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Research Article

Multi-Response Optimization of EDM Parameters by Grey-PCA Method

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Abstract

This paper proposes a arrangement of Response Surface Methodology (RSM), Gray Relational Analysis (GRA) and Principal Component Analysis (PCA) used for optimizing the Electrical Discharge machining responses, such as material removal rate, surface roughness, and Radial overcut (ROC). The input parameters considered for this analysis are pulse current (I_p), discharge time (T_{on}), Duty cycle (Tau) to see the effect on the responses. The PCA is used to compute the weight of the responses during the optimization. Subsequently, the effects of each of these input parameters are analyzed and presented. These results provide the information that how to control the parameters so as to get the maximum MRR without losing the surface accuracy and tool accuracy.
These values of this parameters are observed that Ip= 2A , Ton = 100 µs, and Tou = 80% are the desired optimal combination where the GRG value is maximum (0.771). which are the best combination of this analysis.

Keywords: *Electrical discharge machining; EDM; Response surface methodology; RSM; Grey relational analysis; GRA; Principal component analysis; PCA; Material removal rate; MRR; Surface roughness; Ra. Radial overcut.*

1. Introduction

Electrical discharge machining is an earliest non-traditional machining process, where material is removed by a succession of electrical discharges occurring between an electrode and a workpiece. EDM is used widely in machining conductive hard metals and alloys in aerospace, automotive and die industries . EDM process is removing unwanted material in the form of waste from a part by means of a recurring electrical discharge between tool called electrode and the work material in the presence of dielectric fluid. In this machining process work piece is called a node. Dielectric fluid may be kerosene, transformer oil, distilled water, etc.

The use of a thermoelectric source of energy in developing the non-traditional techniques has greatly helped in achieving an economic machining of extremely low machinability materials and difficult jobs. The process of material removal by a controlled erosion through a series of electric sparks, commonly known as electric discharge machining.

When a discharge takes place between two points of the anode and cathode , the intense heat generated near the zone melts and evaporates the materials in the sparking zone. For improving the effectiveness, the work-piece and tool are submerged in a dielectric fluid. The spark frequency is normally in the range 200-500,00Hz, the spark gap being of the order of 0.025-0.05mm. The efficiency and the accuracy of performance have been found to improve when a forced circulation of the dielectric fluid is provided. The most commonly used dielectric fluid is kerosene. The tool is generally made of brass or a copper alloy.

EDM used from Second World War, when two Russian scientists B.R. and Lazarenko published their study on The Inversion of the Electric Discharge Wear Effect. This related to the application to manufacturing technology of the capacity of electrical discharges, under controlled distribution, to the material removal on the surface of the work piece. The new description on RSM that it provides only the most standard tools for first- and second-order response-surface design and analysis. The package can be quite useful for those standards Condition and it implements many of the analyses presented in textbooks. When number of factors is large then it becomes very complicated to separate the aliased effects and to interpret their significance. For this reason, when q is large, most of the time this kind of design is used for screening designs. After an appropriate design is conducted, the response surface analysis can be done by any statistical computer software and then statistical analyses can be applied to draw the appropriate conclusions. PCA purposes in regression analysis. First this technique is used to change a set of highly connected variables to a set of independent variables by using linear transformations. Second, this technique is used for variable reductions. When a dependent variable for a regression is specified than the PCA technique for

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dimension reduction due to the supervised nature of its algorithm. Principal Component Analysis is used for high dimensional data often runs into time and memory limitations. This is particularly the case if the dimension and the number of data set elements are of about the same size . The experiment uses GRA technique based on the orthogonal design. To other related Experiments, this method is simple. The experiment calculates the best factor combination and the predicted values are closer to the observed values. This approach easily converts the multiple performance characteristics into the GRG, thus simplifying the analysis. The results show that the optimal situation based on the method can offer better overall quality. Grey relation analysis for solving multi criteria optimization problem in the field of friction stir welding process. By Grey relational analysis, the optimal machining parameters setting can be obtained for considering maximum metal removal rate and minimum surface roughness simultaneously. Furthermore, this approach is feasible to obtain optimal machining parameters for a desired surface roughness and maximum metal removal rate by Grey relational analysis.

