# Framework for the parametric optimization of powder mixed EDM using PCA: A case study

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**Abstract —** The proposed framework in this paper tries to explain that how to integrate the design of experiment (DOE) tools with the principal component analysis (PCA) and grey relational analysis (GRA) techniques, such that which gives the best optimal results for the multi-performance characteristics (MPC'S) i.e material removal rate (MRR) and surface roughness (SR) of powder mixed electrical discharge machining process of difficult-to-cut material. These approaches not only helps to obtain the optimal solution but also helps to handled the element of uncertainty fuzziness associated with the uncertain, multi-input and discrete data. Then theoretical prediction of experimental results shows that there is an improvement in the experimental results for the optimal parameters than the predicted results. Finally, an analysis of variance (ANOVA) was performed to identify the sensitivity of each input parameter which may affect the process performance, it can tells the percentage contribution of each parameter to the study.

**Index Terms—** Grey, Powders, design of experiments, discharge and dielectric.

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## 1 INTRODUCTION

Electrical discharge machining (EDM) an important "non-traditional machining method" has been accepted worldwide as a standard process for machining the hard-to-cut materials, to produce die castings, press tools, forging dies etc. According to Fallbohmer et. al., 1996 [1] electrical discharge machining is capable to machine the super-tough, electrically conductive materials such as the newly developed hybrid materials that are difficult-to-machine with conventional machining methods. EDM is successfully used and accepted in the process of mould and die, aerospace, automotive and surgical components manufacturing industries [2, 3]. Although EDM process is not affected by the material properties like hardness, toughness and strength etc., but still this process is much slower comparative to the other conventional process. Speed of EDM process is increased by varying the input parameters for e.g. by increasing the discharge current, but alongside this variation affects the machining process and degrades the quality of the manufactured product. Also when number of debris exists inside the gap increases, it can make the process unstable due to arcing which causes the improper material removal rate and bad surface finish. Therefore, to develop a EDM process with the capability of high material removal rate (MRR), low tool wear rate (TWR) and good surface finish (SF) with minimum no. of surface defects remains a big challenge. Due to above mentioned reasons, many researchers [4, 5, 6] from last few decades are trying to improve the electrical discharge machining process mechanism to make the process stable and more useful. With the addition of additives or foreign particles into the dielectric fluid is a useful approach to improve the EDM process performance.

For example as mentioned as above that material removal rate (MRR) and surface roughness (SR) all are different prospective output responses to achieve the optimal values for e.g. MRR is higher-the-better response and SR is lower-the-better response to get the optimal values for both at the same time is a challenging task and various multi-objective techniques are used to solve this type of problem. This paper mainly focused on the achievement of multi-performance characteristics by using the design of experiment, DOE tools (i.e. Taguchi, RSM and fractional factorial) with grey relational analysis method. Generally many authors used orthogonal array because it can optimize the performance characteristics through the setting of process parameters and reduce the sensitivity of the system performance to source of variation. Therefore due to this reason, OA has become a powerful design of experimental method [7, 8, 9]. Taguchi method is used by many researchers for single performance characteristics but to handle the multi-performance characteristics with this is still an interesting research problem.

As multiobjective optimum problems are centre of attraction for many researchers [10, 11], but very rarely applied for the machining of powder mixed EDM of difficult-to-cut materials. These multi-objective problems are mainly divided into two categories; one is optimal process parameters (OPPs) and second is result prediction. Mainly techniques are available in literature to deal with the multiobjective problems i.e. grey relational analysis, GRA [12], fuzzy logic [13], artificial neural network, ANN [14], response surface methodology, RSM [15] and simulated annealing, SA [16]. The purpose of present work is to introduce the use of grey relational analysis tech-

nique in selecting optimal parameters for PMEDM of difficult-to-cut materials on multi-performance characteristics.

In conjunction with principal component analysis (PCA) as it helps in reducing the dimensions of a set of variables by reconstructing them into uncorrelated combinations. In multiple output responses, there is a lot of uncertainty/fuzziness in the data and it is very difficult to find the relation between the data that whether the data is correlated and uncorrelated which gives us the more clarity about the results. Therefore principle component analysis is used to find the relationship between the outputs. The grey system theory initiated by Deng, 1986 has been proven to be useful for dealing with poor, in complete and uncertain information. It helps to solve the complex inter-relationships between the multiple performance characteristics effectively [17, 18, 19]. This is because grey relational analysis based on the grey system theory is used for solving the complicated inter relationships between the multi-performance characteristics. Further, the grey relational grade (GRG) values are used to evaluate the presence of degree of unceratainity into the experimental data.

