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Multi-Objective Optimization of Carbon-Glass Fiber Polymer Drilling Process Based on Fuzzy Grey Entropy Weighing Method

Purna Surendernath[1,*], P. Kasi V. Rao[2], M. V. Satish Kumar[3], M. Pradeep Kumar[4]

Abstract

In recent years, the machining characteristics of hybrid fiber polymer composites have garnered significant research attention due to their growing industrial applications. This study specifically focuses on the drilling of hybrid carbon-glass fiber reinforced (CGFR) epoxy composites, fabricated using the hand layup technique. The key machining characteristics evaluated in this drilling process include surface roughness and circularity error. The influence of critical drilling process parameters, such as spindle speed, drill bit diameter, and point angle, on these characteristics was systematically investigated. A multi-objective optimization approach was employed to determine the optimal parameter combinations for drilling CGFR composites. The experimental design was based on the Taguchi method, considering spindle speed, drill bit diameter, and point angle as input parameters. The performance characteristics, such as surface roughness and circularity error, were analyzed using grey relational analysis integrated with a fuzzy inference system (FIS) to manage multiple responses effectively. The fuzzy inference system was utilized to convert the performance characteristics into a common factor level setting to optimize the machining process. The study's findings demonstrated that the optimal combination of drilling parameters significantly minimized both surface roughness and circularity error, enhancing the overall quality of the drilled hybrid composite.

Keywords: Hybrid composite, fuzzy logic, grey relational analysis, drilling, optimization

INTRODUCTION

Fiber reinforced polymer (FRP) composites are highly valued for their high strength-to-weight ratio, corrosion resistance, and design flexibility, making them suitable for industries like aerospace, automotive, and construction [1-2]. They perform well in harsh environments and can be tailored for specific applications [3]. However, traditional FRP composites have limitations, particularly in their mechanical performance under diverse loading conditions, which can affect long-term reliability. To overcome these challenges, hybrid fiber polymer composites have been developed [4]. By incorporating multiple fiber types with varying properties, hybrid composites offer enhanced performance, including improved load-bearing capacity and impact resistance [5]. This innovation allows them to adapt better to different conditions, making hybrid composites a superior solution for demanding engineering applications [6]. Researchers have made numerous attempts to combine different composite materials in order to achieve improved mechanical properties.

***Author for Correspondence**
Purna Surendernath

[1]Research Scholar, Department of mechanical engineering, Koneru Lakshmaiah Education Foundation, vaddeswaram, Andhra Pradesh, India.
[2]Associate professor, Department of Mechanical engineering, Koneru Lakshmaiah Education Foundation, vaddeswaram, Andhra Pradesh, India.
[3]Professor & Head, Department of Mechanical engineering, Kamala institute of technology and science, Singapore, Telangana, India.
[4]Lecturer, Department of Mechanical Engineering, JNTUH University College of Engineering Science & Technology, Hyderabad, Telangana, India.

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Dong [7] studied the flexural properties of carbon and glass fiber hybrid laminates, showing that when up to half of the plies are glass/epoxy and placed inside, the hybrid composite achieves similar lexural strength and modulus to full carbon composites. Guermazi et al. [8] examined glass/epoxy, carbon/epoxy, and hybrid composites, finding that carbon/epoxy exhibited superior mechanical properties, while the hybrid structure showed intermediate performance. Jun Hee Song [9] evaluated carbon/glass and carbon/aramid fiber laminates, observing that carbon fiber dominated tensile strength, but the specific pairing sequence altered mechanical properties significantly. Kumar et al. [10] studied the effect of hybridization on compressive instability in composites by varying glass fiber content, identifying failure mechanisms. Abebe et al. [11] improved the mechanical and water absorption properties of hybrid polymer composites reinforced with E-glass fiber and wool. Erkendirci et al. [12] analyzed tensile and impact resistance in epoxy hybrid composites with various layers, while Wu et al. [13] found that tensile and compressive strengths of carbon/glass hybrid composites exceeded theoretical values due to a positive hybrid effect. Abd El-baky et al. [14] demonstrated that hybridization enhances the tensile and flexural properties of jute-glass-carbon fiber composites.

