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Application of Grey Relational Analysis and Simulated Annealing Algorithm for Modeling and Optimization of EDM Parameters on 40CrMnMoS86 Hot Worked Steel

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M. Azadi Moghaddam, F. Kolahan, M.Andalib

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Prof. M. Yaghoobi
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Application of Grey Relational Analysis and Simulated Annealing Algorithm for Modeling and Optimization of EDM Parameters on 40CrMnMoS86 Hot Worked Steel

M. Azadi Moghaddam[1], F. Kolahan[2], M.Andalib[3]

[1]Student, Ferdowsi U. Dept. of Mech. Eng.; Masoud_Azadi88@yahoo.com

[2]Associate Prof, Ferdowsi U. Dept. of Mech. Eng.; kolahan@um.ac.ir

[3] Student, Ferdowsi U. Dept. of Mech. Eng.; morteza.andalib@ymail.com

Abstract

The present study is aimed at optimizing the Material Removal Rate (MRR), Surface Roughness (SR) and Tool Wear Rate (TWR) of die sinking Electrical Discharge Machining (EDM) by considering the simultaneous affect of various input parameters. The experiments are carried out on 40CrMnMoS86 hot worked steel parts. Developed multi objective model is optimized by Simulated Annealing algorithm (SA) and machining optimal parameters setting is found. A confirmation test is also performed to verify the effectiveness of optimization procedure in determining the optimum levels of machining parameters.

Keywords: Electrical Discharge Machining, Grey Relational Analysis, Simulated Annealing Algorithm, Multi Objective Optimization.

Optimum Design

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[1]Student, Ferdowsi /Department of mechanical engineering; Masoud_Azadi88@yahoo.com
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Abstract
The present study is aimed at optimizing the Material Removal Rate (MRR), Surface Roughness (SR) and Tool Wear Rate (TWR) of die sinking Electrical Discharge Machining (EDM) by considering the simultaneous affect of various input parameters. The experiments are carried out on 40CrMnMoS86 hot worked steel parts. Experiments were conducted by varying the peak current (I), voltage (V), pulse on time (T_{on}), pulse off time (T_{off}) and duty factor (η). The corresponding values of material removal rate, tool wear rate and surface roughness were measured. The relation between machining parameters and performance can be found out with the Grey Relational Analysis (GRA). Developed multi objective model is optimized by Simulated Annealing algorithm (SA) and machining optimal parameters setting is found. A confirmation test is also performed to verify the effectiveness of optimization procedure in determining the optimum levels of machining parameters. The consequences show that the combination of Taguchi technique, grey relational analysis and simulated annealing algorithm is quite efficient in determining optimal EDM process parameters.

Keywords: Analysis of Variance (ANOVA), Electrical Discharge Machining (EDM), Grey Relational Analysis (GRA), Simulated Annealing Algorithm (SA),Multi objective optimization.

Introduction

Electrical discharge machining (EDM) is a non-traditional manufacturing process where the material is removed by a succession of electrical discharges, which occur between the electrode and the work piece. These are submersed in a dielectric liquid such as kerosene or deionized water [1]. 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 the greatest significance.

EDM technique is especially useful when the work piece is hard, brittle and requires high surface finish. Therefore, the merits 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.

Like any other machining processes, the performance of the EDM process is significantly affected by its parameters setting. 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 SR, TWR and MRR are the most important ones. 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 [6,7]. A schematic illustration of EDM process is given in Figure 1.

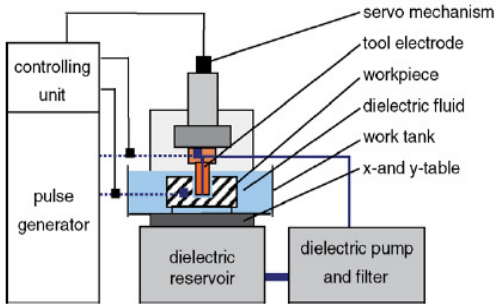

Figure 1: illustration of electrical discharge machining

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 [8].