According to author's best knowledge, there is no literature which describes the issue of principle component analysis to optimize the powder mixed electrical discharge machining of hard-to-cut materials. This paper is organized as; Section 1 presents introduction and literature survey, Section 2 introduces the framework proposed for the study. Section 3 presents the detailed steps of the optimization procedure and finally conclusions are summed up in Section 4.

## 2 FRAMEWORK DEVELOPMENT

Figure A (shown in APPENDIX A) shows the framework of PCA and GRA based optimization procedure to optimize the powder mixed EDM process parameters for the difficult material. This framework is basically divided into mainly 2-parts.

## 3. STEPS IN PCA BASED OPTIMIZATION

**Step 1:** Normalize the responses of quality characteristics
When the range of the series is too large or the optimal value of a response characteristic is too vast, due to this effect of some factors will be ignored. Therefore the experimental data should be normalized to prevent such effect. There are three different types of data normalization according to whether we require the smaller the better, the larger the better, or nominal the better [33]. The normalization is taken by the following equations.

a. Smaller the better (STB)

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{1}$$

b. Larger the better (LTB)

$$x_i^*(k) = \frac{x_i^*(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

Where $x_i^*(k)$ is the value after the grey relational generation

(data pre-processing), max $x_i^0(k)$ is the largest value of $x_i^0(k)$, max $x_i^0(k)$ is the smallest value of $x_i^0(k)$ and $x^0$ is the desired value. (Suffix i stand for run/experiment number and suffix $k$ stands for response).

**Step 2:** Test correlation between the quality characteristics
Let $Q_i$ = { $X_0^*(i)$, $X_0^*(i)$,..........., $X_m^*(i)$ }, $i = 1,2, . . . ,$n, be the normalized series of the $i$th quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following Eqn. no. 3:

$$\rho_{jk} = \frac{C_{ov}(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}} \tag{3}$$

Where $\rho_{jk}$ is the correlation coefficient between quality characteristic $j$ and quality characteristic $k$;

$C_{ov}(Q_j, Q_k)$ is the covariance of quality characteristic j and quality characteristic k; $\sigma_{Q_j}$ and $\sigma_{Q_k}$ are the standard deviation of quality characteristic j and quality characteristic k, respectively.

The correlation is checked by testing the following hypothesis: (As shown in APPENDIX B)

Note if the data in the series $Q_j$ and $Q_k$ follow a normal distribution, the correlation coefficient between two quality characteristics can be transferred to follow a $t$-distribution. The test statistic is calculated by Equation (4).

$$t = \frac{\rho_{jk} \sqrt{n-2}}{\sqrt{1-\rho_{jk}^2}} \sim t(n-2) \tag{4}$$

Set the significant level as $\alpha$. If $|t| > t_{\frac{\alpha}{2}(n-2)}$, reject the null hypothesis and go to Step 3; otherwise, go to Step 4.

**Step 3:** Calculate the principal component score
The research utilizes the following processes modified from the method proposed by Su and Tong [20] to compute the principle component score.

(1) Calculate the eigenvalue $\lambda_k$ and the corresponding eigenvector $\beta_k$ ($k = 1,. . . ,$ n) from the correlation matrix formed by all quality characteristics.

(2) Calculate the principal component scores of the normalized reference sequence and comparative sequences using Eq. (5).

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j) \beta_{kj}, i = 0; 1; …; m; k = 1; 2; …; n \tag{5}$$

Where $Y_i(k)$ is the principle component score of the $k$th element in the $i$th series, $X_i^*(j)$ is the normalized value of the $j$th element in the $i$th sequence, and $\beta_{kj}$ is the $j$th element of eigenvector $\beta_k$.

**Step 4:** Calculate the grey relational grade
(1) Calculate the grey relational coefficient.
Use the following equation to calculate the grey relational coefficient between $X_0(k)$ and $X_i(k)$.

$$r_{0,i}(k) = \frac{\Delta_{\min}(k) + \zeta.\Delta_{max}}{\Delta_{0,i}(k) + \zeta.\Delta_{max}} \tag{6}$$

$i = 1, . . . , m; k = 1, . . . , $n

Where $r_{0,i}(k)$ is the relative difference of kth element between sequence $X_i$ and the comparative sequence $X_0$ (also called as grey relational grade), and $\Delta_{0,i}(k)$ is the absolute value of dif-

ference between $X_0(k)$ and $X_i(k)$ (APPENDIX C)
Note $\zeta$ is a distinguishing coefficient, and its value is between 0 and 1. In general, it is set to 0.5 (Deng, 1989 [21]).