Once materials with desired properties are developed, industries focus on producing high- quality products at low cost within a short time. Among various machining processes, hole-drilling is a key operation, accounting for around 41% of chip removal activities. Although drilling appears simple, it involves challenges such as increased cutting forces, limited chip flow, and difficulty in cooling, which complicate the process [15]. To overcome these issues, selecting the correct cutting tools and parameters is crucial. Surface roughness after drilling impacts mechanical properties like fatigue strength and abrasion resistance, and achieving a perfectly circular hole without ovality is essential [16]. Parameters such as cutting speed, feed rate, cooling method, and workpiece material significantly affect surface quality [17]. Optimum process parameter selection, based on experience or prior data, is vital for achieving high-performance drilled holes.

Meral et al. [18] investigated the performance of the drill geometries in terms of hole quality and determined the optimum parameters by using Taguchi method. Shunmugesh er al. [19] investigated micro-drilling of 2 mm thick CFRP laminates using HSS drill bits, optimizing delamination, circularity, and cylindricity through Taguchi's method. ANOVA and RSM analysis show spindle speed and feed rate significantly impact drilling performance. Babu et al. [20] optimized GFRP drilling using entropy-weighted gray relational analysis with fuzzy logic and Taguchi's L25 array. Results show that lower feed rates and higher spindle speeds improve drilling performance, with feed rate being the most influential factor. Palanikumar [21] optimized drilling conditions (feed and speed) using Taguchi and Grey Relational Analysis, focusing on surface roughness, thrust force, and delamination. The study found that feed rate has a greater impact than spindle speed. Fedai [22] optimized drilling parameters for MWCNT-reinforced GFRP composites using FAHP-GRA, FAHP-WASPAS, and FAHP-VIKOR methods with the Taguchi S/N ratio. FAHP-GRA and FAHP-WASPAS provided better optimization results compared to FAHP-VIKOR, showing significant improvements in drilling quality.

In the present study, synthetic (carbon and glass) fiber reinforced composite materials are developed and tested for mechanical properties like tensile and flexural for suitability in structural applications. These composites were further hybridized by integrating both carbon and glass fibers. The tensile and flexural strengths of the hybrid composites were then compared to those of non-hybrid composites. Comparative analysis shows that hybridization leads to notable improvements in tensile and flexural properties, resulting in significant enhancement in the polymer composite's overall performance. Further, the drilling operation was carried out on the hybrid composite by optimizing its process parameters to achieve an improved surface finish and better circularity. By adjusting factors such as point angle, spindle speed, and drill bit diameter, the study aimed to enhance the quality of the drilled holes, reducing defects like delamination and ovality. Initially the process parameter were optimized using Taguchi method. Using Grey relation and fuzzy logic, multi response optimization was carried out.

METHODOLOGY

Fabrication of Hybrid Fiber Composites

The composite laminates were fabricated using the hand layup technique. First, the fiber mats were cut to dimensions of 360×320 mm to match the mold size. To facilitate easy removal of the laminates after curing, a layer of wax was applied to the mold surface. The epoxy resin and hardener were thoroughly mixed in a glass bowl. The fiber mats, consisting of 10 layers of carbon fiber and 5 layers of glass fiber, were arranged symmetrically in the lower part of the mold, with each layer followed by an application of epoxy resin [4]. Once all layers were in place, the mold was sealed by placing the upper half over the topmost layer of the laminate. The assembly was left to cure at room temperature for 24 hours. After curing, the composite laminate was removed from the mold, trimmed along the edges, and cut into different sizes for drilling and subsequent characterization studies.

