Mechanics of Advanced Composite Structures Vol (Year) First page – Last page

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Mechanics of Advanced Composite Structures

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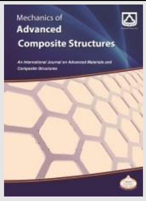

Multi-response Optimization while Drilling of Composite Laminate with Core Drill by Grey Entropy Fuzzy (GEF) Method.

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KEYWORDS

Composites:
Delamination:
Equivalent delamination factor:
Grey relational analysis;
Entropy:
Fuzzy logics

ABSTRACT

Glass-fiber-reinforced polymers' (GFRP), as compared to metallic materials, require more intricate machining. The composite construction experiences delamination as a result of this machining operation. Delamination at the exit and entrance of holes drilled is a significant flaw in composite materials. Superior-drilled holes can be produced by optimizing the drilling process's governing factors. This study's goal is to maximize the drilling settings using entropy weight-coupled gray relational analysis with fuzzy logic to account for multiple performance factors. Taguchi's L25 5-level orthogonal array is used to increase the accuracy of the results in this study. Feed rate and spindle speed are considered the control variables, and torque, thrust force, and delamination at both the exit and entry are the responses. The results show that drilling performance is enhanced by lower feed rates and elevated spindle speeds. Additionally, the present findings show that feed rate has a stronger influence on drilling hole quality. These results also proved that increasing the number of levels increases the accuracy of the results. Entropy-based gray relational analysis with fuzzy logic using more levels of factors can be effectively used for the optimization of the drilling process.

1. Introduction

In industries like the production of automobiles, defense equipment, and airplanes, where the need for structures with low weight, high strength, and stiffness is crucial, designers often turn to composites as an alternative to standard metallic materials [1]. These materials are challenging to machine due to their innate characteristics, such as high heterogeneity and abrasive structure, low thermal conductivity, and heat sensitivity. These materials exhibit a variety of flaws throughout the machining process, including matrix cracking, deboning, and delamination [2–4]. Most scientists who studied the drilling GFRP composite concentrated on thrust force and its influence on machining damages, in particular delamination. A detailed discussion on delamination and the techniques of evaluation and measurement were provided elsewhere [5, 6].

The impact of machining parameters while machining GFRP composites was studied by Khashaba and his colleagues both empirically and analytically, with an emphasis on delamination and thrust force [7]. Formisano et al. [8] looked into how production processes affected the mechanical properties of GFRP composite laminates. The effects of drilling conditions, such as spindle speed, feed rate, and drill bits, on the delamination and temperature of GFRP composite laminates were examined by Erturk et al. [9]. In order to decrease delamination and enhance hole quality, recent research has focused on the geometry and coatings of drill bits [10–12]. A few investigations concentrated on the impact of tool wear [13] as well as exit temperatures

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DOI: ...
Received ... ...; Received in revised form ... ...; Accepted ... ...

[14–18] on delamination and surface degradation.

The prediction of thrust forces because of tool wear during drilling CFRP/Al stack [19] and CFRP [20] unidirectional composites was another recent study's main focus. A thorough analysis of delamination and delamination-free machining techniques for CFRP composites was presented by Jai et al. [21, 22]. Rahmé et al.'s research [22] demonstrated that the addition of woven glass sheets to the CFRP sheets' exit side of the drilled hole helped reduce delamination. Galinska et al. [23] provided a thorough analysis of bolted joints used to link fiber-reinforced composites. The use of unconventional methods to minimize delamination damage during the drilling of composites was the subject of several studies [17, 24].

For thrust forces and delamination damage, the drill bit tip angle is thought to be a key influencing factor. Improper cutting-edge design results in unintended cutting angles being distributed, which leads to poor quality and ineffective cutting ability, which leads to increased thrust forces and delamination [25, 26].

Arrospide et al. [27] looked into the impact of various drill bit geometries on the diameter deviation, surface roughness, and coaxial aspects of hole quality. Liu et al.'s experiments [28] show that thrust forces built by extruding the chisel edge were greater than those produced by cutting the chisel edge. According to Qiu et al. [29], milling CFRP laminates with a compounded drill, dragger drill, or candlestick drill could minimize or completely prevent push-out delamination. Investigations by Hocheng et al. with various drill bits like twist drill, candle stick drill, saw drill, core drill, and step drill concluded that the core drill allows the grater critical feed; below this force, delamination assumed to occur will not occur [30].

According to different delamination factor models, such as the conventional delamination factor, adjusted delamination factor, and equivalent delamination factor, Keerthy & J. Babu [7] studied the influence of speed along with feed on delamination at the exit side of the drilled hole in GFRP composites. The findings showed that feed has a greater impact on push-out delamination. To demonstrate a relationship between speed and feed-on delamination in a composite lamina, Davim and Reis provided a method employing Taguchi's method and ANOVA [8]. Using the Taguchi method with Grey Relational Analysis, Palanikumar suggested an efficient procedure for optimizing drilling conditions (feed and speed) with several performance characteristics (surface roughness, thrust force, and delamination factor). Their research outcome suggests that feed has a larger impact compared to spindle speed [7].

The majority of researchers used Taguchi and ANOVA methodologies to conduct their experiments with 3 or 4 levels to calculate the impact of drilling factors on delamination during drilling composite laminate [6–10]. In variation with past research, the Taguchi L25, a 5-level orthogonal array, was used in the experiments in the current work, which is expected to boost the accuracy of the findings. Feed and speed are the control variables considered in this investigation. The major goal of this work is to use the Taguchi technique and hybrid optimization method. The entropy method was used to calculate weights, which are integrated with grey relational analysis along with fuzzy logic to optimize the drilling conditions during the drilling of GFRP composite by a diamond-coated core drill, which allows a larger critical thrust force while drilling. The most promising equivalent delamination factor was applied to assess the delamination damage affecting composite laminate near the exit and entrance of the hole, which further improves the accuracy of the results. MINITAB 17 was used for the design and analysis of drilling experiments to determine the significant variables that influence the drilling of GFRP composites.

The research questions of this study are: what is the optimum machining factor for minimizing drilling defects, and which is the most influential factor on drilling performance? Selection of a suitable MCDM method to obtain the optimum machining combination.

Brief Review of MCDM Methods

Updates and improvements are still being made to MCDM approaches. By using the MCDM methodology, the shortcomings of more solitary approaches are mitigated. For example, all evaluation criteria and sub-criteria should stand alone when using the analytical hierarchy process (AHP) approach. Nonetheless, certain criteria (or sub-criteria) are dependent on other criteria in a lot of real-world working situations. The analytic network process (ANP) method overcomes this drawback of the AHP method. This approach considers the interdependencies among the criteria [31, 32]. The VIKOR method could resolve decision problems with conflicting and non-commensurable criteria, but it has limitations, like a lack of flexibility. The Complex Proportional Assessment Method (COPRAS) has advantages as it takes both maximizing and minimizing criteria values into account with different methods; however, it has disadvantages as the ranking derived from the COPRAS method is unstable compared to the other MCDM methods [31, 32].

The multi-attributive border approximation area comparison (MABAC) approach and its extensions have demonstrated strong results in a number of application domains. Three primary benefits are offered by MABAC: stable solutions in the event that the type of criteria formulation changes, consistent results in the event that the units of measurement vary, and a streamlined algorithm appropriate for large-scale issues. Though MABAC has structural constraints, it can still be enhanced. The normalizing method used in the classic MABAC is based on a max-min normalization formula, which is one of its major flaws. One normalizing method alone, meanwhile, could produce skewed results [33].

The Multi-Atributive Ideal-Real Comparative Analysis (MAIRCA) method has the following advantages: this method has a mathematical framework that remains the same regardless of the number of alternatives and criteria, hence the possibility of MAIRCA application in cases of a large number of alternatives and criteria. This method has applicability to both qualitative and quantitative criteria types. This method gives stable solutions regardless of changes in the qualitative criteria measurement scale and changes in quantitative criteria formulation [34]. The MAIRCA method can solve the problems under uncertainty. It is an efficient tool that emphasizes the importance of qualitative criteria in real-time problem-solving. Rating the qualitative criteria using an arbitrary scale merely for comparison purposes can yield incorrect results. Therefore, the tool is equipped with experimentally available or statistically evaluated material data along with the opinions of the subject experts to accurately assess the candidate choices in a given engineering problem [35].