## 4. EXAMPLE OF AN PCA BASED APPLICATION TECHNIQUE

In this paper, a set of past experimental data from Patel et al. [22] on the EDM process where some of the responses are correlated are taken here for illustrative analyses and to show the application of the PCA method with grey relational analyses. Patel et al. [22] analyzed the multi objective responses of EDM process i.e. material removal rate (MRR) and surface roughness (SR) with grey relational analysis method and they perform nine experimental runs based on the L9 orthogonal array with four columns and nine rows is used and is presented in Table 1. The original values of MRR and SR with also calculated S/N ratio values are given in Table A shown in the (APPENDIX D). In the present paper, authors try to show the correlation between the responses and if they are correlated than further principle component score will be calculated otherwise directly go for the grey relational grade.

In this example, as S/N ratio is calculated for whom correlation is calculated and as it is noticed from the literature that MRR has "higher-the-better" and surface roughness is "lower-the-better" characteristic therefore following equations are used to calculate the S/N ratios for both.

First the correlation condition was checked and the correlation coefficient between two responses i.e. MRR & SR, variables was calculated and its value was -0.696. After performing the hypothesis test on the correlation between the two quality characteristics, the result showed that they are not correlated under the 95% significance level. Since, we could not reject the null hypothesis that the two quality characteristics are not correlated, it is not necessary to calculate the principal component scores. The next step is to directly execute the grey relational analysis and calculate the grey relational grade.

Pearson correlation of MRR and SR = -0.696

## 4 CONCLUSIONS

This paper described the optimization framework/procedure for the powder mixed electrical discharge machining of very hard-to-cut materials by using DOE tool with the principle component and grey relational analysis techniques. Further author's are working on the application of the proposed framework for the PMEDM of hard-to-cut material i.e. Tungsten Carbide alloy (WC).

**REFERENCES**

1. Fallbohmer P, Altan T, Tonshoff H K, Nakagawa T "Survey of die and mold manufacturing industry", Journal of Material Processing Technology 1996, 59, 158–68.

2. Singh S, Maheshwari S, Pandey P C "Some investigations into the EDM of hardened tool steel using different electrode materials", Journal of Materials Processing Technology 2004,149, 272–277.

3. Abbas N M, Solomon D G, Bahari M F "A review on current research trends in electrical discharge machining (EDM)", International Journal of Machine Tools and Manufacture 2007, 47, 1214–1228.

4. Kumar A, Maheshwari S, Sharma C, Beri N "Research Developments in Additives Mixed Electrical Discharge Machining (AEDM): A State of Art Review", Materials and Manuf. Processes 2010, 25, 1166–1180.

5. Kumar A, Maheshwari, S, Sharma C, Beri N "Analysis of machining characteristics in AEDM of nickel-based Super Alloy Inconel 718", Materials and Manufacturing Processes 2011, 26, 1011–1018.

6. Bhattacharya A, Batish A, Kumar N "Surface characterization and material migration during surface modification of die steels with silicon, graphite and tungsten powder in EDM process", Journal of Mechanical Science and Technology 2013, 27(1), 133-140. 21.

7. Ross P J "Taguchi Techniques for Quality Engineering", 1996, McGraw-Hill, New York.

8. Taguchi G "Introduction to quality engineering", 1990, Asian Productivity Organization, Tokyo.

9. Bendell A, Disney J, Pridmore W A "Taguchi Methods: Applications in world industry", 1989, IFS Publications, UK.

10. Y Y S, Huang W "A grey-fuzzy Taguchi approach for optimizing multi-objective properties of Zirconium containing diamond-like carbon coatings", Expert Systems with Appl. 2012, 39, 743-750.

11. Baraskar S S, Banwait S S, Laroiya S C "Multi-objective optimization of electrical discharge machining process using a hybrid model", Materials and Manufacturing processes 2013, 28, 348-354.

12. Caydas U, Hascalık A "Use of the grey relational analysis to determine optimum laser cutting parameters with multiperformance characteristics", Optics & Laser Technology 2008, 40, 987–994.5.

