Asian Review of Mechanical Engineering
ISSN: 2249-6289 (P) Vol.1 No.2, 2012, pp.45-50

DOI: https://doi.org/10.51983/arme-2012.1.2.2296

Multi-Objective Optimization of the Electro-Discharge Diamond Surface Grinding Process

Shyam Sunder* and Vinod Yadava
Department of Mechanical Engineering, Motilal Nehru National Institute of Technology, Allahabad (U.P.) – 211 004, India
** Corresponding author E-mail: mtr_shyam@yahoo.co.in*

Abstract - **Grinding of Metal matrix composites (MMCs) which are making inroads in various engineering applications have proved to be extremely difficult to machine due to presence of hard ceramic reinforcement. Electro-discharge machining (EDM) of MMCs containing electrically non conducting phases possess few problems in terms of hampering the process stability and impeding the material removal process. Use of combination of grinding and EDM has potential to overcome these problems. This article presents the optimization design of an electro-discharge diamond surface grinding (EDDSG) process performed on aluminum-metal matrix composite (Al-MMC). The major performance characteristics selected to evaluate the process are material removal rate (MRR) and average surface roughness (Ra). The input machining parameters used in the present study were current, pulse on-time, wheel speed, and duty factor. Experiments were carried out on newly self developed surface grinding setup for electro-discharge diamond grinding (EDDG) process for Al-10wt.%SiCp composites. The experimentations are planned as per L9 orthogonal array. Grey relational analysis (GRA) is used for optimizing the machining parameters. Principal component analysis (PCA) is coupled with GRA to evaluate the weighting values corresponding to various performance characteristics that their relative importance can be properly described. The most significant factor has been found as pulse on-time effecting the robustness of electro-discharge diamond surface grinding (EDDSG) process.**

Keywords : **Electro-discharge diamond surface grinding, Aluminium-metal matrix composites, Grey relational analysis, Principal component analysis**

I. Introduction

In recent years the critical need for less expensive structural materials that can provide an optimum level of performance has generated considerable research interest in the development and application of metal matrix composites (MMCs). Clyne and Withers [1] discussed that use of MMCs provide significant benefits including performance such as component's life, and improved productivity. Kannnan and Kishawy [2] mentioned that MMCs provide economic advantage through energy savings or lower maintenance cost and environmental benefits of lower noise levels. Compared to monolithic metals, MMCs have high strength-to-weight ratio, better fatigue resistance, better elevated temperature properties, lower coefficient of thermal expansion, improves thermal conductivity, and excellent wear resistance. However, the utilization of MMCs in different industries is not as generalized as expected due to difficulties in machining of it. Cost effective machining has not been, yet, proven. MMCs have been successfully applied in aerospace industries since 1970s and in the middle of 1980s these materials reached the automobile industry and nowadays its use is gaining importance [3]. Al_2O_3 is widely used in mechanical, optical, and microelectronic applications because of its excellent chemical resistance, good mechanical strength, high hardness, transparency, high abrasive and corrosion resistance [4–5].

In traditional machining processes, grinding is one of the viable method of machining because of high dimensional accuracy and surface quality. But grinding of composite materials using conventional surface grinding process shows poor surface finish and accuracy [6]. The decreasing cutting ability of the wheel during the grinding of MMCs may be caused by the following phenomena: (1) break out and fragmentation of grains due to abrasion of reinforcement; (2) attrition wear of the active grains; (3) clogging of the wheel caused by the adherence of the chips. The last two forms of damage determine the formation of wear flats on the wheel surface [7-8]. EDM is an inefficient machining process. Thermal modeling of the process [9] has indicated that the fraction of molten material which is physically not removed but re-deposited on the parent material could be as high as 80%. EDM of composite materials containing electrically non conducting phases possess a few problems. The non-conducting material particles hamper the process stability and impede the material removal process [10]. These problems can be taken care of in EDDG which is a hybrid machining process comprising of diamond grinding (DG) and electro-discharge grinding (EDG). MRR is enhanced as the abrasive grains eradicate the non-conducting material particles, with spark discharges having thermally softened the surrounding binding material.

This hybrid machining process has been developed by combining EDM with metal bonded diamond grinding. In this process, synergetic interaction effect of electro-discharge action and abrasion action are employed to increase the machining performance of constituent processes. The electrical discharges of EDDG cause considerable decrease in grinding forces, and grinding wheel wear; and also effectively re-sharp the grinding wheel. The abrasive action in this process helps to increase material removal rate (MRR) and surface quality.

