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OPTIMIZATION OF PROCESS PARAMETERS IN THE HOLE SINKING ELECTRO DISCHARGE MICROMACHINING USING GRA-PCA

*Rajesh Kr Porwal[1], Vinod Yadava[2] and Ramkumar J[3]

[1,2]Department of Mechanical Engineering, Motilal Nehru National Institute of Technology, Allahabad, India
[3]Department of Mechanical Engineering, Indian Institute of Technology, Kanpur, India

ABSTRACT

The paper describes the multi-objective optimization of hole sinking electro discharge micromachining (HS-EDMM) process considering material removal rate (MRR), tool wear rate (TWR), hole taper (Ta) and machined hole overcut (MHO) as objectives simultaneously. Optimal combination of process parameters is determined using grey relational analysis that employs grey relational grade as performance indexes. The principal component analysis is applied to evaluate the weighting values corresponding to each performance characteristics so that their relative importance can be properly and objectively described. Optimal combination of the process parameters for the multi-performance characteristics of the hole sinking micro electro discharge machining has been found as gap voltage 90V, capacitance of capacitor 10nF

Keywords: *Hole Sinking Electro Discharge Micro Machining (HS-EDMM), Taguchi Methodology (TM), Multi-Objective Optimization (MOO), GRA and PCA*

1. Introduction

The demand of micro feature, components and products has been increasing in the industries like electronics/ medical/ automotive, and biotechnology etc. To meet the above mentioned demands, development of micro manufacturing processes is needed. In this respect it is required to modify the existing macro manufacturing processes to perform micro manufacturing operations. For this modification, the processing energy, holding technology, control technology, dimension & quality measuring technology, and assembly technology has to be changed in entirely different manner. Micromachining is a type of micromanufacturing process used to create a micro feature of size few to hundreds of micron by selective controlled removal of excess material. Based on the mechanism of material removal rate, micro machining processes are classified as micro electro discharge machining (EDMM), micro ultrasonic machining (USMM), micro beam machining processes (BMMPs), micro jet machining processes (JMMPs), and micro chemical machining processes (CMMPs).

Electro Discharge Micromachining (EDMM) is a micromachining process used to produce micro feature by controlled melting and vaporization of excess material from difficult to machine, electrically conductive material with stringent design requirements using thermal energy generated by spark between two electrodes completely dipped in dielectric and applying a pulsating voltage between them. EDMM is an extension of electric discharge machining (EDM) in which feature size generated is of the order of microns. It is one of the most wide spread application of micro machining used for fabricating complex micro-components and parts, micro-tools and micro structures. The EDMM method can be effectively used for high precision machining operation such as non-contact machining, 3D machining and also in various other applications. The machine setup has a servo control system with the highest sensitivity and positional accuracy of ±0.05μm along with the inter electrode gap of 1-5 μm. The power supply used in EDMM is relaxation or transistor type pulse generator with MHz of pulsating frequency [1]. The efficiency of this process is high as the low specific energy of material removal at low discharge level.

Hole sinking-EDMM process is used to create symmetrical features of relatively large depth to diameter ratio. The other configurations of EDMM are Die Sinking-EDMM, Hole drilling-EDMM, Pocket Milling- EDMM, Wire-EDMM, and grinding EDMM. The micro holes produced by this process are required for many industrial applications such as manufacturing of fluidic filters, grid and biomedical filters, injection nozzles, starting hole for wire EDM.

**Corresponding Author - E- mail: porwal.rajesh@gmail.com*

2. Literature Review

Higher accuracy and miniaturization have always been the goals for the development of EDMM machines. Wong et. al [2] developed a single-spark generator to study the erosion characteristics from the micro crater size due to micro-EDM. Their experimental results suggest that volume and size of the micro craters are found to be more consistent at lower-energy discharges than at higher-energy discharges. An optical sensor has been developed by Lin and

Ho [3] to measure and control the dimension of the thin electrode during the tool fabrication process. They observe that the rotating electrode shows the best performance in the high-aspect ratio tool-electrode fabrication and machining depth is inversely proportional to the feed rate. A 3-axis local actuator module for µ- EDM has been developed by Imai et.al [4]. This module has 200 Hz bandwidth and utilizes the electromagnetic force for the holding and positioning of the electrode. A 60 µm diameter micro-hole with aspect ratio over 16 is machined by this module.