There are several parameters, which influence this process; however, some parameters are most influential. In this research and attempts have been made to see the effect of these parameters on the responses. Using this parameter (Ip, Ton, Tau) in this study was optimized for MRR, Surface Roughness, & Tool wear rate is very good. The best combination achieved using GRA, PCA, RSM methodology in this study by using the above parameters. Input parameters and their random order of input and output parameters, Normalization & deviation sequence of output parameters, and GRC, GRG calculation of Normalization & deviation sequence. And the blow Figure no. 1 Predicted vs. experimental Surface Roughness (SR), Figure 2 Plot of residuals vs. fitted value, Figure 3 Effect of Ip, Ton and Tau on SR and box graph of the mean of GRG and Main effects plot (data means) for GRG. Level Using pulse time, discharge current, and duty cycle. Therefore, using GRA, PCA, RSM process parameters can be successfully optimized for multiple responses through the best combination of above output parameter.

2. Experimentation

Table 1 Inputs & Their Level

Parameters	Units	Level 1	Level 2	Level 3
Discharge current (Ip)	A	2	5	8
Pulse on Time (Ton)	μs	50	100	150
Duty cycle (Tau)	%	70	80	90

There are three process parameters namely, discharge time (IP) , pulse on time (Ton) the duration for which the voltage is applied and duty cycle (Tau) were selected as input variables during the machining process in this study. For the experiments EDM oil is used as dielectric. With fixed value of servo voltage at 30V were applied. All three input parameters, which is a geometrical was kept at three levels. Preliminary experiments were conducted to select the range and values of the machining parameters. Table 1 depicts the value of levels of the selected parameters.

After using this parameters in their different levels in EDM machining process then the mathematical model is developed after analyzed the experimental values then illustrate the connection between the process variable and response then get some outputs namely material removal rate (MRR), surface roughness(SR), and redial over cut (ROC) which is given in Table 2.

Table 2 Experimental Plan with The Responses

Run	Ip	Ton	Tau	MRR	SR	ROC
1	8	50	70	14.15	6.45	0.18
2	5	100	80	9.54	8.24	0.19
3	5	100	80	9.98	8.46	0.24
4	5	100	80	9.28	8.11	0.16
5	2	100	80	2.48	4.29	0.02
6	8	150	70	18.34	10.03	0.20
7	5	150	80	9.39	6.87	0.19
8	2	150	70	1.51	4.40	0.09
9	2	50	70	1.50	4.95	0.00
10	5	100	80	9.55	8.24	0.19
11	5	100	70	7.75	7.31	0.10
12	2	50	90	1.03	5.20	0.01
13	5	100	80	9.34	8.14	0.17
14	5	100	90	9.36	7.87	0.10
15	8	50	90	21.73	7.42	0.15
16	2	150	90	4.54	4.33	0.09
17	8	100	80	18.16	9.74	0.22
18	8	150	90	19.15	9.98	0.24
19	5	50	80	9.33	5.34	0.13
20	5	100	80	9.88	8.41	0.23