EDDG can be operated in three different configurations (1) electro-discharge diamond cut-off grinding (EDDCG) (2) electro-discharge diamond face grinding (EDDFG) (3) electro-discharge diamond surface grinding (EDDSG).

EDDSG is used to machine flat surfaces by using periphery of the metal bonded diamond grinding wheel. Since rectangular workpiece is held in a horizontal orientation, peripheral grinding is performed by rotating the grinding wheel about a horizontal axis perpendicular to the downward motion of servo system. The relative motion of the workpart is achieved by reciprocating the workpiece. While machining the rotating wheel is fed downwards under the control of servo system. The metal bonded grinding wheel and work surface are physically separated by a gap, the magnitude of which depends on local breakdown strength of the dielectric for a particular gap voltage setting. The workpiece is thus simultaneously subjected to heating due to electrical sparks occurring between the periphery of metal bonded grinding wheel and the workpiece, and abrasion action by abrasives of diamond wheel having protrusion height more than the inter-electrode gap (IEG).

Through grey relational analysis (GRA), a grey relational grade is defined as an indicator of the multiple-performance characteristics for evaluation. Lu *et al.* [11] used GRA coupled with principal component analysis (PCA) to optimize process parameters of high-speed end milling of SKD61 tool steel. Yang *et al.* [12] employed GRA method to determine optimal machining parameter setting for the end milling of high-purity graphite under dry machining conditions. Most of the researchers used their subjective judgment to establish the weighting values of various performance characteristics to calculate the values of grey relational grade.

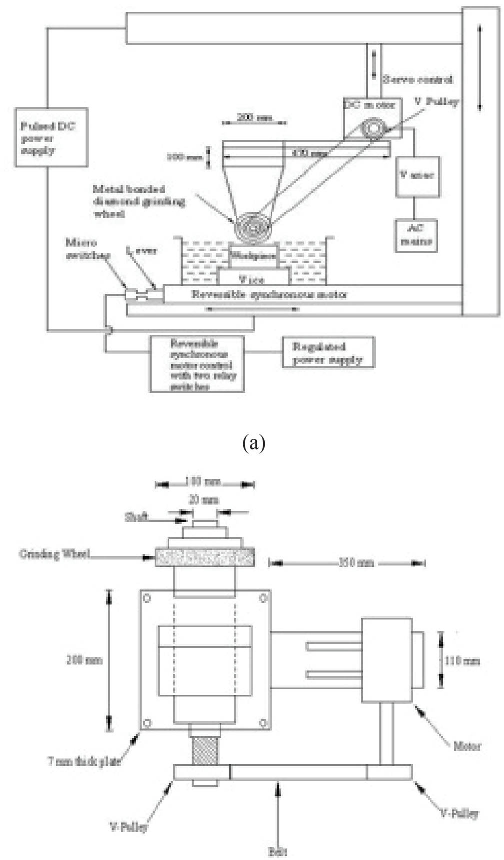
Pearson [13] proposed PCA which was subsequently developed as a statistical tool by Hoteling [14]. This approach preserves as much original information as possible by significantly simplifying a large number of correlated variables into fewer uncorrelated and independent principal components. In recent times, PCA has gradually become an analytical tool for the optimization of a system with multiple-performance characteristics [15].

The context is organized in the following manner. Section 2 describes about newly developed experimental setup on EDM machine and Taguchi methodology based experimentation. Section 3 presents optimization using GRA coupled with PCA and finally paper concludes with confirmation tests and summary of this study.

II. Details About Experimental Set Up And Taguchi Methodology Based Experimentation

An attachment was developed and mounted on a Smart ZNC die-sinking EDM machine. The EDM machine was supplied by Electronica Machine Tools Ltd. Pune, India.

The metal bonded diamond grinding wheel mounted on the ram of the machine with an attachment. Fig.1a,b [16] respectively shows schematic diagram of electro-discharge diamond surface grinding set-up and dimension details of fabricated attachment attached to Z axis replacing original tool holder of ZNC EDM machine. The grinding wheel was driven with the help of variable-speed D.C. motor through a belt pulley arrangement. The speed of the motor was varied by changing supply voltage with the help of a variac. The set up consists of a metal bonded diamond grinding wheel, D.C. motor, shaft, pulley,V-belt, bearing etc.