Sona et. al [5] investigated the influences of electrical pulse condition on the machining properties in micro-EDM, they found that the voltage and current are proportional to the material removal rate, while current is only proportional in the case of tool wear rate. Also shorter pulse on duration is profitable to make accurate machining with a higher removal rate and a lower tool wear rate. Uhlmann et. al [6] studies the process behavior of boron doped CVD-diamond and polycrystalline diamond in micro-EDM well as influences of electrode materials on tool electrode wear and surface formation processes. Johan et. al [7] studied the effect of different tool electrode materials (W, AgW, CuW) on workpiece material (WC) for material removal rate (MRR) and tool wear rate (TWR). It was observed that the AgW electrode produces smoother and defect-free nano surface among the three electrodes. Besides, a minimum amount of material migrates from the AgW electrode to the WC workpiece during the finishing micro-EDM. CuW electrode achieved highest MRR while W electrode have lowest tool wear among all electrodes.

Lin and Lin used orthogonal array combined with GRA for the optimization of die sinking electrical discharge machining of SKD11 alloy steel workpiece using pure copper tool electrode of diameter 8 mm with multi performance characteristics. Their optimization results show that MRR, surface roughness and electrode wear improved significantly [8]. A technique for optimization of abrasive mixed electrical discharge machining process with multiple performance characteristics based on orthogonal array with grey relational analysis has been proposed by Kumar et al. [9]. Their experimental results for optimal settings show that the abrasive concentration has stronger effect on MRR and on average surface finish than peak current, pulse on time and duty factor. These researchers computed grey relational grade by averaging the grey relational coefficient corresponding to each performance characteristics. Since the importance of each quality characteristic is different therefore in the present paper the grey relational grade is computed by using weight values corresponding to each quality characteristics using principal component analysis.

Some researchers [10-11] employed both TM and PCA in various engineering applications and found that it is a relatively practical and effective procedure for dealing with multi response problems. Antony applied PCA approach for multi-objective optimization (MOO) of submerged arc welding process. He found that maximum deposition rate and minimum dilution provide the optimum quality [12]. Ming and Wang have reported that the use of the orthogonal array based on experiments coupled with PCA is a simple, effective and efficient way to develop a robust, high efficiency, high quality electron beam machining process [13]. Other researchers [14-15] have reported that the use of GRA coupled with PCA is an effective methodology for optimization of different machining processes.

In this paper, MOO of HS-EDMM process has been done using GRA coupled with PCA approach. Experiments have been performed for micro drilling of 0.5 mm through hole in an Invar-36 sheet using HS-EDMM process as per L_{18} orthogonal array. During experimentation the input parameter taken are gap voltage and capacitance of capacitor and output parameter as MRR, TWR, T_a, and MHO.

3. Experimental Planning

Hole sinking electro discharge micromachining (HS-EDMM) has been performed on multi process micro electro discharge machine (Model DT-100, Mikrotool Pte, Singapore) with resolution 100nm, accuracy ± 1µm, and having fixed level of capacitance, and adjustable range of both voltage and spindle speed. Tungsten carbide rod of 500 micron diameter is used as tool electrode. The micro HS-EDMM operation is performed on rectangular section cuboid shape workpiece specimens made of Invar-36 having mean thickness of 0.5mm, length 25 mm, and width 15 mm. The properties and composition workpiece of workpiece material is given in Table (1) and Table (2) respectively. The removal of debris was achieved by lateral flushing with dielectric (EDM oil). The depth of cut has been kept constant 510 micron for all experiments. After preliminary investigations, two process parameters are selected as gap voltage and capacitance of capacitor because they directly affect the performance parameters such as MRR, TWR, Ta and MHO. Selection of the range of process parameter settings is made after performing some pilot experiments within the stable domain of the machining. The levels of parameters selected are shown in Table (3).

