MULTI-RESPONSE OPTIMIZATION FOR DRILLING OF GFRP COMPOSITES USING HYBRID GRA-PCA TECHNIQUE

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ABSTRACT
In this work proposed multi-objective optimization technique of Taguchi based Grey relational analysis (GRA) coupled with principal component analysis (PCA) in order to select the optimal processes parameters to minimize the delamination damages during drilling of GFRP composites. Experiments are designed as per the Taguchi L9 orthogonal array. The process parameters selected for experimentation as feed, specimen thickness, cutting speed and fiber orientation. Experimental results are statistically analysed using ANOVA. From the analysis it is found that feed is the most influencing parameter of delamination.

Keywords: delamination, principal component analysis, grey relational analysis, GFRP composites, multi-objective optimization.

Nomenclature
s     Speed
f     Feed
t     Thickness
f_o  Fiber orientation

1. INTRODUCTION
Glass fiber reinforced polymer (GFRP) composite materials are widely using in different fields of engineering applications includes, aircrafts, marine, automobiles and chemical industries because of having major advantages such as high strength to weight ratio, chemical resistance, excellent corrosion and thermal resistance. Conventional machining of composites is a complex task due to anisotropic and hard reinforced fibers thereby affecting the delamination damage.

Paolo C. Priarone (2017), et al, investigated influence of drill diameter, specimen thickness and feed rate on delamination and thrust force. Feed rate is the most influencing parameter on delamination and thrust force. Dhiraj kumar (2016) et al. conducted hole making operation on GFRP composites by considering three dissimilar tools and concluded that helical flute (HSS) drill and carbide (K20) drill has more delamination than the solid carbide drill.

K. Palanikumar (2014) et al investigated effect of 4-flute-end mill cutter and 2-flute twist drill on delamination and surface roughness. From the results it is concluded that 4-flute end mill cutter giving better results than the 2-flute drill. B. Latha (2014) et al, reported that delamination is severely affected by the feed rate and drill diameter during drilling of GFRP composite materials.

Vijayan Krishnaraj (2012) et al, concluded that push-out delamination is strongly affected by the cutting speed and feed than the peel-up delamination. Liu DF (2012) et al found that 60% of aircraft components are severely affected by the delamination damages during drilling operation.

Islam Shyha (2010) et al, conducted experiments on 3 mm thickness of CFRP composite material using carbide tipped tool to examine the delamination. From the results it is found that feed rate having strong effect on delamination. In addition to that push out delamination is more than the peel up delamination. E. Kilickap (2010), conducted experiments by varying the drill point included angle of 118° and 135° to investigate the delamination factor. They reported that delamination damage is less at entrance for angle of 118°; and is also small at exit for an angle of 135°. K. Palanikumar (2011) et al, suggested that high spindle speed and lower feed rate for minimal delamination.

A. M. Abrao (2008), et al, studied influence of tool geometry on delamination damages and thrust force. Optimum results are obtained at lower feed rate and higher speed is concluded by authors. G. V. N. Karnik (2008) et al studied influence of process parameters on delamination damages over CFRP composite material with high speed cutting. They established relationship between delamination damages and input process parameters using Artificial Neural Network (ANN).

N. S. Mohan (2007) et al, studied effect of process parameters on delamination during drilling of GFRP composites. They reported from the results as peel up delamination is significantly affected by the material thickness and cutting speed. Whereas push out delamination is significantly affected by the specimen thickness and feed rate. K. Siva Prasad (2019) investigated that delamination damages during drilling of GFRP composites and concluded that push-down delamination damage is more than the peel-up delamination.

C. C. Tsao (2004) et al, performed drilling operation on CFRP laminate using three different types (Twist drill, candle stick drill and saw drill) of drill tools. From the experimental results they observed as
Delamination is significantly affected by the drill diameter and feed rate. In addition to that it is observed as twist drill giving largest delamination than the candle stick drill and saw drill.

From the literature review, most of the authors investigated the effect of process parameters such as tool geometry, speed and feed on delamination and thrust force. From the literature the gap observed as influence of material thickness and fiber orientation on delamination damage. The present work aiming on the influence of process parameters on peel-up delamination and push-out delamination by applying the Taguchi’s ANOVA. In addition to that applied multi-objective optimization of process parameters using GRG coupled PCA approach.

2. EXPERIMENTAL DETAILS

2.1 Selection of Material and Process Parameters

The material selected for conventional drilling operation as E-Glass/138 with Epoxy resin/LY556. For the experimentation GFRP specimens are laminated by the hand layup method. Each specimen having size of 10 cm x 4 cm. in addition to that specimen thickness varies to 4 mm, 6 mm and 8mm.

