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Predictive modeling and machining performance optimization during drilling of polymer nanocomposites reinforced by graphene oxide/carbon fiber

This paper explores the parametric appraisal and machining performance optimization during drilling of polymer nanocomposites reinforced by graphene oxide/carbon fiber. The consequences of drilling parameters like cutting velocity, feed, and weight % of graphene oxide on machining responses, namely surface roughness, thrust force, torque, delamination (In/Out) has been investigated. An integrated approach of a Combined Quality Loss concept, Weighted Principal Component Analysis (WPCA), and Taguchi theory is proposed for the evaluation of drilling efficiency. Response surface methodology was employed for drilling of samples using the titanium aluminum nitride tool. WPCA is used for aggregation of multi-response into a single objective function. Analysis of variance reveals that cutting velocity is the most influential factor trailed by feed and weight % of graphene oxide. The proposed approach predicts the outcomes of the developed model for an optimal set of parameters. It has been validated by a confirmatory test, which shows a satisfactory agreement with the actual data. The lower feed plays a vital role in surface finishing. At lower feed, the development of the defect and cracks are found less with an improved surface finish. The proposed module demonstrates the feasibility of controlling quality and productivity factors.

Nomenclature

abbreviations:

ANN artificial neural network

ANOVA analysis of variance

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BBD	Box-Behnken design
CFRP	carbon fiber-reinforced polymer
CNC	computer numerical control
CQL	combined quality loss
DFA	desirability function analysis
EDM	electric discharge machining
FIS	fuzzy interface system
GA	genetic algorithm
GFs	glass fibers
GO	graphene oxide
GO/CF	graphene oxide/carbon fiber
OA	orthogonal array
PCA	principal component analysis
PSO	particle swarm optimization
RSM	response surface methodology
SA	simulation annealing
SEM	spectroscopy electron microscopic
TOPSIS	technique for order of preference by similarity to ideal solution
WPCA	weightage principal component analysis
symbols:	
<i>In</i>	delamination at entry
<i>F</i>	feed
<i>Out</i>	delamination at exit
<i>Ra</i>	surface roughness
<i>Th</i>	thrust force
<i>T</i>	torque
TiAlN	titanium aluminum nitride
<i>Vc</i>	cutting velocity
wt.% of GO	weight % of graphene oxide

1. Introduction

From the last two decades, polymer composite plays a vivacious role in engineering appliances due to elevated strength, creep endurance, and higher-yielding points. The composites define the combination of two or more elements in chemically altered compounds, enhancing mechanical, electrical, and thermal properties. Due to its complicated structure and behavior, industry and researchers are facing critical challenges during the machining of polymers reinforced by carbon nanomaterials like carbon-nanorods/nanotubes/graphene/reduced graphene oxide, etc. Graphene is considered as the most recent member of the carbon nanomaterials

group. The tool life and balancing of cutting conditions for product manufacturing is a complex task for the manufacturing sector and academia [1, 2]. The novelty of this graphene material is characterized by high tensile strength, fatigue and creep resistivity, also improved thermal properties as related to the neat epoxy material. The basic properties of the graphene polymer composite are that its rigidity is ten times higher than the glass fiber and density ($1.8\text{--}2\text{ g/cm}^{-3}$) is half of glass fibers (GFs) [3]. It has high thermal and electrical conductivity; lower rupture as compare to GFs and aramids material. As a result, the composites are more frequently used than the metals and their alloys owing to upgraded properties such as module, and strength-to-weight ratios, optical permeability, surface area. Drilling is considered as a primary machining processes in polymer manufacturing, in which one can analyze proper working conditions and tool design [4]. The operating environment of the tool materials and tool geometry should be applied in such a way that minimum heat is generated there during machining to achieve the desired performances, such like surface integrities, low tool wear, and high cutting rates. This creates a significant challenge in machining during the drilling procedure of polymer composites [5]. As per the concept, drilling is the machining of the material to remove the metal and make a precise hole. It is an ideal machining procedure on the plastic fabric for mechanical attachment and installation of the parts in a structure. The hole's quality is affected by the parameters of the tool design and process parameters during the drilling operation of the polymeric materials [6]. Various researchers focused on the relative aspect of the machining of polymer composite materials. Recently, polymer materials have played a highly active role in various engineering fields. Various renowned scholars assessed the drilling issues of carbon fiber reinforced polymer (CFRP) composite material regarding quality, precision, and delamination. The domain of experiments covers drilling velocity, feed rate and drill diameter. A hybrid approach of weighted principal component analysis (PCA) and fuzzy interface system (FIS) method was employed for aggregation of multiple quality and productivity characteristics. The fuzzy concept has been fruitfully explored with various expert rules and opinions to determine the machining response behavior [7]. The experiments were conducted on different set of input parameters. An optimization method has been undertaken to take into account the machining factors such as voltage, wire feed and welding velocity, etc. They outlined the Taguchi strategy with the weightage principal component analysis (WPCA) module for eliminating correlation reactions. The machining operation conducted using the L16 orthogonal array and outcomes was verified through a confirmatory test [8]. The Taguchi concept was applied to optimize the machining parameters of plasma arc cutting. To conduct the experiments, the L27 orthogonal array was used, and the WPCA-based Taguchi approach effectively utilized to transfer multiple responses into a single objective function [9]. A response correlation study was done by using the PCA coupled artificial neural network (ANN) techniques to determine the optimal parametric combination [10]. The electric discharge machining (EDM) process

was explored with the assistance of Taguchi's strategy to optimize it by using the WPCA techniques readily, also to describe the material structure behaviors [11]. A hybrid optimization tool was proposed to optimize the machining constraint during the turning procedure [12]. The effects of carbon composites and graphite weight percentage on the mechanical and tribological aspects was performed. First, the composite wear rate reduced when the pitch coke content increased and then decreased to a minimum [13]. Verma et al. [14] reported the optimised machining parameter to improve the productivity and the quality using the utility concept-based Taguchi approach by applying L16 orthogonal array (OA) experimental array at four discrete levels of the variables. From the prior state of the art, it has been found that eminent scholars extensively investigate the manufacturing and machinability aspects of polymers composites. Palanikumar et al. [15] recognized the mechanical properties and advantages of polymer composites and proposed their applications in aerospace, defense, and transportation sectors. Drilling is the primary indispensable manufacturing process in the polymer composites assembly. In this work, the drilling-induced damages in the form of delamination and their effect on the drilling efficiency of the fiber-reinforced composite were examined. The investigations revealed that the impact of feed rate, drill speed, and tool geometry on the resultant delamination factor was investigated at different drill point angle. Finally, the statistical regression model was suggested to envisage the delamination. Faria et al. [16] scrutinized the effects of tool material, wear in tool, and drilling constraints on the accuracy of the hole drilled in a polymer. The drilling characteristics, such as thrust force and delamination of glass/epoxy composites, were examined by using two types of drill bits, namely high-speed steel (HSS) and cemented carbide (CC) drills. The outcomes of the drilling study revealed that the HSS drill exhibited serious wear after drilling 1000 holes. Gaitonde et al. [17] conducted an experimental analysis for drilling of unreinforced polyamide (PA6) and glass fiber (30%)/polyamide (PA66-GF30) using a cemented carbide (K20) tool. The experiments were performed using a full factorial design of operation and the consequences of process constraints, namely, spindle speed, feed rate, and point angle, were considered. The drilling hole quality was assessed in terms of delamination and circularity error, thrust force, and a specific cutting coefficient. A similar principle of RSM tool was formulated by Niharika et al. [18] for turning of titanium alloys. Tool wear, fiber pull out, matrix debonding, etc., were studied by the researchers, who accordingly developed various robust optimization modules such as ANN, fuzzy, genetic algorithm (GA), simulating annealing (SA), and particle swarm optimization (PSO) algorithm [19, 20]. The influence of constraints like feed, tool materials, cutting velocity on machining responses has been investigated by the utility theory, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the Desirability Function Analysis (DFA), etc. Most of the studies have considered single modules of optimization; hence, very limited studies is available on hybridization approaches [21, 22]. The work is limited up to synthesis and characterization of graphene based polymeric com-

