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PCA-TOPSIS HYBRID TAGUCHI APPROACH FOR MULTI-ATTRIBUTE OPTIMIZATION IN MACHINING OF GLASS FIBER REINFORCED POLYESTER COMPOSITE

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Abstract

Polymer composites are important materials for the engineering & technology primarily used in aerospace, automotive parts and construction technology. In present study, a relatively novel approach i.e. PCA-TOPSIS has been proposed as the multi attribute optimization for turning of GFRP. Carbide K20 tool has been selected and spindle speed (N, rpm), feed rate (f, mm/min) & depth of cut (d, mm) are the process parameters and varied according to L_9 orthogonal based combination.Fiber breakage,matrix de-bonding, matrix cracking,thermal degradation and fiber pull out is major problem during turning operation of FRP composites materials which effects the quality of product and overall product performance.Previous studies assumed the negligible response correlation and assignment of priority weights which totally depends upon the decision makers. Both assumptions create vagueness in the results, but in the present study this situation has been fruitfully tackled by the application of PCA based TOPSIS module. Present work aims to achieve the ultra-precise machining with high accuracy. For this, it is important to use the robust optimization techniques (capable of overcoming drawbacks of existing optimization techniques available) for selection of favorable parametric setting in machining of GFRP composites.

Keywords: *GFRP; Orthogonal array; PCA; TOPSIS; Taguchi*

Introduction

Composites are a class of material in which when the two more different materials combine for achieving different properties that could not be obtained from any one material [1]. Glass reinforced polymer composites are being used in different types of engineering application due to their outstanding properties in contrast to conventional engineering materials. The ease to change the composites properties for some dominated application have been one of their advantage and one of the more real difficulties to think about them as reasonable option in contrast to traditional materials. In generally, every fabricated composite material will go through some machining process for their use in end application. Quality of machining is majorly depending on properties of the work materials. The dimensional precision could affect by the surface roughness. Optimization of cutting parameters to obtained desired characteristic of output has been a continuous research problem.

Composites have anisotropy heterogeneity, high abrasiveness in nature due to reinforcement of fiber therefore machining of composites is difficult task. Composites materials have anisotropy and heterogeneity in nature therefore machining of reinforced materials is an intricate task [2]. Optimization of input parameters is a basic standard in the machining methodology to achieve high quality. Generally, the Taguchi technique is used to improve the performance measures of process parameters to obtain high quality [3]. However, Taguchi application are concerned with optimization of a single performance of machining. Various optimization approach combined with Taguchi used by various researchers. The only restriction with this approach the optima only only to the preselected values of input parameters as per the chosen orthogonal array. Optimization of more than one output attributes at single optimal setting is still a curious research problem. Such type of optimization problem is more complex in compare of Single objective optimization problem [4-5]. In disparity to traditional optimization algorithms, modernistic techniques like artificial bee colony, ant colony, simulated annealing and Particle swarm optimization (PSO) were utilized to look at the convergence rate of the algorithm. Among these algorithms PSO achieves the objective as GA does in another and quicker and yield way. PSO has the highlights of straight forward rationale, straightforward acknowledgment and hidden insight [6]. Hereditary calculation (GA) abuses the possibility of survival of wellness and interbreeding populace and along these lines makes a novel and creative methodology [7-8]. In this examination, moderately new modules (PCA-TOPSIS) has been produced for Multi objective optimization.

Experiment Details

Glass fiber reinforced polyester composites consider as work materials. The following GFRP have following specification shown in Table 1.

Methodology

Initially, this technique was applied to quantify and identify phenomena in social sciences in which it was difficult to directly measure the phenomenal changes. PCA is useful in reduction of data and interpretation of multi-objective sets of data. Currently PCA is finding wide applications in various scientific fields. In this, the focus is on correlation analysis of inter-object using linear combinations for each performance measure. In the available optimization techniques TOPSIS is used deal with multiple criteria decisions problem. The idea of the method is that, it picks the best alternative with shortest distance from the positive solution and the most remote from the negative solution. These theoretical solution relate to the greatest and least quality qualities in the database that comprise satisfy solutions. The nearest hypothetical best and most distant hypothetical most noticeably bad is utilized

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to acquire the best solutions [9]. The substantial characteristics the quantity of choices is productively examined by TOPSIS, however it is required to discover the weight criteria of every objective [10]. Thus, the benefits of the two strategies have been mulled over and displayed as a consolidated PCA-TOPSIS technique. The following techniques are utilized to choose the best alternative in combined PCA and TOPSIS [10].

Step 1: The experimental values of MRR and Surface Roughness are converted into S/N ratio. The S/N ratio with a LTB and HTB represented following equation 1 and 2 respectively.

