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# Empirical Modeling of EDM Parameters Using Grey Relational Analysis

[1]A. Doniavi, [2]M. Eskandarzade, [1]A. Abdi and [2]A. Totonchi
[1]Department of Mechanical Engineering, Urmia University, Urmia, Iran
[2]Department of Mechanical Engineering, Urmia University of Technology, Urmia, Iran

**Abstract:** Optimization of multi criteria problems is a great need of producers to product precision parts with low costs. Many methods such as Taguchi and Response Surface Methodology have been employed for optimization of EDM process. However there are few researches involve the optimization of multi-response problem in EDM process. The attempt of this paper is to optimize multiple performance characteristics of EDM process using Grey relational analysis based on Taguchi orthogonal array. The response table and response graph for each level of the machining parameters is obtained and optimal levels of machining parameters including pulse on time, discharge current, discharge voltage and duty factor are found. The multiple performance characteristics including material removal rate, electrode wear ratio and surface roughness is considered.

**Key words:** Electric discharge machining, Taguchi method, grey relational analysis, multiple response, optimization

## INTRODUCTION

Grey relation analysis (Deng, 1989a, b; Deng, 1987) is an important part of grey system theory. The Grey theory can provide a solution of a system in which the model is unsure or the information is incomplete. It also provides an efficient solution to the uncertainty, multi-input and discrete data problem. The relation between machining parameters and performance can be found out with the Grey relational analysis (Deng, 1989a). It has been widely used in many applications (Chen *et al*., 2000; Bin *et al*., 2002; Edwards *et al*., 1997; Baoqing *et al*., 2004). In recent years, It also provides an efficient solution to the uncertainty, multi-input and discrete data problems.

The relation between machining parameters and performance can be found out with the Grey relational analysis. Grey relation analysis has even been applied in facing recognition combining with other statistical methods (Chen *et al*., 2000). It is important to select machining parameters in Electrical Discharge Machining (EDM) for achieving optimal machining performance (Tarng *et al*., 1995). The Taguchi method (Taguchi, 1990; Ghani *et al*., 2004), is a systematic application of design and analysis of experiments for the purpose of designing and improving product quality. Dr. Taguchi proposes the plan of quality project (called the Taguchi method) with the robust desigu based on desigu of experiment, to simplify a great quantity of fully factor experimentation. It had extensively applied in engineering desigu and the analysis of optimal manufacturing. To deliberate multiple performance characteristics by the Taguchi method it requires further research effect. For the Electrical Discharge Machining (EDM) process, material removal rate is a higher-the-better performance characteristic. However, surface roughness and electrode wear ratio are a lower-the-better performance characteristic. As a result, an improvement of one performance characteristic may require a degradation of another one. Hence, optimization of the multiple performance characteristics is much more complicated than optimization of a single performance characteristic. The grey relational analysis based on grey system theory can be used to solve the complicated interrelationships among the multiple performance

**Corresponding Author:** A. Doniavi, Department of Mechanical Engineering, Urmia University, Urmia, Iran

characteristics effectively. In the grey relational analysis, a grey relational grade is obtained to evaluate the multiple performance characteristics. In this way, optimization of the complicated multiple performance characteristics can be converted into optimization of a single grey relational grade. It is shown by this study that the use of the orthogonal array with the grey relational analysis can greatly simplify the optimization procedure for determining the optimal machining parameters with the multiple performance characteristics in the EDM process. As a result, the method developed in this study is very suitable for practical use in a machine shop.

## MATERIALS AND METHODS

The application of Design-of-Experiments (DOE) requires careful planning, prudent layout of the experiments and expert analysis of the results (Montgomery, 1997; Logothetis and Haigh, 1988). Taguchi has standardized methods for each of these DOE application steps.

A statistical Analysis of Variance (ANOVA) is performed to identify the process parameters that are statistically significant. Based on ANOVA the optimal combinations of the process parameters are predicted.