(a)

(b)

Fig.1a,b (a) Schematic diagram of electro-discharge diamond surface grinding set-up and (b) Dimension details of fabricated attachment attached to Z axis replacing original tool holder of EDM machine

Since the experiment was to be performed in surface grinding mode, so an automatic table feed arrangement was made. The lead screw of the machine table was driven by reversible synchronous motor. Since for automatic to and fro motion of the table motor should automatically rotate both in clockwise and anticlockwise direction as and when it is required, therefore a reversible synchronous motor control circuit was designed using relay switch, two limit switches and regulated power supply. Working of this automatic control is very simple. Suppose the motor is rotating in clockwise direction and as a result table is moving in forward direction. When a lever attached to machine table presses the limit switches, polarity of the motor will automatically changed and motor will start rotating in anticlockwise direction and therefore table will move in reverse direction.

The input process parameters taken are wheel speed, current, pulse on-time, and duty factor. The output parameters analyzed are MRR and R_a. Experiments were performed on aluminum-silicon carbide (Al-SiC) MMC.

Each workpiece was machined for 90 minutes before measuring output parameters. Three repetitions have been done in each set of experiments. Amount of material removal after 90 minutes was obtained by finding weight difference before and after machining using precision electronic digital weight balance with 0.01mg resolution. The MRR is calculated by using the following formula:

$$MRR\ (g/min) = \frac{W_i - W_f}{t} \qquad (1)$$

where W_i is initial weight of workpiece in gram (before machining); W_f is final weight of workpiece in gram (after machining); t is machining time in minutes. A Talysurf surtronic 25 at 0.8 mm cutoff value was applied to measure the R_a of each machined workpiece. The specification of grinding wheel is shown in Table I.

Table I Specification Of Grinding Wheel

Abrasive	Diamond
Grain size	80/100
Grade	M
Concentration	75%
Bonding material	Bronze
Depth of abrasive	5 mm
Wheel diameter	100 mm
Thickness of wheel	10 mm

Three levels of each process parameters have been selected without considering the interaction effect. The numerical value of process parameters at different levels for machining of Al-SiC composite is shown in Table II.

Pilot experiments were performed to decide the range of parameters. The initial level of process parameters for machining Al-SiC composites is: wheel speed- 1000 RPM, current- 8 A, pulse on-time- 100 µs, and duty factor- 0.578. The experiments were performed as per standard L9 orthogonal array (OA) (Table III). Actual photograph of the setup is shown in Fig.2a,b.

(a) (b)

Fig.2a,b EDSSG set up (a) Fabricated attachment attached to Z axis replacing original tool holder of EDM machine and (b) Fabricated attachment attached to X axis for an automatic table feed arrangement

Table II Machining Parameters and Their Levels Used in The Experiment For AL-10WT%SIC Composite

Symbol	Machining parameter	Level 1	Level 2	Level 3
S	Wheel speed (RPM)	1000	1200	1400
C	Current (A)	8	16	24
T	Pulse on-time (µs)	100	150	200
DF	Duty factor	0.578	0.638	0.697

Table III Experimental Observations For AL-10WT%SIC Composite Using L_9 OA

Exp.No.	S	C	T	DF	MRR (g/min)	ASR (µm)
1	1	1	1	1	0.0085	5.96
2	1	2	2	2	0.0099	5.94
3	1	3	3	3	0.0122	6.04
4	2	1	2	3	0.0091	4.45
5	2	2	3	1	0.0133	7.05
6	2	3	1	2	0.0112	5.78
7	3	1	3	2	0.0105	6.28
8	3	2	1	3	0.0119	6.02
9	3	3	2	1	0.0139	6.36

III. Optimization Using GRA Coupled With PCA

In GRA, when the range of sequences is large or the standard value is large, the function of factors is neglected. However, if the factors measured unit, goals and directions are different, the GRA might produce incorrect results. Therefore, original experimental data must be pre-processed to avoid such effects. Data pre-processing is the process of transforming the original sequence to a comparable sequence. For this purpose, the experimental results are normalized in the range of zero and one, the process is called grey relational generating. Three different types of data normalization according to whether we require the smaller-the-better (SB), the larger-the-better (LB), and nominal-the-better (NB). The normalization is taken by the following equations.