The process parameters selected for the experimentation are spindle speed, feed, specimen thickness and fiber orientation. Experiments are designed as per the taguchi’s orthogonal array and each process parameter having 3 levels of design.

2.2 Experimental Setup

Drilling operation carried over specimen by CNC vertical milling machine (Model KMV-8VC) made by KENT-India Co. Ltd, Taiwan. The speed of the machine is varied from 30 rpm to 8000 rpm. The drill size of 10 mm is considered for all the experiments. After machining operation the drilled hole delamination factor is measured by the Tool Maker Microscope.

2.3 Delamination

The Delamination (damage around the drilled hole) factor has been measured by using tool maker microscope. The delamination factor (F_d) determined by the ratio of the maximum diameter (Dmax) of the delamination zone to the hole diameter (D).

The delamination factor calculated by the following equation as: \[ F_d = \frac{D_{\text{max}}}{D} \]

Figure 1. Determination of delamination factor.

3. MULTI-OBJECTIVE OPTIMIZATION USING HYBRID GRA-PCA TECHNIQUES

In this research work, multi-objective optimization approach is proposed to select the optimal process parameters using GRA-coupled PCA. The methodology consists following steps.

3.1 Normalization

In GRA, the ranges of response variables are larger and the functions of variables are neglected this is due to the response variables functions and their units are different, so that it is necessary to preprocess the response variables to normalize the numerical values between the 0 and 1. The normalization for output response is calculated based on the requirement. They are smaller is the better (SB) and larger is the better (LB).

The equation for Smaller the better as follows:

\[ x_i^o(k) = \frac{\text{max} x_i(k) - x_i^o(k)}{\text{max} x_i(k) - \text{min} x_i^o(k)} \]  \hspace{1cm} (1)

Where, \( x_i^o(k) = x_i(k) - \text{min} x_i^o(k) \)

The equation for Larger the better as follows,

\[ x_i^o(k) = \frac{\text{min} x_i(k) - x_i^o(k)}{\text{max} x_i(k) - \text{min} x_i^o(k)} \]  \hspace{1cm} (2)

Where, \( i=1, \ldots, m; k=1, \ldots, n \). \( m \) is the number of experimental data items; \( x_i^o(k) \) Denotes the original sequence; \( \text{min} x_i^o(k) \) is the smallest value of \( x_i^o(k) \); \( \text{max} x_i^o(k) \) is the largest value of \( x_i^o(k) \). Normalized values are calculated by using the equation (1) and tabulated in Table-1.
3.2 Determination of Grey Relational Co-Efficient (GRC)

After normalization, the grey relation coefficient \( \xi_i(k) \) for the \( k \)th quality characteristics in the \( i \)th experiment can be articulated as

\[
\xi_i(k) = \frac{\Delta_{\text{min}} + \Delta_{\text{max}}}{\Delta_{\text{max}}(k) + \Delta_{\text{max}}}
\]

(3)

Where \( \Delta_0(k) \) is the offset in the absolute values flanked by the reference series \( y^*(k) \) and the comparability series \( y^*(k) \), \( \zeta \) is the characteristic coefficient which is generally taken as 0.5, \( \Delta_{\text{max}} \) is the least value of \( \Delta_0(k) \), and \( \Delta_{\text{max}} \) is the biggest value of \( \Delta_0(k) \).

3.3 Calculation of Grey Relational Grade (GRG)

After the grey relational coefficient, \( \xi_i(k) \), is derived, the grey relational grade (GRG) \( \delta_i \) is determined as the mean value of the grey relational coefficients.

\[
\delta_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k)
\]

(4)

Where, \( \delta_i \) representing weighted GRG varying from 0 to 1, \( n \) is the number of experiments conducted. Among all the attainments, the highest value of GRG indicates best optimal process parameters to achieve the multi-objective optimization of various response parameter values.

3.4 Principal Component Analysis (PCA)

PCA is the statistical approach that converts a set of observations of most likely correlated variables into a set of values of uncorrelated variables. The main advantage of PCA is that once the patterns in data are identified, the data can be compressed, i.e. reducing the number of dimensions, without much loss of information. The steps involved in PCA are discussed below:

**Step (i)** Formation of multi-objective response matrix (M):

PCA explains the structure of variance-covariance matrix (M), which is formed from Equation (5) as given.

\[
M = \begin{bmatrix}
    m_1(1) & m_1(2) & \ldots & m_1(n) \\
    m_2(1) & m_2(2) & \ldots & m_2(n) \\
    \vdots & \vdots & \ddots & \vdots \\
    m_o(1) & m_o(2) & \ldots & m_o(n)
\end{bmatrix}
\]

(5)

where form \( i(j), i = 1,2,3,\ldots n \) number of trials, \( j = 1,2,3,\ldots n \) number of output response parameters. In this present research, \( O = 27, n = 2 \) and \( M \) are the GRC of individual response parameters.

