Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

# OPTIMIZATION OF EDM INJECTION FLUSHING TYPE CONTROL PARAMETERS USING GREY RELATIONAL ANALYSIS ON AISI 304 STAINLESS STEEL WORKPIECE

P Siva, A S Rajan, V Rajasubramanian

Department of Mechanical Engineering, Nehru Institute of Technology, Kaliyapuram, Coimbatore 6411 05, Tamilnadu, India

***Correspondent Email:** **nitsrinivasan@nehrucolleges.com**

## ABSTRACT

This paper deals with optimization of Electrical Discharge Machining (EDM) Injection flushing type control parameters on multi-performance optimization characteristics instead of single performance optimization using Grey Relational Analysis (GRA) Method. The experimental control parameters were being optimized according to their various machining characteristics namely material removal rate (MRR), electrode wear ratio (EWR) and surface roughness (SR) using copper as the tool and AISI 304 stainless steel as the workpiece. This parameters optimization was based on Taguchi's orthogonal array (OA) combined with GRA. A grey relational grade (GRG) calculated based on GRA was used to optimize the EDM process with multiple performance characteristics and Taguchi's $L_{18}$ OA was used to plan the experiments. The machining parameters selected are polarity, pulse on duration, discharge current, discharge voltage, machining depth, machining diameter and dielectric liquid pressure. Results shown that machining performance was improved effectively using this approach. The predicted responses at optimum parameter levels are in good agreement with the results of confirmation experiments conducted for verification tests.

***Keywords:*** EDM, multi-performance optimization, orthogonal array, grey relational analysis

## INTRODUCTION

In EDM, the basic process is carried out by producing controlled electric sparks between a tool (electrode) and the workpiece, which both are immersed in a dielectric fluid (Wang and Yan, 1999). When the workpiece and the electrode are separated by a specific small gap, then a pulsed discharge occurs which melts and removes material from the workpiece. A DC pulse generator is used to initiate discrete sparks which have duration in the region of 0.2 – 100 $\mu$s, followed by a similar period during which deionization of the dielectric occurs and the gap is flushed of debris (Wang and Yan, 2000; Lee and Tai, 2003).

A fine surface finish is obtained by a combination of proper electrode material, good flushing condition and proper supply settings. Singh et al. (2004) investigated the effects of discharge current to MRR, electrode wear and surface roughness of En-31 tool steel with copper, copper tungsten, brass and aluminium electrodes. They concluded that, copper is comparatively a better electrode material as it gives better surface finish, low diameter overcut, high MRR and less electrode wear rate for En-31 tool steel workpiece. Aluminium is next to copper in performance and may be preferred when surface finish is not the main requirement.

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

The dielectric fluid must be circulated under a constant pressure to flush away the metal particles efficiently and assist in the machining process, other wise they may form bridges if still remain on. Too much dielectric fluid will remove the chips before they assist in cutting action and thereby causing a slower machining rate. Too little pressure will not quickly enough to remove the chips and thereby cause short circuits. Li and Lee (2001) found that MRR decreases gradually with the flushing pressure. The relative wear ratio decreases with low pressure in flushing and increases with high pressure in flushing. Improper settings of control factors in EDM injection flushing method may result in the causes of poor process performance, increased in process variability and decrease the manufacturability of products and processes.

Taguchi approach is not designed to optimize multiple response characteristics. It is used for optimizing single response characteristic. The lower-the-better characteristic for one factor may affect the performance other factors since other factors may demand higher-the-better characteristics (Roy, 2001). In present study, the use of orthogonal array with the Grey relational analysis (GRA) optimization methodology for multi-response optimization is discussed. The grey-Taguchi method has been applied to optimize multiple performance responses of end milling process (Kopac and Krajnik, 2007), electro discharge machining process (Lin and Lin, 2005) and arc welding process (Tarng *et al.* 2001). Through grey relational analysis, a grey relational grade is obtained to evaluate the multiple performance characteristics. As a result, optimization of the complicated multiple performance characteristics can be converted into optimization of a single grey relational grade.

## EXPERIMENTAL METHOD

### Workpiece

Stainless steel 304 (SS 304) workpiece is being used for the experiment. The chemical composition of the stainless steel (SS 304) workpiece is indicated in Table 1.

Table 1: Chemical composition of SS 304 (wt. %)

| Elements | Ni | Cr | Si | Mn | C | P | S | Fe |
|---|---|---|---|---|---|---|---|---|
| Wt.% | 9.25 | 19.0 | 1.00 | 2.00 | 0.08 | 0.045 | 0.03 | 68.5 |

### Equipment

Sodick A30R EDM electrical installation Mark-20 series and Vitol-2 kerosene dielectric liquid was used for the experiment. This machine has the electrode mover in [X], [Y] and [Z] axis direction according to the program made. In this experiment, only [Z] axis was being used to machine the workpiece.

