PARAMETRIC OPTIMIZATION OF EDM PROCESSES FOR ALUMINUM HYBRID METAL MATRIX COMPOSITE USING GRA-PCA APPROACH

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ABSTRACT

This study is an attempt to identify the key input parameters of the Electric Discharge Machining (EDM) process, during machining of Hybrid Metal Matrix Composite (HMMC) prepared through the Stir casting method. A multi optimization tool mix of Taguchi Methodology (T-M), Grey Relational Analysis (GRA), and Principal Component Analysis (PCA) was used to optimize and verify the model. The response on Material Removal Rate (MRR), Electrode Wear Rate (EWR) and Surface Roughness (R_a) was investigated by selecting input parameters comprising of peak current (I_p), Pulse on Time (T_{on}), Duty factor (τ), Spark gap (S_g), Electrode type (ET), Electrode size (ES) using Taguchi L_{16} orthogonal array (OA). The optimized process parameter context using GRAPCA, demonstrates the enhancement of MRR by 172.5% and reduction in EWR and R_a by 64.17%, 34.4% respectively using $I_{p3}T_{on1}\tau_3S_{g2}ET_2ES_1$ parameter settings against the initial assumed settings. The maximum contributors amongst all parameters were T_{on} and I_p (21%, 14.31%), followed by ET (12.4%), S_g (11.5%) by using Analysis of Variance (ANOVA).

KEYWORDS: Hybrid Metal Matrix Composite, MRR, EWR, Electric Discharge Machining, GRA, PCA, Optimization, Input Parameters

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1. INTRODUCTION

With the advent of technology, the industry of today's time requires materials with improved strength and hardness, reduced weight with low densities, etc. Composite materials, to a greater extent, had fulfilled the requirement of today's industries. Aluminum HMMC has got lots of demand for elaborative applications in automobiles, mineral processing industries, aerospace etc. Metal matrix composites has emerged as an advance engineering materials due to their high stiffness, high strength, less density, better resistance against wear and high thermal properties (Nturanabo et al., 2019). To machine such HMMC, Electric discharge machining (EDM) has been preferred over other non-conventional methods. It is a contactless machining process based on the erosive impact of electrical discharges. Due to the electro-thermal nature of the process, a large variety of conductive materials can be machined independent of their hardness and toughness, its contactless nature has resulted in an acceptable level of accuracy and surface texture (Joshi et al., 2019). One of the most popular types, i.e., die-sinking EDM has a provision of creating mirror shape of the electrode on the workpiece. In EDM process, the input variables such as current (I_p), gap voltage (V), pulse on time (T_{on}), the pulse of time (T_{off}), spark gap (S_g), flushing pressure (FP) duty factor/ cycle (τ) and lift time (T_L) has got more influence on output variables like Material Removal Rate (MRR), electrode wear rate (EWR), surface finish (R_a), overcut (O_c), undercut (U_c), dimensional deviation (DD), etc. (Sahu et al., 2019) had conducted an experiment with