Table 1: Properties of Invar-36

Property	Value (Units)
Density	8080 (kg/m^3)
Thermal Conductivity	10.5 (W/m/ ^{o}K)
Specific heat	515 (J/kg ^{o}K)
Melting point	1427 (^{o}C)
Electrical resistivity	820 (microhm-mm)
Hardness	70 (HRB)
Tensile strength	586 (MPa)

The amount of material removed from the workpiece and tool electrode are measured with the help of citizen make micro weighing balance having least count of 0.0001grams. Material removal rate (MRR) and tool wear rate (TWR) are defined as volume of material removed or wear in unit time from workpiece and tool electrode respectively. Hence, based on their density the MRR and TWR are calculated as:

$$MRR = \frac{Mass\ of\ workpiece\ material\ removed}{Density\ of\ workpiece\ material \times Time\ to\ make\ hole} \quad (1)$$

$$TWR = \frac{Mass\ of\ tool\ electrode\ material\ removed}{Density\ of\ tool\ electrode\ material \times Time\ to\ make\ hole} \quad (2)$$

In order to find machined hole over cut (MHO) and hole taper (T_a), the diameter of hole at entrance and exit sides was measured using optical measuring microscope (Model SDM-TR-MSU, Sipcon Instrument Industries, India) at 10x magnification. The value of T_a and MHO is calculated as:

$$T_a\,(rad) = \frac{(hole\ entrance\ diameter) \quad (hole\ exit\ diameter)}{2 \times Workpiece\ thickness} \quad (3)$$

$$MHO = \frac{(hole\ entrance\ diameter) - (tool\ diameter)}{2} \quad (4)$$

The values of MRR, TWR, Ta and MHO are calculated by using equations (1-4) based on experimental results.

In the present study experiments are carried out using fractional factorial combinations of these factors and their different levels. During experiments the workpiece thickness is kept constant for all experimental run. Dielectric is also kept same for all experiments. As per TM an orthogonal array is selected based on the input parameters and their levels. Interaction effect has not been taken into account. L18 orthogonal array is selected with two input parameters of three levels and one parameter of six levels. To achieve validity and accuracy, each experiment has been repeated three times. The experimental layout of present work is shown in Table (4).

4 Optimization of HS-EDMM Process

Manufacturing industries now a days focus more attention on quality, cost and on time delivery due to fierce competition at market place. Customer want high quality product at reasonable price. Hence industries are forced to have an optimal equilibrium between cost and quality. Ooptimization of process parameters is one of the effective methods to achieve quality and profit without increasing cost to product. Multi objective optimization has become an increasingly important, particularly in situation where more than one correlated responses must be assessed simultaneously.

The Grey theory can provide a solution of a system in which the information is incomplete. Besides, it provides an efficient solution to the uncertainty, multi-input and discrete data problem. Therefore Grey relational analyses are applied to determine the suitable response parameters. The disadvantage of GRA is that it takes effect of each performance parameter same but in real application this is not valid. In order to find the relative influence of each performance parameter PCA is used to calculate the weighting values of each performance parameter. Therefore, Gray Relational Analysis (GRA) coupled with Principal Component Analysis (PCA) is used to optimize performance parameters of HS-EDMM process.

Table 2: Composition of Invar-36

Element	Ni	Mn	Cr	Si	Al	Zr	Mn	Ti	S	P	Fe
Percentage	36	0.50	0.25	0.25	0.10	0.10	0.10	0.10	0.02	0.02	Balance

Table 3: Machining parameters and their levels

Symbol	Machining parameters	Level					
		1	2	3	4	5	6
A	Gap voltage (V)	90	100	110	120	130	140
B	Capacitance (nF)	10	100	400			

Table 4: Experimental layout using L18 orthogonal array

Exp. No.	Factor level A	Factor level B	MRR $(mm^3/min)*10^{-4}$	TWR $(mm^3/min)*10^{-4}$	Hole taper T_a (degree)	Machined hole Overcut MHO (µm)
1	1	1	2.6685	1.3049	0.5713	39.10
2	1	2	12.7800	3.5999	0.5330	71.80
3	1	3	40.0449	15.3727	0.7951	48.45
4	2	1	3.3614	1.3623	1.3381	76.65
5	2	2	15.4652	4.4653	1.0055	57.15
6	2	3	53.6738	16.6775	1.4157	82.80
7	3	1	4.9381	1.8081	0.4507	43.65
8	3	2	15.9412	5.7138	2.4168	41.65
9	3	3	65.5121	18.2508	2.3803	77.45
10	4	1	4.9327	2.0109	1.1092	36.05
11	4	2	27.5781	7.2626	1.3124	81.75
12	4	3	69.6839	19.8320	1.6934	80.60
13	5	1	6.4102	2.8019	0.5925	45.15
14	5	2	28.0535	8.5265	3.9572	80.30
15	5	3	71.7503	26.9535	3.0407	73.95
16	6	1	6.8840	3.1229	1.3051	43.10
17	6	2	30.7900	10.0851	2.0414	51.80
18	6	3	74.3649	38.8059	1.2234	46.55