Machining of Carbon-Glass fiber Hybrid Composite

Before conducting drilling experiments on the hybrid composite laminates, it is important to identify the control parameters that influence the responses, such as surface roughness, thrust force, torque, and delamination factor, in drilled specimens. Previous research [20] has highlighted that key quality indicators for drilled glass and carbon fiber reinforced composites are significantly affected by parameters like spindle speed, drill diameter, and point angle This study selected three control drilling parameters— spindle speed, drill diameter, and point angle—each with three levels, to investigate their impact on the machining characteristics of the composite specimens. Instead of conducting 27 experiments required by a full factorial design, the Taguchi method's orthogonal array (OA) design was employed to achieve the same results with fewer experiments. The total degrees of freedom (DoF) for the three parameters at three levels was calculated to be 8, leading to the selection of the L9 orthogonal array (with 4 columns and 9 rows) for the experimental layout. Drilling was performed on three hybrid composite specimens, each measuring 100 mm × 80 mm × 3 mm, using a vertical CNC machining center and high-speed steel drill bits with diameters of 5 mm, 6 mm, and 7 mm. For each composite specimen, 9 holes were drilled corresponding to each orthogonal array setup, and the process was repeated for all three drill diameters. Images of the drilled holes in the hybrid composite specimens were captured and analyzed for surface quality as shown in the Figure 1.

S/N Ratio Analysis

In the present research work the experiments were carried out following a design based on the Taguchi L9 orthogonal array. This experimental design approach significantly reduces the number of required trials, thereby minimizing both the time and cost associated with the experiments. In the Taguchi method, response variables are converted into signal-to-noise (S/N) ratios, with three common quality characteristics used to calculate the S/N ratio: the smaller-the-better, the larger-the-better, and the nominal-the-better. The goal was to minimize surface roughness and circularity during drilling. Therefore, the smaller-the-better criterion is most appropriate for optimizing these parameters. Equation 1 is used to calculate the S/N ratio of smaller-the-better characteristics.

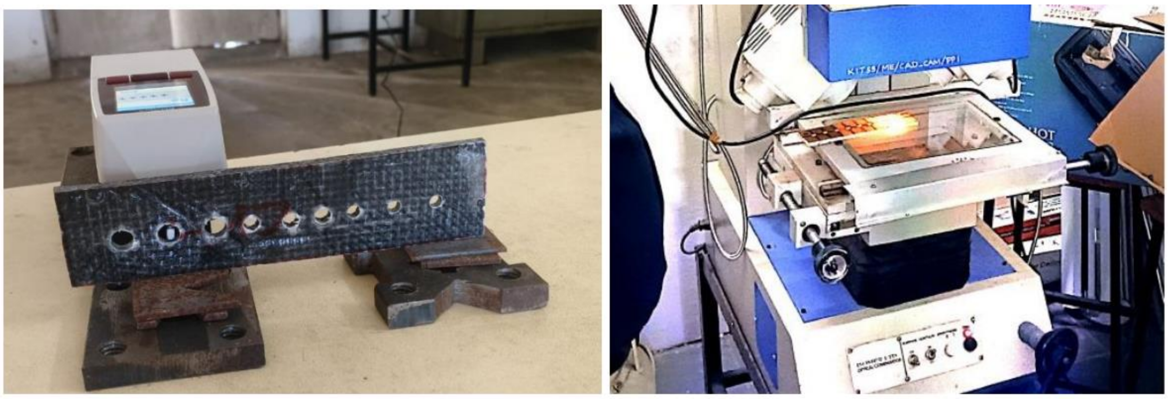

Figure 1. Surface roughness measurement and Circularity error measurement.

$$\frac{S}{N_{SB}} = -10log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

Where 'yi' represents the result of the ith experiment, 'i' is the experiment number, and 'n' indicates the total number of experiments. The optimal conditions were determined by analyzing the mean S/N ratios at each level.

Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA) is a method under Grey System Theory, developed to analyze systems with incomplete or uncertain information. It is used for multi-criteria decision-making in complex systems [19]. The key steps in GRA include normalizing data to make different factors comparable, calculating Grey Relational Coefficients (GRC) to measure the closeness of alternatives to an ideal reference, and determining the overall Grey Relational Grade (GRG) by averaging the GRCs. The alternative with the highest GRG is considered the best. GRA is especially useful for optimizing systems with limited data and is applied in fields like engineering, manufacturing, and decision-making. The procedure for GRA involves several steps, the first of which is the normalization of the measured responses. In GRA, two types of quality characteristics are typically used for normalization: the smaller-the-better and the larger-the-better. As the responses in this study need to be minimized, the smaller-the-better characteristic is applied.