In this study the effects of EDM parameters levels on40CrMnMoS86 hot worked steel have been investigated. As mentioned earlier, SR, TWR and MRR are the most important performance characteristics in EDM process. 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. The article concludes with the verification of the proposed approach and a summary of the major findings.

Experimental equipment and Design of Experiments (DOE)

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

The ranges of machining parameters are shown in Table 1. As shows, pulse off time is considered at two levels, while all other process variables have three levels. The L_{36} sets of data needed for modeling are obtained using L_{36} Taguchi matrix (Table 2).

The MRR, SR and TWR are considered as the performance characteristics to evaluate the machining quality. MRR is expressed as the work piece removal weight (WRW) under a period of machining time in minute (T) as given by Eq. (1). TWR, usually expressed as a percentage, is defined by the ratio of the tool wear weight (TWW) to the work piece removal weight (WRW), which is defined by Eq. (2).

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

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

Table 1: Process parameters and their design levels

Number	Symbol	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

Figure 2: surface roughness tester and electronic balance used

To measure the MRR and TWR an A&D electronic balance 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. Figure 2 illustrates the digital surface roughness tester and electronic balance used.

Table 2: Experimental layout using L_{36}

Number	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
. . .					
19	2	1	2	1	3
20	2	2	3	2	1
21	2	3	1	3	2
22	2	1	2	2	3
. . .					
33	2	3	2	2	2
34	2	1	3	1	2
35	2	2	1	2	3
36	2	3	2	3	1

Grey Relational Analysis

The grey theory, first proposed by "Deng" avoids the inherent defects of conventional, statistical methods and only requires a limited set of data to estimate the behavior of an unknown system. During the past two decades, with hard work by scholars, the grey theory has been successfully applied to research in industry, social systems, ecological systems, economy, geography, traffic, management, education, environment, 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). Test results is then determined by $y_{i,j}$ (i = 1,2, ..., n and j = 1,2, ..., m). In grey relational analysis of this system following steps are performed [1, 2]:

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

When the higher value of a response is desired, the Eq. (3) is used for normalizing which is named "the-higher-the-better" criteria. Thus, 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" criteria. By the same token, Eq. (4) is used to normalize observed SR and TWR.

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

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

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

equation:

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

Where:

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

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):

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

Where:

$\sum_{k=1}^{n} \beta_k \gamma(Z_o, Z_{i,j}) = 1$ and β_k is weighting factor of each response [1, 2].

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 [1].

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

Multi objective modeling

- **Regression 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 [9]. 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:

$$\begin{aligned} \text{Grade} &= 0.823 + 0.001 T_{off} - 0.009 I + 0.006 I^2 \\ &+ 0.001 T_{off} \times \eta + 0.0002 T_{on} \times I - 0.006 I \times \eta \\ &- 0.0002 T_{on} \times \eta + 0.0001 T_{on} \times V \end{aligned} \quad (7)$$

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.

- **Analysis of variance**

Analysis of variance (ANOVA) is a mathematical way to determine precision of modeling for a group of observations, which shows how the proposed model fits with experimental results [9].

According to ANOVA procedure, 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 [9].

The percent contribution of the EDM parameters on Grey Relational Grade (GRG) is shown in Figure. 4. According to Figure. 4, peak current is the major factor affecting the GRG with 38% contribution. Whereas pulse on time, pulse off time, voltage and duty factor have smaller effects on GRG with 31%, 15%, 5% and 2% contributions, respectively.