posites. It is believed that appropriate parametric settings may fruitfully enhance the machining characteristics by using hybridization modules. The experimental investigation on the machining of polymeric composites was conducted by several pioneer scholars [23, 24]. They obtained the preferred machining characteristics, i.e., the lower value of thrust force, surface roughness, torque, and a higher rate of material removal. The productivity and quality of the manufactured component are identified by the rate of material removal and surface finishing, respectively. Finishing of machined hole is considered as an essential design characteristic for a part subjected to creep and fatigue, to ensure accurate fit, tolerance, fastening of rivets, and aesthetic properties [25–27]. Hence, the quality of machined products is the primary aim of manufacturing science. For efficient machining environment, it is highly required to obtain optimal parametric setting and improved machining performances. However, machining of graphene oxide and carbon fiber (GO/CF) reinforced epoxy composites is still in an initial phase, even though these composites possess wide range of application in bio-electronics, sensors, battery application, automotive structure parts, aircraft fuselage components. The machining and machinability aspect of these novel polymer composites is not sufficiently explored in the area of nanocomposites machining. To date, any intensive study was proposed by any scholar using combined quality loss (CQL), WPCA and Taguchi concept for machining of polymer nanocomposites reinforced by GO/CF. Hence, this article highlights the optimization of graphene/CFRP drilling parameters by considering the surface roughness, thrust force, torque, delamination In and Out as the machining characteristics. The unified purpose of the analysis is to propose robust optimization tools for conflicting machining characteristics and to explore the machining feasibility of GO/CF reinforced polymer nanocomposites.

In previous research, it has been observed that machining of polymer composites reinforced by carbon/glass/aramid was fruitfully explored by using various multi-response optimization modules such as grey relation analysis (GRA), Taguchi, coupled with PCA, etc. Recent literature shows that very limited work exists on machining of GO/CF reinforced polymer composites. Also, the proposed hybrid approach (WPCA-CQL) has not been used earlier by any scholars in research on drilling of GO/CF reinforced polymer nanocomposites. Various studies, as mentioned earlier, assume equal priority weight and negligible response during aggregation of multiple responses. This leads to ambiguity, imprecision and errors in the solution. These critical issues of drilling performance optimization are successfully explored in present work by using the hybrid method. In this paper, an effort has been made to overcome the drawback of the custom optimization tools and to create a robust hybrid approach. RSM modeling was done to predict the drilling characteristics of the proposed nanocomposites. The CQL concept allows for a proper analysis, which is not efficiently possible by directly obtained data from the RSM method because sometimes there might appear negative ratio results. The article presents the new approach to control the thrust force (Th), torque (T), surface roughness (Ra), and delamination (In/Out).

2. Experimentation

2.1. Sample preparation

The samples were fabricated by using graphene oxide, CFRP and epoxy resin for drilling objectives. M/s. Platonic Pvt. Ltd. Jharkhand, India, has supplied the graphene oxide. A microstructure investigation was done by performing the SEM analysis of graphene oxide (GO) to check the quality of GO reinforcement, which has shown a crumpled and rippled structure due to deformation upon the exfoliation and restacking process marked by the white circles in Fig. 1. The sample has been developed using the combination of epoxy resin-520, D-hardener, and graphene

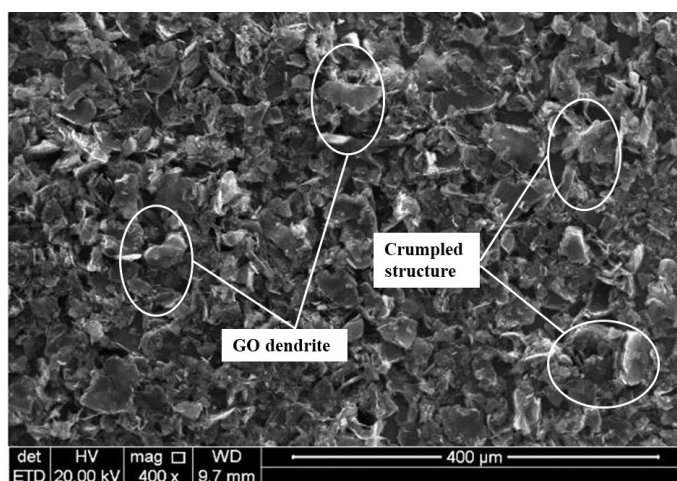


Fig. 1. SEM analysis of GO

oxide. Composite materials are made-up by using the epoxy as a matrix and graphene nanomaterial and carbon fiber as reinforcement. Graphene oxide enhances the essential features of bulk parts and the resin improves the transfer of graphene content into the matrix. The resin (whose density is 1.162 g/cm^3) with a distinct graphene weight ratio, such as 1, 2, and 3% was stirred up for 30 minutes at 60°C . A hardener-D with an equivalent ratio of 10:1 was added after 30 minutes and the mixture was stirred for 24 hours at 27°C . Finally, the mixture was laid on the carbon fiber with layer by layer into a desired shape ($100 \times 100 \times 10$) mm^3 with load assigned using the method of hot pressing (3 MPa, 170°C , 200 min). The properties of composite material are the following: interlaminar shear strength 46.5 ± 0.8 MPa, interlaminar flexural strength 93 ± 3.8 MPa, and tensile strength 130 GPa. Fig. 2 presents a schematic diagram for the development of nanocomposite samples.

A scanning electron microscopy (SEM) test was done to check uniformity of distribution of graphene reinforcement in the epoxy matrix. The SEM image (Fig. 3) clearly shows the uniform dispersion of the graphene content in the epoxy

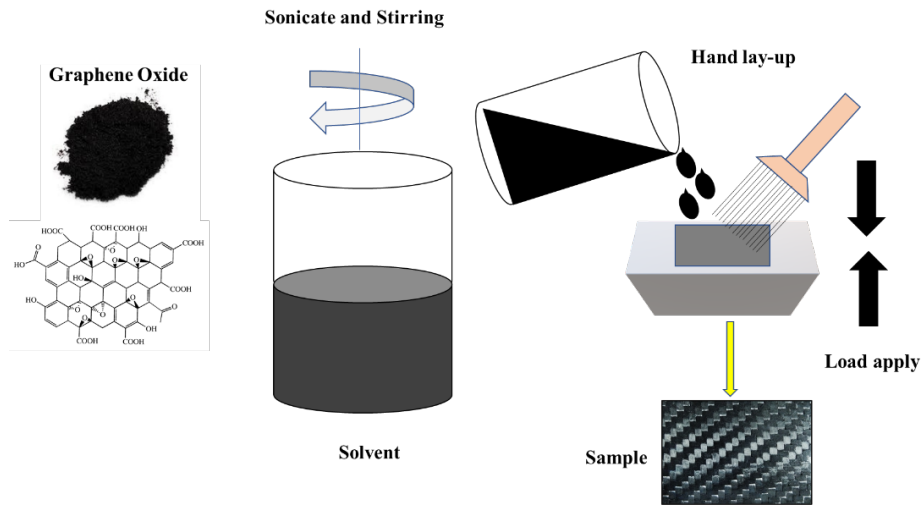


Fig. 2. Developed sample

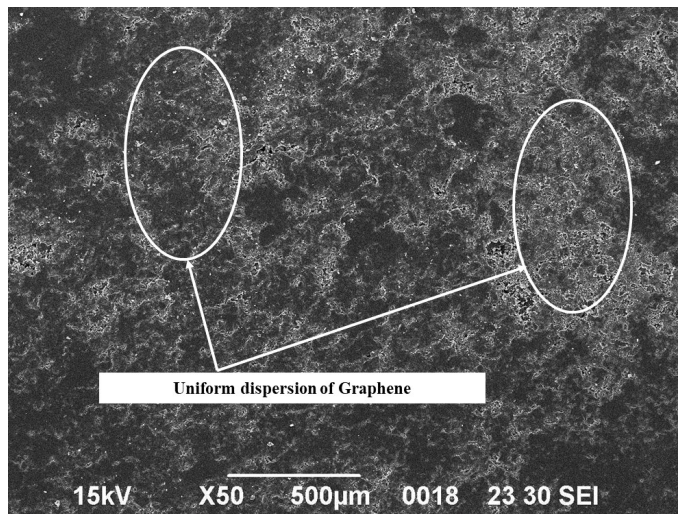


Fig. 3. Graphene oxide dispersion

matrix. The uniform dispersion creates a better interface between the matrix and reinforcement with a desired aspect ratio, which in turn, enhanced the mechanical strength of the polymeric materials [28–30].

