**PCA-GRA Coupled Multi-Criteria Optimization Approach in Machining of Polymer Composites**

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**Abstract**

The present study deals with the machining of graphite reinforced polymer composite (GRPC) using grey relation analysis (GRA) embedded principal component analysis (PCA). L16 orthogonal array established for creating experimental procedure. The evaluation of grey relation grade based on the process of GRA and PCA technique is used to find the correlation array and to find the Eigen value as well as Eigen vector finally for calculating overall value of GRG. The combination of GRA-PCA is used to optimise the machining parameter and get the best optimal setting parameter and to identify the significant factor. ANOVA method is used to find the residual plot for GRG. In this study it has proven that the GRA embedded PCA is efficient method for giving the effective machining environment in order to minimise Thrust (T), Torque (TR), surface roughness (Ra) and maximise the metal removal rate. The optimal setting value through Taguchi method is speed 500rpm, feed rate 25mm/rev. depth of cut -1mm and weight percentage 40% simultaneously. The analysis of variance (ANOVA) is used to identify the significant factors affecting the respective response i.e. in this case weight percentage (49.27%) is most significantly affects GRG followed by speed (8.41%), feed rate (8.30%) and depth of cut (1.64%).

**Keyword:** Grey relation analysis (GRA), Principal component analysis (PCA), Analysis of variance (ANOVA), Machining, Optimization.

**1 Introduction**

Machining (milling) operation is widely apply in the area of manufacturing industry such as aerospace, automobile sector, space vehicle, fuselage component which is the main body the aeroplane, electronic insulator. The importance of doing machining (milling) operation because it has accomplished of making the various types of goods with intricate geometry. Therefore for manufacturing, it is very important to choose the machining parameter in a way that the need of quality has to be maintained without losing any cost or profit. When using the machining (milling) of graphite reinforced polymer composite, there are some important factor which has been considered such as speed (S), feed rate (f), depth of cut (DOC), weight percentage (wt.). The output responses which have been considered such as metal removal rate (MRR), thrust (T), torque (TR), surface roughness (Ra). When doing machining (milling) process, the diameter of milling cutter is to be taken 5mm. Before doing the machining operation, Taguchi based L16 orthogonal array has to be considered since it gives a precise and effective number of process for the experimental work. Taguchi method is used for generating the single response optimisation and also gives the S/N ratio. GRA-PCA method has been used to transform the multi response to single response optimisation and grey relation analysis has been used to find the correlation among multiple responses and then, GRA has been proposed by Deng Julong in 1988. Initially, PCA has proposed through Pearson and hotelling. Analysis of variance (ANOVA) has been used to get the individual optimisation after GRA based Taguchi method is used for obtaining the S/N ratio and effective optimisation. PCA has been used to find the correlation as well as calculate the Eigen value plus Eigen vector, where accountability proportion (AP) has been used to calculate the grey relation grade (GRG) and Eigen value and Eigen vector has been obtained through the use of grey relation coefficient (GRC) and after that use Taguchi method is used to get the best possible solution.

**2** **Literature Review**

Though the power of fascination among the separate coatings in allotropes of carbon having single weak van der Waals forces and the exfoliation of graphite of randomly scattered few-covering is a tedious task. Therefore, numerous chemical intercalation methods have developed for dispersion of graphitic layers [1]. There is subsequent fast heating of the graphite intercalation composites can reason of individual carbon coatings to change a part as well as growth of graphite crystals through the several times in the way normal elevated to the coatings [2-3]. The subsequent extended graphite along with low density as well as great temperature confrontation was a significant manufacturing fresh material. Simply treated through compression and it has been used for construction of great panes as well as shaped parts, like seals as well as applications of seals for high-temperature [4]. The common forms of improved graphitic were graphite oxide (GO), graphite-intercalated compounds (GICs) as well as extended graphite (EG) [5]. Graphene oxide has been called as graphite oxide has typically ready through the action of graphite chips along with oxidizing agents therefore the polar collections has presented on the surface of graphite that’s why spreading the interlayer arrangement of the planes of graphene [6]. GICs has been usually normally shaped through the addition of atomic or molecular coatings of various chemical types among the coatings of the graphite matrix [7-8]. When introduced graphite has heated past high temperature, then a huge development of graphite chips happen along with the c-axis and then in the in-plane way and this product has been called as extended graphite (EG) [9-10]. Recently, the intumescent flame retardant (IFR) flavourings were found since they have not individual additional naturally approachable and then the halogenated holding glow retardants then also have been advanced glow retardant competence than the inorganic paddings. Therefore, the form of graphite (Natural graphite, Extended graphite as well as Graphene oxide) specially expanded graphite has been extensively used to growth carbonize produce as well as encourage the thermal stability due its plentiful foundation for modest fabrication as well as little price for numerous types of polymer compounds plus EVA, , polyolefin, polyurethane, acrylic resin, unsaturated polyester as well as polylactide [11-12]. There are dissimilar types of paddings like carbon nanotubes, metal, carbon fibre as well as graphite have used to make thermally conductive compounds constituents. Mostly it has been used due to its small price, great thermal conductivity (110-130 W/mk) as well as light in weight. The pioneer has applied L16 orthogonal array as well as use of ANOVA method to learning the effect the constraints such as feed rate (f) and speed (S), Thrust (T), Torque (TR) and damage factor to minimize these responses [13].