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

## Experimental Design

Table 2 shows the machining parameters and their respective levels based on literature reviews conducted. Seven (7) factors are selected with a combination of four (4) electrical parameters and three (3) non-electrical parameters. Machining depth and machining diameter were selected for the control factors because they affected MRR, EWR and SR analysis. Based on Taguchi's method DOE, an $L_{18}$ ($2^1 \times 3^6$) orthogonal arrays table with 18 rows (corresponding to the number of experiments) was selected for the experimentation (Roy, 2001). Experimental layout of $L_{18}$ orthogonal array is shown in Table 3.

Table 2: Machining Control Parameters and their respective levels

| Factors | Description | Level 1 | Level 2 | Level 3 | Units |
|---|---|---|---|---|---|
| A | Polarity | Workpiece (-) | Workpiece (+) | - | Positive (+) Negative c |
| F | Machining Diameter | 9.5 | 11.0 | 12.5 | mm |
| G | Dielectric Liquid Pressure | 1.0 | 1.5 | 2.0 | Bar |

Table 3: Results of surface waviness in $L_{18}$ OA

| Exp | $P$ $\tau_{on}$ $I_d$ $V_d$ $l_i$ $D$ $P_l$ | MRR g/min) | Average values for EWR %) | SR ($\mu$m) |
|---|---|---|---|---|

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

Three criteria of machining performance characteristics namely material removal rate (MRR), electrode wear ratio (EWR) and surface roughness (SR) were used in present study. The weighing of the workpiece mass loss minus the initial workpiece mass before machining with the machining time taken will represent the MRR of the workpiece. MRR can be expressed as the workpiece removal weight (WRW) under a period of machining time in minute (T) as illustrated in Equation 1.

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

The weighing of the pipe tool electrode mass loss represents the electrode wear ratio (EWR). The electrode wear ratio (EWR) is defined by the ratio of the electrode wear weight (EWW) to the workpiece removal weight (WRW) and usually expressed as a percentage as shown in Equation 2.

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

The surface roughness (SR) of the machined workpiece is measure using Perthometer surface roughness measuring machine. Due to the variability of surface finish data, multiple measurements were taken of each surface evaluated so that averages could be calculated.

**Criteria for Optimization of Multiple Performance**

The optimization of the process includes the following steps:

(i) Normalizing the experimental results.
(ii) Calculating the Grey relational coefficients (GRC).
(iii) Averaging the GRC to calculate the Grey relational grade (GRG).
(iv) Analyzing the experimental results using the grey relational grade
(v) Selecting the optimal levels of process parameters
(vi) Verifying the optimal parameters setting through the confirmation experiment

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

Table 4: Normalized results, GRCs and GRGs

| Exp. | Normalized Values | | | Grey Relational Coefficients | | | Grey Relational Grade |
|---|---|---|---|---|---|---|---|
| | MRR | EWR | SR | MRR | EWR | SR | |
| 1 | 0.8084 | 0.3018 | 0.2809 | 0.8245 | 0.5631 | 0.5559 | 0.6478 |
| 2 | 0.7010 | 0.3958 | 0.4197 | 0.7507 | 0.5983 | 0.6080 | 0 |
| 3 | 0.4577 | 0.5145 | 0.0000 | 0.6240 | 0.6496 | 0.4737 | 0 |
| 4 | 0.8217 | 0.0000 | 0.4981 | 0.8347 | 0.4737 | 0.6420 | 0 |
| 5 | 0.5256 | 0.3827 | 0.5596 | 0.6548 | 0.5932 | 0.6714 | 0 |
| 6 | 0.0000 | 0.6111 | 0.8216 | 0.4737 | 0.6983 | 0.8346 | 0 |
| 7 | 0.5332 | 0.3826 | 0.7617 | 0.6585 | 0.5931 | 0.7906 | 0 |
| 8 | 0.342 | 0.5224 | 0.6916 | 0.5778 | 0.6533 | 0.7448 | 0.6586 |
| 9 | 0.6986 | 0.3712 | 0.4510 | 0.7491 | 0.5887 | 0.6211 | 0.6530 |
| 10 | 0.5755 | 0.9256 | 0.4159 | 0.6795 | 0.9236 | 0.6064 | 0.7365 |
| 11 | 1.0000 | 0.7921 | 0.5856 | 1.0000 | 0.8123 | 0.6847 | 0.8323 |
| 12 | 0.6286 | 1.0000 | 1.0000 | 0.7079 | 1.0000 | 1.0000 | 0.9026 |
| 13 | 0.799 | 0.8336 | 0.5128 | 0.8175 | 0.8440 | 0.6488 | 0.7701 |
| 14 | 0.3142 | 0.9210 | 0.2768 | 0.5676 | 0.9193 | 0.5545 | 0.6804 |
| 15 | 0.830 | 0.8749 | 0.5792 | 0.8416 | 0.8780 | 0.6814 | 0.8003 |
| 16 | | | | | | | |
| 17 | | | | | | | |
| 18 | | | | | | | |