Nimonic alloy workpiece with the copper electrode to study the effect of I_p and T_{on} on MRR, EWR, and R_a . They reported that with the variation of I_p and T_{on} , MRR, and EWR increases. (Dikshit et al., 2019) had investigated by an empirical formula the output variables R_a and MRR during EDM of Inconel 625 superalloy. They concluded that MRR is influenced mainly by I_p and T_{on} , R_a by T_{on} , and then by T_{off} . (Singh et al., 2019) had investigated the effects of S_g , V , I_p & T_{on} on MRR, EWR and R_a using one variable at a time (OVAT) approach on H13 alloy with Cu electrode. They reported a significant direct effect of I_p and T_{on} on MRR and inverse relation of I_p on R_a and EWR. (Choudhary et al., 2017) had investigated the influence of I_p , T_{on} and T_{off} on MRR and R_a observed during EDM of Hastelloy C-4 material as per T-M L_{18} OA with cryogenic treated and normal electrode. They reported better R_a , using a cryogenic treated electrode. (Ram Prasad et al., 2019) had conducted Wire-EDM of Ti-6Al-4V (Lead-induced) with Zn coated brass wire to find out the effects of I_p , T_{on} , V , and T_{off} on MRR, R_a , DD in a L_{27} OA. Analytic Hierarchy Process (AHP) coupled with the technique for order of preference by the similarity of ideal solution (TOPSIS) method has been employed to ascertain the most notable settings of input parameters. (Singh Bains et al., 2018) had performed trials on EDM of Al-SiC composites under magnetic field strength impact using different electrodes (Cu, Gr & W). They reported that the regularity of the experiment has improved, MRR and R_a to be significantly affected due to the magnetic field, I_p apart from T_{on} . Copper has been reported to be the best to machine Al-SiC composite. (Meshram et al., 2020) had conducted L_{18} OA based DOE on semi-circular curved Cu electrode used for EDM on OHNS steel to ascertain the effects of input variables comprising of I_p , T_{on} , FP, model validated by use of ANOVA. (Kumar et al., 2018) had attempted EDM of monel 400 material with Copper-TitaniumDi-boride (Cu-TiB₂) electrode fabricated through the powder metallurgy process. Central rotatable composite design (CCRD) and Response Surface Methodology (RSM) approach have been used to validate the model of input variables (TiB₂% wt, I , T_{on} , and FP) on MRR and EWR. They suggested that the best settings of input parameters is %wt of TiB₂ to be 16 %, I = 6Amp, FP of 1 Mpa, and T_{on} of 35 μ s. (Payal et al., 2019) had conducted EDM on Inconel 825 with input parameters V , T_{on} , τ , T_L , dielectric fluid (D_f), I_p and 3 different types of electrode material (Cu, CuW, GR) using L_{36} orthogonal array to find the effect on MRR, EWR, and R_a . GRA along with PCA has been used to optimize the model. They confirmed an increase in MRR by 109.2% and reduction in EWR, R_a by 51.9%, 7.27% respectively by application of GRAPCA model.

From the literature survey, it is evident that almost negligible work has been reported in EDM of Al 6063-10SiC-5B₄C-Mg HMMC using different sets of electrodes and sizes and modeling optimized using GRA based PCA approach. Therefore, the present work has been aimed towards to optimize the input parameters for the matchless conditions in EDM machining of Al 6063-10SiC-5B₄C-Mg HMMC using copper and graphite (of different sizes) as an electrode by GRA based PCA approach.

2. HYBRID METAL MATRIX COMPOSITE

The HMMC (AL-10SiC-5B₄C-1Mg) consists of metal matrix in the form of 84% (wt) of Aluminium 6063 and reinforcement material in form of SiC of micron size 45 μ m in 10 % (wt) and B₄C of micron size 52 μ m in 5% (wt) and to improve wettability Mg in 1% (wt) has been used. The HMMC was developed by stir casting route. Table 1 shows the constituents of Al-6063. Table 2 shows the mechanical properties of HMMC (Reddy et al., 2018).

Table 1: Composition of Al-6063

Al-6063 Composition	Wt. %	Al-6063 Composition	Wt. %
Al	Max 97.5	Mn	Max 0.1
Cr	Max 0.1	Si	0.2 - 0.6
Cu	Max 0.1	Ti	Max 0.1
Fe	Max 0.35	Zn	Max 0.1
Mg	0.45 - 0.9		

Table 2: Mechanical Properties of HMMC ^[12]

Hybrid Metal Matrix Composite Material	Tensile Strength (N/mm ²)	Yield Strength (N/mm ²)	Density (Kg/m ³)	Brinell Hardness (HB)	Break Load (kN)
84wt.% Al-- 10wt.% SiC--5 wt.% B ₄ C	120.32	98.75	2537.5	71.58	9.45
	Maximum displacement	Elongation	Flexural break load	Flexural Maximum deflection	Flexural strength
	(mm)	%	(kN)	(mm)	(MPa)
	9.7	7.53	3.68	5.6	214.12

3. EXPERIMENTAL SETUP

This section covers the EDM of HMMC using Ecoline die-sinking EDM, model: ECO 250 series with three-phase power input with maximum current of 35 Amp, as shown in Figure 1. With direct polarity, electrodes (pure copper and graphite) of different sizes (15mm and 10mm) Figure 4, is used for experimentation; the experimental facility used is shown in Table 3. Based on exhaustive pilot experiments, Taguchi L₁₆ OA is used for the Design of Experiments (DOE) with 6 factors out of which 3 factors are of 4 levels and 3 factors of 2 levels each. (Wakjira et al., 2019) The Input parameters selected for the experimentation includes current (I_p), pulse on time (T_{on}), duty factor (τ), spark gap (S_g), electrode type (ET) and electrode size (ES). EDM input parameters with corresponding levels is shown in Table 4.