**3 Experimental Detail**

Taguchi based L16 orthogonal array (DOE) has been used to perform the experiment. In this experiment we have consider four factor such as speed (S), feed rate (f), depth of cut (doc) as well as weight percentage (wt.) which has shown in Table 1.

**Table 1**. Process parameter and their levels

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Factors | Unit | Level 1 | Level 2 | Level 3 | Level 4 |
| Drill Speed | [RPM] | 500 | 1000 | 1500 | 2000 |
| Feed rate | [mm/rev] | 150 | 200 | 250 | 300 |
| Depth of cut | [mm] | 0.5 | 1 | 1.5 | 3 |
| Weight % |  | 10 | 20 | 30 | 40 |

The software Minitab 18 has been used for graphical analysis and optimisation of machining parameter. The size of the mould is (8.6 cm×7 cm×1cm) and the sample is based on the graphite reinforced polymer composite (GRPC) and Table 2 shows the output parameter based on DOE. The operation of milling along with numerous cutters is committed on the arbor at the similar time, therefore rising MRR for permitting several sides of machining at the corresponding period and established the precision of machining.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| S.No. | Speed (rpm) | Feed rate (mm/rev.) | Depth of cut (mm) | Weight  % |
| 1 | 500 | 10 | -0.5 | 10 |
| 2 | 500 | 15 | -1 | 20 |
| 3 | 500 | 20 | -1.5 | 30 |
| 4 | 500 | 25 | -3 | 40 |
| 5 | 1000 | 10 | -1 | 30 |
| 6 | 1000 | 15 | -0.5 | 40 |
| 7 | 1000 | 20 | -3 | 10 |
| 8 | 1000 | 25 | -1.5 | 20 |
| 9 | 1500 | 10 | -1.5 | 40 |
| 10 | 1500 | 15 | -3 | 30 |
| 11 | 1500 | 20 | -0.5 | 20 |
| 12 | 1500 | 25 | -1 | 10 |
| 13 | 2000 | 10 | -3 | 20 |
| 14 | 2000 | 15 | -1.5 | 10 |
| 15 | 2000 | 20 | -1 | 40 |
| 16 | 2000 | 25 | -0.5 | 30 |

**Table 2.** DOE based on L16 orthogonal array

**Tool material** – HSS Milling cutter (milling cutter diameter = 5mm)

**Machine specification =** CNC vertical machining centre manufactured by BHARAT FRITZ WERNER LTD.

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**Fig. 1**. CNC vertical machining centre and milling process of GRPC

Machining (milling) operation has been performed in CNC vertical machining centre and HSS milling cutter used for machining and the obtained experimental parameters such as MRR, Thrust (T) Torque (TR) and then surface roughness (Ra) has given in Table 3.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| SI.NO | MRR  (mm3/sec) | Thrust  (N) | Torque  (N-mm) | Ra  (µm) |
| 1 | 0.6287 | 0.28 | 0.1 | 1.40 |
| 2 | 1.29385 | 0.31 | 0.18 | 0.8 |
| 3 | 2.60233 | 0.5 | 0.08 | 0.9 |
| 4 | 5.5404 | 0.36 | 0.13 | 0.9 |
| 5 | 0.826183 | 0.42 | 0.05 | 1.1 |
| 6 | 0.597195 | 0.39 | 0.11 | 0.8 |
| 7 | 5.7360 | 0.44 | 0.11 | 1.20 |
| 8 | 3.19013 | 0.39 | 0.25 | 1.1 |
| 9 | 1.17894 | 0.31 | 0.06 | 0.7 |
| 10 | 4.01136 | 0.42 | 0.16 | 0.9 |
| 11 | 0.958750 | 0.44 | 0.13 | 1.6 |
| 12 | 2.1732 | 0.28 | 0.16 | 1.50 |
| 13 | 2.8615 | 0.5 | 0.19 | 2.4 |
| 14 | 2.30162 | 0.33 | 0.13 | 1.0 |
| 15 | 1.8593 | 0.36 | 0.09 | 0.7 |
| 16 | 1.15410 | 0.25 | 0.13 | 1.4 |