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

0 0.7972 0.8396

0.312 0.9573 0.1327 0.5670 0.9547 2

0.5093 0.6770 0.608 0.9039 0.1014 0.6970 0.9036

6 0.5004 0.7003 7

0.851 0.8577 0.7711 0.8581 0.8635

## RESULTS AND DISUSSIONS

### Grey Relational Analysis

The first step of GRA is the linear normalization of DOE data according to the type response. Material removal rate (MRR) is the bigger-the-better performance criteria.

Meanwhile, electrode wear ratio (EWR) and surface roughness (SR) are the lower-the-better performance response. The raw experimental results are shown in Table 3. The normalized experimental results for MRR which observes the bigger-the-better performance criteria, $\chi_{ij}$ can be calculated as shown in Equation 3.

$$\chi_{ij} = \frac{y_{ij} - \min_i y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \tag{3}$$

where $y_{ij}$ is the $i$ th experimental results in the $j$ th experiment. Meanwhile, in case of EWR and SR which observe the lower-the-better performance criteria, the normalized experimental results, $\chi_{ij}$ can be calculated as shown in Equation 4.

$$\chi_{ij} = \frac{\min_i y_{ij} - y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \tag{4}$$

Larger normalized results correspond to the better performance and the best normalized result should be equal to 1 (Deng, 1989). The normalized values are ranged between zero and one. The larger values yield better performance and the ideal value should be equal to one. The normalized results for each machining response are shown in Table 4. Next, the Grey relational coefficient is calculated to express the relationship between the ideal and actual normalized experimental results. The grey relational coefficient can be calculated as shown in Equation 5.

$$\xi_{ij} = \frac{\min_i \min_j \left| x_i^o - x_{ij} \right| + \zeta \max_i \max_j \left| x_i^o - x_{ij} \right|}{\left| x_i^o - x_{ij} \right| + \zeta \max_i \max_j \left| x_i^o - x_{ij} \right|} \tag{5}$$

where $x_i^o$ is the ideal normalized result for the $i$ th performance characteristics. $\zeta$ is the distinguishing coefficient which is set between zero and one; in our case it was set to $\zeta$ = 0.9. The grey relational grades are calculated by averaging GRCs for each performance characteristic. The GRG values are tabulated in the last column of Table 4. The higher the GRG represents that the experimental result is closer to the ideally normalized value (Deng, 1989). In the present work, experiment 12 has the best multi response characteristics amongst the 18 experiments conducted. The mean GRG for each level of the machining parameters can be calculated by averaging the GRG based on OA as shown in Figure 1.

The optimal process parameter level yields the highest particular GRG in Figure 1. The optimal machining parameter setting is A2B1C3D1E2F1G2 or maintaining polarity at level 2 (workpiece (-) and tool (+)), pulse on duration at level 1 (4 μs), discharge current at level 3 (75 A), discharge voltage at level 1 (60 V), machining depth at level 2 (2.0 mm), machining diameter at level 1 (9.5 mm) and dielectric liquid pressure at level 2 (1.5 Bar).

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

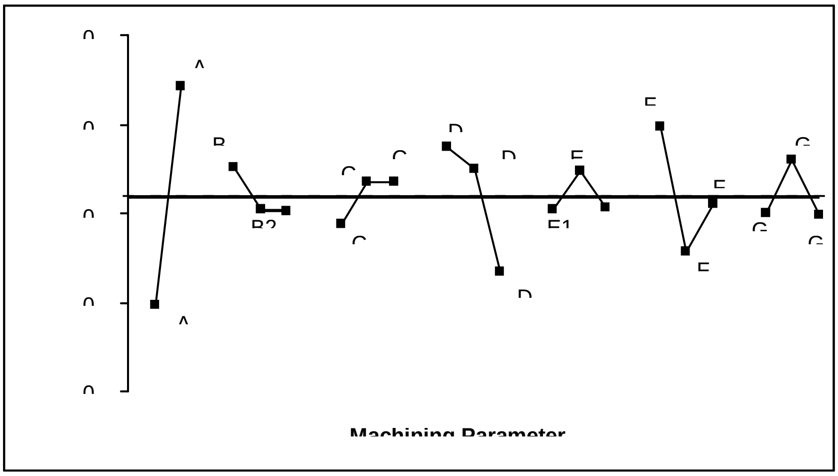

Figure 1: Grey relational grade plot

## Confirmation Test

The confirmation tests were conducted using the optimum combinations of machining factors. These confirmation tests were used to predict and verify the improvement in the quality characteristics for machining of stailess steel with respect to the chosen initial parameters setting. The predicted Grey relational grade $\alpha$^ using the optimal level of the machining parameters can be calculated as shown in Equation 6.

