Optimization of Maghemite ($\gamma$-Fe$_2$O$_3$) Nano-Powder Mixed micro-EDM of CoCrMo with Multiple Responses Using Gray Relational Analysis (GRA)

Nagwa Mejid Elsiti¹*, M.Y. Noordin¹, Ani Idris², Faraj Saed Majeed¹

¹Dept. of Materials, Manufacturing and Industrial Engineering, Faculty of Mechanical Engineering Universiti Teknologi Malaysia, 81310, UTM, Skudai, Malaysia
²Department of Bioprocess Engineering, Faculty of Chemical Engineering, c/o Institute of Bioproduct Development, Universiti Teknologi Malaysia, UTM, Skudai 81310, Malaysia

Email: nagwa.mejid@yahoo.com

Abstract. This paper presents an optimization of process parameters of Micro-Electrical Discharge Machining (EDM) process with ($\gamma$-Fe$_2$O$_3$) nano-powder mixed dielectric using multi- response optimization Grey Relational Analysis (GRA) method instead of single response optimization. These parameters were optimized based on 2-Level factorial design combined with Grey Relational Analysis. The machining parameters such as peak current, gap voltage, and pulse on time were chosen for experimentation. The performance characteristics chosen for this study are material removal rate (MRR), tool wear rate (TWR), Taper and Overcut. Experiments were conducted using electrolyte copper as the tool and CoCrMo as the workpiece. Experimental results have been improved through this approach.

1. Introduction
Electrical Discharge Machining (EDM) is known as a thermal erosion process that electrically produces a spark vaporizing materials that are electrically conductive [1]. This process works through the application of a series of disconnected discharges between a tool, which is generally cathode, and an electrically conductive workpiece, which is normally anode, disjointed using a dielectric liquid medium. For the generation of the spark discharge, an appropriate gap, recognized as spark gap, is upheld between the workpiece and the tool [2]. A spark is created between the closest points between the electrode and the workpiece; then the material is removed by a spark from both the workpiece and the electrode [3]. Powder mixed EDM (PMEDM) is a promising technique which leads to the development of process capabilities and generates near-mirror-like surface finish with reduced surface cracks and homogenization of the white layer [4]. Performance of the PMEDM process depends upon characteristics like powder type, concentration, particle size, electrode area, workpiece constituents and properties [5]. The process parameters play a significant role for material removal. Determination of optimal machining parameters is continuous engineering task whose goals are to reduce the production costs and to achieve the desired product quality [6]. Many researchers studied the
optimizations of powder mixed EDM/micro-EDM. Singh and Yeh (2012) found that multiple performance characteristics evaluated for aluminum matrix composite during APM-EDM using grey relational analysis (GRA) result in improvement of material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR) [7]. Response surface methodology has been used with desirability approach for modeling and optimization of the process parameters during EDM of CK-45 die steel using Al2O3 powder suspension into dielectric fluid. The optimal condition of process parameters was found to maximize the MRR [8]. A simplified model based on Taguchi and Utility approach has been used for multi characteristic optimization of the process parameters and to obtain the optimal setting during machining of H-11 die steel using Si powder and copper tool [9]. Technique for order of preference by similarity to ideal solution (TOPSIS) was used to optimize multiple responses while machining Al-CuTiB2 to obtain the optimum parameters for machining [10]. Multi-objective optimization of PMEDM has been conducted using Taguchi, GRA, and principal component analysis to control the process parameters [11]. A new approach for the optimization of micro-wire EDM process with multiple performance characteristics based on the statistical-based ANOVA and GRA has been implemented which shows improved machining performance [12]. Multi-objective optimization using Grey Relational Analysis (GRA) was proposed to determine the optimal combination of process parameters [7, 13]. The study by Tripathy and Tripathy (2016), examined the hybrid multi-response optimization by employing TOPSIS and GRA during the EDM of H-11 die steel using chromium powder-mixed dielectric [14].