3. Experimental Result

Table 3 Normalization & Deviation Sequence

	Normalized			Deviational sequence		
Ru	MRR	SR	ROC	MRR	Sr	ROC
1	0.634	0.624	0.264	0.366	0.376	0.736
2	0.411	0.312	0.205	0.589	0.688	0.795
3	0.433	0.273	0.019	0.567	0.727	0.981
4	0.398	0.335	0.313	0.602	0.665	0.687
5	0.070	1.000	0.934	0.930	0.000	0.066
6	0.836	0.000	0.170	0.164	1.000	0.830
7	0.404	0.551	0.226	0.596	0.449	0.774
8	0.023	0.982	0.636	0.977	0.018	0.364
9	0.023	0.886	0.987	0.977	0.114	0.013
10	0.411	0.311	0.200	0.589	0.689	0.800
11	0.325	0.474	0.603	0.675	0.526	0.397
12	0.000	0.842	0.962	1.000	0.158	0.038
13	0.402	0.329	0.286	0.598	0.671	0.715
14	0.402	0.376	0.579	0.598	0.624	0.421
15	1.000	0.455	0.375	0.000	0.545	0.625
16	0.170	0.993	0.618	0.830	0.007	0.383
17	0.827	0.051	0.076	0.173	0.949	0.924
18	0.876	0.009	0.005	0.124	0.991	0.995
19	0.401	0.818	0.473	0.599	0.182	0.528
20	0.428	0.282	0.061	0.572	0.718	0.939

Based on the experimental layout showed in the Table no. 2 the experiment were performed in random order and each specific experiment was repeated in two times. Three machining characteristic namely MRR, SR and ROC were measured. Normalization and deviation sequence of these variables were calculated as per the formula show in the Table no. 3

After finding the normalization and deviational sequence, find out the gray relational coefficient , GRG and RANK from these parameters and looking the higher value in the column of the GRG which is the best combination of MRR, SR and ROC. The Observed machining charactristric are show in the Table no. 4.

Table.4 GRC , GRG & Order

S. No.	Grey relational coefficient			GRG	Order
	MRR	SR	ROC		
1	0.577	0.571	0.405	0.515	8
2	0.459	0.421	0.386	0.420	17
3	0.468	0.408	0.338	0.401	20
4	0.454	0.429	0.421	0.434	15
5	**0.350**	**1.000**	**0.883**	**0.771**	**1**
6	0.753	0.333	0.376	0.470	11
7	0.456	0.527	0.393	0.459	14
8	0.339	0.965	0.579	0.648	5
9	0.339	0.814	0.975	0.732	2
10	0.459	0.421	0.385	0.419	18
11	0.425	0.487	0.558	0.494	9
12	0.333	0.760	0.930	0.696	3
13	0.455	0.427	0.412	0.430	16
14	0.455	0.445	0.543	0.482	10
15	1.000	0.478	0.444	0.618	6
16	0.376	0.987	0.567	0.662	4
17	0.743	0.345	0.351	0.463	13
18	0.801	0.335	0.335	0.470	12
19	0.455	0.733	0.487	0.566	7
20	0.466	0.411	0.347	0.405	19

4. Method of Modeling

Response Surface Methodology

Response-surface methodology (RSM) comprises a body of methods for exploring the best possible operating conditions by experimental methods. The RSM was developed to modeling and data analysis of problems by BOX and DRAPER in 1987. In RSM, the objective is obtained the correlation between the responses and variables & output is affected by various input variables. When the response function is unknown then the second order model is normally used and adopted. The mathematical model is developed after analyzing the experimental values then illustrate the connection between the process variable and response. The following second-order model explains the behavior of the system.

$$Y = \beta_0 + \sum_{i=1}^{k}\beta_i X_i + \sum_{i=1}^{k}\beta_{ii} X_i^2 + \sum_{i,j=1,\ i\neq j}^{k}\beta_{ij} X_i X_j + \varepsilon \qquad \text{………………I}$$

Where Y = corresponding response.

X_i = input variables.

X^2_{ii} = square of input variables

$X_i X_j$ = interaction terms of input variables.

The unknown regression coefficients are $b_{o,}$ b_i, $b_i j$ and b_{ii} and the error in the model is depicted as e .