The above-mentioned method has its relative advantages and limitations. The present study uses Grey Relational Analysis (GRA). The reason for using GRA is to reduce uncertainty in decision-making processes by providing a quantitative measure of the relationship between different factors. GRA is particularly useful when dealing with small sample sizes or data. It is also effective in situations where there is a lack of complete information about the variables being analyzed. Recent research shows GRA, along with fuzzy logic, can be effectively used for different multi-criteria decision-making applications [36–38]. The present study uses the same method for optimizing the machining factors during the drilling of GFRP composite laminate.

The pairwise comparison and deviation from maximum consistency concepts are applied in the comparison-based MCDM process known as the full consistency technique (FUCOM). Just n − 1 pairwise comparisons are needed by FUCOM to assign weights to n mappable targeting criteria in MPM. The FUCOM results are validated using the comparisons' deviation from maximum consistency (DMC). The FUCOM weighting method, as compared to other methodologies, yields more trustworthy results because it makes the fewest potential comparisons in its theory. The most significant shortcoming of FUCOM has been considered to be its subjectivity [39, 40].

A subjective weighing technique called Level Based Weight Assessment (LBWA) is suggested as a solution to pairwise comparison problems. In comparison to both the BWM and AHP approaches, it is based on a (n-1) comparison. One of the main advantages of the LBWA approach is its capacity to maintain its basic structure regardless of how complex the model gets. Furthermore, the ideal values of weight coefficients are obtained by a straightforward mathematical apparatus, which eliminates the conflicting expert preferences allowed by other subjective models like BWM and AHP. Finally, sensitivity analysis of the MCDM mode is made possible by the elasticity coefficient of the LBWA model, which permits extra coefficient corrections based on the preferences of decision-makers [41].

Unlike the above subjective methods, objective methods do not require any sort of initial information or judgment from the decision-makers [42]; they merely assess the structure of the data available in the decision matrix to determine the weights. These methods are known for eliminating possible bias associated with subjective evaluation, thus increasing objectivity. Criteria Importance Through Inter-criteria Correlation (CRITIC) has an advantage, as it considers both the contrast intensity and the conflicting relationship held by each decision criterion [43, 44].

Ecer and Pamucar [45] recently introduced an objective weighting method named LOgarithmic Percentage changedriven Objective Weighting (LOPCOW) with the advantages of eliminating the gap due to the size of the data, generating more reasonable weightings, and considering both positive and negative data in the weighting process. Famucar et.al. [46] proposed a novel multicriteria decision support tool called Weights by ENvelope and SLOpe (WENSLO) and Aczel-Alsina Weighted ASsessment (ALWAS) to identify the green growth performance of countries.

By removing the impact of human variables on criteria weights, the entropy technique has the advantage of improving the evaluation results' objectivity and scientificity [37]. As per the review on the benefits of the entropy weight method (ewm), it has the following benefits in optimizing the machining process [47]. One very effective method for evaluating indications is the EWM weight calculation process. This method is proven to be sufficiently consistent in determining the combined contrast intensity and divergence of responses, as well as inappropriately allocating weights to them [37, 47].

From the above discussion, entropy weight-based gray relational analysis with fuzzy logic can be effectively used for multi-criteria decision-making processes. The present study aims to use the same for determining the optimum drilling conditions during the drilling of composite laminate. The methodology used in this study is shown in Fig. 1.

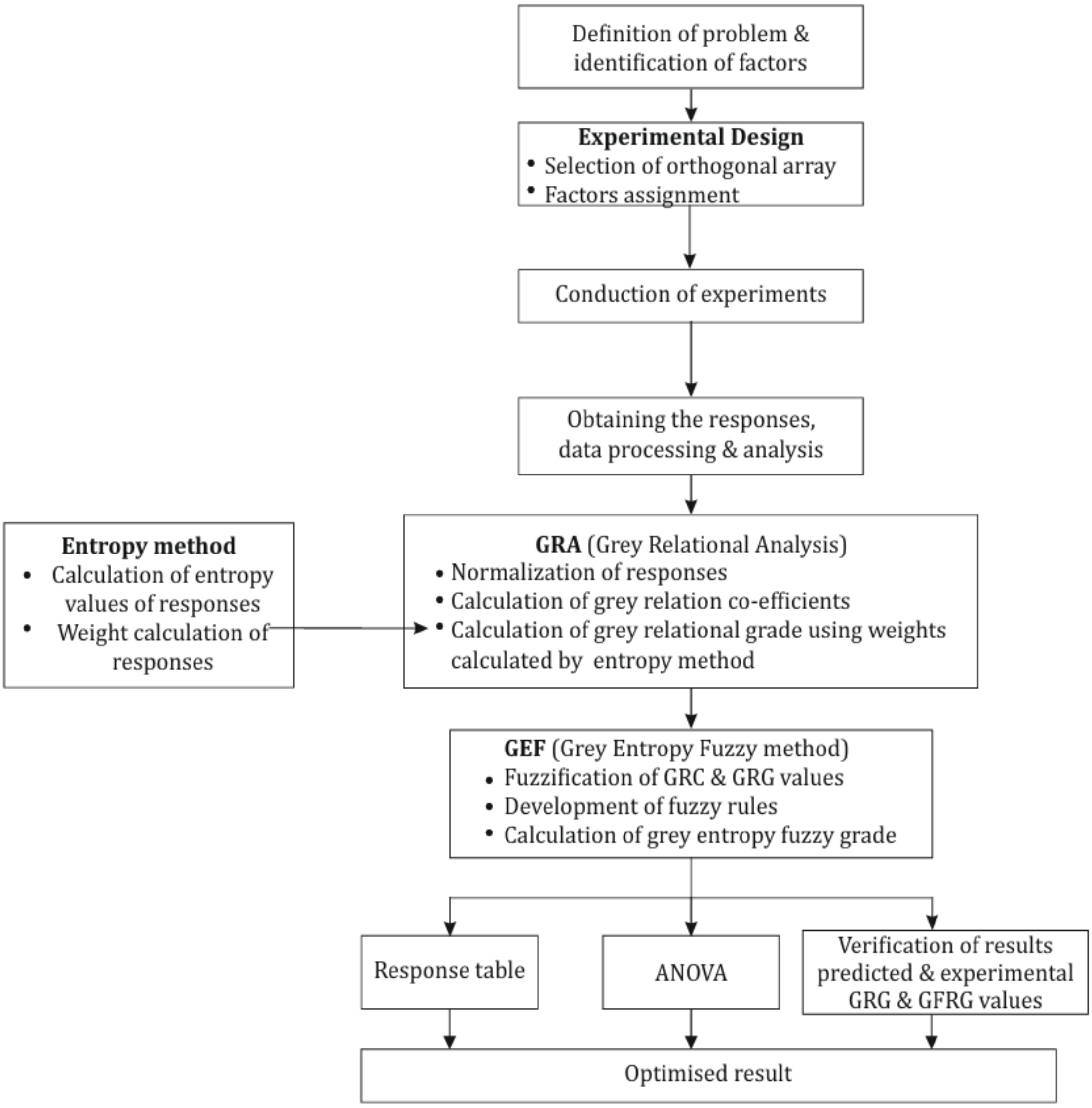


Fig.1. Methodology used in this study.