Past work reveals that PMEDM involves a huge number of input process variables which influence the quality of the machined component and thus investigating the relative importance of the process variables on the output performance characteristics becomes vital. Though several studies have reported the use of different powders mixed to the dielectric fluid, no study has been done to explore the combined effect of process variables on performance characteristics of the PMEDM process for CoCrMo. Multi-attribute decision-making techniques like GRA have not yet been implemented to find the optimal setting during PMµEDM of CoCrMo. The present work is a stride in this direction. An effort has been made to find an optimal set of process variables using multi-objective optimization using GRA to get maximum MRR and minimum TWR, Overcut and Taper using Fe2O3 nano-powder mixed to the dielectric fluid.

2. Experimental setup, procedure and equipment

For conducting experiments, the work material CoCrMo is cut into the sample pieces with the dimensions of 50 mm X 90 mm X 1 mm. The electrode copper of diameter 300µm and length 6000µm was used as tool material for machining CoCrMo. The commercially available “EDM 23” oil was selected as the dielectric fluid. All the experiments were conducted on AG40L Sodick die sinking EDM machine. Modified working fluid circulating system has been designed for experimentation. In modified system, a separate tank mounted with pump is installed for better circulation of (γ-Fe2O3) nano-powder and surfactant-mixed dielectric fluid. A motorized stirring system is incorporated to avoid settling of powder particles. The chosen process parameters and experimental conditions are presented in the Table 1. The design of experiment (DOE) chosen for this study was a 2-Level factorial design and is presented in Table 2. A digital weighing balance having capacity up to 200 grams with a resolution of 0.1mg was used for weighing the workpieces and electrodes before and after machining. Then the material removal rate (MRR), tool wear rate (TWR), Overcut and Taper are calculated using equations (1-4).
Table 1. Process parameters and experimental EDM conditions

| Tool electrode          | Copper (300μm diameter and 6mm length) |
|-------------------------|----------------------------------------|
| Workpiece material      | Co-Cr-Mo                                |
| Dielectric fluid        | EDM 23                                  |
| Nano-powder             | γ-Fe₂O₃, size less than 10nm (4 g/l)    |
| Peak current (A)        | 1.5, 2.25, 3A                           |
| Voltage (V)             | 60, 90, 120V                            |
| Pulse on-time (μs)      | 10, 105, 200μs                          |
| Duty factor             | 95%                                     |

\[
MRR = \frac{(W_1 - W_2)}{t \times \rho} \times 1000 \text{ (mm}^3/\text{min)} \tag{1}
\]

\[
TWR = \frac{(T_1 - T_2)}{t \times \rho} \times 1000 \text{ (mm}^3/\text{min)} \tag{2}
\]

\[
OC = \frac{D_w}{2} \text{ (mm)} \tag{3}
\]

\[
\text{Taper Angle (θ)} = \tan^{-1} \times \left(\frac{D_{\text{top}} - D_{\text{bottom}}}{2h}\right) \tag{4}
\]

Where The terms \( W_1 \) and \( W_2 \) represent the initial and final weights of the workpiece, respectively. The terms \( T_1 \) and \( T_2 \) denote the weights of the tool before and machining, respectively. The terms \( \rho \) denote the density (g/mm\(^3\)) of the workpiece whereas \( t \) denotes the machining time (min). The terms \( D_w = D_1 - D \), where \( D_1 \) and \( D \) represent the entry hole and electrode (tool) diameters, respectively. The terms \( \theta \) represent the taper angle; \( h \) is machining depth; \( D_{\text{top}} \) and \( D_{\text{bottom}} \) are the entry and exit diameters, respectively.