13. Cochran G, Cox G M "Experimental Design", 1962, Asia Publishing House, New Delhi.

14. Lin J L, Wang K S, Yan B H, Tarng Y S "Optimization of the EDM process based on the Taguchi method with fuzzy logics", Journal of Materials Processing Technology 2000, 102, 48-55.

15. Markopoulos, Angelos P, Manolakos, Dimitrios E, Vaxevanidis, Nikolaos M "ANN models for the prediction of surface roughness in electrical discharge machining", J Intell. Manuf. 2008, 19, 283–292.

16. Golshan A, Ghodsiyeh D, Izman S "Multi-objective optimization of wire electrical discharge machining process using evolutionary computation method: Effect of cutting variation", Proc. of the Institution of Mech. Engineers, Part B: Journal of Engineering Manufacture 2014, March 20, 0954405414523593.

17. Chen C B, Lin C T, Chang C W, Ho C P "Grey relation for solving multi-quality characteristics problems of Taguchi methods", Journal of Technology 2000, 15(1), 25–33.

18. Tan X, Yang Y, Deng J "Grey relational analysis factors in hypertensive with cardiac insufficiency", Journal of Grey System 1998, 10 (1), 75–80.

19. Wang Z, Zhu L, Wu J H "Grey relational analysis of correlation of errors in measurement", Journal of Grey System 1996, 8 (1), 73–78.

20. Zhu F, Yi M, Ma L, Du J "The grey relational analysis of the dielectric constant and others", Journal of Grey System 1996, 8 (3), 287–290.

21. Su C T, Tong L I "Multiresponse robust design by principal components analysis", Total Quality Management 1997, 8(6), 409–416.

22. Deng J "Introduction to grey system", Journal of Grey System 1989, 1(1), 1–24.

23. Patel K M, Pandey P M, Rao P V "Optimization of process parameters for multi-performance characteristics in EDM of $Al_2O_3$ ceramic composite", Int. J Adv. Manuf. Technol 2010, 47, 1137–114.