2.2. Machine specification

The experiments were carried out on a CNC vertical drilling machine Model No. BMV35 TC20 to which a dynamometer tool, model number MLB-PML-300, was attached using a TiAlN (SiC coated) drill bit (ϕ 5 mm). In Fig. 4, there is

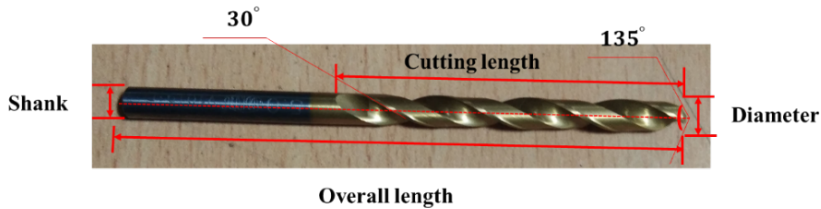


Fig. 4. Drill bit

shown a TiAlN-coated SiC drill tool having a diameter of 5 mm used for the drilling experiments. The drill bit (tool No. K816005002A01) was supplied by the M/s. Addison & Co., Ltd. Tamil Naidu, India. The interfaces between coating layers give higher hardness and durability. With a point angle of 135 degrees and a helix angle of 30 degrees, the drill bit was used to create a hole in the composite. An appropriate CNC clamping setup was employed to fix the board in the machining center. Fig. 5 represents the drilling setup with a proper clamping system used to attach the workpiece at the center.

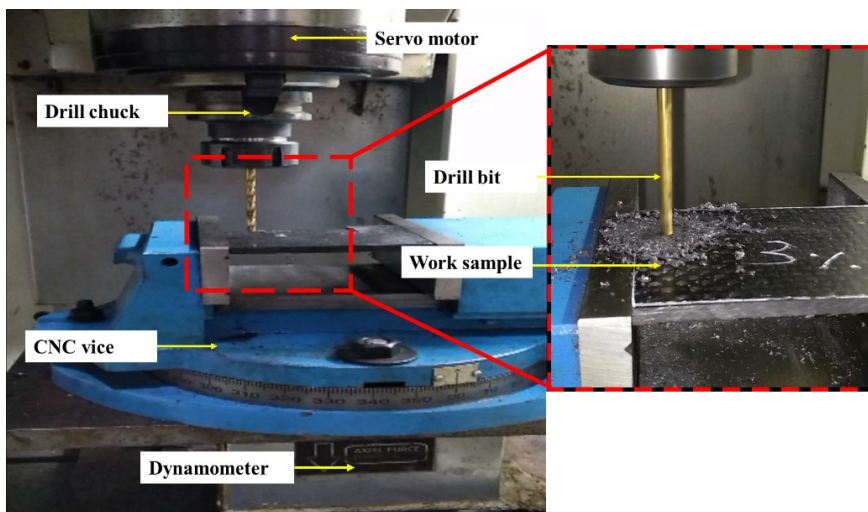


Fig. 5. Machining setup

The computerized dynamometer (Fig. 6) was used to obtain online data for thrust force and torque. The attained signal has been transferred to the data acquisition system through the analog-digital converter. The cutting forces (thrust force and torque) are the predominant factors during the machining of polymers. Both of them significantly affect the surface features, tool wear, interface temperature, and tool replacement rate. The control of these factors can decide on various machining damages such as delamination, fiber pullout, matrix debonding, etc. [31, 32]. The existing data on the drilling operation of graphene oxide/carbon

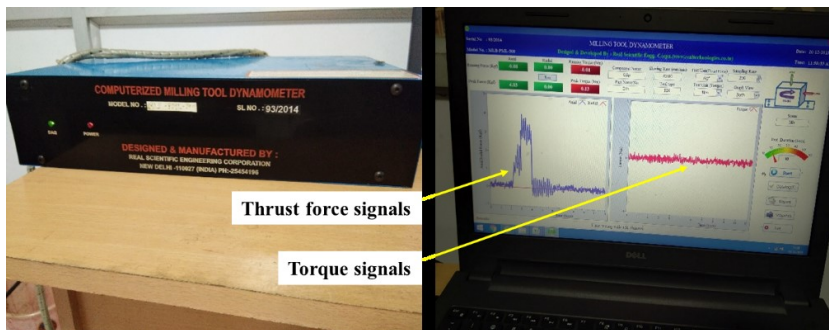


Fig. 6. Measurement of thrust force and torque

fiber polymer nanocomposites is passing through the initial phase, i.e., maximum studies focus on the development and characterization of the polymer composites. Machining of the polymer composites is very complex and challenging due to plastic deformation and the nonhomogeneous nature of the material. Besides, the carbon fiber reinforced polymer composites have a very complex anisotropic structure that causes uneven cutting behavior in the area of contact between the tool and the workpiece, which results in increases in the cutting forces and high tool wear [33, 34]. For a better understanding of these novel nanomaterial composites, it is highly desired to develop an efficient machining model and determine an optimal set of process parameters to control the effect of thrust force (Th) and torque (T). The control of these factors can significantly improve the machinability and machining aspects. The thrust force (Th) and torque (T) play an important role in producing a high-quality machined product. They also ensure the machinability of the polymer composites during drilling of GO reinforced unidirectional carbon fiber epoxy composites.

The surface roughness has been assessed by Mitutoyo SJ-400 surface tester, as shown in Fig. 7. It is an apparatus for evaluating surface evenness with a stylus navigated within the surface; its perpendicular motion can be transformed into an

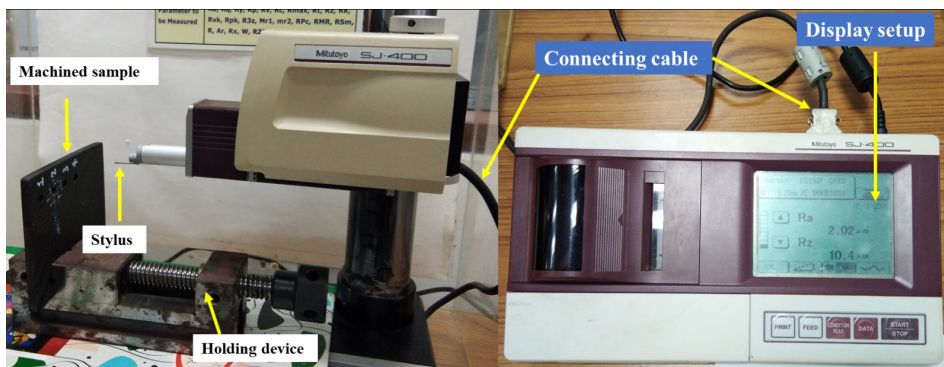


Fig. 7. Surface roughness measurement setup

electrical signal. The Ra value is obtained after the signal is filtered and displayed on a digital-type meter. The arithmetic means of surface roughness (Ra) are calculated to evaluate the quality features of surface roughness. The measurement stylus moves across the machined surface in distinct places. The delamination value was measured on a high-resolution ($0.7\times$) vision setup (Model no. SDM -TRZ-3D), as shown in Fig. 8. All the damages are gauged by the detection of several points across the drilled hole at the entry and the exit side. The maximum diameter of

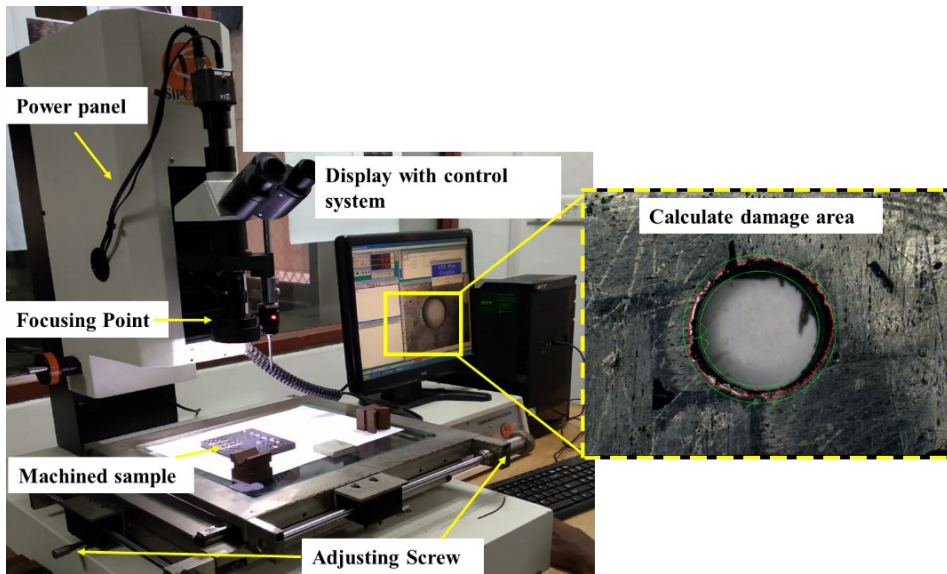


Fig. 8. Delamination measurement setup

delamination at the entry/exit of the hole has been taken as the delamination. The drilling constraints, namely, cutting velocity (m/min), feed (mm/min) and wt.% of GO and their levels are presented in Table 1. The observed data of the machining responses is given in Table 2.