4.1 Grey relational analysis

In GRA, all information represents in terms of black and white. Black represents having no information and white represents having all information [16]. Grey relational analysis can be used to represent the grade of correlation between two sequences so that the distance of two factors can be measured discretely. It helps to compensate the shortcomings of statistical regression by means of conducting less number of experiments, as experiments are ambiguous or experimental methods do not allow doing the exact number of experiments [17]. Grey relational analysis is an effective means of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of statistical method [18].

In the grey relational analysis method, experimental data (MRR, TWR, T_a and MHO) are first normalized in the range between zero and one which is also called the grey relational generation Table 5. Next, the values of deviation sequences are to be calculated as these values of deviation sequences are used for further calculation of grey relational coefficients. The grey relational coefficient is calculated from the normalized experimental data to express the relationship between the desired and actual experimental data [19]. Table 6, lists the grey relational coefficient for each experiment. After obtaining the grey relational coefficient, the grey relational grade is defined as follows:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} w_k \quad \xi_i(k) \ , \ \sum_{k=1}^{n} w_k = 1, \tag{5}$$

where w_k represents the normalized weighting value of factor k, ξ is the distinguishing coefficient which is defined in the range $0 \le \xi \le 1$, $\xi = 0.5$ is generally used. In the grey relational analysis, the grey relational grade is used to show the relationship among the sequences. If the two sequences are identical, then the value of grey relational grade will be equal to 1. The grey relational grade also indicates the degree of influence that the comparability sequence could exert over the reference sequence. Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference sequence, then the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades [20]. In this research the corresponding weighting values i.e. w_k are obtained from the principal component analysis.

Table 5: The Sequences of each Performance Characteristic after data Pre-Processing

Exp. No.	MRR	TWR	T_a	MHO
Reference sequence	1.0000	1.0000	1.0000	1.0000
1	0.0000	1.0000	0.9656	0.9348
2	0.1410	0.9388	0.9765	0.2353
3	0.5213	0.6249	0.9018	0.7348
4	0.0097	0.9985	0.7469	0.1316
5	0.1785	0.9157	0.8418	0.5487
6	0.7114	0.5901	0.7248	0.0000
7	0.0317	0.9866	1.0000	0.8374
8	0.1851	0.8824	0.4393	0.8802
9	0.8765	0.5481	0.4497	0.1144
10	0.0316	0.9812	0.8122	1.0000
11	0.3474	0.8411	0.7543	0.0225
12	0.9347	0.5060	0.6456	0.0471
13	0.0522	0.9601	0.9596	0.8053
14	0.3541	0.8074	0.0000	0.0535
15	0.9635	0.3161	0.2614	0.1893
16	0.0588	0.9515	0.7563	0.8492
17	0.3922	0.7659	0.5463	0.6631
18	1.0000	0.0000	0.7796	0.7754

4.2 Principal component analysis

Principal component analysis (PCA) has been developed by [21]. This approach explains the structure of variance-covariance by the way of the linear combinations of each quality characteristic. The procedure which is adapted to calculate the weight in the present research is as follows [22]; first we convert the content of table 7 in matrix form as represented in equation (6), where m is the number of experiment and n is the number of the quality characteristic. In present study, x is the grey relational coefficient of each quality characteristic and m = 18, n = 4. The above matrix is used to find the correlation coefficient. The array of correlation coefficient is calculated by using equation (7)

$$X = \begin{matrix} x_1(1) & x_1(2) & \ldots\ldots & \ldots\ldots\ldots & x_1(n) \\ x_2(1) & x_2(2) & \ldots\ldots & \ldots\ldots\ldots & x_2(n) \\ \vdots & \vdots & \ldots\ldots & \ldots\ldots\ldots & \vdots \\ \vdots & \vdots & \ldots\ldots & \ldots\ldots\ldots & \vdots \\ x_m(1) & x_m(2) & \ldots\ldots & \ldots\ldots\ldots & x_m(n) \end{matrix} \tag{6}$$