In the grey relational analysis, the experimental results of electrode wear ratio, material removal rate and surface roughness are first normalized in the range between zero and one, which is also called the grey relational generating. Next, the grey relational coefficient is calculated from the normalized experimental results to express the relationship between the desired and actual experimental results. Then, the grey relational grade is computed by averaging the grey relational coefficient corresponding to each performance characteristic. As a result, optimization of the complicated multiple performance characteristics can be converted into optimization of a single grey relational grade. Optimal level of the process parameters is the level with the highest grey relational grade. Furthermore, a statistical Analysis of Variance (ANOVA) is performed to see which process parameters are statistically

Table 1: Experimental layout using L27 orthogonal array

| No. | Pulse on time (A) | Discharge current (B) | Discharge voltage (C) | Duty factor (D) |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 1 | 1 |
| 3 | 1 | 1 | 1 | 1 |
| 4 | 1 | 2 | 2 | 2 |
| 5 | 1 | 2 | 2 | 2 |
| 6 | 1 | 2 | 2 | 2 |
| 7 | 1 | 3 | 3 | 3 |
| 8 | 1 | 3 | 3 | 3 |
| 9 | 1 | 3 | 3 | 3 |
| 10 | 2 | 1 | 2 | 3 |
| 11 | 2 | 1 | 2 | 3 |
| 12 | 2 | 1 | 2 | 3 |
| 13 | 2 | 2 | 3 | 1 |
| 14 | 2 | 2 | 3 | 1 |
| 15 | 2 | 2 | 3 | 1 |
| 16 | 2 | 3 | 1 | 2 |
| 17 | 2 | 3 | 1 | 2 |
| 18 | 2 | 3 | 1 | 2 |
| 19 | 3 | 1 | 3 | 2 |
| 20 | 3 | 1 | 3 | 2 |
| 21 | 3 | 1 | 3 | 2 |
| 22 | 3 | 2 | 1 | 3 |
| 23 | 3 | 2 | 1 | 3 |
| 24 | 3 | 2 | 1 | 3 |
| 25 | 3 | 3 | 2 | 1 |
| 26 | 3 | 3 | 2 | 1 |
| 27 | 3 | 3 | 2 | 1 |

significant. With the grey relational analysis and statistical analysis of variance, the optimal combination of the process parameters can be predicted. Based on the above discussion, the orthogonal array with the grey relational analysis to optimize the process is investigated.

The Taguchi method is devised for process optimization and identification of optimal combinations of factors for given responses (Cox and Reid, 2000; Logothetis and Haigh, 1988). In the present analysis, an L27 orthogonal array with four columns and twenty seven rows is used. This array can handle four-three level process parameters and has twenty six degrees of freedom. Therefore only twenty seven experiments are required to study the entire machining parameters using the L27 orthogonal array.

The experimental layout for the machining parameters using the L27 orthogonal array is shown in Table 1.

## ELECTRICAL DISCHARGE MACHINING PROCESS

Electrical Discharge Machining is one of the most accurate manufacturing processes available for creating complex or simple shapes and geometries within parts and assemblies. EDM works by eroding material in the path of electrical discharges that form an arc between an electrode tool and the work piece. EDM manufacturing is quite affordable and a very desirable manufacturing process when low counts or high accuracy is required.

The EDM system consists of a shaped tool or wire electrode and the part. The part is connected to a power supply. Sometimes to create a potential difference between the work piece and tool, the work piece is immersed in a dielectric (electrically nonconducting) fluid which is circulated to flush away debris.

EDM removes metal by discharging an electric current across a narrow dielectric filled gap between the tool and the workpiece. It uses heat to produce a tiny crater by melting and vaporization. Common methods of evaluating machining performance in the EDM operation are based on the following performance characteristics: material removal rate, surface roughness and electrode wear ratio. Basically, material removal rate, surface roughness and electrode wear ratio are correlated with the machining parameters such as workpiece polarity, pulse on time, duty factor, open discharge voltage, discharge current and dielectric fluid. Proper selection of the machining parameters can obtain higher material removal rate, better surface roughness and lower electrode wear ratio.

### Machining Parameter Selection

The essential steps include identifying the factors that are to be included in the study and determining the factor levels. It was decided to study the effect of the parameters viz., pulse on-time (A) in the range 20-300 μsec, Discharge current (B) in the range 1.5-6 A, Discharge voltage (C) in the range 100-150 V and Duty factor (D) in the range 0.3-0.7 on.

The responses viz., Material Removal Rate (MRR), Electrode Wear Ratio (EWR) and Surface Roughness (SR). The range of the input parameters was fixed as shown in Table 2.

In this study, $L_{27}$ orthogonal array was chosen that include 13 columns that can be used to assign test factors and their interactions. For 3 factor with 3 level setup the total number of experiments to be conducted is given by $3^3 = 27$.