The formula for the smaller-the-better normalization mode, applicable to surface roughness, cutting force, and temperature shown in equation 2:

$$y_i^*(k) = \frac{max\, x_i^o(k) - x_i^o(k)}{max\, x_i^o(k) - min\, x_i^o(k)} \tag{2}$$

$xi^0(k)$ represent the response obtained from the experiments. The value max $xi^0(k)$ refers to the maximum value among $xi^0(k)$, while min $xi^0(k)$ refers to the minimum value among $xi^0(k)$. The term 'i' refers to the experiment number, and the quality characteristic is denoted as 'k'.

The second step in Grey Relational Analysis (GRA) involves determining the grey relational coefficient, which is calculated by using equation 3.

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \tag{3}$$

Fuzzy Inference System

Fuzzy Logic, introduced by Lotfi Zadeh, addresses uncertainty in engineering problems [23]. It handles imprecise information by using qualitative terms like "low" and "medium" to generate linguistic rules [24]. Fuzzy logic is based on graded membership, mapping elements to values between 0 and 1, with the membership function tailored to specific problems [25]. Fuzzy Inference System (FIS) uses fuzzy set theory to create rules and convert data into readable outputs [26]. FIS operates as a decision-making unit in fuzzy logic systems, transforming crisp inputs into fuzzy data, applying rules, and then converting fuzzy results back into numerical outputs [27]. Fuzzification transforms precise input into fuzzy values by assessing uncertainties [23]. Membership values range from 0 to 1 [25], with functions like triangular, Gaussian, and trapezoidal being common [26]. This research uses the Gaussian function, defined by mean (μ) and standard deviation (σ). Fuzzy rules, expressed as "IF-THEN" statements, are key to converting fuzzy inputs into crisp outputs [25]. Antecedents describe conditions, while consequents define outputs if conditions are met. These rules form a decision matrix [28]. The inference engine processes inputs according to the established rules, serving as the central function of FIS. Defuzzification converts fuzzy outputs into numerical results [29]. Five main methods are used: Center of Gravity, Mean of Maximum, Bisector of Area, Largest of Maximum, and Smallest of Maximum [30]. There are two main fuzzy inference methods are Mamdani and Sugeno [31]. Mamdani's method, widely used, was developed for controlling a steam engine and requires defuzzification to produce a crisp output.

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RESULTS AND DISCUSSIONS

The values of surface roughness and circularity error are shown in Table 1. The surface roughness was observed to decrease with a decrease in drill diameter, as indicated by the steep decline in the S/N ratio when the diameter increased from 6 mm to 10 mm. A smaller drill diameter reduces the contact area during drilling, leading to smoother surfaces, whereas larger diameters increase the contact area, resulting in higher roughness. The surface roughness remained relatively constant across the spindle speed levels, as shown by the nearly flat trend in the S/N ratio for this factor in Figure 2. This suggests that spindle speed has a negligible effect on surface roughness within the tested range, indicating stability in the cutting process.

For the point angle, the surface roughness improved (i.e., the S/N ratio increased) as the point angle increased from 116° to 124°. This can be attributed to a larger point angle distributing the cutting forces over a wider area, reducing the intensity of thrust force and enabling a smoother cut. Smaller point angles likely concentrate forces, causing higher surface roughness. The S/N ratio graph suggests that the optimal factor settings for achieving minimal surface roughness are a drill diameter of 6 mm (Level 1), a spindle speed of any level (2000–3000 rpm, as it has minimal effect), and a point angle of 124° (Level 3). These settings are expected to produce the smoothest surface with minimal variability. The mean of S/N ratios of surface roughness is show in Figure 2.

Table 1. Response values for L9 orthogonal array.