Figure 1: Ecoline Di Sinking EDM Model ECO 250.

Figure 2: Leveling Operation of Electrode.

Figure 3: Setting the Input Parameters.

Table 3: Experimental Facility used

Facility	Specifications
EDM Machine	Ecoline ECO 250 series
Surface roughness tester	Mitutoyo SJ-201 Sr.no 500829 surface finish meter (-200μm to +150 μm)
Digital weigh balancer	Generic Digital Scale 0.001gm To 200gm
Electrode	2 piece (15mm, 10mm) each of copper and graphite(Figure 4)
Flushing speed	Flow rate of 1.2 Kg/cm ² kept constant through all experiments.
Dielectric medium	Kerosene based EDM oil

Table 4: EDM Input Parameters with Levels

I/P parameters	Units	Level 1	Level 2	Level 3	Level 4
Current (I)	amp	3	6	9	12
Pulse on Time(T_{on})	μs	25	50	75	100
Duty Factor (T)	%	2	4	6	8
Spark Gap (S_g)	mm	3	6		
Electrode Type (ET)		Cu	Gr		
Electrode Size (ES)	mm	10	15		

The HMMC 16 samples (Figure 5) were cut into equal sizes of 20 X 30 X 4 mm using wire EDM to maintain the composite grain structure. As per the T-M L_{16} OA the proper electrode is first selected. (Figure 4). The selected electrode and sample initial weight (E_b & W_b) were measured using electronic weight balancer (0.001gm to 200gm) Figure 6.

Figure 4: Copper and Graphite Electrode of 15mm and 10mm Diameter.

Figure 5: HMMC Samples for EDM.

Figure 6: Electronic Weight Balancer.

Table 5: L_{16} Orthogonal Array Observation Table

Exp. No.	I	Ton	T	Sg	ET	ES	MRR	EWR	Ra
	(Amp)	(μs)	(%)	(mm)		(mm)	(mm ³ /min)	(mm ³ /min)	(μm)
1	3	25	2	3	CU	10	2.5684	0.55803	4.36
2	3	50	4	3	CU	15	1.2804	0.57603	4.68
3	3	75	6	6	GR	10	5.7618	0.48567	5.06
4	3	100	8	6	GR	15	5.3911	0.45755	5.41
5	6	25	4	6	GR	10	4.8794	0.32543	4.25
6	6	50	2	6	GR	15	4.2574	0.37453	6.25
7	6	75	8	3	CU	10	5.4712	0.58076	8.16
8	6	100	6	3	CU	15	5.2766	0.62146	8.86
9	9	25	6	3	GR	15	5.8746	0.35749	4.09
10	9	50	8	3	GR	10	6.1895	0.87942	5.16
11	9	75	2	6	CU	15	7.2476	1.26113	7.25
12	9	100	4	6	CU	10	7.5454	1.69491	5.63
13	12	25	8	6	CU	15	6.1475	0.38764	8.09
14	12	50	6	6	CU	10	6.4173	0.53538	9.21
15	12	75	4	3	GR	15	8.2144	2.23657	12.15
16	12	100	2	3	GR	10	8.1475	2.82487	12.45

The workpiece and electrode were mounted on the workbench and chuck respectively, and alignment and leveling were being done. (Figure 2) As per the design of experiment (Table 5), the input parameters were fed into the EDM (Figure 3). Before starting the EDM machine, the input voltage was being checked for any faults in terms of fluctuations, etc. The side flushing method is being used by manually setting the flow of flushing pressure directly on the top of the surface of the workpiece for maximum cleaning action and thus better R_a . The EDM was then switched on, and the electrode was set near to the workpiece, and lift was adjusted accordingly. The flushing motor & spark action was then started. The machine was allowed to run for 15 minutes. During this period, the electrode approaches near to the surface of the workpiece, created a spark, and then lifts off. During lift off the flushing mechanism flushes the debris of the workpiece from its surface. After 15 minutes of EDM action, the machine was switched off and the workpiece and electrode were removed from the EDM and weighted (W_a and E_a) again for final weight measurement with the electronic weigh balancer. The MRR and EWR were calculated from Equation (1,2), respectively. R_a was calculated using Mitutoyo SJ-201 surface finish meter.

$$MRR = \frac{W_b - W_a}{\rho \times t} \quad (1)$$

$$EWR = \frac{E_b - E_a}{\rho \times t} \quad (2)$$

Where, w_b and w_a = Initial & final weight of samples in gm

E_b and E_a = Initial & final weight of electrode in gm

ρ = Density of workpiece material in gm/mm³

t = Time of machining in minutes.