Table 2: Machining parameters and their levels

| Symbol | Machining parameter | Unit | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| A | Pulse on-time | μsec | 20.0 | 150.0 | 300.0 |
| B | Discharge current | A | 1.5 | 4.0 | 6.0 |
| C | Discharge voltage | V | 100.0 | 120.0 | 150.0 |
| D | Duty factor | | 0.3 | 0.5 | 0.7 |

**Machining Performance Assessment**

Material removal rate, surface roughness and electrode wear ratio are used to evaluate machining performance. The Material Removal Rate (MRR) is expressed as the Work Piece Removal Weight (WRW) over a period of machining time (T) in min, that is:

$$\text{MRR (g min}^{-1}) = \frac{\text{WEW}}{\text{T}} \tag{1}$$

The Electrode Wear Ratio (EWR) is defined as the ratio of the Electrode Wear Weight (EWW) to the Work Piece Removal Weight (WRW) and is usually expressed as a percentage, that is:

$$\text{EWR (\%)} = \frac{\text{EWW}}{\text{WRW}} \times 100 \tag{2}$$

The higher the material removal rate in the EDM process, the better is the machining performance. However, the smaller the electrode wears ratio and surface roughness in the EDM process, the better is the machining performance. Therefore, the material removal rate is the higher-the-better performance characteristic and the electrode wear ratio and surface roughness are the lower-the-better performance characteristics.

**Experimental Runs**

The experimental runs conducted on Aristech LS-350 model EDM machine. a pure copper with diameter 6.00 mm is used as a electrode. The work piece has been made by tool steel SKD11. IonoPlus 3000 is used as a dielectric. After removing material from work piece, the result surface roughness is measured using profile meter (3D-Hommelewerk). The experimental results are shown in Table 3.

Table 3: Experimental results for machining parameters

| No. | Material removal rate (g min$^{-1}$) | Electrode wear ratio (%) | Surface roughness (μm) |
|---|---|---|---|
| 1 | 0.00135 | 23.171 | 2.111 |
| 2 | 0.00122 | 33.862 | 3.152 |
| 3 | 0.00151 | 39.721 | 2.956 |
| 4 | 0.00425 | 21.962 | 3.322 |
| 5 | 0.00275 | 24.718 | 3.215 |
| 6 | 0.00355 | 28.151 | 2.617 |
| 7 | 0.00410 | 21.775 | 4.352 |
| 8 | 0.00395 | 27.532 | 3.719 |
| 9 | 0.00352 | 30.212 | 5.211 |
| 10 | 0.00212 | 35.944 | 3.325 |
| 11 | 0.00325 | 44.575 | 2.567 |
| 12 | 0.00292 | 58.382 | 2.952 |
| 13 | 0.00385 | 9.512 | 3.851 |
| 14 | 0.00452 | 8.257 | 3.647 |
| 15 | 0.00432 | 7.476 | 2.925 |
| 16 | 0.00395 | 4.445 | 4.254 |
| 17 | 0.00447 | 4.432 | 4.553 |
| 18 | 0.00383 | 5.125 | 3.622 |
| 19 | 0.00412 | 2.359 | 3.351 |
| 20 | 0.00395 | 6.948 | 2.159 |
| 21 | 0.00387 | 8.844 | 2.498 |
| 22 | 0.00432 | 110.342 | 1.954 |
| 23 | 0.00518 | 90.751 | 3.365 |
| 24 | 0.00417 | 95.597 | 2.743 |
| 25 | 0.00125 | 40.524 | 4.927 |
| 26 | 0.00132 | 35.345 | 2.786 |
| 27 | 0.00147 | 65.753 | 3.578 |

## RESULTS AND DISCUSSION

### Normalization of the Experimental Results and Computing the Grey Relational Analysis for the Experimental Results

A linear normalization of the experimental results for the responses viz. MRR, EWR and SR is performed in the range between 0 and 1, which is called as the Grey relational generating. In the study, a linear data preprocessing method (Hsia and Wu, 1998) for the material removal rate can be expressed as:

$$X_{ij} = \frac{y_{ij} - \min_j y_{ij}}{\max_j y_{ij} - \min_j y_{ij}} \qquad (3)$$

And for electrode wear ratio and surface roughness can be expressed as:

$$X_{ij} = \frac{\max_j y_{ij} - y_{ij}}{\max_j y_{ij} - \min_j y_{ij}} \qquad (4)$$

where, $y_{ij}$ is the ith experimental results in the jth experiment. According to Deng (1989b), larger normalized results correspond to the better performance and the best-normalized result should be equal to 1.