Table 1.

Process parameters

Parameters	Notation (unit)	Level		
		Lower	Medium	Higher
Cutting velocity	V_c (m/min)	12.56	25.12	37.68
Feed	F (mm/min)	80	160	240
Graphene oxide	GO (wt.%)	1	2	3

Table 2.

L15 array and observed data

Exp. No.	V_c (m/min)	F (mm/min)	GO (wt.%)	Ra (μm)	Th (N)	T (Nm)	D_{In} (mm)	D_{Out} (mm)
1	12.56	80	2	0.18	61	0.78	5.378	5.218
2	37.68	80	2	0.26	36.77	1.68	5.568	5.311
3	12.56	240	2	0.16	46.88	2.125	5.6	5.539
4	37.68	240	2	0.04	46.29	2.49	5.421	5.409
5	12.56	160	1	0.2	45.5	1.9	5.678	5.332
6	37.68	160	1	0.2	32.66	2.9	5.513	5.394
7	12.56	160	3	0.11	65.7	1.64	5.654	5.456
8	37.68	160	3	0.06	41.19	1.655	5.404	5.267
9	25.12	80	1	0.4	38.15	1.8	5.433	4.93
10	25.12	240	1	0.25	47.37	2.9	5.567	5.06
11	25.12	80	3	0.12	46.09	1.2	5.532	5.019
12	25.12	240	3	0.1	47.95	2.04	5.299	5.09
13	25.12	160	2	0.11	48.9	1.7	5.305	4.998
14	25.12	160	2	0.15	50.99	1.9	5.388	5.121
15	25.12	160	2	0.07	47.66	1.7	5.383	5.21

3. Methodology

3.1. Weighted Principal Component Analysis

WPCA procedure is effectively employed to recognize the correlation between the responses and estimation of response weight during aggregation of various outputs into a single objective function known as the Multiple Performance Index (MPI) [35]. This is because aggregation of different output functions is not possible by the traditional RSM techniques. It is possible through the exploration of the principles of WPCA in this paper. In 1901, Karl Pearson [36] created the principal component analysis (PCA) method, which consists of basic statistical techniques to evaluate the major principal component (PC). The orthogonal transformation has been used to change the set of linearly uncorrelated factors known as the principal components (PCs) [37]. The initial step is to normalize the machining responses from the range from zero to one.

(1) The following equation has been used for normalizing the data responses For lower the better (LB)

$$X_i(k) = \frac{\min X_i(k)}{X_i(k)}, \quad (1)$$

where: $i = 1, 2, 3, 4, \dots, n$, $k = 1, 2, 3, 4, \dots, m$, n – number of experiments run, m – machining performance, $X_i(k)$ – normalized response function of the k -th element in the i -th order.

(2) Calculate the correlation coefficient

$$R_{jl} = \frac{\text{Cov}\{X_i(j), X_i(l)\}}{\sigma_{x_i(j)} \times \sigma_{x_i(l)}}, \quad (2)$$

where: $j = 1, 2, 3, 4, \dots, m$, $l = 1, 2, 3, 4, \dots, n$, R_{ij} – correlation coefficient, $X_i(j)$ – normalized response, $\text{Cov}\{X_i(j), X_i(l)\}$ – covariance between the responses of constraints j and l , $\sigma_{x_i(j)}$, $\sigma_{x_i(l)}$ – standard deviation of constraints j and l .

(3) Determine the eigenvalue and eigenvector

$$(R - \gamma_k I_m) \times V_{ik}, \quad (3)$$

where: R – descision matrix, γ_k – eigen values, I_m – identity matrix, V_{ik} – eigenvector.

(4) Calculate PC values

$$PC_{mk} = \sum_{i=1}^n X_m(i) \times V_{ik}. \quad (4)$$

Here $PC1, PC2, \dots, PC_{mk}$ means first, second, etc., principal component.

3.2. Combined Quality Loss (CQL)

CQL concept is described as the deviation of an individual PCs value from its optimal value. The minimization of an absolute value (modulus), is regarded as a single objective optimization function [38]. This objective function was used to finds out the optimum combination/process setting. This setting is highly desired for efficient machining performances [39, 40]. The combined approach of the WPCA and quality loss concept exert a significant impact on quality control and productivity concerns of manufacturing processes. Such an approach has been introduced according to the flow chart of the proposed hybrid module, as detailed in Fig. 9.

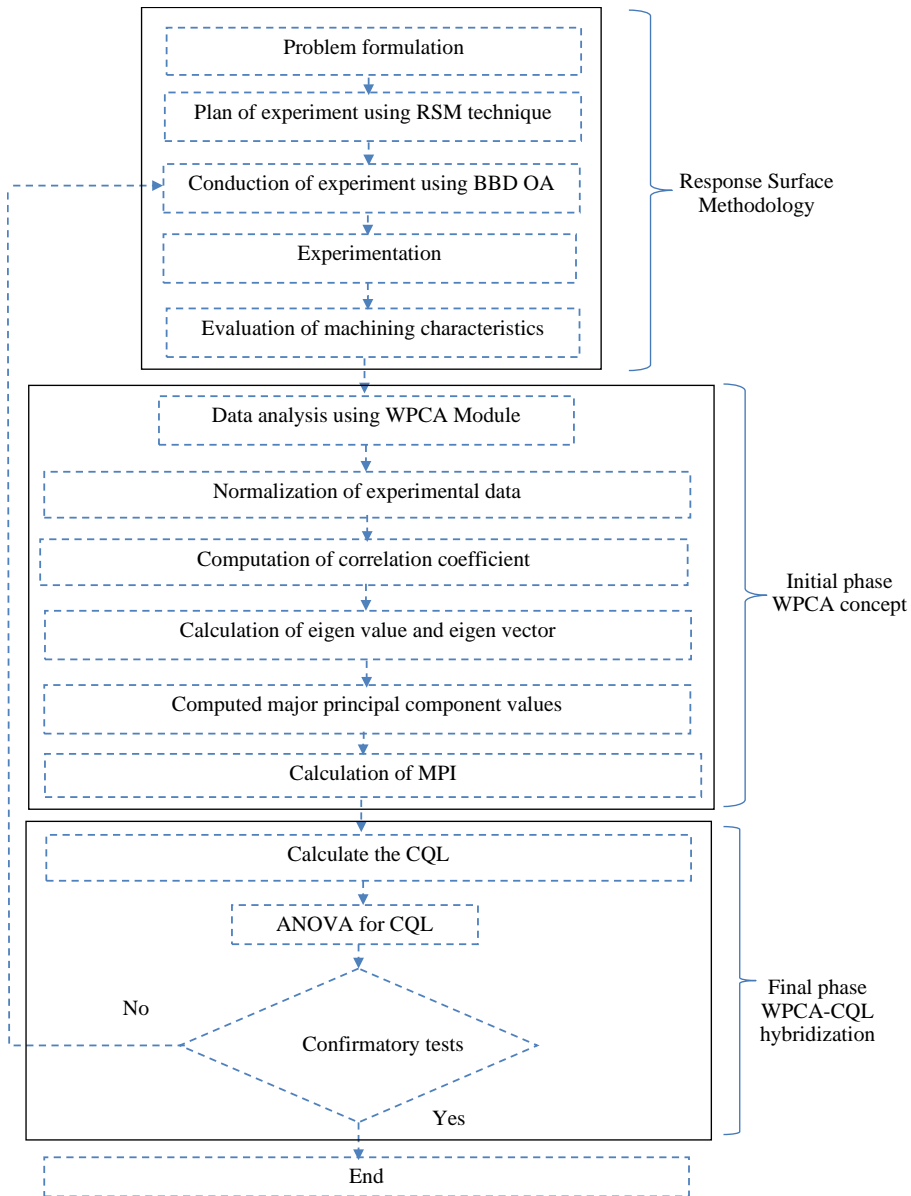


Fig. 9. Flow chart of the proposed hybrid module

4. Result and discussion

In this article, machining of polymer nanocomposites reinforced by GO and carbon fiber was analyzed. The consequence of drilling parameters, namely, cutting velocity, feed and wt.% of GO has been investigated to achieve the desired machin-

ing characteristics viz, surface roughness, thrust force, torque and delamination *In* and *Out*. After conducting the drilling experiment and computation of machining response, the next step is to analyze the observed data by using the WPCA tool.