The Table 5 also shows the observations table of experimentation performed. Figure 7 shows pictures of 16HMMC samples after EDM operation.

Figure 7: HMMC Samples after Machining at different Input Variables.

4. OPTIMIZATION USING GRA-PCA APPROACH

This section covers the optimization of the model using the GRA-PCA approach. Optimization is a technique in which an alternative is ascertained under the accepted constraints to have a higher achievable performance with the least cost involved. The various factors are streamlined, and the best factors are maximized, and undesired ones are being minimized. The motive of this study is to maximize the MRR and reduce the EWR and R_a . The composite Al-10SiC-5B₄C-Mg, prepared through the stir casting route, is machined using copper & graphite electrode of different diameters, as per DOE. A hybrid multi-response optimization approach such as principal component analysis (PCA) based grey relational analysis (GRA) has been attempted for composite Al-10SiC-5B₄C-Mg by the EDM process.

5. GREY RELATIONAL ANALYSIS

In the GRA approach, the analysis is being done by comparing the relational degree in distinct succession. In this technique, the data needs to be pretreated since the span and unit in one data succession may vary from the others. In this case, the key objective is to increase the MRR and EWR, R_a needs to be minimized. Due to different objectives, the output parameters need to be normalized using the following. Equation (3, 4). (Bhuyan et al., 2014)

$$\frac{y_i^p(r) - \min y_i^p(r)}{\max y_i^p(r) - \min y_i^p(r)} = y_i^*(r) \text{ for higher the better approach (Hb)} \quad (3)$$

$$\frac{\max y_i^p(r) - y_i^p(r)}{\max y_i^p(r) - \min y_i^p(r)} = y_i^*(r) \text{ for lower the better approach (Lb)} \quad (4)$$

where $y_i^*(r)$ is the value after normalization. $y_i^p(r)$ is the corresponding table value, $\min y_i^p(r)$ & $\max y_i^p(r)$ are the minimum and maximum values in a column of a parameter under study. Table 6 shows the normalized value of each output parameter.

Table 6: Sequence of Output Parameters after Normalization

Exp. No	Output Parameters Value			Comparability Sequence			Deviation Sequence		
	MRR	EWR	Ra	MRR	EWR	Ra	MRR	EWR	Ra
1	2.5684	0.55803	4.36	0.8142	0.9069	0.9677	0.8142	0.0931	0.0323
2	1.2804	0.55803	4.68	1.0000	0.9069	0.9294	1.0000	0.0931	0.0706
3	5.7618	0.48567	5.06	0.3537	0.9359	0.8840	0.3537	0.0641	0.1160
4	5.39119	0.45755	5.41	0.4072	0.9471	0.8421	0.4072	0.0529	0.1579
5	4.8794	0.32543	4.25	0.4810	1.0000	0.9809	0.4810	0.0000	0.0191
6	4.2574	0.37453	6.25	0.5707	0.9804	0.7416	0.5707	0.0196	0.2584
7	5.4712	0.58076	8.16	0.3956	0.8978	0.5132	0.3956	0.1022	0.4868
8	5.2766	0.62146	8.86	0.4237	0.8816	0.4294	0.4237	0.1184	0.5706
9	5.8746	0.35749	4.09	0.3374	0.9872	1.0000	0.3374	0.0128	0.0000
10	6.1895	0.87942	5.16	0.2920	0.7784	0.8720	0.2920	0.2216	0.1280
11	7.2476	1.26113	7.25	0.1394	0.6256	0.6220	0.1394	0.3744	0.3780
12	7.5454	1.69491	5.63	0.0965	0.4521	0.8158	0.0965	0.5479	0.1842
13	6.1475	0.38764	8.09	0.2981	0.9751	0.5215	0.2981	0.0249	0.4785
14	6.4173	0.53538	9.21	0.2592	0.9160	0.3876	0.2592	0.0840	0.6124
15	8.2144	2.23657	12.15	0.0000	0.2354	0.0359	0.0000	0.7646	0.9641
16	8.1475	2.82487	12.45	0.0096	0.0000	0.0000	0.0096	1.0000	1.0000