### Computing the Grey Relational Coefficients

In the grey relational analysis, experimental data (electrode wear ratio, material wear rate and surface roughness) are first normalized in the range between 0 and 1, which is also called the grey relational generating. Next, the grey relatioual coefficient is calculated from the normalized experimental data to express the relationship between the desired and actual experimental data. The Grey relational coefficient $\delta_{ij}$ can be expressed as:

Table 4: The gray relational coefficient

| No. | Material removal rate | Electrode wear ratio | Surface roughness |
|---|---|---|---|
| 1 | 0.3408 | 0.7218 | 0.9121 |
| 2 | 0.3333 | 0.6315 | 0.5761 |
| 3 | 0.3504 | 0.5910 | 0.6191 |
| 4 | 0.6804 | 0.7337 | 0.5434 |
| 5 | 0.4490 | 0.7071 | 0.5636 |
| 6 | 0.5200 | 0.6767 | 0.7106 |
| 7 | 0.6492 | 0.7355 | 0.4044 |
| 8 | 0.6168 | 0.6820 | 0.4799 |
| 9 | 0.5440 | 0.6597 | 0.3333 |
| 10 | 0.3929 | 0.6166 | 0.5429 |
| 11 | 0.5064 | 0.5612 | 0.7265 |
| 12 | 0.4646 | 0.4908 | 0.6200 |
| 13 | 0.5982 | 0.8831 | 0.4619 |
| 14 | 0.7500 | 0.9015 | 0.4903 |
| 15 | 0.7046 | 0.9134 | 0.6265 |
| 16 | 0.6168 | 0.9628 | 0.4145 |
| 17 | 0.7361 | 0.9649 | 0.3852 |
| 18 | 0.5946 | 0.9513 | 0.4940 |
| 19 | 0.6513 | 1.0000 | 0.5382 |
| 20 | 0.6168 | 0.9216 | 0.8888 |
| 21 | 0.6018 | 0.8927 | 0.7496 |
| 22 | 0.6971 | 0.3333 | 1.0000 |
| 23 | 1.0000 | 0.3792 | 0.5358 |
| 24 | 0.6622 | 0.3667 | 0.6736 |
| 25 | 0.3350 | 0.5859 | 0.3539 |
| 26 | 0.3391 | 0.6207 | 0.6619 |
| 27 | 0.3480 | 0.4600 | 0.5166 |

$$\delta_{ij} = \frac{\min_i \min_j \left|x_i^0 - x_{ij}\right| + \xi \max_i \max_j \left|x_i^0 - x_{ij}\right|}{\left|x_i^0 - x_{ij}\right| + \xi \max_i \max_j \left|x_i^0 - x_{ij}\right|} \quad (5)$$

where, $x_0^i$ is the ideal normalized results for the ith performance characteristics and $\xi$ is the distinguishing coefficient which is defined in the range $0 \le \xi \le 1$.

Table 4 shows the grey relational coefficient for each experiment using the L27 orthogonal array.

## COMPUTING THE GREY RELATIONAL GRADES

The grey relational grade is computed by averaging the grey relational coefficient corresponding to each performance characteristic. The overall evaluation of the multiple performance characteristics is based on the grey relational grade.

$$\gamma_j = \frac{1}{m} \sum_{i=1}^{m} \delta_{ij} \quad (6)$$

where, $\gamma_j$ is the Grey relational grade for the jth experiment and m is the number of performance characteristics. The higher the Grey relational grade represents that the experimental result is closer to the ideally normalized value. in here, experiment 20 has the best multi response characteristics among the 27 experiments conducted (Table 5). The mean of the Grey relational grade for each level of the machining parameter can be calculated by averaging the Grey relational grade for pulse on time for experiment number 1-9 as level 1, experiment number 10-18 as level 2 and experiment number 19-27 as level 3. Similarly, it is calculated for the respective levels for discharge current, discharge voltage and duty factor and in addition, the total mean of the grey relational grade for the 27 experiments is also calculated and is shown in Table 6. The larger the value of the Grey relational grade, the better is the multi response characteristics.