2. Experimental Procedure

In this investigation, 26-layer GFRP composite laminates that were set up symmetrically in the form [0, 90] were utilized. Bidirectional E-Glass fibers were used, and grade L-12 resin with K-5 hardener was used as the applied resin. The laminate had a 6 mm thickness. A laminate was cut to the workpiece material sample size of 250 x 40 x 6 mm^3. Drilling experiments were carried out using a 10 mm diamond-coated core drill on GFRP laminates in accordance with Taguchi's L25 orthogonal array. Experiments were done using a CNC computer numerical control vertical machining center (Makino Vertical Machining Centre, Model S33) at PSG College of Engineering in Coimbatore, India. To reduce experimental error, each experiment was run twice. Figure 2 depicts the experimental setup with the dynamometer. The strain gauge theory underlies how the dynamometer operates. The torque and thrust force values that generate voltage are proportionate to the force applied, and torque is responsible for the Wheatstone bridge circuit imbalance. The force and torque fluctuations while drilling were captured and then stored with a digital storage oscilloscope (Tektronix TDS210). The trials also took push-out and peel-up delamination effects into account. No coolant was applied during any of the testing. The drilling conditions considered for this investigation are shown in Table 1.

Fig.2. Drilling set-up with dynamometer and digital display

Table 1. Drilling conditions with their levels

Level of parameters	Speed (rpm)	Feed (mm/min)
1	1500	50
2	1750	75
3	2000	100
4	2250	125
5	2500	150

3. Delamination Measurement and Assessment

Different researchers have used a variety of techniques to assess the delamination of composites caused by drilling, although X-ray [12], optical microscope [7–9], ultrasonic C-scan [13], and digital photography [16] are the most popular. Acoustic emission [15] and the shadow Moire laser-based imaging technology [16] are other delamination measurement techniques. Babu et al. [5] give a thorough analysis of the assessment methods of delamination in a review paper. In this investigation, the delamination damage at the entrance and exit of the drilled hole was determined using digital image processing technologies. A scanner with a resolution of 1200 dpi was used to scan these drilled holes in order to calculate the amount of delamination. The image-editing application Image J received the scanned images and imported them.

A number of parameters, including brightness intensity, image enhancement, noise suppression, and edge detection, which are discussed in more depth elsewhere [48, 49], must be carefully chosen in order to produce a picture of acceptable quality. The threshold filter was applied to the binary image to remove the black and gray points, and only then can the damage zone be measured. Figure 3 illustrates the image processing procedure followed for obtaining the delaminated area of the drilled hole with acceptable quality. The damage intensity to the composite material at the exit and entry sides of the hole is characterized in the present investigation using the equivalent delamination factor, which is schematically represented in Fig. 4 and computed using Eq. (1).

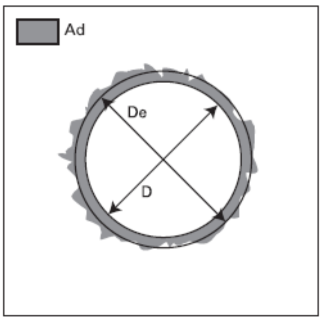


Fig.4. Schematic for calculation of equivalent delamination factor

$$F_{ed} = \frac{D_e}{D} \quad (1)$$

here D_o is the diameter of the nominal hole. De is the equivalent delamination diameter which may be expressed as Eq. (2).

$$D_e = \left[\frac{4(A_d+A_0)}{\Pi}\right]^{0.5} \tag{2}$$

A_d = the delamination damage area in the surroundings of the drilled hole.

A_o = the drilled area with diameter D_o.

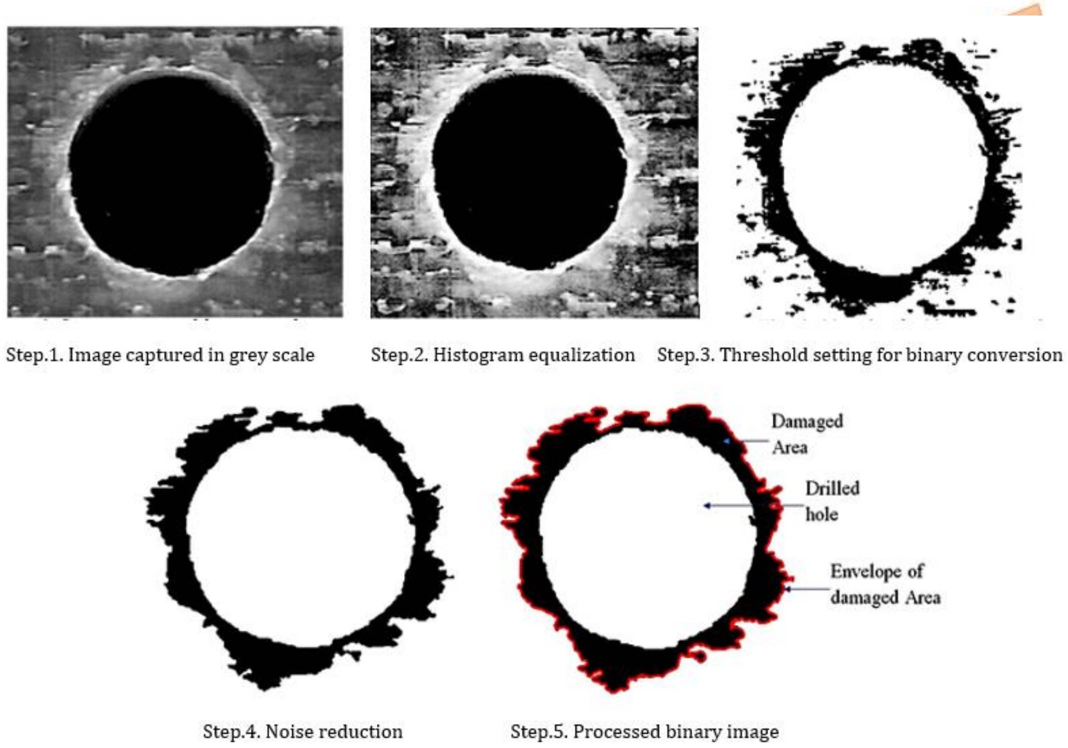


Fig.3. Image processing steps to assess delamination damage.

4. Results and Discussion

Responses from the experiments are delaminations, both push-out and peel-up, torque, hole diameter, and thrust force for various drilling conditions, as shown in Table 2.

Due to their excellent mechanical qualities, GFRP composites are employed in fairings, storage room doors, passenger compartments, and wind turbine blades. Prior to assembly, drilling is a typical machining procedure on these pieces. Drilling without errors is necessary to guarantee their effective operation in service. The literature on drilling GFRP composites reveals that because these materials have a composite structure containing hard fibers in a soft matrix, their machining mechanisms differ from those of traditional metals. These materials can be machined through shearing or plastic deformation. The process of machining these composite materials was affected by the fibers' hardness, toughness, orientation, and flexibility [9]. For these composite materials, it is particularly challenging to optimize many features simultaneously. In the current work, drilling process parameters for GFRP composites are optimized for numerous performance factors. Performance parameters of drilling include thrust and torque, as well as delamination at both the entry and exit. For better hole quality, lower torque, delamination factor, and thrust force values are preferred. The feed rate and spindle speed input parameters. Using response graphs, the influence of these variables on the machining of GFRP composites is studied.

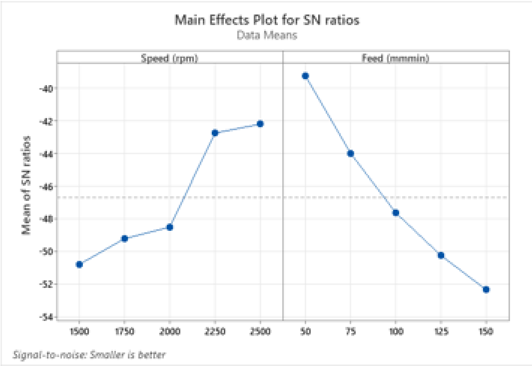
A response table of average responses was used to construct the response graphs. Table 3 displays the response table with torque, delamination factors (entry and exit), and thrust force. "Delta" in the response table denotes the variation between the response's minimum and maximum average values at a specific level. The rank denotes the strength of a parameter's influence. According to the analysis of this response table, feed has a greater impact on the drilling of GFRP composites' output characteristics.