Table 2. Experimental plan and results

| Exp no | Levels of parameters | MRR   | TWR   | Taper | Overcut |
|--------|----------------------|-------|-------|-------|---------|
|        | Current (A)          | Voltage (V) | Pulse on (μs) |       |         |
| 1      | 1.50                 | 60    | 10    | 0.00240 | 0.00032 | 0.77 | 54.02 |
| 2      | 3.00                 | 60    | 10    | 0.01730 | 0.00500 | 4.63 | 56.67 |
| 3      | 1.50                 | 120   | 10    | 0.01162 | 0.02915 | 1.10 | 61.02 |
| 4      | 3.00                 | 120   | 10    | 0.05540 | 0.03376 | 5.04 | 66.44 |
| 5      | 1.50                 | 60    | 200   | 0.00063 | 0.00020 | 1.77 | 83.67 |
| 6      | 3.00                 | 60    | 200   | 0.01621 | 0.00248 | 3.73 | 103.98 |
| 7      | 1.50                 | 120   | 200   | 0.00295 | 0.00023 | 0.54 | 62.00 |
| 8      | 3.00                 | 120   | 200   | 0.02946 | 0.01781 | 8.86 | 100.57 |
| 9      | 2.25                 | 90    | 105   | 0.00765 | 0.00997 | 1.42 | 65.86 |
| 10     | 2.25                 | 90    | 105   | 0.00630 | 0.00646 | 0.85 | 69.68 |
| 11     | 2.25                 | 90    | 105   | 0.01804 | 0.00672 | 1.83 | 69.77 |
3. Analysis method

3.1. Grey rational analysis
Initiator of the Grey system theory (1982) was Deng [15] and it is widely used for measuring the degree of relationship between sequences by Grey relational grade [16]. In GRA, the experimental values of the measured quality characteristics are normalized in a range from zero to one [17]. This is known as grey relational generation. Then the grey relational coefficient (GRC) is calculated. The overall Grey relational grade is then computed by averaging the Grey relational coefficient corresponding to each performance characteristic. As a result, optimal combination of process parameters is evaluated considering the highest Grey relational grade by using the Taguchi method. The overall performance characteristic depends on the computation of the grey relational grade (GRG). Thus, a multiple response process optimization is transformed into a single objective problem [6]. The highest GRG will be evaluated as the optimal parametric combination. Typically the normalization process involves two concepts into the Taguchi’s technique (nominal the smaller is the better and higher is the better) [18]. The “higher is the better” concept is used for normalizing the MRR by using Eq5, while the lower is the better concept is used for normalizing the variables TWR, Taper, and Overcut by using in Eq 6.

\[
x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)}
\]

\[
x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)}
\]

The terms \(x_i(k)\) is the \(i^{th}\) series in the original value of \(k\); order \(x_i^*(k)\) is the \(i^{th}\) series and \(k\) order after normalization, \(\min x_i(k)\) is the minimum value in the \(i^{th}\) series, \(\max x_i(k)\) is the maximum value in the \(i^{th}\) series. Table 3 shows the normalized results of experimental results obtained for performances.

| Exp no | MRR     | TWR     | Taper   | Overcut  |
|--------|---------|---------|---------|----------|
| 1      | 0.03232 | 0.99637 | 0.97236 | 1.00000  |
| 2      | 0.30436 | 0.85699 | 0.50841 | 0.94696  |
| 3      | 0.20066 | 0.13744 | 0.93269 | 0.85989  |
| 4      | 1.00000 | 0.00000 | 0.45914 | 0.75140  |
| 5      | 0.00000 | 1.00000 | 0.85216 | 0.40653  |
| 6      | 0.28446 | 0.93207 | 0.61659 | 0.00000  |
| 7      | 0.04236 | 0.99908 | 1.00000 | 0.84027  |
| 8      | 0.52638 | 0.47521 | 0.00000 | 0.06826  |
| 9      | 0.12817 | 0.70886 | 0.89423 | 0.76301  |
| 10     | 0.10352 | 0.81343 | 0.96274 | 0.68655  |
| 11     | 0.31788 | 0.80571 | 0.84495 | 0.68475  |

3.2. Grey rational coefficients (GRC)
Normalization creates a new matrix of difference vectors. From this matrix, a GRC is calculated, expressed as:
\[ \vartheta_i(k) = \frac{(\Delta \text{min} + \zeta \Delta \text{max})}{(\Delta_0(k) + \zeta \Delta \text{max})} \tag{7} \]

The term \( \vartheta_i(k) \) denotes GRC for the \( k \) output parameter and \( \Delta_0(k) = |x_0(k) - x_i*(k)| \) is the deviation sequence. Lastly, \( \Delta \text{min} = \min |x_0(k) - x_i*(k)| \) whereas \( \Delta \text{max} = \max |x_0(k) - x_i*(k)| \) and \( \zeta \) = weighting coefficient that is 0.5.