$$R_{jl} = \frac{Cov\left(x_i(j), x_i(l)\right)}{\sigma_{(x_i)}(j) \times \sigma_{(x_i)}(l)} \ , \ j = 1,2,3,4,.......,n; \ l = 1,2,3,4,...............,n \quad (7)$$

here $Cov\left(x_i(j), x_i(l)\right)$ is the covariance of sequences $x_i(j)$ and $x_i(l)$, $\sigma_{(x_i)}(j)$ is the standard deviation of sequence $x_i(j)$, and $\sigma_{(x_i)}(l)$ is the standard deviation of sequence $x_i(l)$. After calculating correlation coefficient array, eigenvectors and eigenvalues are calculated by using equation (8). The procedure of getting eigenvectors and eigenvalues from correlation coefficient array is as follows

$$\left(R \quad \lambda_k I_m\right) V_{ik} = 0 \quad (8)$$

where, λ_k eigenvalues, $\sum_{k=1}^{n} \lambda_k = n, k = 1,2,3,............,n$ $V_{ik} = \left[a_{k1} a_{k2} a_{k3} ....a_{kn}\right]^T$ is the eigenvectors corresponding to the eigenvalue λ_k. The eigenvectors and eigenvalues are further used to find principal components by using equation (9)

$$Y_{mk} = \sum_{i=1}^{n} x_m(i) \quad V_{ik} \quad (9)$$

where Y_{m1} is called the first principal component, Y_{m2} is called the second principal component and so on. The principal components are aligned in descending order with respect to variance, and therefore the first principal component Y_{m1} accounts for most variance in the data given in Table 8. Next step is to find percentage contribution or to explain variation of eigenvalues. The eigenvector corresponding to each eigenvalue is listed in Table 7. The eigenvectors corresponding to the largest eigenvalue are selected and the square of the eigenvalue vectors corresponding to the first principal component represents the contribution of the respective performance characteristic to the principal component.

Table 6: The Calculated Grey Relational Coefficients, Grey Relational Grade and its Order

Exp. No.	Grey relational coefficient				Grey relational grade	Order
	MRR	TWR	T_a	MHO		
1	0.3333	1.0000	0.9356	0.8846	0.7642	1
2	0.3679	0.8910	0.9552	0.3953	0.6603	7
3	0.5109	0.5713	0.8358	0.6534	0.6190	10
4	0.3355	0.9970	0.6639	0.3654	0.6226	9
5	0.3784	0.8558	0.7596	0.5256	0.6353	8
6	0.6340	0.5495	0.6450	0.3333	0.5578	17
7	0.3405	0.9739	1.0000	0.7546	0.7486	2
8	0.3803	0.8096	0.4714	0.8067	0.6111	11
9	0.8020	0.5253	0.4761	0.3609	0.5724	13
10	0.3405	0.9637	0.7270	1.0000	0.7327	3
11	0.4338	0.7589	0.6705	0.3384	0.5712	14
12	0.8845	0.5030	0.5852	0.3441	0.6090	12
13	0.3453	0.9261	0.9252	0.7198	0.7137	4
14	0.4363	0.7219	0.3333	0.3457	0.4945	18
15	0.9320	0.4223	0.4037	0.3815	0.5675	15
16	0.3469	0.9116	0.6724	0.7683	0.6677	6
17	0.4514	0.6811	0.5243	0.5974	0.5658	16
18	1.0000	0.3333	0.6941	0.6900	0.6684	5

Table 7 The Eigenvalues and Explained Variation for Principal Components

Principal component	Eigenvalue	Explained variation (%)
First	2.6159	65.41
Second	0.7502	18.76
Third	0.5666	14.17
Fourth	0.0672	1.68

Table 8: The Eigenvectors for principal components

Quality characteristic	Eigenvectors			
	First principal component	Second principal component	Third principal component	Fourth principal component
Material removal rate	-0.5527	-0.4612	0.1344	0.6810
Tool wear rate	0.5730	0.3712	-0.0600	0.7282
Hole taper	0.4445	-0.4121	0.7918	-0.0746
Machined hole overcut	0.4106	-0.6926	-0.5927	-0.0189