Grey Relational Analysis

Developer of the GRA was DENG in 1982. GRA is based on the incomplete and uncertentity of small samples. GRA theory developed for the new methods for solving the complicated interrelationship among the multiple performing characteristics. There are two systems, first is black and second is white. White indicates having all collections of data and black indicates having no collection of data. In Gray system is an another system in GRA which is situated between black and white system. The gray words were named as the color, by this system is represented the amount of known collection of data is control theory. It need selected data to show the behavior of the uncertain system.

Whenever the limit of a sequence is increased or standard values is increasing in GRA the function of factor is avoided. The GRA might give incorrect results data must be pre-processed. Means of data pre-processing changing the original sequence into the comparable sequence, the range of normalization is 0 to 1. For the data pre-processing.

Table 5 Types of normalization

Normalization	Formulae
Lower the better	$X_i^*(k) = \frac{\max X_i(k) - X_i(k)}{\max X_i(k) - \min X_i(k)}$ …II
Higher the better	$X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)}$ ..III
Nominal the best	$X_i^*(k) = \frac{1 - \lvert X_i(k) - X_0 b(k)\rvert}{\max X_i(k) - X_0 b(k)}$ ..IV

If the expectancy is the small as possible, then the original sequence should be normalized by the lower the better equation, if expected value of original sequence is as high then normalization by the equation of higher the better and if there is a specific target value to be achieved, then the original sequence will be normalized through the equation of nominal is better. Which (equation) are given in the above chart.

where I = 1, 2n, k = 1, 2, y, p; X^*_i (k) is normalized value of the k^{th} element in the i^{th} sequence, X_0b(k)] is desired value of the k^{th} quality characteristic, *max X*i* (k) is the largest value of $X_i(k)$, and *min X*i* (k) is the smallest value of X_i(k), n is the number of experiments and p is the number of quality characteristics.

Usually grey relational coefficient is calculated after normalizing the data to display the relational ship between the actual and optimal normalized experimental result. The grey relational coefficient can be expressed as

$$\gamma_i(k) = \gamma(x_0(k)) = \frac{\Delta \min + \zeta \Delta \max}{\Delta_{0,i}(k) + \zeta \Delta \max} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{V}$$

, $i = 1, \ldots.n$; $k = 1, \ldots\ldots p$.

where $\Delta_0, i(k)$ = $|x_0(k) - xi(k)|$ is the difference of the absolute value called deviation sequence of the reference sequence $x_0(k)$ and comparability $xi(k)$. The Δ is the distinguishing coefficient or identification coefficient $0 \le \zeta \le 1$.

The grey relational grade g (x0, xi) identify the level of relationship between the reference sequence and the comparability sequence. for illustration, if the two sequences are identically coincidence, then grg is equal to 1. this grade also specifies the degree of influence that the comparability sequences could employ over the reference sequence. as a result, if a specific comparability sequence is more vital than the other comparability sequences to the reference sequence, then the grg for that comparability sequence will be greater than other. thus, grey analysis is basically a measurement of the absolute value of data dissimilarity between sequences, and it could be used to measure approximation relationship between sequences.

Principal Component Analysis

Principle Component Analysis (PCA) methodology is generally used in the Data analysis and Statistics and for the formation of predictive models , because it is a effortless , non-parametric technique for extracting appropriate information from confusing data sets in different region. PCA was discovered by Karl Pearson in 1901. The number of original variables is greater than or equal to the number of principal components. PCA is responsive to the relative scaling of the original variables. PCA can be done by eigenvalue/singular value decomposition of a data covariance matrix, usually after mean centering the data matrix for each characteristic by normalization. The major benefit of PCA is that the data can be compressed without much loss of information when the patterns in data have been identified.

The goals of PCA are to

1. Take out the most significant information from the data,
2. Compress the size of the data set by observance only this significant,
3. Simplify the justification of the data set, and
4. Study the structure of the explanation and the variables.