4.1. Calculation of MPI and CQL

Initially, one performs normalization of all process responses in the range from zero to one using Eq. (1), and the results are tabulated in Table 3. The next step is to evaluate the correlation between machining performance characteristics by calculating the Pearson correlation coefficient. We calculate the correlation and tabulate it in Table 4 using Eq. (2). The PCA study was carried out using Eqs. (3) and (4) and the results are shown in Table 5. It contains the eigenvalue (EV), the eigenvector (EV), accountability proportion (AP), and cumulative accountability proportion (CAP). Accountability proportion for surface roughness, thrust, torque, delamination *In* and *Out* was found to be 0.342, 0.262, 0.253, 0.1, and 0.043, respectively, and these will be considered as response weight during the MPI calculation. The eigenvalue results from the estimation of the corresponding performance weights characteristic of the principal component analysis.

Table 3.

Normalized (N) data

Exp. No	N – <i>Ra</i>	N – <i>Th</i>	N – <i>T</i>	N – <i>In</i>	N – <i>Out</i>
Ideal	1	1	1	1	1
1	1	0.5354	0.2222	0.9853	0.9448
2	0.4642	0.8882	0.1538	0.9516	0.9282
3	0.3670	0.6966	0.25	0.9462	0.8900
4	0.3132	0.7055	1	0.9774	0.9114
5	0.4105	0.7178	0.2	0.9332	0.9246
6	0.2689	1	0.2	0.9611	0.9139
7	0.4756	0.4971	0.3636	0.9372	0.9035
8	0.4712	0.7929	0.6666	0.9805	0.9360
9	0.4333	0.8560	0.1	0.9753	1
10	0.2689	0.6894	0.16	0.9518	0.9743
11	0.65	0.7086	0.3333	0.9578	0.9822
12	0.3823	0.6811	0.4	1	0.9685
13	0.4588	0.6678	0.3636	0.9988	0.9863
14	0.4105	0.6405	0.2666	0.9834	0.9627
15	0.4588	0.6852	0.5714	0.9843	0.9462

Table 4.

Correlation check

Correlation response	Correlation coefficient Pearson value	Remark	P-Value
<i>Th</i> and <i>Ra</i>	-0.453	Correlated	0.090
<i>T</i> and <i>Ra</i>	-0.129		0.647
<i>In</i> and <i>Ra</i>	0.193		0.49
<i>Out</i> and <i>Ra</i>	0.161		0.567
<i>T</i> and <i>Th</i>	-0.165		0.558
<i>In</i> and <i>Th</i>	-0.07		0.805
<i>Out</i> and <i>Th</i>	0.009		0.973
<i>In</i> and <i>T</i>	0.35		0.201
<i>Out</i> and <i>T</i>	-0.254		0.36
<i>Out</i> and <i>In</i>	0.514		0.05

Table 5.

Principal component analysis (PCA)

	Φ_1	Φ_2	Φ_3	Φ_4	Φ_5
Eigen Value	1.7114	1.3098	1.2633	0.5008	0.2148
	0.5	-0.163	-0.5	-0.646	-0.236
	-0.395	0.533	0.343	-0.639	-0.184
Eigen vector	0.113	-0.571	0.624	-0.062	-0.518
	0.584	0.115	0.489	-0.179	0.612
	0.489	0.592	0.06	0.372	-0.518
AP	0.342	0.262	0.253	0.1	0.043
CAP	0.342	0.604	0.857	0.957	1

The relationship between the values of PCs and the response is as follows:

$$Z_1 = 0.5NRa - 0.395NTh + 0.113NT + 0.584NIn + 0.489NOut, \quad (5)$$

$$Z_2 = -0.163NRa + 0.533NTh - 0.571NT + 0.115NIn + 0.592NOut, \quad (6)$$

$$Z_3 = -0.5NRa + 0.343NTh + 0.624NT + 0.489NIn + 0.06NOut, \quad (7)$$

$$Z_4 = -0.646NRa - 0.639NTh - 0.062NT - 0.179NIn + 0.372NOut, \quad (8)$$

$$Z_5 = -0.236NRa - 0.184NTh - 0.518NT + 0.612NIn - 0.518NOut. \quad (9)$$

Here Z_1, Z_2, Z_3, Z_4, Z_5 are major principal component values, NRa, NTh, NT, NIn and $NOut$ are normalized surface roughness, thrust force, torque, delamination at inlet and outlet, respectively.

Accountability proportion (AP) values of individual responses were taken as priority weights for the calculation of the principal components using Eqs. (5)–(9)

as shown in Table 6. Later, the Multi-Performance Index (MPI) was calculated using Eq. (10) and tabulated in Table 7 [41].

$$\text{MPI} = 0.342Z_1 + 0.262Z_2 + 0.253Z_3 + 0.1Z_4 + 0.043Z_5 . \quad (10)$$

Table 6.

PCs values

Exp. No.	Z_1	Z_2	Z_3	Z_4	Z_5
Ideal	1.291	0.506	1.016	-1.154	-0.844
1	1.3510	0.6681	0.3608	-0.8268	-0.3360
2	0.9083	0.9688	0.6895	-0.7020	-0.2511
3	0.9244	0.8044	0.7275	-0.5360	-0.2262
4	1.0074	0.4059	1.2420	-0.5511	-0.5956
5	0.9414	0.8561	0.6775	-0.5593	-0.2403
6	0.7703	1.0265	0.8581	-0.6572	-0.2362
7	1.0717	0.6225	0.6721	-0.4790	-0.2865
8	1.0281	0.6320	0.9879	-0.6797	-0.4872
9	0.9484	1.0327	0.6763	-0.6357	-0.2326
10	0.9125	0.9185	0.7257	-0.4321	-0.1953
11	1.1224	0.7730	0.6533	-0.6994	-0.3790
12	1.0249	0.7607	0.8391	-0.5257	-0.3124
13	1.0723	0.7723	0.7742	-0.5575	-0.3191
14	1.0275	0.8052	0.7195	-0.5089	-0.2496
15	1.0609	0.6375	0.9003	-0.5939	-0.4180

The main effects of the process parameters are given in Table 8, and used to evaluate the importance of performance measures of input process variables in every process. The cutting velocity has the highest value of 0.1238, and it is the most prominent parameter, followed by feed (0.0164) and GO (0.0070).

The effect plot has been designed by using LB criteria and this plot shows the optimum parametric settings (Fig. 10), which corresponds to $V_c = 37.68$ m/min, $F = 160$ mm/min and $\text{GO}\% = 2\%$. It has been found that optimal parametric setting significantly improved the desired quality and productivity characteristics.

It shows that the delamination factor at the same filler level (2 percent), feed (160 mm/min), and cutting velocity (37.68 m/min) was low. A higher cutting velocity leads to an increase in the temperature during the drilling process, which softens the matrix and reduces the induced delamination [42, 43]. However, by adding the GO content, one can control the delamination factor by crystallizing the content of filler. It is evident that the required wt.% of GO content reduces the delamination factor; due to GO content, the materials produce high bonding

Table 7.