Table 9: The Contribution of each Individual Quality Characteristic for the Principal Component

Quality characteristic	Contribution
Material removal rate	0.3055
Tool wear rate	0.3283
Hole taper	0.1976
Machined hole overcut	0.1686

4.3 Experimental results and discussion

The contribution of material removal rate, tool wear rate, hole taper and machined hole overcut is shown in Table 9. These contributions are indicated as 0.3055, 0.3283, 0.1976 and 0.1686 for MRR, TWR, T_a and MHO respectively. Moreover, the variance contribution for the first principal component characterizing the four performance characteristics is as high as 65.41%. Hence, for this study, the squares of its corresponding eigenvectors are selected as the weighting values of the related performance characteristic, and coefficients w_1, w_2, w_3 and w_4 for equation (5) are thereby set as 00.3055, 0.3283, 0.1976 and 0.1686 respectively. Based on equation (5) and data listed in Table 6 the grey relational grades are calculated by using these weights of corresponding performance parameter and grey relational coefficients after taking sum of these values for each set of experiment, the values of grey relational grades are shown in Table 6. Since the grey relational grade represents the level of correlation between the reference sequence and the comparability sequence, the larger value of grey relational grade means that the comparability sequence has a stronger correlation to the reference sequence. In other words, regardless of category of the performance characteristics, a larger grey relational grade value corresponds to better performance Tosun et al. (2003). Thus, the optimization design is performed with respect to a single grey relational grade rather than complicated performance characteristics. According to performed experiment design, it is clearly observed from Table 6 that the HS-EDMM parameters setting of experiment No. (1) has the highest grey relational grade. Thus, the first experiment gives the best multi performance characteristics among the eighteen experiments.

Table 10: Response Table for the Grey Relational Grade

Symbol	HDM-EDM parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Max-Min
A	Gap voltage	0.6811*	0.6052	0.6440	0.6376	0.5919	0.6340	0.0893
B	Capacitance	0.7082*	0.5897	0.5990				0.1185
Average grey relation grade = 0.6323								

* Optimum level

The response table has been employed to calculate the average grey relational grade for each HS-EDMM parameter level. It is done by sorting the grey relational grades corresponding to levels of the HS-EDMM parameter in each column of the orthogonal array, and taking an average on those with the same level. Using the same method, calculations are performed for each HS-EDMM parameter level and the response table is constructed as shown in Table 10. Basically, as the larger the grey relational grade is the better multiple-performance characteristics will be. In Table (10), A_1 and B_1 show the largest value of grey relational grade for factors A, and B respectively. Therefore, A_1B_1 is the condition for the optimal parameter combination of the HS-EDMM. When the last column of performance parameters in Table 10 is compared with each other, it is observed that the difference between the maximum and minimum value of the grey relational grade for factor B is the largest one followed by factor A. This indicates that the capacitance of capacitors has stronger effect on the multi-performance characteristics followed by gap voltage. Quantitative contribution of the different factors can be obtained by the decomposition of the variance, popularly known as analysis of variance (ANOVA). It is a computational technique used to estimate quantitatively the relative significance and contribution of each factor. In the present case the ANOVA given in Table 11 shows the contribution of different factors as gap voltage (15.92%), capacitance of capacitor (56.24%).

Table 11: Results of ANOVA for Grey Relational Grade

Symbol	Factor	DOF	Sum of squares	Mean squares	F	Contribution (%)
A	Gap voltage	5	0.014765	0.002953	1.14	15.92
B	Capacitance	2	0.052146	0.026073	10.1	56.24
Error		10	0.025813	0.002581		
Total		17	0.092724			

5. Conclusions

Grey relational analysis coupled with principal component analysis optimization strategy has been used to determine the optimal combination of control parameters in HS-EDMM of invar-36. The findings of the present study are as:

Optimal combination of the process parameters for the multi-performance characteristics of the hole sinking electro discharge micromachining is A1B1.
The percentage contributions of each individual quality characteristic for the principal component in increasing order are MHO (16.86%), Ta (19.76%), MRR (30.55%) and TWR (32.83%) respectively.

It is observed that the capacitance of capacitors has stronger effect on the multi-performance characteristics followed by gap voltage.

Quantitative contributions of the different factors are 15.92% of gap voltage, 56.24% of capacitance of capacitor.

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