LTB response variable

$$\eta_{ij} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^{-2}\right] \quad (1)$$

HTB response variable

$$\eta_{ij} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^{2}\right] \quad (2)$$

Where η_{ij} denotes the S/N ratio (for i^{th}experiment and j^{th} response) calculated from observed values, $y_i$represents the experimentally observed value of the i^{th}experiment and n=1 is the repeated number of each experiment in L_9 OA is conducted. The second step is to conduct PCA on the S/N ratios to obtain uncorrelated PCSs corresponding to each experimental run, in the form of PCS_{il}it can be obtained by follows:

$$PCS_{il} = a_{l1}\eta_{i1} + a_{l2}\eta_{i2} + \dots\dots\dots + a_{lj}\eta_{ij} \quad (3)$$

Where $a^2_{l1}+a^2_{l2}\dots\dots +a^2_{lj} = 1$. The a_{l1}, $a_{l2}\dots\dots$ $a_{lj}$are the elements of eigenvector equivalent to the l^{th} eigenvalue of response variables. It can be calculated by MINITAB software. The eigenvalue and eigenvector are shown in Table 3. The third steps normalized the PCSs value by using equation 4.

$$X_{il} = \frac{PCS_{il} - PCS_{il}^{\min}}{PCS_{il}^{\max} - PCS_{il}^{\min}} \quad (4)$$

Where X_{il} and $PCS_{il}$are normalized and observed data, respectively for i^{th} experiment using l^{th}principal component score. The smallest and largest values of PCS_{il} for the l^{th} PCS are min PCS_{il}^{min} and max PCS_{il}^{max} respectively.

Result and discussion

Experimental output and relating S/N ratio listed in Table 4 have been examined by developed approach. In this approach after S/N ratio correlation check has been done by PCA method Eigen vector has been computed and it has recorded in Table 5. The PCA results shows the non-zero value of Pearson correlation coefficient, which has been successfully eliminated by this technique and then Normalization of Principal components (PCs) has been done in Table 7. For the MRR and Ra; Lower-is-Better (LB) has been taken in consideration for Normalized Principal components and corresponding Quality loss (Table 8). These calculated values (Table 8) are treated individual alternatives of decision matrix in TOPSIS. The ideal positive and anti-ideal solution has been determined by using Eq.5 & 6 and listed in Table 9. Now, separation distance measure has been evaluated from both positive ideal and negative ideal solution by using Eq. 7, 8 and tabulated in

Table 10. Overall performance coefficient closest to the ideal solution have been evaluated by using Eq.9 and tabulated in Table 11. Finally ranking has been implemented to determine favorable machining condition. The optimal machining condition 06 has been determined as Spindle speed 860 rpm, feed rate 0.331mm/rev and depth of cut 3.0 mm and it has been observed from Table 3. Confirmatory test has been performed which shows the satisfactory result.

Conclusions

Into this paper relatively, new hybrid optimization module is applied for various response optimization in turning of GFRP composites. The developed hybrid model can be obtain a near optimial solution for lower surface rougness and higher surface roughness. The non-zero value of Pearson correlation coefficient shows the response closeness which has been successfully eliminated by PCA technique. The optimal setting obtained is Spindle speed 860 rpm, feed rate 0.331mm/rev and depth of cut 3.0 mm which has been effectively tested by confirmatory test and shows satisfactory results. The planned procedure is straight forward, effective in developing a robust, versatile and flexible mass production process. This approach can be endorsed for constant quality improvement and off-line quality control of a process/product in any manufacturing/ production environment.

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Table 1: *Specifications of work material*

Resin used	Polyester resin
Fiber orientation	Random
Method of preparation	Hand molding method
Composition	75:25 (Resin: Fiber)
Weight percentage of hardener	5%
Density	2 gm/cm^3

For the turning purpose Carbide tool has been used. In this investigation spindle speed, feed rate and depth of cut have been consider as input parameters and other parameters assumed to be constant at the same. Every input parameters varied at three level and details about it listed in table 2. The selection of values for the variables have been done by taking the capacity and the limiting values of the machine into account together with the recommended specifications of different work piece and tool material combinations. In the present investigation, Taguchi's L_9 orthogonal array (OA) design (without factorial interaction) has been considered for experimentation Table 3.

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***Table 2:** Domain of experiment*

	Input parameters		
Level	Spindle Speed N (RPM)	Feed Rate f (mm/rev)	Depth of cut d (mm)
1	530	0.298	3.0
2	860	0.308	4.0
3	1400	0.331	5.0

***Table 3:** Design of experiments (L_9 orthogonal array)*

Sl. No.	Factor setting		
	N	f	d
1	530	0.298	3.0
2	530	0.308	4.0
3	530	0.331	5.0
4	860	0.298	4.0
5	860	0.308	5.0
6	860	0.331	3.0
7	1400	0.298	5.0
8	1400	0.308	3.0
9	1400	0.331	4.0