	Drill Bit Diameter (mm)	Cutting Speed (rpm)	Point Angle (°)	Surface Roughness (µm)	Circularity Error, mm	S/N Ratio for Surface Roughness (dB)	S/N Ratio for Circularity Error (dB)
1	6	2000	116	1.214	0.0624	−1.69	−24.09
2	6	2500	120	1.114	0.0982	−0.94	−20.15
3	6	3000	124	1.041	0.2122	−0.35	−13.47
4	8	2000	120	1.514	0.0393	−3.60	−28.12
5	8	2500	124	1.615	0.1834	−4.17	−14.73
6	8	3000	116	1.694	0.0909	−4.58	−20.82
7	10	2000	124	1.632	0.0810	−4.25	−21.83
8	10	2500	116	1.714	0.1294	−4.69	−17.76
9	10	3000	120	1.790	0.0350	−5.06	−29.13

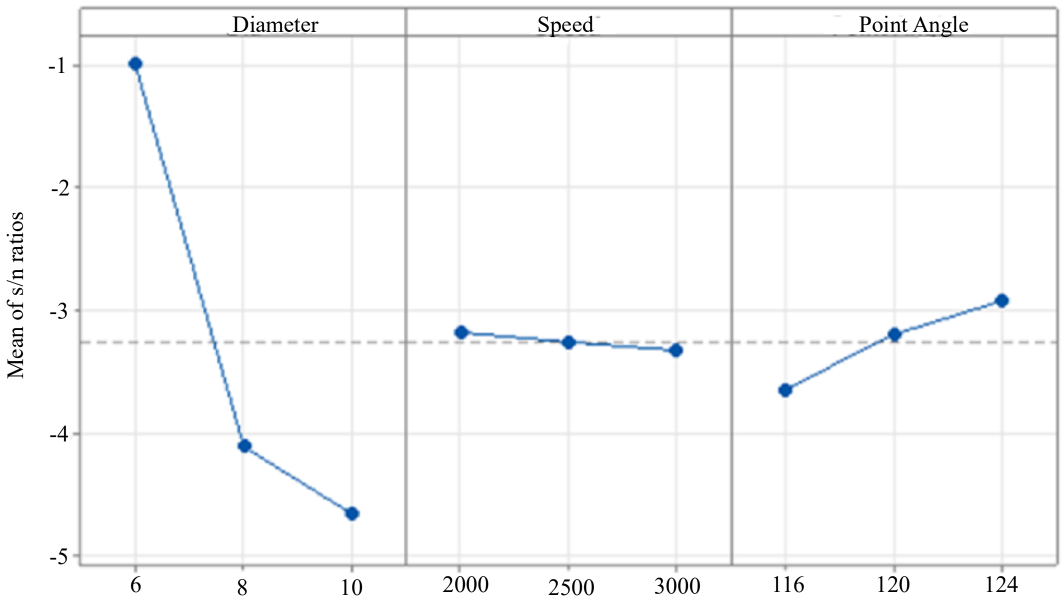

Figure 2. Mean of S/N ratios of surface roughness.

The diameter plot shows an upward trend from 6 to 10. As the diameter increases from 6 to 10, the S/N ratio improves, indicating that larger diameters result in lower circularity error (better hole quality). This is due to the reason that a larger diameter tool is generally stiffer and less prone to bending under load, leading to more accurate hole shapes, thus reducing circularity errors. A diameter of 10 provides the best circularity. A larger diameter, particularly around 10, minimizes circularity error and should be chosen for optimal hole accuracy.

The Speed plot shows a V-shaped curve with a peak at 2000 and 3000, and a significant dip at 2500.The lowest circularity error (highest S/N ratio) is observed at 2000 rpm and 3000 rpm, while the circularity error is significantly worse (lowest S/N ratio) at 2500 rpm. This indicates that 2500 rpm results in a high circularity error, while the lower and higher speeds provide better results. Speeds of 2000 rpm or 3000 rpm are preferable for minimizing circularity error, whereas 2500 rpm should be avoided.

The Point Angle plot shows a peak at 120° and a sharp drop at 116° and 124°. The point angle of 120° yields the lowest circularity error (highest SN ratio), while both 116° and 124° result in higher circularity error. The results indicate that 120° is the optimal point angle for improving circularity. A point angle of 120° should be selected for the best circularity, while 116° and 124 ° produce less favorable results. The mean of S/N ratios of circularity error is shown in Figure 3.