Table 2. Orthogonal array of experimental design with variable and experiment responses

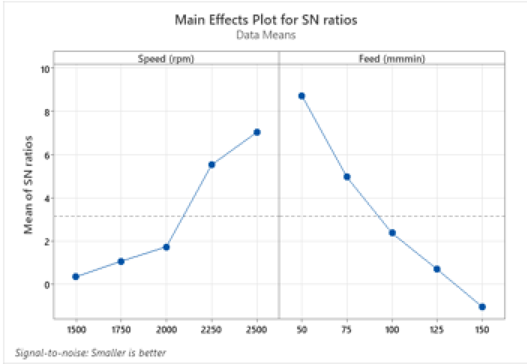
Exp. No	Speed (rpm)	Feed (mm/min)	Delamination Factor		Thrust Force (N)	Torque (Nm)
			Push-out	Peel-up		
1	1500	50	1.15	1.14	143.50	0.48
2	1500	75	1.17	1.14	246.00	0.77
3	1500	100	1.19	1.15	398.50	1.06
4	1500	125	1.21	1.15	522.50	1.30
5	1500	150	1.21	1.16	680.50	1.60
6	1750	50	1.14	1.14	103.00	0.44
7	1750	75	1.15	1.14	220.00	0.73
8	1750	100	1.16	1.15	334.00	0.99
9	1750	125	1.17	1.15	455.50	1.18
10	1750	150	1.21	1.15	586.00	1.44
11	2000	50	1.14	1.13	108.50	0.45
12	2000	75	1.14	1.14	203.00	0.67
13	2000	100	1.15	1.14	308.00	0.91
14	2000	125	1.16	1.15	406.50	1.08
15	2000	150	1.20	1.15	487.50	1.24
16	2250	50	1.12	1.12	67.00	0.35
17	2250	75	1.14	1.14	94.50	0.48
18	2250	100	1.14	1.14	145.50	0.47
19	2250	125	1.15	1.14	209.50	0.66
20	2250	150	1.18	1.15	255.00	0.80
21	2500	50	1.13	1.11	61.50	0.20
22	2500	75	1.15	1.12	96.50	0.32
23	2500	100	1.16	1.13	136.50	0.57
24	2500	125	1.16	1.14	180.50	0.61
25	2500	150	1.19	1.14	246.00	0.79

Table 3. Response table for thrust force, torque, peel-up, and push-out delamination

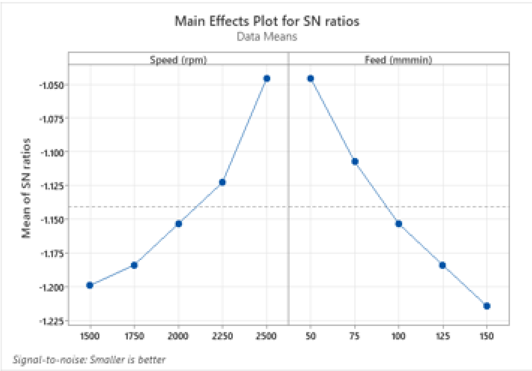
Level	Thrust force		Torque		Peel-up delamination		Push-out delamination	
	Spindle speed	Feed rate	Spindle speed	Feed rate	Spindle speed	Feed rate	Spindle speed	Feed rate
1	398.2	96.7	1.041	0.380	1.188	1.135	1.147	1.129
2	339.7	172.0	0.951	0.591	1.167	1.152	1.144	1.136
3	302.7	264.5	0.867	0.797	1.156	1.160	1.142	1.141
4	154.3	354.9	0.549	0.967	1.148	1.171	1.138	1.145
5	144.2	451.0	0.495	1.172	1.156	1.197	1.129	1.149
Delta	254	354.3	0.546	0.792	0.040	0.062	0.018	0.020
Rank	2	1	2	1	2	1	2	1



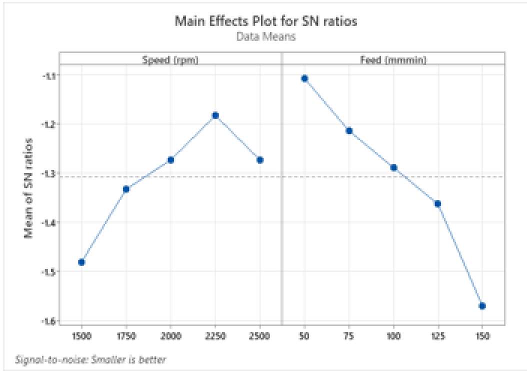
(a) Thrust force



(b) Torque



(c) Peel-up delamination



(d) Push-out delamination

Fig.5. S/N graphs for responses

Figures. 5 (a) to 5 (d) show the S/N curves for thrust force, torque, and delamination factors. The influence of speed and feed on torque and thrust force during drilling is depicted in Figs. 5 (a) and 5 (b). The findings show that when speed increases, torque and thrust force decrease. This occurs because increasing speed leads to more accumulated heat that softens the polymer matrix, resulting in reduced thrust force and torque. The stress on the drill, however, rises as the feed increases. When drilling composites, this results in increased torque and thrust force values. Figs. 5 (c) and 5 (d) show how drilling parameters affect the delamination damage at the exit and entry. High feed rates with low spindle speeds are more conducive to the delamination factor being seen. The delamination damage and thrust force increase with an increase in feed. Delamination and thrust force are related phenomena; when thrust force increases, the delamination also rises, and vice versa. Numerous scholars have examined the features of individual performance [8–12]. To boost production and enhance the performance of manufactured components, it is required to optimize several performance attributes. Researchers employ a variety of strategies to optimize several performance parameters, including the utility idea, gray relational analysis [49], and desirability approach [50]. In variation with past research, in this study, Grey-Entropy-Fuzzy (GEF), a hybrid method was employed in order to get the best drilling conditions for these multiple response optimizations. This is a mix of fuzzy logic with gray relational analysis [51, 52], and response weights were determined using the entropy approach.

5. Optimization Using Entropy Weighted Grey Relational Analysis.

5.1. Grey Relational Analysis.

The drilling issue that occurred during the drilling of GFRP laminate was optimized using GRA (grey-relational analysis). The generalized additive model (GRA) is a quantitative technique for identifying disparity and equality among input conditions. Every output response has a unique range and unit. Hence, it is necessary to normalize these values between 0 and 1. When solving problems involving several objectives, certain responses could be considered as maximization, some responses as minimization, and some responses as nominal, which are better responses. GRA condenses multi-response issues into a single response known as the Grey Relational Coefficient.

Responses with maximization can be normalized by utilizing Eq. (3).

$$X_i^*(k) = \frac{X_i^0(k) - min X_i^0(k)}{max X_i^0(k) - \min X_i^0(k)} \quad (3)$$

Responses of minimization are normalized by using Eq. (4).

$$X_i^*(k) = \frac{max\, X_i^0(k) - X_i^0(k)}{max X_i^0(k) - \min X_i^0(k)} \quad (4)$$

Responses with nominal values the better can be normalized by using Eq. (5).

$$X_i^* = 1 - \frac{|X_i^0(k) - X^0|}{\max\, X_i^0(k) - X_i^0} \quad (5)$$

i= 1 to n,
n = number of drilling conditions
m = number of experimental data
$X_i^0(k)$ is the original sequence
$X_i^*(k)$ is the sequence after data pre-processing
the max $X_i^0(k)$ is greatest value in $X_i^0(k)$,
min $X_i^0(k)$ = least value in $X_i^0(k)$
X^0= desired value.

In this investigation, all output responses are lower the better performance characteristic type, Eq. (4) is used to obtain the normalized values.
Normalized values for all the responses are calculated and tabulated in Table 5.

Grey Relational Coefficients (GRC)

Now Grey Relational Coefficients were determined by using Eq. (6).

$$\xi(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}(k) + \zeta\Delta_{max}} \quad (6)$$

, $\Delta_{0i}(k)$, Δ_{max}, Δ_{min} are determined using the Eq's (7), (8) and (9)

$$\Delta_{0i}(k) = \|X_0^*(k) - X_i^*(k)\| \quad (7)$$

$$\Delta_{max} = \max\max \|X_0^*(k) - X_i^*(k)\| \quad (8)$$

$$\Delta_{min} = \min\min \|X_0^*(k) - X_i^*(k)\| \quad (9)$$

ζ is the coefficient, whose values range [0,1].
ζ = 0.5 is generally used.

