% within 95% confidence level. This verifies the adequacy of this model for the process under study

5. Multi objective optimization

In this section, a Genetic Algorithm (GA) procedure is employed to determine the optimal machining parameters set in multi objective model. In the optimization process, the purpose is to maximize this objective function (Eq. (7)). By doing so, the process parameters are calculated in such a way that the EDM parameters approach their desired values [12]. The best tuning parameters found for the algorithm are found through several test runs and are presented in Table 4.

Table 4 The best tuning parameters for the GA procedure

No. of Generations	Population size	Crossover rate	Crossover mechanism	Mutation rate
800	30	80%	scatter	1%

Fig. 2 shows the convergence curve towards the optimal solution.

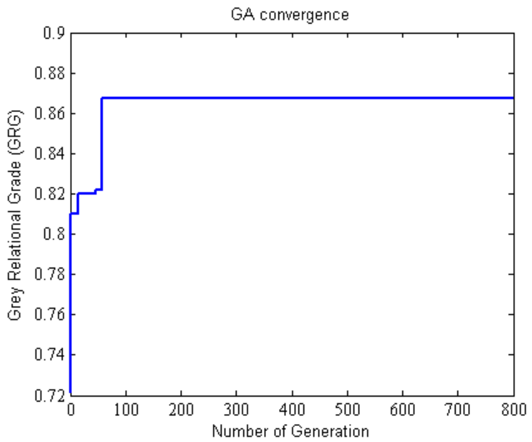

Fig. 4 Genetic Algorithm convergence curve

6. Running confirmation experiment

The estimated Grey relational grade ($\hat{a}$) using the optimal level of the machining parameters can be calculated by [11]:

$$\hat{\alpha} = \alpha_m + \sum_{i=1}^{q} (\alpha_i - \alpha_m) \quad (8)$$

Where α_m is the total mean of the Grey relational grade, α_i is the mean of the Grey relational grade at the optimal level and q is the number of the machining parameters that significantly affects the multiple response characteristics. Based on Eq. (8), the estimated Grey relational grade using the optimal machining parameters can be found out even for the setting not available in the Taguchi design (Table 5).

From the optimization results for the GRG, given in Table 6, the optimal machining parameter setting is to maintain pulse off time at level 2 (75 µs), pulse on time at level 1(25 µs) , peak current at level 1(2.5A), voltage at level 3(60 V) and the duty factor at level 1(0.4 S). The result of confirmation experiment manifests an improvement in GRG (0.851 - 0.771 = 0.096).

Table 5 Results of confirmation experiment

	Initial machining parameters	Prediction	Experimentation
Setting level	$A_1B_3C_3D_2E_1$	$A_2B_1C_1D_3E_1$	$A_2B_1C_1D_3E_1$
MRR	0.236	0. 195	0.0202
TWR	0.007	0.009	0.011
SR	13.7	3.2	5.1
GRG	0.771	0.851	0.867

Improvement in Grey relational grade: 0.096.

7. Conclusion

Taguchi design with Grey relational analysis and Genetic Algorithm (GA) were employed to optimize the multi response characteristics of Electric Discharge Machining of 40CrMnMoS86 hot worked steel. The application of GRA technique converts the multi response variable to a single response Grey Relational Grade and, therefore, simplifies the modeling and optimization procedure. Statistical analyses reveal that the proposed regression model can accurately represents the actual process. Then a GA technique was employed to find optimal set of process parameters. The experimental result for the optimal setting shows that there is considerable improvement in the multiple performance characteristics such as material removal rate, tool wear rate and surface roughness.

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