Optimization using Grey Relation Analysis Based on Entropy Weight

In the Grey Relational Analysis (GRA), the response variables are initially normalized using the "smaller-the-better" criterion, as outlined in equation (2). The Grey Relational Coefficient (GRC) values are then calculated using equation (3), and the Grey Relational Grade (GRG) is determined by assigning equal weight to each of the response variables considered in the study.

Table 2 presents the ranking based on the GRG values, with the parameter combination yielding the highest GRG being identified as the optimal condition among the 9 experiments. Experiment 1 is identified as having the best parameter combination, demonstrating superior multi-response characteristics compared to the other experiments.

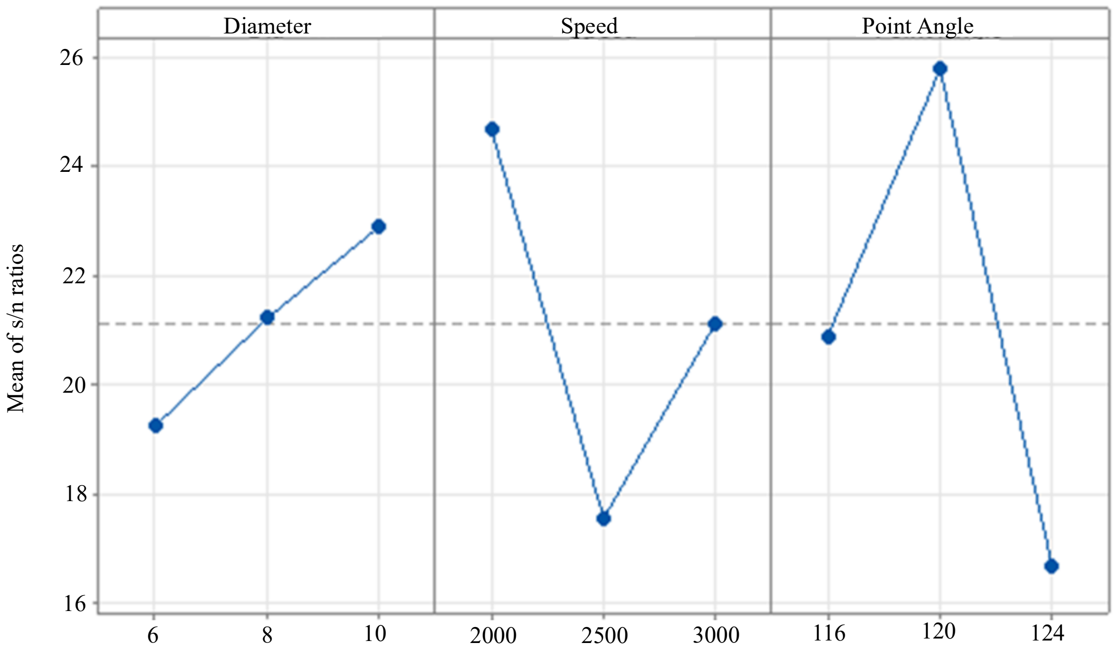

Figure 3. Mean of S/N ratios of circularity error.

The novelty of our work lies in the integrated optimization framework combining Taguchi Design of Experiments (DOE), Grey Relational Analysis (GRA), and a Fuzzy Inference System (FIS) for drilling of hybrid carbon-glass fiber reinforced (CGFR) epoxy composites. While previous studies have extensively examined either carbon or glass fiber composites independently, our study uniquely focuses on hybridization of carbon and glass fibers within a single matrix, investigating not only mechanical performance but also machining behavior, particularly surface roughness and circularity error during drilling.

In contrast to conventional optimization approaches which focus on single-response analysis, our method offers a multi-objective optimization strategy, enabling simultaneous minimization of both surface roughness and circularity error—two critical quality metrics in precision drilling of fiber composites. The incorporation of fuzzy logic further enhances decision-making by accounting for the inherent uncertainty and subjectivity in multi-response optimization.