5. Result And Discussion

In this study Table no. 1 is show the input parameters and their levels after using this parameters in their different levels in edm machiing process then the mathematical model is obtained which is analyzed the experimental values then illustrate the connection between the process variable and response then get some outputs namely MRR, SR, ROC are show in table no. 2. Normalization andf deviation sequence of these variables observed

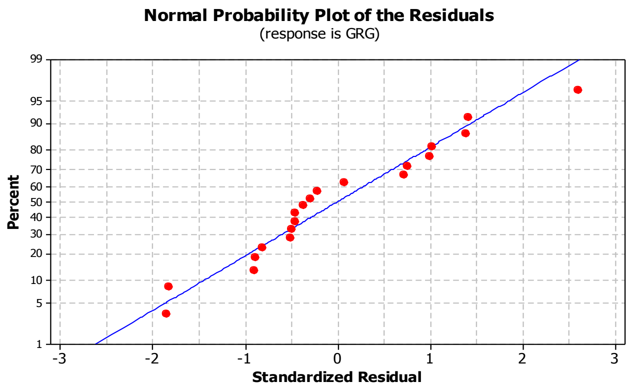

Figure 1 Predicted vs. experimental SR

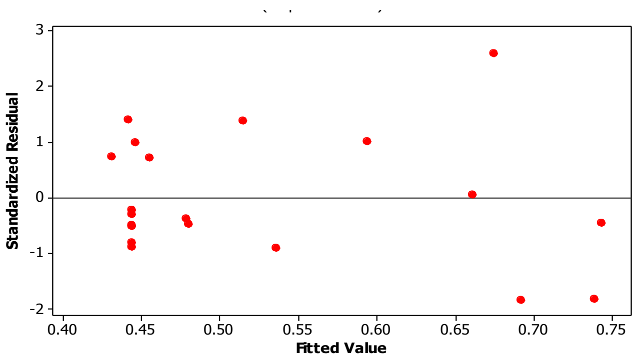

Figure 2 Plot of residuals vs. fitted value

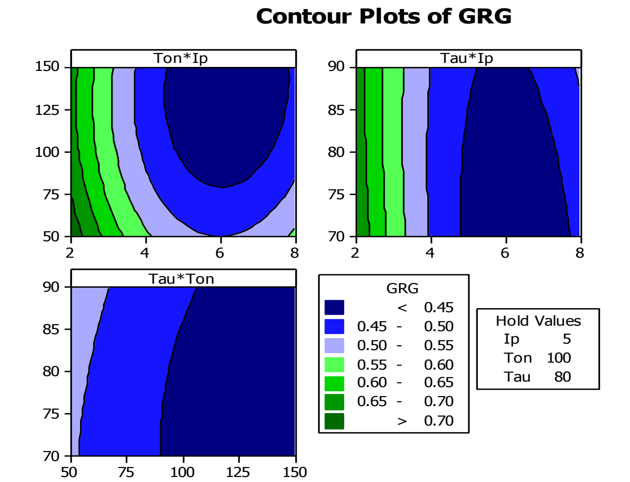

Figure 3 contour plots for GRG

machining charactristric are show in the Table. 3 and Table 4 shows the mean of the GRG for every levels of the machining parameters chosen for this study . The orthogonal experiment design individual at the effect of one by one machining parameter on the GRG at different levels. The GRG for the 20 experiment is also calculated and listed in table 4. The grey relational grad represent the level of co-relation between the references sequence and the comparability sequence. Therefore the optimal level of the machining parameters is the level with greatest GRG value . the best combination of the MRR, SR and ROC is obtained on the basis of GRG value from table 4. This higher value indicates that the pulse on time has the strongest effect on the multiple performance charactristrics between other machining pamameter. Figure 3 shows the main effect plot (data means) for the GRG the greater value in the figure 4 shown the higher MRR , lower SR and ROC.