$\Delta_{0i}(k)$= deviation sequence of the sequence $X_0^*(k)$
$X_i^*(k)$ = comparability sequence.
The deviation sequences of the responses were calculated after data pre-processing and are shown in Table 4. The values Δ_{max} and Δ_{min} can be found in Table 4.
GRCs calculated with Eq. (6) for drilling conditions are represented in Table 7.
Notations used for output responses are,

A- Thrust Force.
B- Torque.
C- Peel-up Delamination.
D- Push-out Delamination.

5.2. Grey Relational Grade.

According to Eq. (10), the grey relational grade is often determined as the mean of all the GRCs of the relevant responses. Only when each response is given the same weight can this equation be used:

$$GRG = \frac{1}{n}\sum_{k=1}^{n} \zeta_i(\mathrm{k}) \quad (10)$$

For experimental problems such as drilling all output responses may not be equally significant, hence by assigning different weights to the responses, then Eq. (10) may be modified as Eq. (11).

$$GRG = \frac{1}{n}\sum_{k=1}^{n} W_k\, \zeta_i(k), \ \sum_{k=1}^{n} W_k = 1 \quad (11)$$

where W_k is the normalized weight of the response k; when weights are the same Eq. (10) and (11) both are the same. In the present study an objective method, that is entropy method [24,25] was used for the determination of criteria weights of output responses.

Table 4. Normalized and Deviation sequences of output responses.

Experiment No.	Normalized Values				Deviation Sequence			
	A	B	C	D	A	B	C	D
1	0.353	0.423	0.680	0.352	0.648	0.577	0.321	0.648
2	0.577	0.653	0.703	0.585	0.423	0.348	0.297	0.415
3	0.777	0.804	0.764	0.807	0.223	0.196	0.236	0.193
4	0.890	0.901	0.831	0.970	0.110	0.099	0.169	0.030
5	1.000	1.000	1.000	1.000	0.000	0.000	0.000	0.000
6	0.215	0.381	0.565	0.270	0.786	0.619	0.435	0.730
7	0.530	0.624	0.674	0.392	0.470	0.376	0.326	0.608
8	0.704	0.770	0.760	0.419	0.296	0.231	0.240	0.581
9	0.833	0.853	0.820	0.567	0.167	0.147	0.180	0.433
10	0.938	0.948	0.903	0.981	0.062	0.052	0.098	0.019
11	0.236	0.392	0.522	0.194	0.764	0.608	0.478	0.806
12	0.497	0.583	0.618	0.293	0.503	0.417	0.382	0.707
13	0.670	0.729	0.722	0.338	0.330	0.271	0.278	0.662
14	0.786	0.813	0.803	0.426	0.214	0.187	0.197	0.574
15	0.861	0.879	0.837	0.816	0.139	0.121	0.164	0.184
16	0.036	0.278	0.337	0.000	0.964	0.722	0.664	1.000
17	0.179	0.423	0.565	0.232	0.821	0.577	0.435	0.768
18	0.358	0.413	0.663	0.286	0.642	0.587	0.337	0.714
19	0.510	0.576	0.747	0.398	0.490	0.424	0.254	0.602
20	0.592	0.671	0.776	0.696	0.408	0.329	0.224	0.304
21	0.000	0.000	0.000	0.123	1.000	1.000	1.000	0.877
22	0.187	0.235	0.329	0.358	0.813	0.765	0.671	0.642
23	0.332	0.510	0.447	0.431	0.668	0.490	0.553	0.569
24	0.448	0.538	0.618	0.473	0.552	0.462	0.382	0.527
25	0.577	0.662	0.740	0.733	0.423	0.338	0.260	0.267

5.3. Entropy Method

Entropy, which is an estimate when there is uncertainty in information or data, was proposed by Shanon and Weaver in 1947. Zeleney improved it further in 1982 for determining the objective weights of responses. It applies the theory of probability. The weights of responses by this method can be calculated by normalizing the data with Eqs. (2) and (3). The values of entropy for individual output responses are determined using Eq. (12).

$$e_j = -\frac{1}{lnm}\sum_{i=1}^{m} P_{ij}\ln P_{ij} \qquad (12)$$

here $P_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}$ and m = total no of experimental conditions, in present study m=25.

The performance response or characteristics is increasing or decreasing with entropy(e_j) values. The weights of the individual responses may be determined by Eq. (13).

$$w_j = \frac{(1-e_j)}{\sum_{i=1}^{n}(1-e_j)} \qquad (13)$$

Calculated normalized values of responses are tabulated in Table 5. Using these entropy values and also weights for the responses, they are calculated using Eqs. (12) and . (13) respectively, which are presented in Table 6.

The determined weights using Eq. (13) obtained for the responses are thrust force, torque, entry delamination factor, exit delamination factor, which are 0.28, 0.24, 0.17, and 0.31, respectively. These weights are used in determining the Grey relational grade with Eq. (11). Table 7 represents the obtained GRCs, gray relation grades, and ranks for all the test runs.

Table.6. Weightages of the responses using entropy method.

Response	e_j	$(1-e_j)$	w_j
A	0.965	0.035	28
B	0.971	0.029	24
C	0.979	0.021	17
D	0.962	0.038	31
Sum		0.123	100

UNCORRECTED PROOF

Table.5. Normalized, P_{ij}, *and* $P_{ij}\ln P_{ij}$ values for output responses

Experiment No.	Normalized Values				P_{ij} Values				$P_{ij}\ln P_{ij}$ Values			
	A	B	C	D	A	B	C	D	A	B	C	D
1	0.8676	0.8133	0.5000	0.7000	0.0520	0.0533	0.0405	0.0490	-0.154	-0.156	-0.130	-0.148
2	0.7022	0.6200	0.5000	0.5000	0.0421	0.0406	0.0405	0.0350	-0.133	-0.130	-0.130	-0.117
3	0.4560	0.4267	0.3333	0.3000	0.0273	0.0279	0.0270	0.0210	-0.098	-0.100	-0.098	-0.081
4	0.2559	0.2667	0.3333	0.1000	0.0153	0.0175	0.0270	0.0070	-0.064	-0.071	-0.098	-0.035
5	0.0008	0.0667	0.1667	0.1000	0.0000	0.0044	0.0135	0.0070	0.000	-0.024	-0.058	-0.035
6	0.9330	0.8400	0.5000	0.8000	0.0560	0.0550	0.0405	0.0559	-0.161	-0.160	-0.130	-0.161
7	0.7441	0.6467	0.5000	0.7000	0.0446	0.0423	0.0405	0.0490	-0.139	-0.134	-0.130	-0.148
8	0.5601	0.4733	0.3333	0.6000	0.0336	0.0310	0.0270	0.0420	-0.114	-0.108	-0.098	-0.133
9	0.3640	0.3467	0.3333	0.5000	0.0218	0.0227	0.0270	0.0350	-0.083	-0.086	-0.098	-0.117
10	0.1533	0.1733	0.3333	0.1000	0.0092	0.0113	0.0270	0.0070	-0.043	-0.051	-0.098	-0.035
11	0.9241	0.8333	0.6667	0.8000	0.0554	0.0546	0.0541	0.0559	-0.160	-0.159	-0.158	-0.161
12	0.7716	0.6867	0.5000	0.8000	0.0463	0.0450	0.0405	0.0559	-0.142	-0.139	-0.130	-0.161
13	0.6021	0.5267	0.5000	0.7000	0.0361	0.0345	0.0405	0.0490	-0.120	-0.116	-0.130	-0.148
14	0.4431	0.4133	0.3333	0.6000	0.0266	0.0271	0.0270	0.0420	-0.096	-0.098	-0.098	-0.133
15	0.3123	0.3067	0.3333	0.2000	0.0187	0.0201	0.0270	0.0140	-0.075	-0.078	-0.098	-0.060
16	0.9911	0.9000	0.8333	1.0000	0.0594	0.0589	0.0676	0.0699	-0.168	-0.167	-0.182	-0.186
17	0.9467	0.8133	0.5000	0.8000	0.0568	0.0533	0.0405	0.0559	-0.163	-0.156	-0.130	-0.161
18	0.8644	0.8200	0.5000	0.8000	0.0518	0.0537	0.0405	0.0559	-0.153	-0.157	-0.130	-0.161
19	0.7611	0.6933	0.5000	0.7000	0.0456	0.0454	0.0405	0.0490	-0.141	-0.140	-0.130	-0.148
20	0.6877	0.6000	0.3333	0.4000	0.0412	0.0393	0.0270	0.0280	-0.131	-0.127	-0.098	-0.100
21	1.0000	1.0000	1.0000	0.9000	0.0600	0.0655	0.0811	0.0629	-0.169	-0.178	-0.204	-0.174
22	0.9435	0.9200	0.8333	0.7000	0.0566	0.0602	0.0676	0.0490	-0.163	-0.169	-0.182	-0.148
23	0.8789	0.7533	0.6667	0.6000	0.0527	0.0493	0.0541	0.0420	-0.155	-0.148	-0.158	-0.133
24	0.8079	0.7267	0.5000	0.6000	0.0485	0.0476	0.0405	0.0420	-0.147	-0.145	-0.130	-0.133
25	0.7022	0.6067	0.5000	0.3000	0.0421	0.0397	0.0405	0.0210	-0.133	-0.128	-0.130	-0.081
Sum of $\sum_{i=1}^{m} P_{ij}\ln P_{ij}$									-3.107	-3.126	-3.152	-3.098