**Table 3.** Calculation of Experimental Data

**4 Concept of GRA and PCA**

Deng Julong in 1988 has proposed the concept of grey relation analysis which shows the interrelationships among the multi-response of changing parameters. In this method the grey relation grade (GRG) has obtained through examining the degree of relation of the multiple output responses. There are following steps which have been considered for getting the value of grey relation grade (GRG).

1. Experiment parameter
2. Normalised data (N)
3. Deviation sequence (D)
4. Grey relational coefficient (GRC)
5. Grey relational grade (GRG)

**Normalised data:**

First the output responses based on the L16 orthogonal array is normalise between the values 0 to 1.The preferable design featuresuch as MRR, Thrust (T), Torque (TR), Surface roughness (Ra) have three aspect such as Nominal is best, Higher the better (HB) , Lower the better (LB), equation 1 and 2 is used to normalise the machining parameter.

**Higher-the-better (HB)**

(1)

**Lower-the-better (LB)**

(2)

Where xi (j) is comparability sequence and xi\*(j) sequence after data pre-processing.

**Deviation Sequences**

(3)

Where, Δoi(j) Deviation sequence of the reference sequence xo\* (j) and the comparability sequence xi\*(j).

**Grey Relational Coefficient**

The equation of GRC,

(4)

Where, *ξ* is defined as an identification coefficient

**Methodology of PCA:**

Principal component analysis (Hotelling1993) is a multivariate numerical technique mainly used to identify the correlation among the various responses.

**Collection of multi-response**

X1(1) X1(2)…. ……. X1(n)

X = X2(1) X2(2)…. ……. X2(n)

Xm(1) Xm(2)…. ……. Xm(n)

Xi (j), where i = 1 2 3 …..m and j = 1 2 3………n, Where, “m” has shown the number of assessment trial also the “n” has shown the number of the output response.

**Considering the correlation coefficient array:** The correlation coefficient array of the standardised parameter collection has assessed as given below: Rji = Covar. (Xi\*(j), X\*(l) ̸ 𝜎xi\*(j)\*× 𝜎xi\*(1), Wherever, Covari. (Xi\*(j), X\*(l) is the covariance of sequences xi\*(j) and xi\* (l); 𝜎xi\* (1): The standard deviation of sequence is xi\*(l).

**Considering the eigenvalues as well as the eigenvectors**: The eigenvalues as well as the eigenvectors have been considered from the array of association factor.

|  |
| --- |
| (R- גkIm)Vik = 0 |

∑ גk = n where, k = 1 2 3 …… …… n

Where, גk is the Eigen values and the Vik= [ak1 ak2 …. akn] T: Eigen vectors corresponding to the Eigen value of גk.

**Assessment of principal modules**

The uncorrelated principal components has given below:

|  |
| --- |
| Ymk = ∑ Xm\*(i)Vik |

Ymk is called the principal component, where,i= 1, 2………..n.

**5 Result and Discussion**

Initially normalised the experimental data such as MRR, Thrust (T), Torque (TR) and surface roughness (Ra) has shown in Table 3 by the use of GRA method and then calculate the deviation sequence. After finding the deviation data is used for calculating the GRC value and that GRC value which helps to find the Eigen value and Eigen vector for calculating grey relation grade (GRG) and whole calculation of experimental data is based on the combination of data obtained from the Taguchi based DOE technique and the obtained data has been shown in Table 4 which shows the calculated value of GRC and GRG. PCA analysis of experimental data is shown in Table 5 and the best optimal setting parameters as shown in table 6 and Fig. 2 shows the main effect plot of S/N ratio. ANOVA is used to find the contribution of the considered parameter and the obtained data is shown in Table 7. The residual plot for GRG as well as represents the variation between residual and their expected value shows in Fig.3. The value of GRG is calculated by GRA procedure and the higher value of GRG decides the rank which is closer to the optimal setting value. ANOVA also gives the information about how much part is affected during the machining (MRR, T, TR, Ra). ANOVA has been used to know about the contribution of percentage of the considered parameters.