Smaller-the-better (SB)

$$X_i^*(k) = \frac{\max X_i(k) - X_i(k)}{\max X_i(k) - \min X_i(k)} \qquad (2)$$

Larger- the-better (LB)

$$X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)} \qquad (3)$$

Nominal-the-better (NB)

$$X_i^*(k) = 1 - \frac{|X_i(k) - X_{ob}(k)|}{\max X_i(k) - X_{ob}(k} \qquad (4)$$

Where $i = 1,2,\ldots.n;\ k = 1,2,\ldots.p;\ X_i^*(k)$ is normalized value of the kth element in the ith sequence, $X_{ob}(k)$ is desired value of the kth quality characteristic, max $X_i^*(k)$ is the largest value $X_i(k)$, and min $X_i^*(k)$ is the smallest value of , $X_i(k)$ n is the number of experiments and p is the quality characteristics.

A grey relational coefficient is calculated to display the relationship between the optimal and actual normalized experimental results. The grey relational coefficient can be expressed as

$$\xi_{o,i}(k) = \frac{\Delta \min + \zeta\Delta \max}{\Delta_{o,i}(k) + \zeta\Delta \max} \quad i = 1,\ldots,n;k \quad = 1,\ldots,p \qquad (5)$$

where $\xi_{0,i}(k)$ is the relative difference of kth element between comparative sequence X_i and the reference sequence X_o, $\Delta_{0,i}(k)$ is the absolute value of difference between $X_o(k)$ and $X_i(k)$,

$$\Delta_{0,i}(k) = |X_o^*(k) - X_i^*(k)|$$

$$\Delta\max = \underset{i}{\max}\,\underset{k}{\max}|X_o^*(k) - X_i^*(k)|$$

$$\Delta\max = \underset{i}{\min}\,\underset{k}{\min}|X_o^*(k) - X_i^*(k)|$$

ξ is a identification coefficient and its value lie between zero and one. In general it is set to 0.5

The average grey relational coefficient is the grey relational grade but, the importance of each quality characteristic may be different The grey relational grade is a weighting-sum of the grey relational coefficients. It is defined as follows:

$$\Gamma_{0,i} = \sum_{k=1}^{n} \beta_k\, \xi_{0,i}(k) \qquad (6)$$

where β_k represents the weighting value of the kth performance characteristic, and the corresponding weighting values are obtained from the principal component analysis.

A. Principal Component Analysis

Pearson and Hotelling initially developed PCA to explain the structure of variance-covariance by way of the linear combinations of each quality characteristic.

1. The Original Multiple Quality Characteristic Array

$x_i(j),\qquad i = 1,2,\ldots.m;\ j = 1,2,\ldots.n$

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \cdots\cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \cdots & \vdots \\ x_m(1) & x_m(2) & \cdots & x_m(n) \end{bmatrix} \qquad (7)$$

where is the number of experiment and is the number of quality characteristic. X is the grey relational coefficient of each quality characteristic.

2.Correlation Coefficient Array

The Correlation coefficient array is evaluated as follows:

$$R_{jl} = \left(\frac{Cov(x_i(j), x_i(l))}{\sigma_{x_i}(j) \times \sigma_{x_i}(l)}\right),\ j = 1,2,\ldots\ldots,n;\ l = 1,2,\ldots\ldots,n \qquad (8)$$

where $Cov(x_i(j), x_i(l))$: the covariance of sequences $X_i(j)$ and $X_i(l)$; $\sigma_{x_i}(j)$: the standard deviation of sequence $X_i(j)$; $\sigma_{x_i}(l)$: the standard deviation of sequence $x_i(l)$.

3. Determining the Eigenvalues and Eigenvectors

The eigenvalues and eigenvectors are determined from the correlation coefficient array,

$$(R - \lambda_k I_m)V_{ik} = 0 \qquad (9)$$

where λ_k eigenvalues,

$\sum_{k=1}^{n} \lambda_k = n,\ k = 1,2,\ldots,n;\ V_{ik} = [a_{k1}\ a_{k2}\ \ldots.\ a_{kn}]^T$: eigenvectors corresponding to the eigenvalues .

4. Principal Components

The uncorrelated principal component is formulated as:

$$Y_{mk} = \sum_{i=1}^{n} x_m(i).V_{ik} \qquad (10)$$

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. In order to objectively reflect the relative importance for each performance characteristic in grey relational analysis, PCA is specially introduced here to determine the corresponding weighting values for each performance characteristic.