Optimization using Fuzzy-Grey relation analysis

Fuzzy GRA provides a tool that can work in a better way with uncertain concepts using insufficient information as compared to conventional GRA. In fuzzy GRA, Surface Roughness (SR) and Circularity Error (CE) are used as input variables in the analysis and the output variable as fuzzy grey entropy grade. The crisp input values SR and CE are transformed into non-crisp fuzzy values from the linguistic terms using membership functions. These linguistic input variables are fed into the fuzzy engine. Linguistics terms can be used as interpreting models to determine membership functions. These fuzzified forms of SR and CE form the basis for obtaining Fuzzy Grey Entropy Grade. After obtaining degree of membership for input and output variables, fuzzy rules need to be designed using the qualitative statements. To design the rules, “if-then” type rules are generated using the linguistic classes of SR, CE and the corresponding FGED class. These fuzzy linguistic variables are the input to the defuzzification stage where the result is a crisp numerical value. This crisp value is known as fuzzy GED in fuzzy GRA.

There are many techniques of defuzzification among which centroid method is the most commonly used, where it returns the central point of the area under the fuzzy set, which is a crisp value. A fuzzy GED is thus obtained as the output of the fuzzy inference system which considers rule base approach. The overall procedure for performing Fuzzy GRA is shown in the Figure 4.

Execution Of Fuzzy GEG

The execution of fuzzy GRA is carried out using Fuzzy logic tool box of MATLAB where two input and one output variables are used. The Fuzzy Logic Toolbox in MATLAB provides two options of methods, Mamdani and Sugeno. In this research work, Mamdani method of inference is used with center of gravity (centroid) as defuzzification method. Figure 5 shows the FIS editor in MATLAB where the fuzzy GRA is performed. The execution was carried out by three stages namely fuzzification, establishing fuzzy rules and defuzzification which are explained in the consequent sections.

Table 2. Normalized and deviational values and grey relation coefficients.

Normalized values		Deviational Sequence		Grey Relational Coefficients		GRG	Rank
SR	CE	SR	CE	SR	CE		
0.7690	0.8454	0.2310	0.1546	0.6840	0.7638	0.7335	3
0.9025	0.6433	0.0975	0.3567	0.8369	0.5837	0.6799	4
1.0000	0.0000	0.0000	1.0000	1.0000	0.3333	0.5867	5
0.3685	0.9757	0.6315	0.0243	0.4419	0.9537	0.7592	1
0.2336	0.1625	0.7664	0.8375	0.3948	0.3738	0.3818	9
0.1282	0.6845	0.8718	0.3155	0.3645	0.6131	0.5187	7
0.2109	0.7404	0.7891	0.2596	0.3879	0.6582	0.5555	6
0.1015	0.4673	0.8985	0.5327	0.3575	0.4842	0.4360	8
0.0000	1.0000	1.0000	0.0000	0.3333	1.0000	0.7467	2

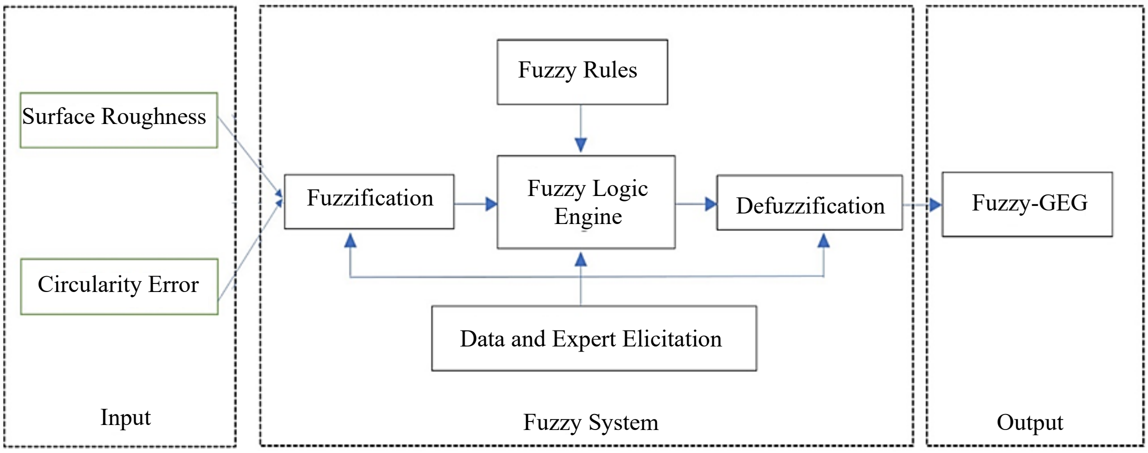

Figure 4. Fuzzy grey entropy grade procedure.