The normalized sequence is being used to calculate the grey relational coefficient (Ψ_{0i}^r) Equation 5, $\Delta_{0,i}(r)$ is the corresponding continuance sequence minus comparatibility sequence. It is given by $\Delta_{0,i}(r) = |y_0^*(r) - y_i^*(r)|$, $\Delta_{max} = \max|y_0^*(r) - y_i^*(r)|$ and $\Delta_{min} = \min|y_0^*(r) - y_i^*(r)|$. In this case the distinguishing coefficient (ζ) has been assumed the value of (0.5). Table 7 displays the corresponding value of grey relational coefficient.^[14]

$$\Psi_{0i}^r = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{0,i}(r) + \zeta \Delta_{max}} \quad (5)$$

Table 7: GR Sequence, Grey Relational Grade, Rank for All Experiments

Exp. No	Grey Relation Sequence			Grey Relational Grade	Rank
	MRR	EWR	SR		
1	0.3804	0.8431	0.9393	0.7276 ($\phi_{0,i}$)	5
2	0.3333	0.8431	0.8763	0.6916	9
3	0.5857	0.8864	0.8117	0.7655	3
4	0.5512	0.9044	0.7600	0.7435	4
5	0.5097	1.0000	0.9631	0.8313	2
6	0.4670	0.9622	0.6593	0.7031	7
7	0.5583	0.8304	0.5067	0.6355	13
8	0.5413	0.8085	0.4670	0.6093	14
9	0.5971	0.9750	1.0000	0.8628	1
10	0.6313	0.6929	0.7962	0.7078	6
11	0.7819	0.5718	0.5695	0.6382	12
12	0.8382	0.4771	0.7308	0.6772	10
13	0.6265	0.9526	0.5110	0.7011	8
14	0.6586	0.8562	0.4495	0.6574	11
15	1.0000	0.3954	0.3415	0.5704	15
16	0.9811	0.3333	0.3333	0.5401	16

6. PRINCIPAL COMPONENT ANALYSIS

In PCA, the reduction in variables takes place by taking out the most important one from a large sample size. It helps in retaining the most data, as well as reducing the size of the data without altering the accuracy. In PCA, the actual data is converted into uncorrelated variables or Principal component ($\square_{\square\square}$) Equation 7 by computing the eigenvectors of the covariance matrix of the original data. The eigenvalues ($\square_{\square}$) or characteristic value is any value that makes the matrix “A” solution possible. The eigenvector ($\square_{\square\square}$) Equation 6 corresponds to the value. The eigenvalue problem is generally denoted as

$$V_{ip}(A - \lambda_p I_n) = 0 \quad (6)$$

$$Y_{pc} = \sum_{i=1}^p y_n(i) V_{ip} \quad (7)$$

$$\phi_{0,i} = \frac{1}{q} \sum_{n=1}^q W_n \Psi_{o,i}(n) \quad (8)$$

Table 8: Eigen value, Proportion(%), Cumulative, Eigenvector

Principal Component	Eigenvalue	Proportion (%)	Cumulative	Eigen Vector
First	2.3156	0.772	0.772	[0.565, 0.796,-0.216]
Second	0.3889	0.13	0.902	[0.589,-0.206,0.782]
Third	0.2955	0.098	1	[0.578, -0.569, -0.585]

The grey relational grade ($\phi_{0,i}$) has been calculated as per Equation 8, Table 8 shows that the square of eigenvector correlates to the input of corresponding principal component (Y_{pc}).

Table 9: Grey Relational Grade Response Table

Input Parameters	Grey Relational Grade				Max-Min (Delta value)	Rank
	Level 1	Level 2	Level 3	Level 4		
Current (I)	0.7321*	0.6948	0.7215	0.6173	0.1148	1
Pulse on time(Ton)	0.7807*	0.6899	0.6524	0.6425	0.1382	3
Duty Factor(T)	0.6523	0.6926	0.7237*	0.697	0.0715	4
Spark Gap(Sg)	0.6681	0.7147*			0.0465	5
Electrode Type (ET)	0.6672	0.7156*			0.0484	2
Electrode Shape (ES)	0.6928*	0.69			0.0028	6
*optimum parameter value						