APPENDIX A
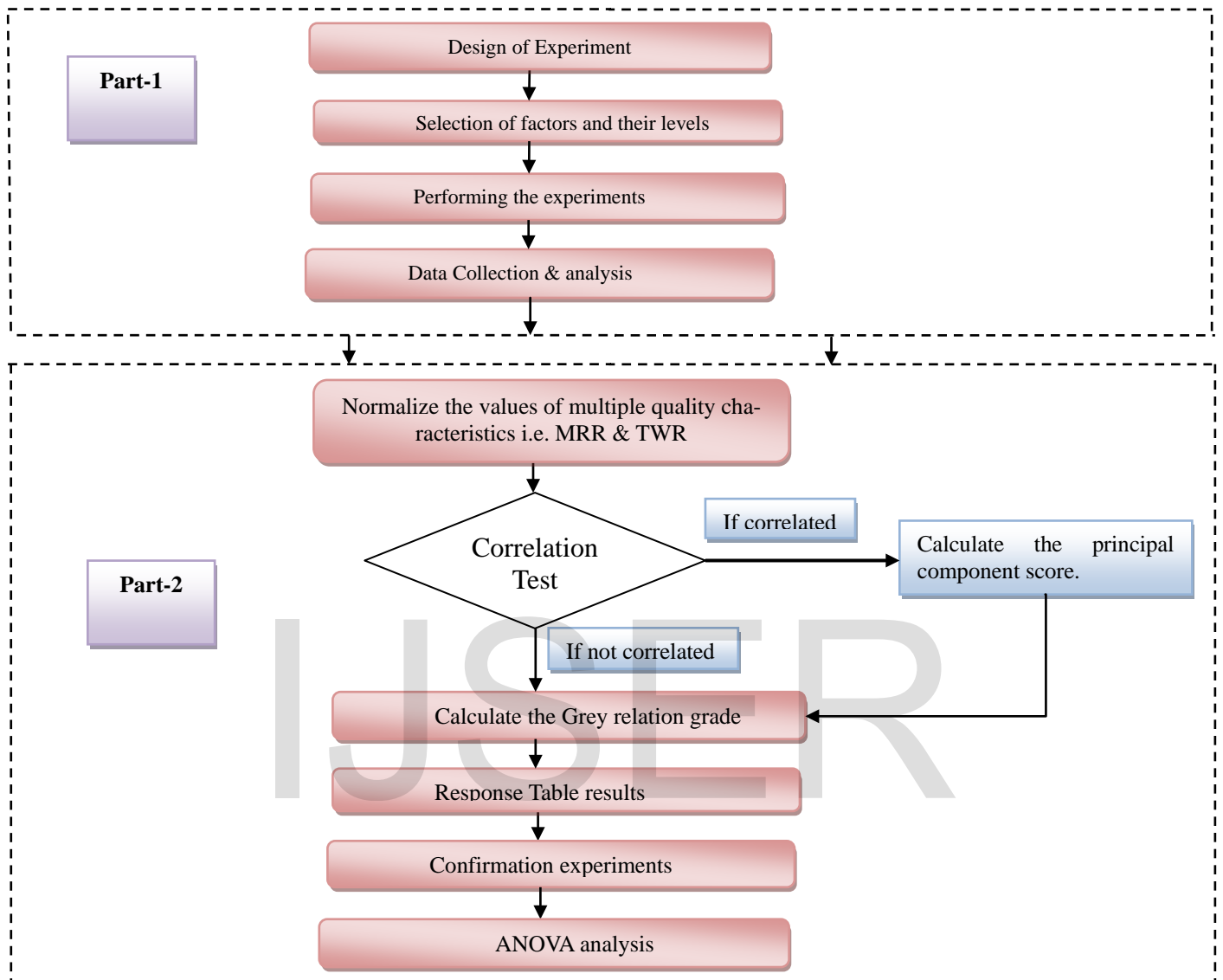


**Figure A** Principle component analysis & Grey relational analysis based optimization framework

APPENDIX B

$$\begin{cases} H_0: \rho_{jk} = 0 \ (\text{There is no correlation between quality characteristic } j \text{ and quality characteristic } k) \\ H_1: \rho_{jk} \neq 0 \ (\text{Quality characteristic } j \text{ and quality characteristic } k \text{ has correlation }) \end{cases}$$

APPENDIX C

$$\Delta_{0,i}(k) = \begin{cases} \left| X_0^*(k) - X_i^*(k) \right|, & \text{no significant correlation between quality characteristics} \\ \left| Y_0(k) - Y_i(k) \right|, & \text{there is significant correlation between quality characteristics} \end{cases}$$

$$\Delta_{max} = \begin{cases} \max_i \max_k \left| X_0^*(k) - X_i^*(k) \right|, & \text{no significant correlation between quality characteristic s} \\ \max_i \max_k \left| Y_0(k) - Y_i(k) \right|, & \text{there is significant correlation between quality characteristics} \end{cases}$$

$$\Delta_{min} = \begin{cases} \max_i \max_k \left| X_0^*(k) - X_i^*(k) \right|, & \text{no significant correlation between quality characteristics} \\ \max_i \max_k \left| Y_0(k) - Y_i(k) \right|, & \text{there is significant correlation between quality characteristics} \end{cases}$$

APPENDIX D

## **Table A** Experimental value of MRR and SR

| Exp. no. | Level | | | | Original Values | | S/N Ratio | |
|---|---|---|---|---|---|---|---|---|
| | Discharge Current (A) | Pulse-on time (D) | Duty cycle (C) | Gap voltage (D) | MRR (g/min) | Surface roughness, Ra (μm) | MRR | Surface roughness |
| 1. | 1 | 1 | 1 | 1 | 0.000688 | 2.2785 | -63.2482 | -7.1530 |
| 2. | 1 | 2 | 2 | 2 | 0.000895 | 2.8901 | -60.9635 | -9.2183 |
| 3. | 1 | 3 | 3 | 3 | 0.001822 | 2.6478 | -54.7890 | -8.4577 |
| 4. | 2 | 1 | 2 | 3 | 0.001400 | 1.6472 | -57.0774 | -4.3349 |
| 5. | 2 | 2 | 3 | 1 | 0.004097 | 4.0162 | -47.7507 | -12.0763 |
| 6. | 2 | 3 | 1 | 2 | 0.001407 | 3.5158 | -57.0341 | -10.9205 |
| 7. | 3 | 1 | 3 | 2 | 0.003968 | 3.3016 | -48.0286 | -10.3745 |
| 8. | 3 | 2 | 1 | 3 | 0.000985 | 2.3122 | -60.1313 | -7.2805 |
| 9. | 3 | 3 | 2 | 1 | 0.004212 | 5.1807 | -47.5102 | -14.2878 |

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