MPI, CQL and corresponding S/N ratio computation

Exp. No.	MPI	CQL	S/N ratio
Ideal	0.6794	0	0
1	0.6312	0.0481	26.3418
2	0.6579	0.0214	33.3606
3	0.6476	0.0317	29.9553
4	0.6844	-0.0049	46.0303
5	0.6514	0.0279	31.0588
6	0.6736	0.0057	44.7444
7	0.6394	0.0400	27.9578
8	0.6782	0.0012	58.3890
9	0.6924	-0.0130	37.7176
10	0.6847	-0.0053	45.5201
11	0.6655	0.0139	37.1110
12	0.6961	-0.0166	35.5507
13	0.6955	-0.0160	35.8868
14	0.6827	-0.0033	49.5320
15	0.6802	-0.0008	61.4884

Table 8.

Response Table for CQL

Level	V_c	F	GO
1	0.1179	0.0176	0.0038
2	-0.0058	0.0078	0.0108
3	0.0058	0.0012	0.0096
Delta	0.1238	0.0164	0.0070
Rank	1	2	3

and shear strength [44]. However, the cutting velocity had a prominent effect on delamination during previously reported works [45, 46]. The delamination factor was also increased by increasing the feed due to the thrust force generated between the tool and the workpiece during the machining interface [47, 48]. The feed forces of a higher value of cause that the drilling tool is pushed inside the layer rather than to cut it. Hence, a higher rate of feed raises the thrust force and torque. Most of the related investigations demonstrate that the feed is the most prominent factor affecting the machinability of the polymer composites [48, 49]. The impact on the cutting tool edges is very high against the laminated composite; in turn, the resistance force rises, i.e., the rubbing of drill tool interfaces against the inner surface of the hole increases. It is mainly due to an increased thrust force [50, 51].

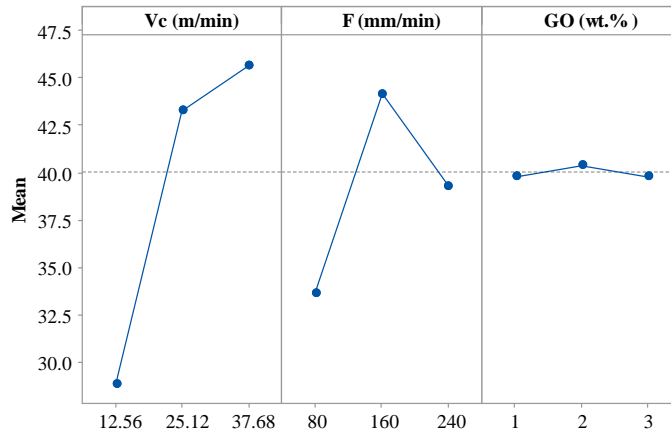


Fig. 10. Optimum condition

4.2. Variance analysis for CQL

ANOVA is mainly directed to evaluate the impact of drilling factors on responses [52, 53]. Here, the model adequacy is justified with the P-value (< 0.05 with 95% confidence level) and the Fisher's test (F) (with higher value of F) acceptable. If the P-value is lower than 0.05, the value is acceptable and significant. The same applies to the Fisher's test, if the F higher value is acceptable and significant [39, 54–56]. The assessment was done at a level of $\alpha = 0.05$ (95% confidence interval) and Fisher's F-test was used to determine the situation in which the composite drilling parameter affects various performance aspects [57–59]. The analysis of variance examines the influence of control factors on response effect and allows one to develop a prediction model. Furthermore, in terms of these factors, the final regression for WPCA-based combined quality loss (CQL) was proposed. The objective function of WPCA-CQL was defined according to ANOVA as shown in Table 9, which illustrates the nonlinear model and confirms that cutting velocity (32.03%) is the most significant parameter and the following one is feed (8.95%). The conclusion from this study is that the feed significantly affects the drilling responses and its lower value is preferential for an improved surface feature and minimum damages during the drilling process [39, 60, 61]. The model adequacy (96.83%) shows the satisfactory performance of the developed module in terms of R^2 , R^2 adjustable [52].

The model shows that the error of model adequacy is very low (3.17%) and the corresponding Lack-of-Fit ($F = 0.29$, $P = 0.831$) is insignificant. The adequacy of the model is 96.83% which shows good agreement between prediction through the linear model and experimentally observed results [62].

Regression equation for the combined quality loss is

$$\text{CQL} = 0.0857 - 0.00014V_c + 0.000029F + 0.0V_c^2 - 0.00012F \text{ GO}. \quad (11)$$

Table 9.

Variance analysis

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value	Mark
Model	9	0.00585	96.83%	0.00585	0.000651	16.95	0.003	Significant
V_c	1	0.00193	32.03%	0.00193	0.001937	50.47	0.001	Significant
F	1	0.00054	8.95%	0.00054	0.000541	14.10	0.013	Significant
GO	1	0.00006	1.09%	0.00006	0.000066	1.72	0.247	
V_c^2	1	0.00278	46.10%	0.00277	0.002779	72.40	0.000	Significant
F^2	1	0.00004	0.78%	0.00004	0.000043	1.13	0.337	
GO^2	1	0.00001	0.23%	0.00001	0.000014	0.36	0.574	
$V_c \times F$	1	0.00002	0.42%	0.00002	0.000025	0.66	0.453	
$V_c \times GO$	1	0.00006	1.14%	0.00006	0.000069	1.79	0.238	
$F \times GO$	1	0.00036	6.08%	0.00036	0.000368	9.58	0.027	Significant
Error	5	0.00019	3.17%	0.00019	0.000038			
Lack-of-Fit	3	0.00005	0.97%	0.00005	0.000020	0.29	0.831	
Pure Error	2	0.00013	2.20%	0.00013	0.000067			
Total	14	0.00604	100.00%					

$S = 0.0061954$, $R\text{-sq} = 96.83\%$, $R\text{-sq}(\text{adj}) = 91.11\%$

CQL residual plots show the residual plot versus fitted values in Fig. 11. It shows that all points on the ANOVA plot are near the straight line (mean line) and it indicates that the distribution of data is normal and the deviation from

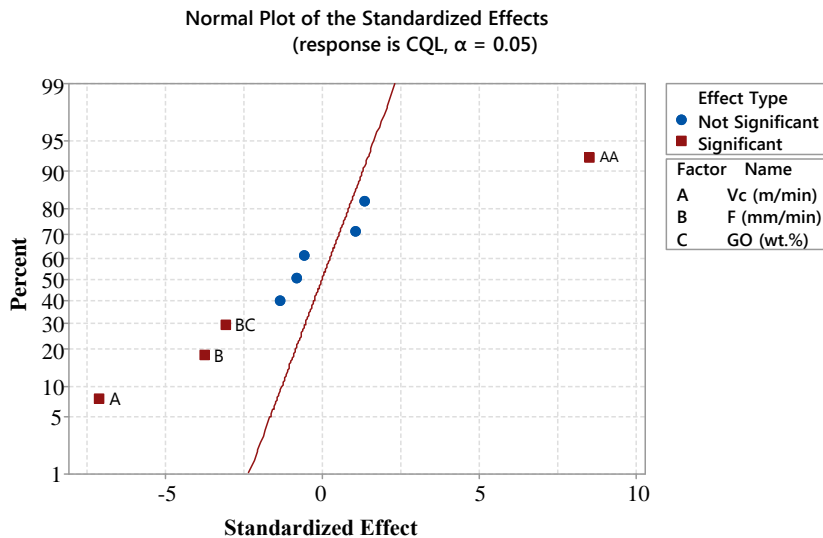


Fig. 11. ANOVA plot for CQL

the standard is small. Also, it has been noticed that the CQL function does not contain any noticeable pattern or uncommon structure. The plot shows a mild non-normality bias; however, there is no abnormality in the plots of these residuals, and no undesirable effect indicates residual versus fitted value.