Entropy value for the response A is $e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} P_{ij} = -\frac{1}{\ln 25}(-3.107) = 0.965$

Table.7. GRCs with the entropy-based weights (in brackets), Grey Relational Grades and ranks for the test runs.

Experiment. No.	Grey Relational Coefficients				Grey Relational Entropy Grade	Rank
	Thrust Force **(0.28)**	Torque **(0.24)**	Peel-up Delamination **(0.17)**	Push-out Delamination **(0.31)**		
1	0.5865	0.5417	0.4239	0.5868	0.5482	8
2	0.4644	0.4338	0.4158	0.4609	0.4477	15
3	0.3914	0.3833	0.3957	0.3825	0.3874	21
4	0.3597	0.3568	0.3757	0.3402	0.3557	23
5	0.3333	0.3333	0.3333	0.33333	0.3333	25
6	0.6998	0.5674	0.4695	0.6493	0.6132	6
7	0.4853	0.4449	0.4258	0.5603	0.4887	13
8	0.4153	0.3939	0.3969	0.5440	0.4469	16
9	0.3751	0.3695	0.3788	0.4685	0.4033	20
10	0.3478	0.3452	0.3565	0.3376	0.3455	24
11	0.6792	0.5605	0.4893	0.7209	0.6314	4
12	0.5016	0.4617	0.4470	0.6307	0.5228	10
13	0.4273	0.4067	0.4093	0.5967	0.4718	14
14	0.3889	0.3807	0.3837	0.5400	0.4329	17
15	0.3673	0.3626	0.3741	0.3799	0.3712	22
16	0.9335	0.6427	0.5977	1.0000	0.8272	2
17	0.7367	0.5417	0.4695	0.6832	0.6279	5
18	0.5826	0.5477	0.4300	0.6364	0.5650	7
19	0.4951	0.4648	0.4011	0.5569	0.4910	12
20	0.4580	0.4271	0.3919	0.4181	0.4270	19
21	1.0000	1.0000	1.0000	0.8031	0.9390	1
22	0.7274	0.6800	0.6029	0.5830	0.6501	3
23	0.6012	0.4952	0.5281	0.5368	0.5434	9
24	0.5275	0.4817	0.4470	0.5139	0.4986	11
25	0.4644	0.4304	0.4033	0.4056	0.4276	18

5.4. Optimization with GREG

With grey relational analysis with entropy-based weights, the grey relational entropy grade was determined. Experiment number 21 shows the greatest value of GREG, which represents the optimum values of input factors. The GREG values varied from 0.9390 to 0.3333. The experimental results of all output responses at optimized drilling conditions are entry delamination factor 1.13, exit delamination factor 1.11, thrust force 61.5 N, and torque 0.02 Nm.

6. Optimization Using Grey Entropy Fuzzy Method (GEFM).

Using GRA reduces ambiguity in decision-making processes by offering a numerical representation of the interplay between several components. When working with small sample sizes or low-quality data, GRA is especially helpful. A mathematical technique for expressing ambiguity and uncertainty in decision-making is fuzzy logic. It permits the possibility of partial truths, in which a claim may be made that is only partially true or untrue.

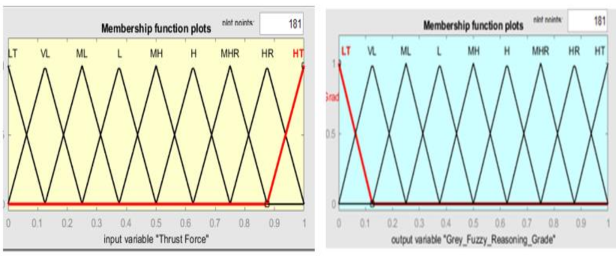
Fuzzy logic is based on the notion that there are frequently many shades of gray in between and that the concept of true or false is overly limiting. Hence, it is used to deal with imprecise or ambiguous information. Fuzzy rules, which are if-then statements that represent the relationship between input and output variables in a fuzzy manner, are used to create fuzzy logic. A fuzzy set, or a set of membership degrees for every conceivable output value, is the result of a fuzzy logic system [53, 54]. Hence, in this study, grey relational analysis with fuzzy logic was used to optimize the drilling parameters.

Early optimization studies in the literature either employed subjected methods like the SIMO method or applied equal weights to all responses; this may be an inappropriate or incorrect method to optimize the drilling parameters. In order to make a multi-objective problem into a single objective known as GREG, the entropy approach, which is an objective method, was used combined with fuzzy logic to obtain the most scientific weights. Complex multi-objective optimization issues can be resolved by using a combination of grey relational analysis, the entropy method, and fuzzy logic [52]. However, relationships with assessing replies are disregarded during this conversion procedure. The improved optimization using the proper weights for each response is now presented by this approach.

Grey Entropy Fuzzy Model.

In order to further optimize drilling using artificial intelligence techniques like fuzzy logic, a sound prediction model must be developed. Because GREG includes weighted sums that depend on entropy for each of the four GRCs, the GREG problem can be optimized without taking response criteria into consideration. For this, the GREG desirability function was applied with a fuzzy model for all input factors. The important phases of the fuzzy method are the fuzzification of the input and output data, the development of fuzzy rules, and eventually the defuzzification of outcomes.

The matching values of GEFG are obtained using the fuzzy-logic toolbox of MATLAB (R2021a). Inputs to the fuzzy-logic model are the values of the GREG of the torque, thrust force, exit and entry delamination, and diameter of the hole. The fuzzy modeling is done using triangular membership functions. Nine linguistic membership functions were used for all the input GREGs and output Grey Entropy Fuzzy Grade: lowest (LT), very low (VL), medium-low (ML), low (L), medium-high (MH), high (H), medium higher (MHR), higher (HR), and highest (HT). In Fig. 6, these membership functions are shown. The obtained GEFG values are shown in Figs. 7 and 8, as displayed in the fuzzy rule viewer. In this figure, twenty-five rows show the fuzzy rules used, and the five columns represent GRC values, and the last column gives the de-fuzzified GEFG values. These GEFG values captured for all twenty-five experiments are shown in Table 8. It may be noted from Table 8 that the experiment. 21 (speed of 12000 rpm, feed of 1000 mm/min) has the greatest GEFG value; this indicates the optimum conditions of input variables for high drilling performance.



(a) (b)

Fig.6. Membership functions (a) for input factors and (b) for output GEFG.