**Table 4**. Calculations of GRC and GRG

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Grey Relation Coefficient** | | | | **Grey Relation Grade** |
| **MRR** | **Thrust** | **Torque** | **Ra** | **GRG** |
| 0.334701 | 0.806452 | 0.666667 | 0.548387 | 0.144434 |
| 0.366453 | 0.675676 | 0.434783 | 0.894737 | 0.137578 |
| 0.45053 | 0.333333 | 0.769231 | 0.809524 | 0.129797 |
| 0.929259 | 0.531915 | 0.555556 | 0.809524 | 0.178829 |
| 0.343539 | 0.423729 | 1 | 0.68 | 0.144589 |
| 0.333333 | 0.471698 | 0.625 | 0.894737 | 0.126799 |
| 1 | 0.396825 | 0.625 | 0.62963 | 0.171335 |
| 0.5023 | 0.471698 | 0.333333 | 0.68 | 0.121269 |
| 0.360544 | 0.675676 | 0.909091 | 1 | 0.162395 |
| 0.598364 | 0.423729 | 0.47619 | 0.809524 | 0.136856 |
| 0.349738 | 0.396825 | 0.555556 | 0.485714 | 0.105283 |
| 0.419002 | 0.806452 | 0.47619 | 0.515152 | 0.142082 |
| 0.471978 | 0.333333 | 0.416667 | 0.333333 | 0.070063 |
| 0.427964 | 0.609756 | 0.555556 | 0.73913 | 0.138055 |
| 0.398598 | 0.531915 | 0.714286 | 1 | 0.14515 |
| 0.359292 | 1 | 0.555556 | 0.548387 | 0.157243 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 5.** PCA analysis | | | | |
| Eigenvalue | 1.4274 | 1.3006 | 0.7363 | 0.5357 |
| Accountability Proportion (AP) | 0.357 | 0.325 | 0.184 | 0.134 |
| Cumulative accountability proportion (CAP) | 0.357 | 0.682 | 0.866 | 1 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Level |  | Machining parameter |  |  |
|  | Speed(S) | Feed (f) | DOC | Wt. % |
|  |  |  |  |  |
| 1 | 0.053547 | 0.13037 | 0.13344 | 0.148976 |
| 2 | 0.089695 | 0.134822 | **0.14235** | 0.108548 |
| 3 | 0.023537 | 0.137891 | 0.137879 | 0.142121 |
| 4 | **0.127628** | **0.149856** | 0.139271 | **0.153293** |

**Table 6.** Evaluation of optimal setting

**Table 7.** ANOVA table for GRG

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value |
| Speed | 3 | 0.000846 | 8.41% | 0.000846 | 0.000282 | 0.26 |
| Feed | 3 | 0.000835 | 8.30% | 0.000835 | 0.000278 | 0.26 |
| Doc | 3 | 0.000164 | 1.64% | 0.000164 | 0.000055 | 0.05 |
| Wt | 3 | 0.004954 | 49.27% | 0.004954 | 0.001651 | 1.52 |
| Error | 3 | 0.003256 | 32.38% | 0.003256 | 0.001085 |  |
| Total | 15 | 0.010055 | 100.00% |  |  |  |

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**Fig. 2.** S/N ratio plot for GRG **Fig. 3.** Residual graph for GRG

**6 Conclusions**

Generally, when using optimisation of machining (milling) data with multi-performance characteristics (high MRR, low thrust, torque and Ra) for the milling operation of GRPC and to get the higher optimal setting value for GRG is obtained through Taguchi based main effect of S/N ratio plot which shows the optimal setting parameters such as Speed (N) 500rpm, Feed rate (f) 25mm/rev., Depth of cut (doc) -1mm and weight percentage (wt.) 40%. After that ANOVA method coupled GRG for getting the residual plot for GRG and also obtained the significant factor for surface roughness (Ra), Thrust (T), Torque (TR) and MRR and it has found that the most effective factor for MRR is depth of cut. ANOVA for Ra has been acceptable the goodness of fitting and their percentage contribution in the considered parameter such as weight percentage 49.27%, speed 8.41%, feed rate 8.30% and depth of cut 1.64%. Feed rate effect the surface roughness (Ra) of the composite material during machining. It has been found that the GRA based Taguchi technique coupled with PCA is the most effective and desirable for solving the problem of quality during the milling machining of GRPC material.

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