4.3. Surface plots for process parameters

One can notice that the cutting velocity and feed are the most significant interaction effects, followed by feed and wt. percent of graphene oxide. Fig. 12 displays the contour diagram of interactions between these parameters. From these surface plots, the effect of process parameters on machining responses can be evaluated. The optimal machining parameters leading to a minimum CQL value can be obtained by examining the 3D surface plots. Two parameters for each graph are varied, whereas the third parameter is kept constant [63]. The cutting velocity (V_c) and feed effect on CQL are depicted in Fig. 12a. When cutting velocity is 37.68 m/min and feed is 160 mm/min, it is observed that minimum CQL can be reached. It is also visible that the cutting velocity effect on the CQL is higher than that of the feed. The result of cutting velocity (V_c) and wt.% graphene oxide on

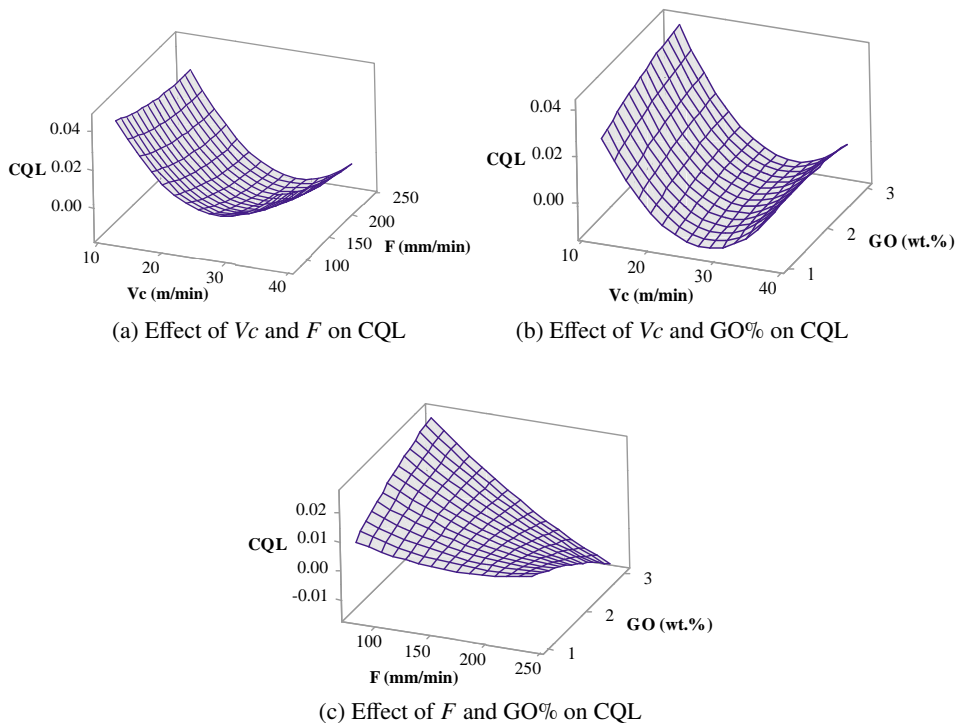


Fig. 12. The effect on CQL assessment of (a) cutting velocity and feed (b) cutting velocity and wt.% of GO (c) feed and wt.% of GO

CQL is presented in Fig. 12b. The minimum CQL is observed when the speed is 37.68 m/min and 2% wt. % of GO. The effect of speed on CQL is also found to be more important than the wt.% of GO. By analyzing Fig. 12b one can notice that the CQL value is the highest when wt.% of GO is 2%. Fig. 12c shows the effect of feed (F) and wt.% and GO on CQL. In this work, it is observed that at GO 2% by weight and feed at 160 mm/min. gives the lower value of CQL. The feed also substantially affects the CQL value.

4.4. Confirmatory test

The confirmatory test was done in optimal condition (Vc37.68F160GO%2) of the objective function value, as indicated in Table 10. The validated results show a significant improvement in machining performances. The value of Ra , Th , T , and delamination In/Out reduced from 0.18 to 0.05 μm , 0.78 to 0.75 N, 61 to 30.04 Nm, and 5.378 to 5.172 mm and 5.218 to 5.015 mm, respectively.

Table 10.

Confirmatory test

Response	Condition		
	Orthogonal	Optimal	Confirmatory
	Vc2F3GO3	Vc3F2GO2	Vc3F2GO2
Ra	0.18		0.05
Th	0.78		0.75
T	61		30.04
D_{In}	5.378		5.172
D_{Out}	5.218		5.015
Assessed value	0.0481	-0.0215	-0.0037

The optimal setting (Vc3F2GO%2) suggests that lower value of feed plays a vital role in improving surface finishing because, at lower feed, the development of the defect and cracks are observed less frequently. Also, decreasing the feed reduced the cutting force, surface roughness and enhanced the MRR. The weight percentage also plays a crucial role in the quality of the machined component. The higher value of wt.% can increase the agglomeration, which can decrease the strength of the machined sample [64]. The objective function value demonstrates the feasibility of the proposed hybridization approach.

The optimal condition can be predicted by taking the most significant factors at their best levels. In the current investigation, cutting velocity and feed are the

most significant factors at V_{c2} and F_3 levels from Table 8.

$$\begin{aligned}\mu V_{c2}F_3 &= V_{c2} + F_3 - CQL_{avg}, \\ \mu V_{c2}F_3 &= -0.0058 + 0.0012 - 0.0086, \\ \mu V_{c2}F_2 &= -0.0133\end{aligned}$$

where: $\mu V_{c2}F_3$ – optimum value, V_{c2} – minimum value of speed at level, F_3 – minimum value at level

$$CI = \sqrt{\frac{DF, 95\%, df \text{ error} \times \text{Adj MS error}}{\gamma_{eff}}}$$

Here, CI – confidence interval, $\gamma_{eff} = \frac{N}{1 + dof}$, where N – total trial of experiments, dof – degree of freedom,

$$\gamma_{eff} = \frac{15}{1 + 1 + 1} = 5, \quad CI = \sqrt{\frac{5 \times 0.000067}{5}} = 0.0081.$$

The optimum range $\mu V_{c2}F_3 - CI \leq \mu V_{c2}F_3 \leq \mu V_{c2}F_3 + CI$,

$$-0.0215 \leq \mu V_{c2}F_3 \leq -0.0051.$$

The optimization module used in this paper covers various correlated response that is totally neglected in traditional optimization modules. All the correlated responses become independent. i.e., uncorrelated responses were computed by using the WPCA method. It is considered as a statistical tool to solve critical issues during multi-criteria decision making (MCDM). As specified in state of the art, there are different modules and formulas for the combination of several characteristics to calculate the MPI. This research investigates the correlation among machining responses and the aggregation of multiple conflicting functions. The CQL concept incapacitates the issue of calculation when MPI delivers negative results. The idea of MPI-CQL coupling provides practical feasibility and an effective way to solve complex optimization issues. The scanning electron micrograph (MEV) test for the walls of holes generated by drills was done to evaluate the surface features and damages. The C-scan result shows the quality of the hole developed by applying a different set of response surface methodology based on parametric conditions, as depicted in Fig. 13 and Fig. 14. A similar method was used by the pioneer researchers in previous works [46, 49, 65, 66]. Three different weights % of graphene oxide were used for the comparative study of machined quality a different case of the same C-scan analysis of drilled hole [46, 50]. The lower value of the feed plays an important role in improving surface finishing, and decreasing the feed can lower the cutting force, surface roughness, and delamination.