7. RESULTS AND DISCUSSIONS

In case of first Y_{pc} , the contribution of variance clearly explains the initial variables, i.e., 77.1%, therefore it has been decided to include the square of all eigenvectors to calculate $\phi_{0,i}$, the corresponding weight of output parameter (W_n) calculated for three principal components is taken to be MRR=0.319, EWR=0.346 and R_a =0.334. The grey relational grade ($\phi_{0,i}$) and corresponding Rank is shown in Table 7. The substantial estimate of Grey relational grade shows the best performance irrespective of the output parameter category.^[14] Table 9.shows the values of optimum input parameters and their effect on grey relational grade. Figure 8 shows the related graph.

Figure 8: Input Parameter Effects on Grey Relational Grade.

8. CONFIRMATION OF EXPERIMENTATION

It is evident from the Table 9 the most favorable input parameters for best grey relational grade is $I_p = 5$ Amp (level 1), $T_{on}=25 \mu s$ (level 1), $T_r = 6$ (level 3), $S_g = 6$ mm (level 2), ET= Graphite, ES= 10 mm.

Table 10: ANOVA Results for GRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Current	3	0.032267	0.010756	14.31	0.028
Pulse on time	3	0.047555	0.015852	21.09	0.016
Duty Factor	3	0.010441	0.00348	4.63	0.12
Spark Gap	1	0.008655	0.008655	11.52	0.043
Electrode Type	1	0.009351	0.009351	12.44	0.039
Electrode Size	1	0.000032	0.000032	0.04	0.851
Error	3	0.002255	0.000752		
Total	15	0.110555			

ANOVA is applied (Minitab 18) to determine the most significant input parameter, which affects the output parameters. Table 10 shows the ANOVA results for the grey relational grade. It shows that for the model, T_{on} (21%) and I_p (14.3%) are the most influential parameters followed by ET (12.44%), S_g (11.52%) and T_r (4.6%). It is a requirement to intensify the output variable by using the optimized input variables. Table 11 and Figure 9 depict the testimony of trials, which are acquired by designing the conclusions from the optimized and preliminary process parameters.

Table 11: Result of Confirmation Experiments

Best Combination		MRR	EWR	RA
Initial Design	$I_1T_{on1}T_r1S_g1ET_1ES_1$	2.568	0.558	4.36
Optimal design	$I_3T_{on1}T_r3S_g2ET_2ES_1$	6.997	0.1999	2.86
Final improvement		172.50%	64.17%	34.40%

It is noticeable that the MRR has shown improvement of about 172.5% whereas EWR has shown substantial decrease of 64.17% The R_a has also reduced by 34.4%. Thus, it is evident that Principal Component Analysis (PCA) based Grey Relational Analysis (GRA) has been successfully applied to multi-optimization of Aluminum based composite EDM process.

Figure 9: Optimum Value of Input Parameters.

9. CONCLUSIONS

The Hybrid Metal Matrix Composite (Al-10SiC-B₄C-1Mg) was successfully tested on Electric Discharge Machining using Copper and Graphite electrode of different sizes. Grey relational analysis coupled with Principal component analysis was successfully applied for optimization with following observations.

- It can be mentioned from analysis of variance that out of 6 input variables T_{on} (21%) and I_p (14.3%) are the most influential parameters followed by ET (12.44%), S_g (11.52%) and T (4.6%) on output parameters MRR, EWR and R_a .
- The Electrode size has negligible influence as compared to other input parameters on output parameters.
- The Principal Component Analysis is applied to enumerate the related weights of discrete output parameters such as for MRR (0.319), EWR (0.346) & R_a (0.334) during application of Grey relational analysis for multi-response optimization are proficient enough to indicate the importance for each output parameters.
- The optimal mixture of input parameters as devised through the GRA-PCA approach is $I_3T_{on1}T_3S_{g2}ET_2ES_1$. Through acceptance trial, it is observed that MRR improves by 172.5% and EWR reduced by 64.17% and R_a reduced by 34.4%.
- The Grey relational grade rank is highest for Exp. No. 9 (0.8628) and corresponding values of output parameters observed experimentally is MRR=5.87 mm³/min, EWR=0.357 mm³/min and R_a =4.09µm and corresponding values of Input variables are I =9 amp, T_{on} =25 µs, T =6, S_g =3 mm, ET =Graphite and ES = 15mm

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