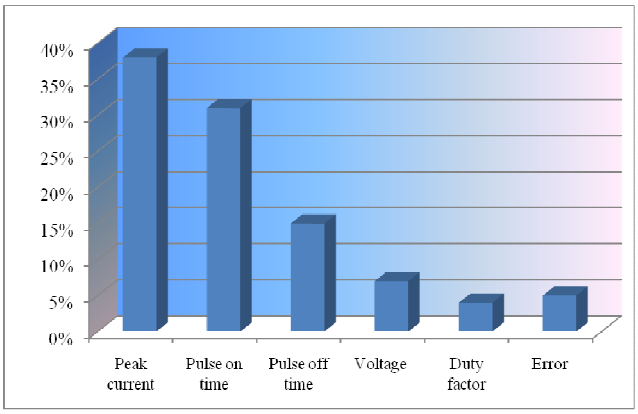

Figure 3: The effect of machining parameters on GRG

Multi objective optimization

Once the process model is ready, the optimum process parameters have to be determined. Unlike other non-conventional optimization schemes, Simulated Annealing (SA) process uses single point search method. This algorithm begins with an initial reasonable solution in solution field. Then a new solution in neighborhood of initial solution is formed. If the objective functions value of this new condition be better than initial value or the probability function implemented in SA has a higher value than a randomly generated number between zero and one, SA accepts this solution. The probability function implemented in SA given as follows [10].

$$P = \exp\left(\frac{\Delta F}{T_i}\right) \quad (8)$$

ΔF is absolute difference between the objective function of the current solution and the new solution in each step and Ti is system's temperature. In SA, Ti is updating corresponding to annealing coefficient (λ) and according to relationship:

$Ti+1=\lambda Ti$, i= 0, 1… n and $0.8 < \lambda < 1$ (9)

Small amount of λ accelerates algorithm convergence, but larger amounts increases fortune of non healing solutions acceptance. In optimization of developed multi objective model, every solution is a combination of peak current (I), voltage (V), pulse on time (T_{on}), pulse off time (T_{off}) and duty factor (η). Figure 4 shows

Simulated Annealing algorithm's performance in optimal solution finding.

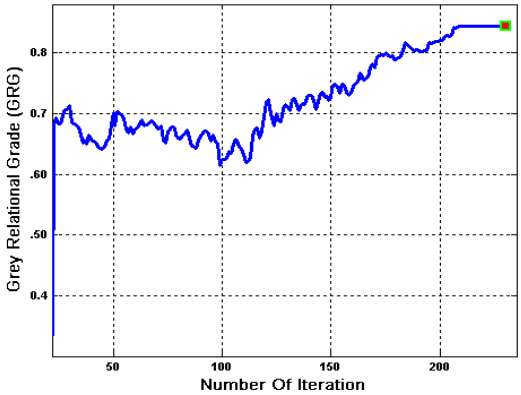

Figure 4: Simulated Annealing Algorithm performance

Running confirmation experiment

The estimated grey relational grade (α□) using the optimal level of the machining parameters can be calculated as [2]:

$$\hat{\alpha} = \alpha_m + \sum_{i=1}^{q} (\alpha_i - \alpha_m) \qquad (10)$$

Where αm is the total mean of the grey relational grade, αi 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. (10), 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 4).

From the response table for the grey relational grade (Table 5), the optimal machining parameter setting is to maintain pulse on time at level 2, pulse off time at level 1 , peak current at level 1, voltage at level 3 and the duty factor at level 1 for maximizing GRG.

Table 4 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.

Conclusion

Taguchi design with grey relational analysis and simulated annealing algorithm were employed to optimize the multi response characteristics of electric discharge machining of 40CrMnMoS86 hot worked steel. The application of this technique converts the multi response variable to a single response grey relational grade and, therefore, simplifies the optimization procedure. From ANOVA results of regression model, in developed multi objective model, selecting pulse on time (Ton) in 25 µs, pulse off time (Toff) in 75 µs, peak current (I) in 2.5A, voltage (V) in 60 V, and duty factor (η) in 0.4 S concludes optimum machining condition in multi performance characteristics. The experimental result for the optimal setting shows that there is considerable improvement in the grey relational grade.

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