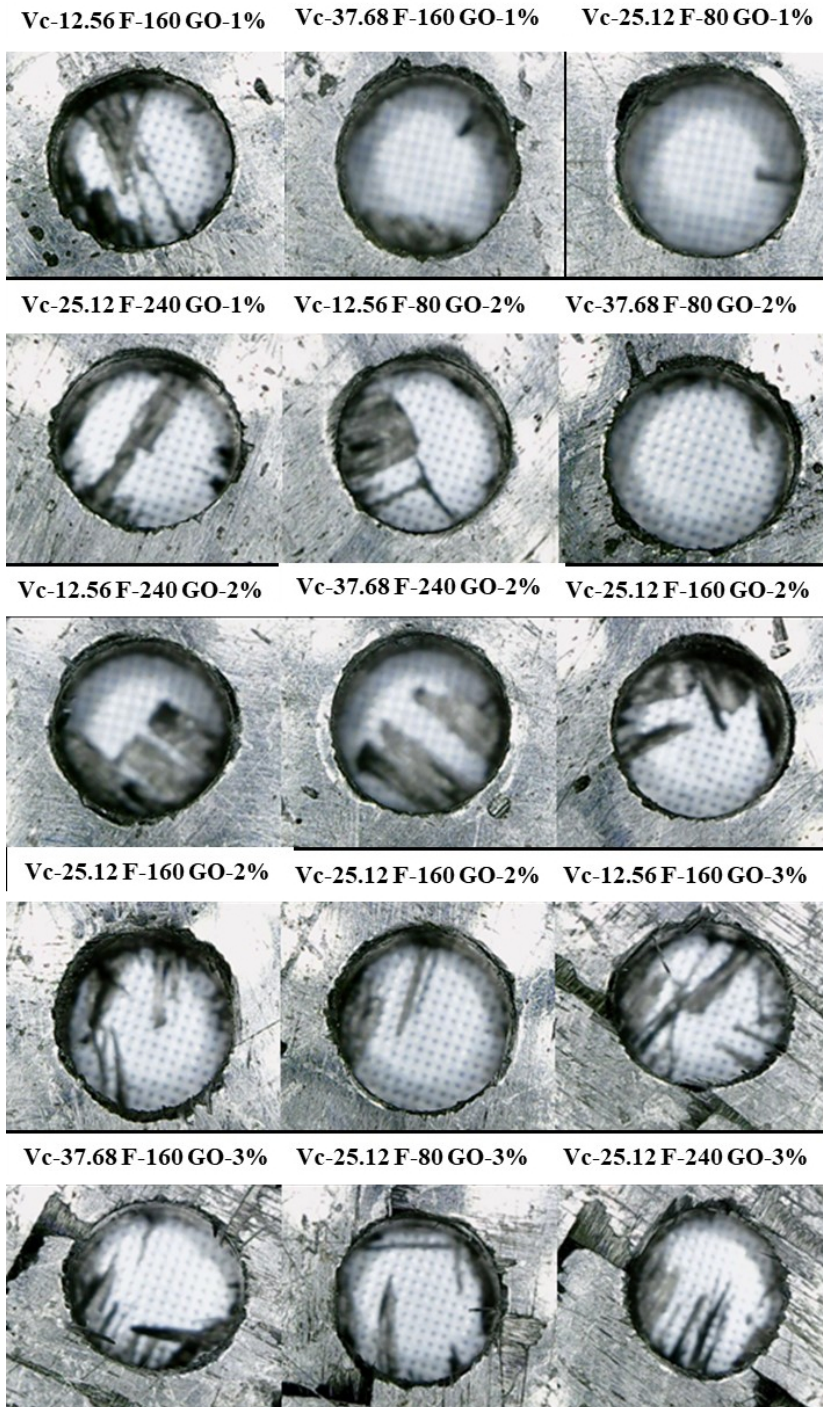


Fig. 13. Delamination effect using C-scan images of 1%, 2% and 3% of GO doped CFRP nanocomposite at inlet

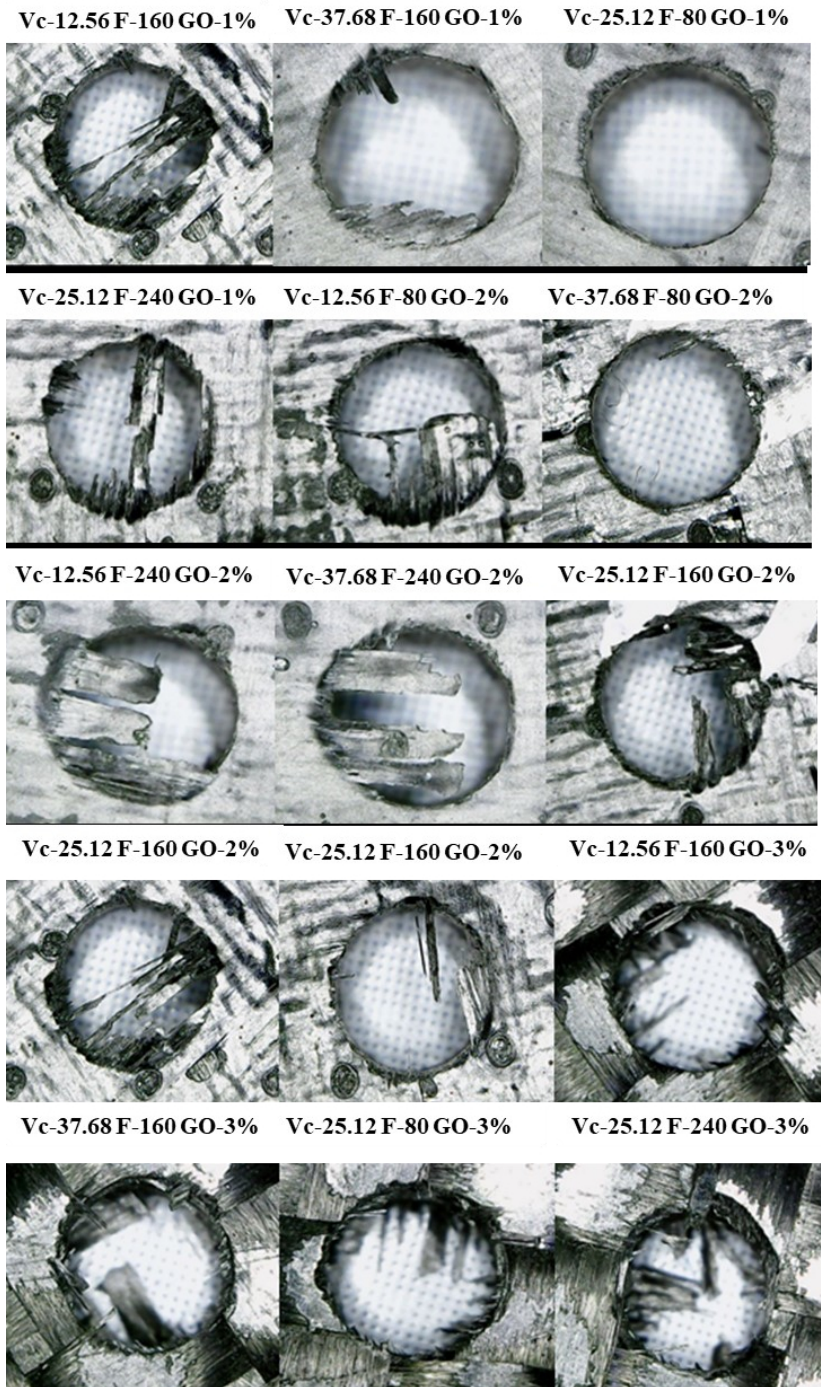


Fig. 14. Delamination effect using C-scan images of 1%, 2% and 3% of GO doped CFRP nanocomposite at exit

5. Conclusions

The present article highlights the machining (drilling) aspects of graphene/CFRP reinforced-epoxy composite. The multi-objective optimization of drilling indices, such as thrust surface roughness (Ra), force (Th), torque (T), delamination In and Out , have been carried out by applying the proposed hybrid approach. The following conclusions can be drawn from this paper:

- Identification of the correlation coefficient between the machining responses and elimination of correlation among the responses has been done by using the PCA tool. AP is intended for assigning weights to machining responses, in a different way to most of the studies where equal response weight is assumed, which creates ambiguity, inaccuracy and error in the results.
- ANOVA results for CQL have shown that cutting velocity is the most dominant factor followed by feed and wt.% of graphene oxide, and demonstrate the capability of the established model.
- The CQL concept allows for a proper analysis, which is not efficiently possible by applying the outcomes directly obtained from the RSM technique, as sometimes negative ratio results may be there.
- The lower value of the feed plays a critical role in improving surface finishing, and decreasing the feed can lower the cutting force, surface roughness and enhance the MRR.
- The optimum parametric combination through the CQL effect is found as $Vc - 37.68$ m/min, $F - 160$ mm/min, and $GO\% - 2$, which has been validated by a confirmatory test that shows a satisfactory performance of the proposed hybrid approach.
- The hybridization approach can be implemented in various polymer manufacturing sectors for online and offline control of process/product.

This article efficiently explores the machining aspects of graphene oxide modified epoxy in CFRP nanocomposites. The proposed optimization modules are used to formulate a generalized method that can be adapted for other machining procedures, such as turning, milling, etc., and can be used in other complex case studies of multiple conflicting responses. The other factors, such as tool-material, geometry, mechanics of material removal, etc., can be considered in future scope of work for the understanding of machining behavior of these novel polymer nanocomposites.

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