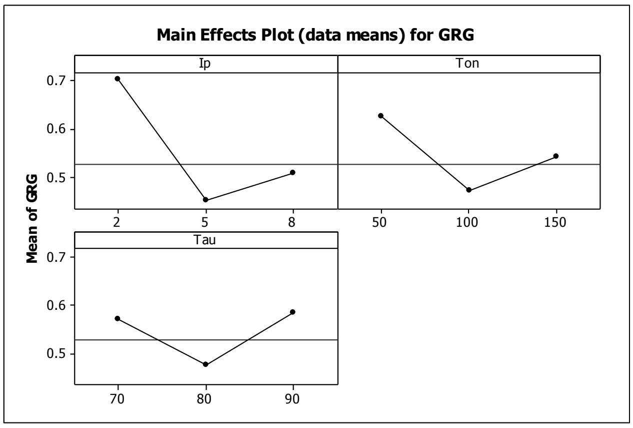

Figure 4 Effect of Ip, Ton and Tau on GRG

Conclusion

This study is an attempt to optimize EDM process using a hybrid technique of RSM, GRA and PCA. Initially the experiments were planed as per RSM, latter GRA was used, PCA was used to find weightage of the responses. Three process parameter namely discharge time (Ip), pulse current (Ton) and the duty cycle (Tau) were used in this study and found that all f hem are significant and affecting the MRR, SR and ROC under confidence level. The experiment no 5 i.e Ip= 2A , Ton = 100 μs, and Tou = 80% are the desired optimal combination where the GRG value is maximum (**0.771**). This is an attempt to combine three different techniques which was succecefuly implemented on EDM process and can be extended to other processes also.

References

Pradhan MK (2010) Experimental investigation and modelling of surface integrity, accuracy and productivity aspect in EDM of AISI D2 steel. PhD thesis, National Institute of Technology, Rourkela

Maitra, S., & Yan, J. (2008, November). Principle component analysis and partial least squares: Two dimension reduction techniques for regression. Paper presented at Casualty Actuarial Society, Seattle, WA.

Andre´.khuri and siuli mukhopadhy advanced revew on response surface methodology volume 2, march/april 2010, 2010 john wiley & sons, inc page no.128 to 149.

Sebastian klenk sebastian.klenk@vis.uni-stuttgart.de gunther heidemann ais@vis.uni-stuttgart.de a new method for principal component analysis of high-dimensional data using compressive sensenig . intelligent system department stuttgart university germany aprail 8, 2010.

T. Rajmohan at.al. optimization of machining parameter in drilling hybrid aluminium metal matrix composite online available science direct . trance non ferrous mat. soc. china22(2012)1286-1297.doi10.1016/s1003-6326(11)61317-4. recived 17oct 2011 and accepted 26dec 2011.

A.bhattyacharya at al. experimental investigation for multi-response optimization of bead geometry in submerged arc welding using grey analysis. journal of the institution of engineers (india): series c.june 2012, volume 93, issue 2, pp 123-132.

Jangra, kamal and jain, ajai and grover, sandeep , optimization of multiple-machining characteristics in wire electrical discharge machining of punching die using grey relational analysis, journal of scientific and industrial research, vol-69, pp-606--612 , 2010

Dvivedi, a., kumar, p. and singh, i. (2008) experimental investigation and optimisation in edm of al 6063 sicp metal matrix composite, *international journal of machining and machinability of materials*, vol. 3, nos. 3–4, pp.293–308.

El-taweel, t. (2008) multi-response optimization of edm with al–cu–si–tic p/m composite electrode, *international journal of advanced manufacturing technology*, pp.1–14, in press.

Ho, k.h. and newman, s.t. (2003) state of the art electrical discharge machining (edm), *int. j*

Neural network-based prediction of various responses in electrical discharge machining of aisi d2 steel. *international journal of advance manufacturing technology*, 50:591–610.

Pradhan, m. k. and biswas, c. k. (2011). multi-response optimization of edm aisi d2 tool steel using response surface methodology. *international journal of machining and machinability of materials(ijmmm)*, 9:66–85.