**Step (ii)** Formation of correlation matrix \( P_{ji} \):

Now, the correlation matrix \( P_{ji} \) is attained from Eq. (6)

\[
P_{ji} = \frac{\text{Cov}(x_i(j), x_i(l))}{\sigma_x(j) \times \sigma_x(l)}
\]

(6)

Where \( j = 1,2,\ldots,n \) and \( l = 1,2,\ldots,n \). Herein, \( \text{Cov}(x_i(j), x_i(l)) \) is the co-variance of sequences \( x_i(j) \) and \( x_i(l) \); \( \sigma_x(j) \) is the standard deviation of the sequence \( x_i(j) \); and \( \sigma_x(l) \) is the standard deviation of sequence \( x_i(l) \).

Eigen vectors and Eigen values are obtained from correlation coefficient matrix presented as Eq. (7)

\[(R-\lambda_k I_n)V_k=0\]

(7)

Where, \( k = 1, 2, \ldots, n \),
\[V_k = [a_{k1}, a_{k2}, \ldots, a_{kn}] \] T Eigen vectors corresponding to the Eigen value \( \lambda_k \).

Here the response parameters such as surface roughness and circularity error are analyzed by using ANOVA. The multi-objective optimization of process parameters are carried using GRA coupled PCA. The response quality decides weighting value \( o_k \) for each
parameter is estimated via PCA. The GRG-PCA value is expressed as in Table-2.

Table-2. Eigen values and explained variation for PCs.

<table>
<thead>
<tr>
<th>Principal component</th>
<th>Eigen Values</th>
<th>Explained variation %</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>1.3681</td>
<td>76.95</td>
</tr>
<tr>
<td>Second</td>
<td>0.4096</td>
<td>23.04</td>
</tr>
</tbody>
</table>

Table-2 shows that the first principal component carries Eigen value of 1.3681 followed by second PC of 0.4096. The first PC contributes 76.95% of the total and rank as one followed by the second PC contributes 23.04% and holding the second rank. The Eigen vectors are used to transforming the data into principal components. The Eigen vectors define only directions they are of arbitrary length. The sign of the eigenvectors is arbitrary. Generally negative values are preferred.

Table-3. The Eigenvectors for principal components and contribution.

<table>
<thead>
<tr>
<th>Response variable</th>
<th>Eigen Vectors</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First principal component</td>
<td>Second principal component</td>
</tr>
<tr>
<td>Surface roughness</td>
<td>-0.7071</td>
<td>0.7071</td>
</tr>
<tr>
<td>Circularity error</td>
<td>0.7071</td>
<td>0.7071</td>
</tr>
</tbody>
</table>

4. RESULTS AND DISCUSSIONS

Experiments are conducted as per the Taguchi’s design of experiments for that selected L9 orthogonal array with 4 factors and 3 levels of design. Here multi-objective optimization is carried using GRA coupled PCA approach. From the results GRC and GRG values are listed in Table-4.

Table-4. GRC, GRG and Rank of delamination at top and bottom.

<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>Grey Relational Coefficient (GRC)</th>
<th>Grey Relational Grade (GRG)</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Surface Roughness</td>
<td>Circularity Error</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.945946</td>
<td>1</td>
<td>0.972778</td>
</tr>
<tr>
<td>2</td>
<td>0.813953</td>
<td>0.450292</td>
<td>0.631997</td>
</tr>
<tr>
<td>3</td>
<td>0.853659</td>
<td>0.392857</td>
<td>0.623133</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.939024</td>
<td>0.69318</td>
</tr>
<tr>
<td>5</td>
<td>0.897436</td>
<td>0.487342</td>
<td>0.69225</td>
</tr>
<tr>
<td>6</td>
<td>0.333333</td>
<td>0.413978</td>
<td>0.37358</td>
</tr>
<tr>
<td>7</td>
<td>0.686275</td>
<td>0.334783</td>
<td>0.510426</td>
</tr>
<tr>
<td>8</td>
<td>0.538462</td>
<td>0.616</td>
<td>0.577115</td>
</tr>
<tr>
<td>9</td>
<td>0.636364</td>
<td>0.333333</td>
<td>0.484752</td>
</tr>
</tbody>
</table>