3.3. Grey Relational Grades (GRG)

Finally, the GRG is obtained by averaging the GRC corresponding to each performance measures. Thus by applying (Eq 8), all GRGs can be computed

\[ (\gamma)^i = \frac{1}{n} \sum_{i=1}^{n} \vartheta_i(k) \tag{8} \]

The term \( \gamma \) denotes the Grey Relational Grade (GRG) while \( n \) is the number of output parameters.

Table 4 shows the grey relational coefficient and grades for each output. Table 4 presents the grey rational coefficients and grades for each response.

| Expt. no | Grey Relational Coefficient | GRG (\( \gamma \)) | Rank |
|----------|-----------------------------|-------------------|------|
|          | MRR | TWR | Taper | Overcut |          |       |
| 1        | 0.34067 | 0.99278 | 0.94761 | 1.00000 | 0.82027 | 1 |
| 2        | 0.4181 | 0.7775 | 0.50424 | 0.90409 | 0.65103 | 4 |
| 3        | 0.3848 | 0.3669 | 0.88136 | 0.78111 | 0.60356 | 9 |
| 4        | 1.0000 | 0.3333 | 0.48037 | 0.66791 | 0.62040 | 8 |
| 5        | 0.3333 | 1.0000 | 0.77180 | 0.45726 | 0.64060 | 5 |
| 6        | 0.4113 | 0.8803 | 0.56599 | 0.33333 | 0.54776 | 10 |
| 7        | 0.3430 | 0.9981 | 1.00000 | 0.75789 | 0.77477 | 2 |
| 8        | 0.5135 | 0.4879 | 0.33333 | 0.34922 | 0.42100 | 11 |
| 9        | 0.36448 | 0.63200 | 0.82540 | 0.67844 | 0.62508 | 7 |
| 10       | 0.3580 | 0.7282 | 0.93065 | 0.61467 | 0.65790 | 3 |
| 11       | 0.4229 | 0.7201 | 0.76330 | 0.61331 | 0.62994 | 6 |

4. Results and discussion

Table 5 shows the mean of the GRG for each level of the machining parameters chosen for this study. The orthogonal experiment design separates out the effect of each machining parameter on the GRG at different levels. For example, the mean of GRG for the factor A at level 1 can be calculated by taking the average of the GRG for the experiment no. 1, 3, 5 and 7, respectively (shown in Table 4). Similarly, mean of the GRG for each level of other machining parameters can also be computed. In addition, the total mean of the GRG for the 11 experiments is also calculated and listed in Table 5. The total mean value of the GRG is 0.63566. As stated by Fung, "the grey relational grade represents the level of co-relation between the reference sequence and the comparability sequence" [19]. The greater value of the GRG means that the comparability sequence has a stronger correlation to the reference sequence. Therefore, the optimal level of the machining parameters is the level with the greatest GRG value. The level value marked asterisks (*) in response table, indicates that they results in a better PMuEDM performance. Based on the GRG given in Table 5, the optimal machining performance for
MRR, TWR, Overcut and Taper was obtained for peak current (level 1), voltage (level 1) and pulse current (level 1), pulse on time (level 1). Accordingly, the level constitution of optimal machining parameters are A1, B1 and C1 in the case of multiple performance characteristics optimization for PMµEDM, since higher GRG values yield better quality. The difference between the maximum and the minimum value of the GRG for PMµEDM machining parameters is also calculated and tabulated in Table 5. The tabulated results are follows: 0.1497 for current, 0.0599 for voltage, and 0.0777 for pulse on time, respectively. The most significant factor affecting performance characteristics is determined by comparing these values. This comparison gives the level of significance of the process parameters over the multiple performance characteristics. The most effective controllable factor was the maximum of these values. As per Table 5, the maximum value among the controllable factors is for peak current viz. 0.14975. This higher value indicates that the peak current has the strongest effect on the multiple performance characteristics among the other machining parameters. The order of importance of the machining parameters to the multiple performance characteristics in the PMµEDM process, in sequence can be ranked as: factor A (peak current), C (pulse on time), B (voltage). Figure 1 shows the main effects plot (response graph) based on GRG where the dash line indicates the value of the total mean of the GRG (viz. 0.63563). Accordingly A1, B1 and C1 are the optimal level of PMµEDM parameters in the case of multiple performance characteristics.