Table 5: Gray relational grade for each experiment

| No. | Gray relation grade |
|---|---|
| 1 | 0.6582 |
| 2 | 0.5139 |
| 3 | 0.5202 |
| 4 | 0.6525 |
| 5 | 0.5732 |
| 6 | 0.6358 |
| 7 | 0.5964 |
| 8 | 0.5929 |
| 9 | 0.5123 |
| 10 | 0.5175 |
| 11 | 0.5980 |
| 12 | 0.5251 |
| 13 | 0.6477 |
| 14 | 0.7139 |
| 15 | 0.7482 |
| 16 | 0.6647 |
| 17 | 0.6954 |
| 18 | 0.6800 |
| 19 | 0.7298 |
| 20 | 0.8087 |
| 21 | 0.7480 |
| 22 | 0.6768 |
| 23 | 0.6383 |
| 24 | 0.5675 |
| 25 | 0.4249 |
| 26 | 0.5406 |
| 27 | 0.4415 |

Table 6: Response table for the gray relational grade

| Symbols | Machining parameter | Grey relational grad Level 1 | level 2 | level 3 | Max-min |
|---|---|---|---|---|---|
| A | Pulse on time | 0.5839 | 0.6434 | 0.6196 | 0.0595 |
| B | Discharge current | 0.6243 | 0.6504 | 0.5721 | 0.0783 |
| C | Discharge voltage | 0.6238 | 0.5454 | 0.6775 | 0.1321 |
| D | Duty factor | 0.5787 | 0.6876 | 0.5805 | 0.1089 |

Mean value of the Gray relational Grade = 0.6156

Table 7: The analysis of variance table for process parameters. Analysis of variance table [classical sum of squares-type II]

| Source | Sum of squares | df | Mean square | F-value | p-value Prob>F |
|---|---|---|---|---|---|
| Model | 0.194088 | 8 | 0.024261 | 9.03112 | < 0.0001 significant |
| Pulse on-time | 0.016117 | 2 | 0.008058 | 2.99969 | 0.0751 |
| Discharge current | 0.028661 | 2 | 0.014331 | 5.33457 | 0.0152 |
| Discharge voltage | 0.079435 | 2 | 0.039717 | 14.7847 | 0.0002 |
| Duty factor | 0.069875 | 2 | 0.034938 | 13.0055 | 0.0003 |
| Cor total | 0.242443 | 26 | | | |

**Analysis of Variance**

Since the experimental design is orthogonal, it is then possible to separate out the effect of each process parameter at different levels. The mean of the gray relational grade for each process parameter is calculated (Table 6). The optimal level of the process is the level with the greatest gray relational grade. According to Ghani *et al*. (2004), from figure of the gray relational grade for various levels (Table 6), it can be visually understood about to be significance of each parameter. Where there is a large slope for the graph lines, it can be understood that the parameter has significant effect on process. In this study, it can be found that there is no line with a significant slope for a pulse on time; however the slope of line for discharge voltage and duty factor is fairly high. May be it can visnally understood that discharge current has a significant effect too. But judge about that is relatively hard. However, visually judgment about the process is a strait forward method and there is no need for complex analysis of variance and everybody without more knowledge can get useful information about the process. However, for more precision it has been came ANOVA analysis too to do confirmation on conceptual approach (Table 1).

From statistical analysis it known that p-value less than 0.05 shows that specific parameter has significant effect on process and also p-value between 0.05 and 0.1 shows the low significant parameter (Table 7). If the p-value is more than 0.1 it understood that the specific parameter has not significant effect on process. the ANOVA result for this study indicates that pulse on time is low significant, while three other process parameters means, Discharge current, discharge voltage and duty factor are most significant affecting the multiple process response.

As it can be seen (Table 6), the conceptual approach for grey relational analysis is confirmed by the ANOVA analysis.

## CONCLUSION

Electric Discharge Machining (EDM) is a relatively new method to product a precision parts. The optimization of multiple performance characteristics of EDM process using Grey relational analysis based on Taguchi orthogonal array is investigated. The response table and response graph for each level of the machining parameters is obtained. The study of grey relational graph for machining parameters shows that pulse on time is low significant, while three other process parameters means, discharge current, discharge voltage and duty factor are most significant affecting the multiple process response. While the greater grey relational grade is the best, so level 2 for Pulse on-time, Discharge current as well as Duty factor and level 3 for Discharge voltage is proposed.

It means that by selecting these levels for parameters, it result the maximum material removal rate, minimal electrode wear ratio and low Surface roughness. These optimal points are for condition that three responses are important simultaneously and where there is ouly one criterion for example surface roughness; maybe different optimal point will be achieved by analysis. It seems that Gray relational analysis is a strait forward method for optimizing multi-criteria problems in EDM process where two or more response can be study simultaneously.

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