GRA coupled PCA based multi-objective optimization method has been adopted in order to achieve the least delamination damages. From the Table-4, it is observed that ranks are assigned as per the GRG value, higher value of GRG is considered as rank one, which shows the optimal combination to achieve the minimum delamination damages at top and bottom drilled hole surfaces. The corresponding optimal process parameters setting shows the cutting speed at level 1(400 rpm), feed at level 1 (0.02 mm/feed), thickness at level 1 (4 mm) and fiber orientation at level 1 (0°). From the response Table-5, it is observed that feed is assigned as rank 1 which means that feed is the most significant parameter affecting delamination damages, followed by the speed, fiber orientation and material thickness.
Table 5. Response table for Means.

<table>
<thead>
<tr>
<th>Level</th>
<th>Speed (rpm)</th>
<th>Feed (mm/rev)</th>
<th>Thickness (mm)</th>
<th>Fiber orientation (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7426</td>
<td>0.8175</td>
<td>0.6412</td>
<td>0.7166</td>
</tr>
<tr>
<td>2</td>
<td>0.6784</td>
<td>0.6338</td>
<td>0.6954</td>
<td>0.5053</td>
</tr>
<tr>
<td>3</td>
<td>0.5241</td>
<td>0.4938</td>
<td>0.6086</td>
<td>0.7232</td>
</tr>
<tr>
<td>Delta</td>
<td>0.2185</td>
<td>0.3237</td>
<td>0.0868</td>
<td>0.2179</td>
</tr>
</tbody>
</table>

Figure 2. Main effects plot for GRG.

From the Figure-2 optimal process parameters are selected to minimize the delamination damages at top and bottom of the drilled hole. Optimal process parameters selected as speed at level 1 (400 rpm), feed at level 1 (0.04 mm/rev), specimen thickness at level 2 (6 mm) and fiber orientation at level 1 (0°). The significant effect of each process parameters on GRG is carried using ANOVA. Among all the selected process parameters, feed is the most significant factor affecting the top delamination and bottom delamination with 46.85 % of contribution this is observed from the table 6, followed by contribution of speed (at 22.43%), fiber orientation (at 27.30%) and specimen thickness (at 3.41%).

Table 6. Analysis of Variance.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj SS</th>
<th>Adj MS</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed (rpm)</td>
<td>2</td>
<td>0.07569</td>
<td>0.07569</td>
<td>0.037846</td>
<td>22.43%</td>
</tr>
<tr>
<td>Feed (mm/rev)</td>
<td>2</td>
<td>0.15812</td>
<td>0.15812</td>
<td>0.079058</td>
<td>46.85%</td>
</tr>
<tr>
<td>Thickness (mm)</td>
<td>2</td>
<td>0.01152</td>
<td>0.01152</td>
<td>0.005762</td>
<td>3.41%</td>
</tr>
<tr>
<td>Fiber orientation (degree)</td>
<td>2</td>
<td>0.09213</td>
<td>0.09213</td>
<td>0.046067</td>
<td>27.30%</td>
</tr>
</tbody>
</table>
Figure-3 shows the interactive effects of process parameters on delamination damages. Non-parallelism lines in interaction plot show significant effect on response parameters. It is observed that combinations of speed & feed, speed & thickness, feed & thickness and thickness & fiber orientation having much influence on response parameters. 

Regression Equation

\[
GRG = 1.236 - 0.000273s + 8.09 f - 0.00811 t + 0.00007 f_o
\]  

Figure-4 shows the normal probability plot for standardized residual. The model adequacy (Eq. 8) is checked by using normal probability plot. It is evident that the process follows the normal distribution without any deviation (no outlier). Hence, it may be concluded that the proposed model performs satisfactory.

4. CONCLUSIONS

Using multi-objective optimization approach such as grey relational analysis (GRA) coupled principal component analysis (PCA) the following conclusions are a)

From the results it is found that top and bottom delamination of the drilled hole is highly affected by the feed rate followed by spindle speed. Also
observed that material thickness having least effect on the delamination damages.

b) Optimal process parameters are selected to minimize the delamination damages using GRA coupled PCA analysis such as speed at level 1 (400 rpm), feed at level 1 (0.06 mm/rev), specimen thickness at level 1 (4 mm) and fiber orientation at level 1 (45°).

c) Feed is the most significant factor affecting the top delamination and bottom delamination with 46.85% of contribution this is observed from the table 6, followed by contribution of speed (at 22.43%), fiber orientation (at 27.30%) and specimen thickness (at 3.41%).

REFERENCES