| Machining parameters | Grey Relational Grade | Main Effect Max-Min | Rank |
|----------------------|-----------------------|---------------------|------|
| Level 3 | Level 2 | Level 1 | |
| Current | 0.7098* | 0.63764 | 0.56005 | 0.14975 | 1 |
| Voltage | 0.66491* | 0.63764 | 0.60493 | 0.05998 | 3 |
| Pulse on | 0.67381* | 0.63764 | 0.59603 | 0.07778 | 2 |

Total mean value of GRG = 0.63566
* Levels for optimum GRG

Fig.1. Effects plot for GRG
5. Confirmation tests
Once the optimal level of the process parameters is identified, the final step is to predict and validate the improvement of the performance measures using the optimal level. A good indication of the satisfactory experimental runs is observed by subsequently comparing the results of the confirmation tests with the predicted value. The purpose of the confirmation experiment is to verify the conclusions drawn during the analysis phase. The estimated $\gamma^*$ using the optimal levels of the process parameters can be computed by using the following formula:

$$\gamma^* = \gamma m + \sum_{i=1}^{q} (\gamma i - \gamma m)$$  \hspace{1cm} (9)

Where $\gamma m$ is the total mean of the GRG, $\gamma^*$ is the mean of the GRG at the optimal level, and $q$ is the number of the process parameters that significantly affects the performance characteristics. The confirmation tests were carried out at the optimum levels predicted by the analysis of the results. From Eq 9, the estimated GRGs using the optimal PMµEDM parameters are computed. Table 6 shows the results of the confirmation tests using the optimal levels of PMµEDM parameters. As noted from Table 6, the MRR is decreased from 0.01162 to 0.0024 mm³/min, when the tool wear overcut and taper are minimized from 0.02915 to 0.00032 mm³/min, 61.02 m to 54.02 m and 0.872 to 0.43, respectively. An improvement of 0.20776 is noted in GRG, after validation.

Table 6. Results of performance measures for initial and optimal process parameters

| Responses | Initial Conditions | Optimal Factors | Prediction | Experiment |
|-----------|--------------------|-----------------|------------|------------|
| Level     | A3C3B3             | -               | A1B1C1     |            |
| MRR       | 0.01162            | -               | 0.00240    |            |
| TWR       | 0.02915            | -               | 0.00032    |            |
| T         | 0.87200            | -               | 0.43000    |            |
| OC        | 61.02000           | -               | 54.02000   |            |
| GRG       | 0.56193            | 0.78318         | 0.76969    |            |

Improvements in GRG = 0.20776

6. Conclusions
The GRA based on the 2-Level Factorial Design was proposed as an approach to investigate the optimization of powder mixed micro-EDM processes parameters for Co-Cr-Mo. The optimal machining parameters were determined by Grey Relational Grade (GRG) for the multi-performance characteristics; MRR, TWR, Taper and Overcut. According to the response table of the average GRG, the optimal process parameters were; 1.5A discharge current, 60V open voltage, 10μs pulse on time with improvement (0.20776) in GRA

Acknowledgement
Sincere regards are to the center for graduate studies of Universiti Teknologi Malaysia for its support during the conduct of this research.