$$\alpha^{\wedge} = \alpha + \sum_{i=1} (\alpha_i - \alpha_m) \tag{6}$$

where $\alpha_m$is the total mean of the Grey relational grade, $\alpha_i$is the mean of the Grey relational grade at optimal level and $q$ is the number of the machining parameters.

Table 5 shows the comparison of the predicted and actual machining performance for all machining criteria using their respective optimal cutting parameters. The improvement in grey relational grade is 0.1639. The predicted Grey relational grade using optimal cutting parameters (0.8953) is comparable to the actual machining performance (0.9540). It is clearly shown that all machining criteria are greatly improved through this approach.

Table 5: Result of the confirmation experiment

| | Initial cutting parameters | Optimal cutting parameters | |
|---|---|---|---|
| | | Predicted | Experim |
| Setting level | A2B2C2D2E2F2G2 | A2B1C3D1E2F1G2 | |
| MRR (g/min) | 0.002556 | | 0.003658 |
| EWR (%) | 78.658 | | 65.368 |
| SR ($\mu$m) | 3.214 | | 2.143 |
| GRG | 0.7901 | 0.8953 | 0.9540 |

Special Issue on Proceedings of International Conference on Materials Manufacturing and Nanotechnology, June 2021. International Journal of Aquatic Science, Vol 12, Issue 03, 2021

## CONCLUSIONS

The use of the Taguchi's OA with GRA to optimize the EDM process of stainless steel with multiple performance characteristics has been successfully reported in this paper. Optimization of multiple performance characteristics was simplified through this approach. The experimental result for the optimal setting shows that there is considerable improvement in the process. It is shown that the performance characteristics of the EDM process namely material removal rate (MRR), electrode wear ratio (EWR) and surface roughness (SR) are improved together by using this method.

## REFERENCES

Deng, D.L. (1989) Introduction to Grey System, *Journal of Grey System* **1** (1) 1-24.

Kopac, J. and Krajnik, P. (2007) Robust Design of Flank Milling Parameters Based on Grey-Taguchi Method, Journal of Materials Processing Technology 191 400-403.

Lee, H.T. and Tai, T.Y. (2003) Relationship between EDM parameters and surface crack formation, *Journal of Materials Processing Technology* **142** 676-683.

Li, X.P. and Lee, S.H. (2001) Study of the effect of machining parameters on the machining characteristics in electrical discharge machining of tungsten carbide, *Journal of Materials Processing Technology* **115** 344-358.

Lin, C.L., Lin, J.L. and Ko, T.C. (2002) Optimisation of the EDM Process Based on the Orthogonal Array with Fuzzy Logic and Grey Relational Analysis Method, *International Journal of Advanced Manufacturing Technology* **19** 271-277.

Lin, J.L. and Lin, C.L. (2005) The use of Grey-Fuzzy Logic for the Optimization of the Manufacturing Process, *Journal of Materials Processing Technology **160** (1)* 9-14.

Roy, R.K. (2001) Design of Experiments Using the Taguchi Approach: 16 Steps to Product and Process Improvement, John Wiley & Sons, Inc, New York.

Singh, S., Maheshwari, S. and Pandey, P.C. (2004) Some investigations into the electric discharge machining of hardened tool steel using different electrode materials, *Journal of Materials Processing Technology* **149** 272-277.

Tarng, Y.S., Juang, S.C. and Chang, C.H. (2002) The use of Grey-based Taguchi Methods to Determine Submerged Arc Welding Process Parameters in Hard facing, *Journal of Materials Processing Technology* 128 1-6.

Wang, C.C. and Yan. B.H. (2000) Blind-hole drilling of Al2O3/6061 Al composite using rotary electro-discharge machining, *Journal of Materials Processing Technology* **102** 90-102.

Wang, C.C. and Yan., B.H. (1999) The machining characteristics of Al2O3/6061 Al composite using rotary electro-discharge machining with a tube electrode, *Journal of Materials Processing Technology* **95** 222-231.