Table. 8. GRCs, GEG, and GEFG of all experiments

Experiment. No.	Grey Relational Coefficients				Grey Relational Entropy Grade	Grey Entropy Fuzzy Grade
	Thrust Force **(0.28)**	Torque **(0.24)**	Peel-up Delamination **(0.17)**	Push-out Delamination **(0.31)**		
1	0.5865	0.5417	0.4239	0.5868	0.5482	0.500
2	0.4644	0.4338	0.4158	0.4609	0.4477	0.434
3	0.3914	0.3833	0.3957	0.3825	0.3874	0.385
4	0.3597	0.3568	0.3757	0.3402	0.3557	0.375
5	0.3333	0.3333	0.3333	0.33333	0.3333	0.375
6	0.6998	0.5674	0.4695	0.6493	0.6132	0.618
7	0.4853	0.4449	0.4258	0.5603	0.4887	0.442
8	0.4153	0.3939	0.3969	0.5440	0.4469	0.423
9	0.3751	0.3695	0.3788	0.4685	0.4033	0.375
10	0.3478	0.3452	0.3565	0.3376	0.3455	0.375
11	0.6792	0.5605	0.4893	0.7209	0.6314	0.670
12	0.5016	0.4617	0.4470	0.6307	0.5228	0.500
13	0.4273	0.4067	0.4093	0.5967	0.4718	0.462
14	0.3889	0.3807	0.3837	0.5400	0.4329	0.419
15	0.3673	0.3626	0.3741	0.3799	0.3712	0.375
16	0.9335	0.6427	0.5977	1.0000	0.8272	0.925
17	0.7367	0.5417	0.4695	0.6832	0.6279	0.673
18	0.5826	0.5477	0.4300	0.6364	0.5650	0.500
19	0.4951	0.4648	0.4011	0.5569	0.4910	0.455
20	0.4580	0.4271	0.3919	0.4181	0.4270	0.424
21	1.0000	1.0000	1.0000	0.8031	0.9390	0.952
22	0.7274	0.6800	0.6029	0.5830	0.6501	0.714
23	0.6012	0.4952	0.5281	0.5368	0.5434	0.500
24	0.5275	0.4817	0.4470	0.5139	0.4986	0.469
25	0.4644	0.4304	0.4033	0.4056	0.5482	0.415

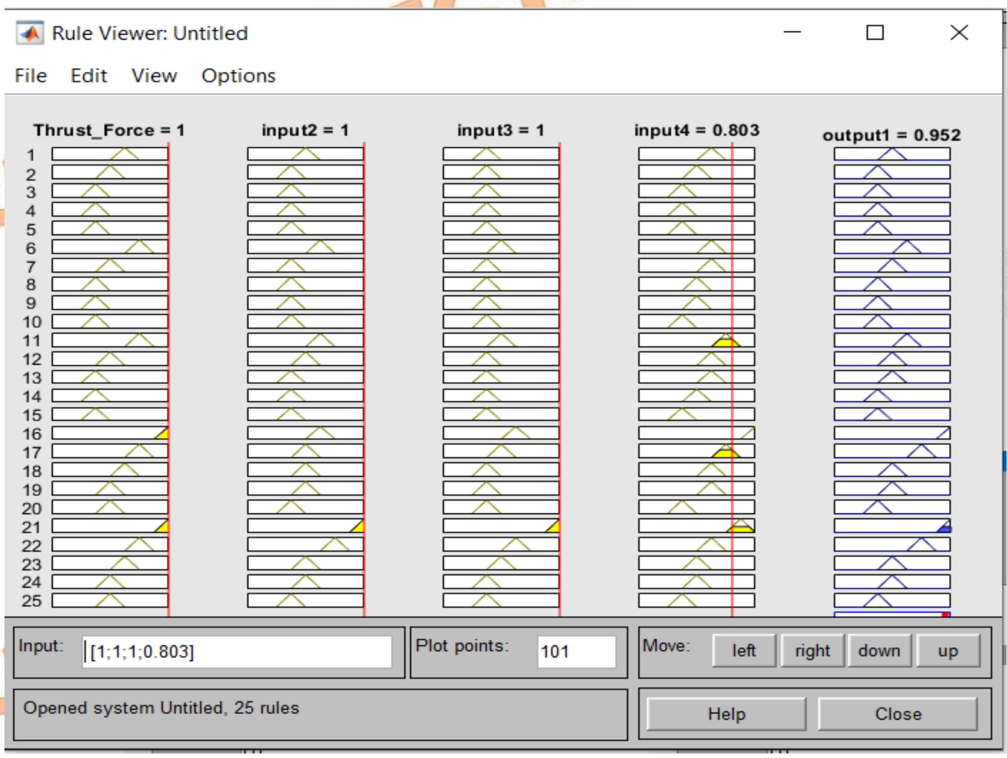


Fig.7. Fuzzy-logic rule viewer for Experiment number.21 (Greatest GEFG).

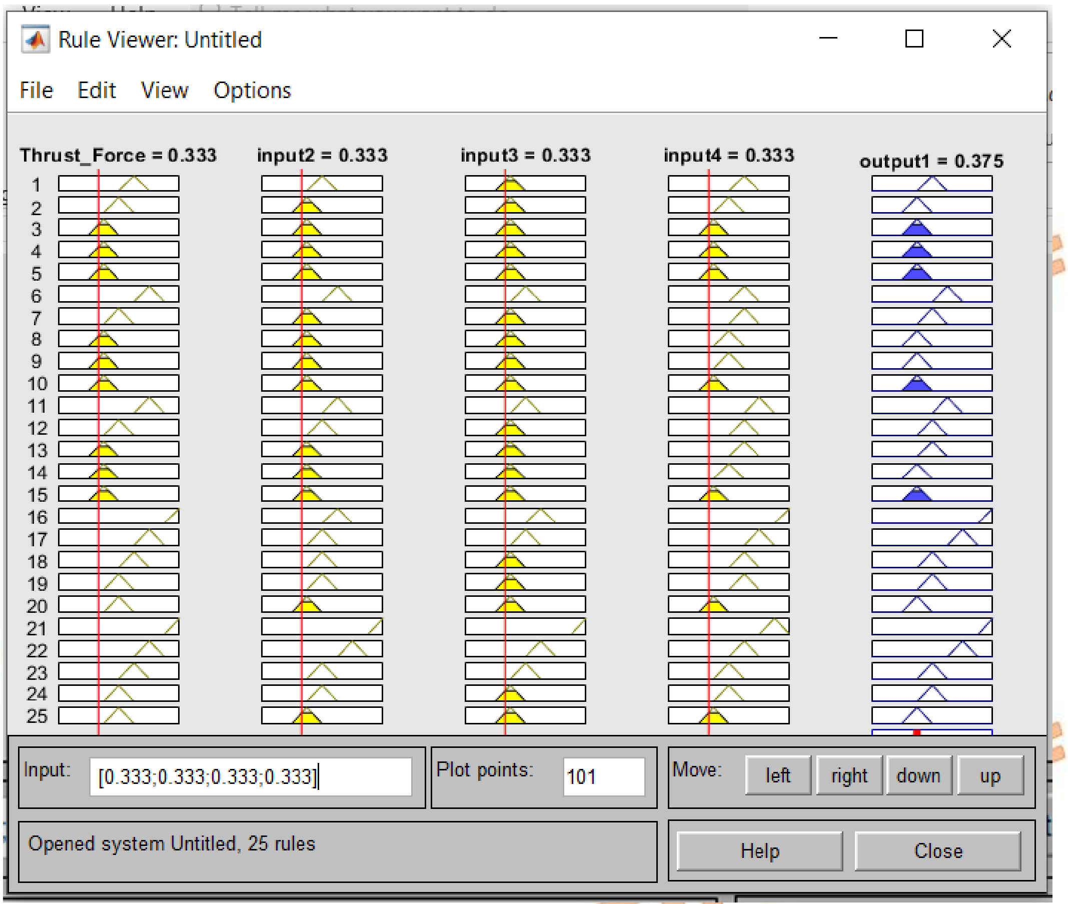


Fig.8. Fuzzy-logic rule viewer for Experiment number.5 (Least GEFG).