Table IV The Calculated Grey Relational Co-Efficient, Grey Relational Grade And Rank

Exp. No.	Grey relational co-efficient		Grey relational grade	Rank
	MRR	R_a		
1	0.4627	0.3979	0.3333	9
2	0.4659	0.4343	0.4029	7
3	0.4498	0.5315	0.6135	4
4	1.0000	0.6790	0.3599	2
5	0.3320	0.5753	0.8180	3
6	0.4942	0.4970	0.5000	6
7	0.3987	0.4205	0.4425	8
8	0.4529	0.5135	0.5744	5
9	0.4049	0.7023	1.0000	1

Table V The Eigen Values And Explained Variation For Principal Components

Principal component	Eigen value	Explained variation (%)
First	1.4669	62.76
Second	0.5331	37.24

Table IV represent the grey relational coefficient of each performance characteristic. These data are used to evaluate the correlation coefficient matrix, and determine the corresponding eigen values shown in Table V. The eigenvector corresponding to each eigenvalue is listed in Table VI & and its square can represent the contribution of the corresponding performance characteristic to the principal component.

Table VI The Eigenvectors For Principal Components

Quality characteristic	First principal component	Second principal component
MRR	0.7071	0.7071
R_a	0.7071	0.7071

Table VII shows that the contributions of MRR and Ra are indicated as 0.4999 and 0.4999. Moreover, the variance contribution for the first principal component characterizing the whole original variables, i.e. the two performance characteristic, is as high as 62.76%.Hence for this study, the squares of its corresponding eigenvectors are selected as the weighing values of the related performance characteristic, and the coefficients β_1 , β_2 in are thereby set as 0.4999 and 0.4999 respectively.

The main effects of each control factor on grey relational grade are given in Table VIII. The use of the grey relational grade to perform the ANOVA analysis is shown in Table IX. Wheel speed, duty factor and pulse on time are the most significant process parameters for affecting the multiple process responses. From the response table for grey relational grade the best combination of input parameters is the set with $S_2C_3T_2DF_3$ i.e., wheel speed at 1200 RPM, current at 24 A, pulse on-time 150 µs and duty factor 0.697. The percentage contribution of each control factor to the total variance is pulse on-time 31.14%, duty factor 29.08%, wheel speed 28.15%, current 11.63%.

Table VII Contribution Of Quality Characteristic

Quality characteristic	Contribution
MRR	0.4999
R_a	0.4999

IV. Confirmation Experiment

Once the optimal level of the machining parameters is identified, the next step is to verify the improvement of the performance characteristics using this optimal combination. Table X compares the results of the confirmation experiment using the optimal machining parameters ($S_2C_3T_2DF_3$) with those of the initial machining parameters ($S_1C_1T_1DF_1$). Three confirmation experiments were conducted at the optimum setting of the machining parameters. The average value of MRR, and R_a at optimum level were found to be 0.137 g/min, and 6.12 µm.The result of confirmation test shows that quality characteristics MRR has been improved considerably, while Ra deteriorates slightly.

Table VIII Response Table

Symbol	Machining parameter	Grey relational grade			Effect	Rank
		Level 1	Level 2	Level 3		
S	Wheel speed	0.4545	0.5840	0.5454	0.1295	3
C	Current	0.4994	0.5077	0.5769	0.7750	1
T	Pulse on-time	0.4694	0.6054	0.5091	0.1360	2
DF	Duty facyor	0.5585	0.4527	0.5749	0.1222	4

Table IX Result of Anova

Symbol	Machining Parameters	SS	dof	Variance	F	PC (%)
S	Wheel speed	0.026419	2	0.013209	2.44	28.15
C	Current*	0.010919	2	0.0054	Pooled	11.63
T	Pulse on-time	0.029230	2	0.014615	2.70	31.14
DF	Duty factor	0.027296	2	0.01364	2.52	29.08
Pooled error		0.010919	2	0.0054		
Total		0.093864	8			100

* Pooled factors

Table X Results Of Confirmation Experiment At Optimum Parameter Level (Using Gra And Pca)

	Initial machining parameters $S_1C_1T_1DF_1$	Optimal EDDSG machining parameters $S_2C_3T_2DF_3$
MRR (g / min)	0.0085	0.137
R_a (µm)	5.96	6.12

V. Conclusions

Based on experiments, results the conclusions are summarized as follows:

1. The principal component analysis, used to determine the corresponding weighting values of each performance characteristics while applying grey relational analysis to a problem with multiple performance characteristics, is proven to be capable of objectively reflecting the relative importance for each performance characteristic.