The results obtained from the experimental runs are shown in Table. 4

***Table 4:** Experimental data, corresponding SN ratios*

Sl. No.	MRR (mm^3/min)	Ra (µm)	SN Ratio of MRR (dB)	SN Ratio of Ra (dB)
1	13767.7	5.1333	82.7773	-14.2079
2	13843.4	5.8533	82.8248	-15.3480
3	18525.7	5.9933	85.3555	-15.5533
4	30763.1	5.2933	89.7606	-14.4745
5	27686.8	4.9533	88.8454	-13.8979
6	14648.2	4.5400	83.3157	-13.1411
7	37492.5	5.0200	91.4789	-14.0141
8	28794.2	5.2800	89.1861	-14.4527
9	35762.1	5.2066	91.0685	-14.3311

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Table 5 *PCA analysis of the correlation matrix*

Variable	Eigen vectors (EV_s)			Eigen Value (EV)	Proportion
	PC1	PC2	PC3		
SN-MRR	0.595	0.289	0.750	2.6616	0.887
SN-SR	0.584	0.485	0.651	0.2786	0.093

Table 6: *Pearson's correlation coefficient*

Correlation between the responses	Pearson's correlation coefficient	Comment	P-value
MRR and R_a	0.142	Both are correlated	0.715

The next step is to calculate the ideal (best) and negative ideal (worst) solutions:

a) The ideal solution:

$$A^+ = \left\{\left(\max_i y_{ij} | j \in J\right), \left(\min_i y_{ij} | j \in J' | i = 1,2, \dots \dots \dots, m\right)\right\} \quad (5)$$
$$= \{y_1^+, y_2^+, \dots \dots \dots, y_j^+, \dots \dots y_n^+\}$$

b) The negative ideal solution:

$$A^- = \left\{\left(\min_i y_{ij} | j \in J\right), \left(\max_i y_{ij} | j \in J' | i = 1,2, \dots \dots \dots, m\right)\right\} \quad (6)$$
$$= \{y_1^-, y_2^-, \dots \dots \dots, y_j^-, \dots \dots y_n^-\}$$

Here,

$J = \{j = 1,2, \dots \dots, n | j\}$: Associated with the beneficial attributes

$J' = \{j = 1,2, \dots \dots, n | j\}$: Associated with non-beneficial attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by n- dimensional Euclidean distance from the following equation

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^+\right)^2} \; i = 1,2, \dots \dots \dots, m \quad (7)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^-\right)^2} \; i = 1,2, \dots \dots \dots, m \quad (8)$$

Step 6: The relative closeness is calculated to the ideal solution.:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1,2, \dots \dots \dots, m; 0 \le C_i^+ \le 1$$

Table No:7 *Calculated Principal components*

S.No.	PC1	PC2
1.	48.4785	-68.5685
2.	47.7062	-69.4082

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3.	49.3502	-71.3425
4.	53.2273	-73.6942
5.	52.988	-72.6396
6.	49.6134	-68.195
7.	54.7676	-74.5836
8.	52.8365	-73.2726
9.	54.2533	-74.5175

Table 8: *Normalized Principal components and corresponding Quality loss*

Sl. No.	Normalized PC1	Normalized PC2	DNPC1	DNPC2
1	0.10937	-0.05846	0.89063	1.05846
2	0	-0.18991	1	1.18991
3	0.23281	-0.49268	0.76719	1.49268
4	0.78187	-0.86079	0.21813	1.86079
5	0.74798	-0.69571	0.25202	1.69571
6	0.2701	0	0.7299	1
7	1	-1	0	2
8	0.72653	-0.7948	0.27347	1.7948
9	0.92717	-0.98966	0.07283	1.98966

Table 9: *positive ideal solution (A+) and the negative ideal solution (A-).*

A+	A+	A-	A-
0.89063	0.05846	-0.10937	-0.94154
1	0.18991	0	-0.81009
0.76719	0.49268	-0.23281	-0.50732
0.21813	0.86079	-0.78187	-0.13921
0.25202	0.69571	-0.74798	-0.30429
0.7299	0	-0.2701	-1
0	1	-1	0
0.27347	0.7948	-0.72653	-0.2052
0.07283	0.98966	-0.92717	-0.01034

Table 10: *Separation measure of positive, negative ideal solutions and relative closeness value*

SUM SQ+	SUMSQ-	S+	S-
0.796639	0.898459	0.892547	0.947871
1.036066	0.656246	1.017873	0.81009

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0.831314	0.311574	0.911764	0.558188
0.78854	0.6307	0.887998	0.794166
0.547526	0.652066	0.73995	0.807506
0.532754	1.072954	0.7299	1.035835
1	1	1	1
0.706493	0.569953	0.840531	0.754952
0.984731	0.859751	0.992336	0.927228

Table 11: *Overall performance coefficient closest to ideal solution*

S. N	Ci	Rank
1	0.515030394	3
2	0.443165382	8
3	0.379732147	9
4	0.472109882	7
5	0.521828079	2
6	0.586631047	1
7	0.5	4
8	0.473180836	6
9	0.483040799	5