To more precisely find the optimum combinations of drilling parameters, it is still necessary to examine the relative importance of drilling factors for the different performance characteristics. The analysis of variance is used to analyze the outcomes. An analysis of variance (ANOVA) was utilized to determine which drilling variables have a substantial impact on performance characteristics. The complete variability of the Grey relationship grades is divided to achieve this. This is done in order to deconvolute the contributions made by individual drilling variables and errors from the total sum of the squared deviations of the Grey relational grade. To ascertain which machining factors significantly influence the drilling performance, the F-test may also be performed. When F is large, changing the drilling parameter typically has a considerable impact on performance characteristics. The percentage of influence is also estimated for the analysis of the important variables and their contribution to composite machining. Table 9 displays these values.

Table 9. shows that the feed rate's F value is 26.34, which is higher than the spindle speed's 12.30 value. In light of this, and in good accord with results from Palanikumar [9], the feed rate is the variable that shows the most impact on torque, thrust force, and delamination variables while drilling GFRP laminate. The percentage error in the current study is 9.38, compared to 14.78 in a study of a similar nature by Palanikumar [9]. The employment of a larger number of levels is what accounts for the lower percentage error, or high accuracy, in the current work. Compared to Palanikumar's work, which only used 4 levels of input parameters, the current study uses 5.

Table 9. ANOVA for Grey Entropy Reasoning Grade

Source	DF	Sum of squares	Mean square	F	% Contribution
Speed (rpm)	4	0.14064	0.035159	12.30	28.85
Feed(mm/min)	4	0.30115	0.075288	26.34	61.77
Residual Error	16	0.04574	0.002858		9.38
Total	24	0.48752			

Figure 9 shows how the parameters feed and speed interact to influence the drilling performance of GFRP composite laminate. If the lines are parallel, there is little interaction between the parameters. It will have an interaction effect if the lines diverge. According to the graph, the effect of interaction between feed and speed is greatest at high speeds, i.e., 2500 rpm, while it is minimal at middle and low speeds. The image also shows that low feed rates are where feed rate and spindle speed interact most. These numbers show that when drilling GFRP composites with a core drill, small feed rates with high spindle speeds are preferred.

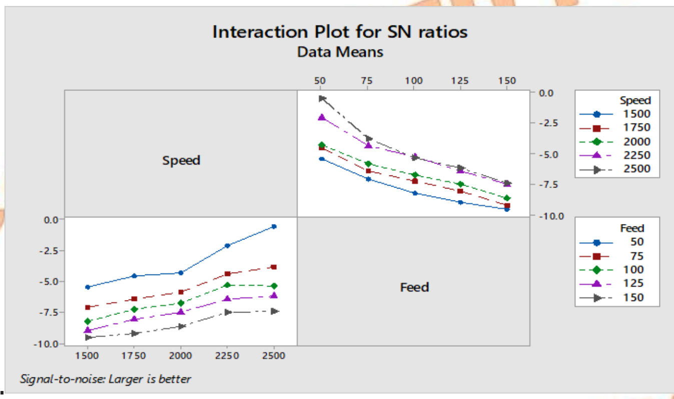


Fig.9. Interaction between the parameters on SN ratio of Grade Entropy Reasoning Grade

7. Prediction and Verification of Experimental Results of Grey Relational Grade and Grey Fuzzy Reasoning Grade

After finding the suitable optimal parameters, it is necessary to predict the grey fuzzy reasoning grade theoretically. The grey fuzzy reasoning grade can be predicted by using the following equation:

$$\eta_{predicted} = \eta_{om} + \sum_{i=1}^{m}(\eta_{olm} - \eta_{om}) \qquad (14)$$

where η_{om} is the mean value of the gray fuzzy reasoning grade and is the gray fuzzy reasoning grade at the optimal level and m is the number of influential parameters that affect the multiple performance characteristics. Table 10 shows the comparison results of the initial drilling parameters and the optimal drilling parameters. It is seen that thrust force at the initial setting level of s1f1 decreases from 143.5 to 61.5 (experiment number 21), a drastic decrease. Similarly, torque reduces from 1.37 to 0.39, delamination at the entry and exit decreases from 1.5211 and 1.4317 to 1.4287 and 1.41, respectively, and eccentricity reduces from 0.0619 to 0.0156. It is seen that the gray fuzzy reasoning grade is higher than that of the gray relational grade. From the above results, it has been asserted that fuzzy fuzzy reasoning can be useful for optimizing the multiple performances of CFRP composites in drilling.

Table 12 shows the response table for the gray fuzzy reasoning grade. In the gray fuzzy approach, to produce the best output, the optimal combination of the parameters as determined from the response table shows that spindle speed must be maintained at level 5 and feed rate at level 1. Feed rate has more influence on machining performance.

The percentage error in the current study is 9.38, compared to 14.78 in a study of a similar nature in the literature [55]. This shows that the proposed method can be effectively used for optimizing machining parameters during the drilling of composite laminates.

Table. 10. Results of initial and optimal machining performance

Setting level	Initial drilling parameters	Optimal drilling parameters	
	S1f1	Prediction s5f1	Experiment s5f1
Push-out delamination	1.15	---	1.13
Peel-up delamination	1.14	---	1.11
Thrust force	143.5	---	61.5
Torque	0.48	---	0.2
Grey relational grade	0.548	0.831	0.939
Grey fuzzy reasoning grade	0.5	0.828	0.952

Table. 11. Response table of initial and optimal machining performance

Machining condition	Level 1	Level 2	Level 3	Level 4	Level 5	Max-Min
Spindle speed, s	0.414	0.446	0.485	0.595	**0.610**	0.196
Feed rate, f*	**0.733**	0.552	0.454	0.418	0.393	0.340*
Overall mean grey entropy fuzzy grade=0.51						

The bold values indicate optimal levels, * more influencing parameter.

8. Conclusion, Limitation of Present Study and Scope for Future Research

This study presents multi-response optimization of the drilling of GFRP laminate by applying an innovative method combining the entropy method for weights, grey relational analysis, and fuzzy logic. Input factors are feed and speed, and the output responses are torque, thrust force, entry/peel-up, and exit/push-out delamination factors. Depending on the results obtained, the below conclusions are drawn:

The results show that an increase in feed rate increases the delamination factor, thrust force, and torque. The delamination factor, thrust force, and torque decrease slightly with the increase in spindle speed. The greater the gray relational grade, the better the performance. Therefore, cutting speed at 2500 rpm and feed rate at 50 mm/min result in lower delamination, thrust force, and torque.

The experimental results indicate that proper selection of drilling factors improves the performance of drilling. Experiment Number 21 indicates the greater value of GERG 0.952, which is the optimum combination of input factors (i.e., speed 2500 rpm, feed 50 mm/min) for multi-response optimization.

The ANOVA results reveal that feed is the drilling variable, having a greater impact on the gray relational grade. The percentage error in the current study is 9.38, compared to 14.78 in a study of a similar nature in the literature [55]. This shows that the proposed method can be effectively used for optimizing machining parameters during the drilling of composite laminates.

However, this study has the following limitations:.

One limitation is that the GRA with the Fuzzy Logic model's accuracy is dependent on the dataset's properties, which are highly uncertain. Hence, when utilizing GRA with fuzzy logic models, it is crucial to thoroughly assess their applicability for a given use case. Accuracy may change from case to case.

Future research can be focused on optimizing machining factors by extending the recently developed MCDM methods like MABAC, MAIRCA, and FUCOM with criteria weight calculation using methods like CRITIC and WENSLO.

This study considers only the delaminated area in the calculation of the delamination factor; future studies can be focused on considering the perimeter of the damaged zone in the vicinity of the drilled hole in the calculation of the delamination factor. Future studies may also be focused on the thermo-mechanical effect of delamination and other drilling defects.

Authorship contribution statement

Jalumedi Babu: Conceptualization,Methodology,Investigation, Writing originaldraft.

Lijo Paul: Formalanalysis, Projectadministraion.

M.Ven kataRamana: Validation,Writing–review&editing.

AnjaiahMadarapu: Resources,Datacuration.

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