2. The factors setting found as best combination of process variables is wheel speed- level 2 (1200 RPM), current- level 3 (24A), pulse on-time- level 2 (150 µs) and duty factor - level 3 (0.698). The percentage contribution of each control factor to the total variance is pulse on-time 31.14%, duty factor 29.08%, wheel speed 28.15%, current 11.63%.for simultaneous optimization of MRR. and R_a. Hence, the most significant factor affecting the EDDSG robustness has been identified as pulse on-time.

3. Improvement in MRR by 61.17%, but deterioration in R_a by 2.68% have been found during EDDSG at the optimum parameter setting against initial parameter setting while performing simultaneous optimization of multiple quality characteristics.

References

[1] Clyne T, W., and Withers P. J. (1992), *An Introduction to Metal Matrix Composites,* Cambridge University Press London.

[2] Kannan S., and Kishawy H. A. (2006), "Surface Characteristic of Machined Aluminum Metal Matrix Composites, *International Journal of Machime Tools and Manufacture,* Vol. 46/15, pp. 2017-2025.

[3] Mohan B., Rajadurai A. and Satyanarayana K. G. (2002), "Effect of SiC and Rotation of Electrode on Electric Discharge Machining of Al-SiC Composite," *Journal of Material Processing Technology,* Vol. 124, pp. 297-304.

[4] Handke B., Simonsen J. B. Bech M. Li. Z. and Møller P. J. (2006), "Iron Oxide Thin Film Growth on Al2O3/NiAl," *Surface science*, Vol. 600, pp. 5123 - 5130.

[5] Murakami T., Ouyang J. H. Sasaki S. Umeda K. and Yoneyam, Y. (2007), "High Temperature Tribological Properties of Spark-Plasma-Sintered Al2O3 Composites Containing Barite-Type Structure Sulfates," *Tribology International* , Vol 40(2), pp. 246-253

[6] Aguair P. R., Dotto F. R. L. and Bianch E. C. (2005), "Study of Thresholds to Burning in Surface Grinding Process," *Journal of the Brazillian Society of Mechanical Sciences and Engineering,* Vol. 27(2), pp. 150-156.

[7] Zhu, Y., and Kishawy H. A. (2004), "Influence of Alumina Particles on the Mechanics of Machining Metal Matrix Composites," *International Journal of Machime Tools and Manufacture,* Vol. 45, pp. 389–398.

[8] Di Ilio A., Paolett, A. Tagliaferrz V. and Venial F. (1996), "An Experimental Study on Grinding of Silicon Carbide Reinforced Aluminium Alloys," *International Journal of Machime Tools and Manufacture,* Vol. 36/6, pp. 673–685.

[9] Erden A., and Kaftanoglu B. (1981), "Heat Transfer Modeling of Electric Discharge Machining, in: Proc. 21st *Int. Mach. Tool Des. Research Conf.,* London.

[10] Konig W., Dauw D. F. Levy G. and Panten U. (1998), "EDM—Future Steps Towards the Machining of Ceramic," *Ann. CIRP.,* Vol. 37(2), pp. 623–631.

[11] Lu H. S., Chan C. K. Hwang N.C. and Chung C. T. (2009), "Grey Relational Analysis Coupled With Principal Component Analysis for Optimization Design of the Cutting Parameters in High-Speed End Milling," *Journal of Material Processing Technology,* Vol. 209, pp. 3808–3817.

[12] Yang Y.Y., Shi R. and Huang C.H. (2006), "Optimization of Dry Machining Parameters for High Purity Graphite in End-Milling Process," *Mateials and Manufacturing Processes,* Vol. 2, pp. 832–837.

[13] Pearson K., (1901), "On Lines and Planes of Closest Fit to Systems of Points in Space," Philosiphical Magazine series, Vol 62, pp. 559–572.

[14] Hotelling H. (1993), "Analysis of a Complex of Statistical Variables into Principal Components," *Journal of Education Psychology,* Vol. 24, pp. 417–441.

[15] Fung H.C., and Kang P.C. (2005), "Multi-Response Optimization in Friction Properties of PBT Composites Using Taguchi Method and Principal Component Analysis," *Journal of Material Processing Technology,* pp 602–610.

[16] Yadav S K S., and Yadava Vinod. (2008), "Experimental study and parameter design of electro-discharge diamond grinding,"*International Journal of Advanced Manufacturing Technology,* pp. 34-42.