References
1. N. M. Elsiti, M.Y.N., Experimental Investigations into the Effect of Process Parameters and Nano-Powder (Fe2O3) on Material Removal Rate during Micro-EDM of Co-Cr-Mo. Key Engineering Materials, 2017. 740: p. 125-132.
2. Singh, P.N., K. Raghukandan, and B.C. Pai, Optimization by Grey relational analysis of EDM parameters on machining Al–10%SiCP composites. Journal of Materials Processing Technology, 2004. 155-156: p. 1658-1661.
3. Jahan, M.P., Y.S. Wong, and M. Rahman, A study on the quality micro-hole machining of tungsten carbide by micro-EDM process using transistor and RC-type pulse generator. Journal of Materials Processing Technology, 2009. 209(4): p. 1706-1716.
4. Peças, P.H., E., Influence of silicon powder-mixed dielectric on conventional electrical discharge machining. International Journal of Machine Tools and Manufacture, 2003. 43(14): p. 1465-1471.
5. Peças, P. and E. Henriques, Electrical discharge machining using simple and powder-mixed dielectric: The effect of the electrode area in the surface roughness and topography. Journal of Materials Processing Technology, 2008. 200(1-3): p. 250-258.
6. Franko Puh, Z.J., Mladen Perinic, Miran Brezocnik, Stipo Buljan, Optimization of machining parameters for turning operation with multiple quality characteristics using Grey relational analysis. Tehnicki vjesnik - Technical Gazette, 2016. 23(2).
7. Singh, S. and M.F. Yeh, Optimization of Abrasive Powder Mixed EDM of Aluminum Matrix Composites with Multiple Responses Using Grey Relational Analysis. Journal of Materials Engineering and Performance, 2011. 21(4): p. 481-491.
8. Assarzadeh, S. and M. Ghoreishi, A dual response surface-desirability approach to process modeling and optimization of Al2O3 powder-mixed electrical discharge machining (PMEDM) parameters. The International Journal of Advanced Manufacturing Technology, 2012. 64(9-12): p. 1459-1477.
9. H K Kansala, S.S., Pradeep Kumarc, Performance parameters optimization (multi-characteristics) of powder mixed electric discharge machining (PMEDM) through Taguchi’s method and utility concept. Indian Journal of Engineering & Materials Sciences, 2006. Vol. 13: p. 209-216.
10. Senthil, P.V., S.; Singh, A.K, Parametric optimisation of EDM on Al-Cu/TiB2 insitu metal matrix composites using TOPSIS method. International Journal of Machining and Machinability of Materials, 2014. 16: p. 80-94.
11. Talla, G., et al., Modeling and multi-objective optimization of powder mixed electric discharge machining process of aluminum/alumina metal matrix composite. Engineering Science and Technology, an International Journal, 2015. 18(3): p. 369-373.
12. Somashekkar, K.P., J. Mathew, and N. Ramachandran, Multi-objective optimization of micro wire electric discharge machining parameters using grey relational analysis with Taguchi method. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 2011. 225(7): p. 1742-1753.
13. Talla, G., S. Gangopadhyay, and C.K. Biswas, Multi Response Optimization of Powder Mixed Electric Discharge Machining of Aluminum/Alumina Metal Matrix Composite Using Grey Relation Analysis. Procedia Materials Science, 2014. 5: p. 1633-1639.
14. Tripathy, S. and D.K. Tripathy, Multi-attribute optimization of machining process parameters in powder mixed electro-discharge machining using TOPSIS and grey relational analysis. Engineering Science and Technology, an International Journal, 2016. 19(1): p. 62-70.
15. Deng, J.L., Introduction to Grey System Theory. J. Grey Syst, 1989. 1: p. 1-24.
16. Senthilkumar, N., J. Sudha, and V. Muthukumar, A grey-fuzzy approach for optimizing machining parameters and the approach angle in turning AISI 1045 steel. Advances in Production Engineering & Management, 2015. 10(4): p. 195-208.
17. Sanjay Kumar Majhi, M.K.P., Hargovind Soni, OPTIMIZATION OF EDM PARAMETERS USING INTEGRATED APPROACH OF RSM, GRA AND ENTROPY METHOD. International Journal of Applied Research in Mechanical Engineering (IJARME), 2013. 3: p. 1-8.
18. Kumar. S, V. and P. Kumar. M, Optimization of cryogenic cooled EDM process parameters using grey relational analysis. Journal of Mechanical Science and Technology, 2014. 28(9): p. 3777-3784.
19. Fung, C.-P., Manufacturing process optimization for wear property of fiber-reinforced polybutylene terephthalate composites with grey relational analysis. Wear, 2003. 254(3-4): p. 298-306.