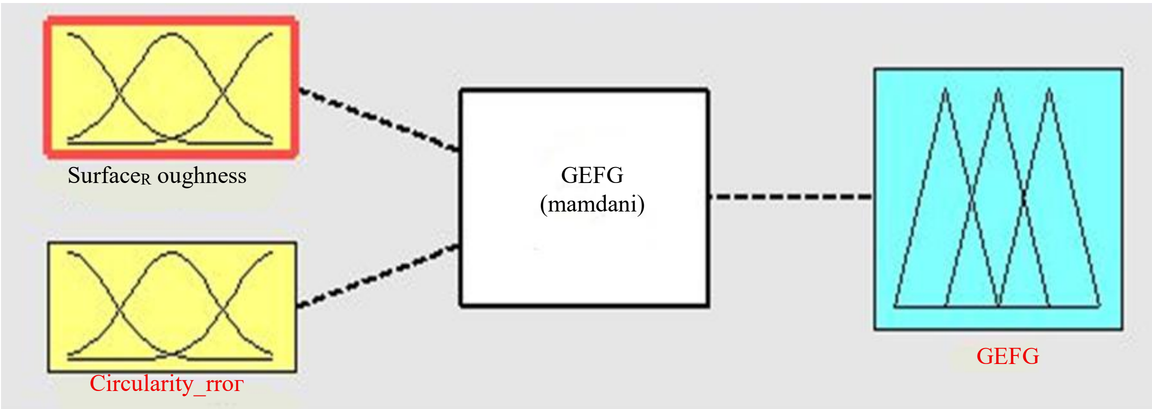

Figure 5. FIS editor in MATLAB.

Fuzzification

In Fuzzification, the crisp quantities are transformed into fuzzy, which can be represented by the membership function. The crisp knowledge SR and CE are represented as fuzzy model using qualitative terms and membership functions. Tables 3 summarize the classification criteria for SR and CE described in linguistic term. Each input variable is classified into ten levels which lead to the formation of 1000 fuzzy rule base combinations. The membership function that is applied in the present research work is triangular type member function due to the varying degree of input and output variables. Figures 6 (a), and 6 (b) depicts the fuzzy model representation of SR and CE membership functions respectively. This forms the basis for providing non-crisp input variable for fuzzy GRA.

Likewise, the degree of membership is also designed for the output variable (i.e. GEG) using triangular type, to convert grey value to fuzzy GEG. For this, the output GRG values are categorized into ten interval classes. Figure 6(c) shows the membership function for the output variable GEG, represented in the fuzzy form. This representation is employed to defuzzify the qualitative term into a numerical digit.

Establishing Fuzzy rules

Formulating the rules is the major part of FIS model. These rules are generally and more easily modelled in natural language using qualitative terms and are stated often using if-then type of rules. These rules are defined to establish the relation between the input and output membership function. Total100 *if then* rules (10 (SR) x 10 (CE)) were established in the present work for the analysis. These rules are designed to include all possible combinations of SR and CE. These established rules are mapped in the rule viewer tab of MATLAB as shown in Figure 7.

Table 3. Linguistic terms and crisp values.

Level	Fuzzy Number	Short Form
Lowest	(0.0, 0.0, 0.1)	(LST)
Very Low	(0.0, 0.1, 0.2)	(VL)
Low	(0.1, 0.2, 0.3)	(L)
Fairly Low	(0.2, 0.3, 0.4)	(FL)
Moderate	(0.3, 0.4, 0.5)	(M)
Fairly High	(0.4, 0.5, 0.6)	(FH)
High	(0.5, 0.6, 0.7)	(H)
Very High	(0.6, 0.7, 0.8)	(VH)
Extremely High	(0.7, 0.8, 0.9)	(EH)
Highest	(0.8, 0.9, 1.0)	(HST)

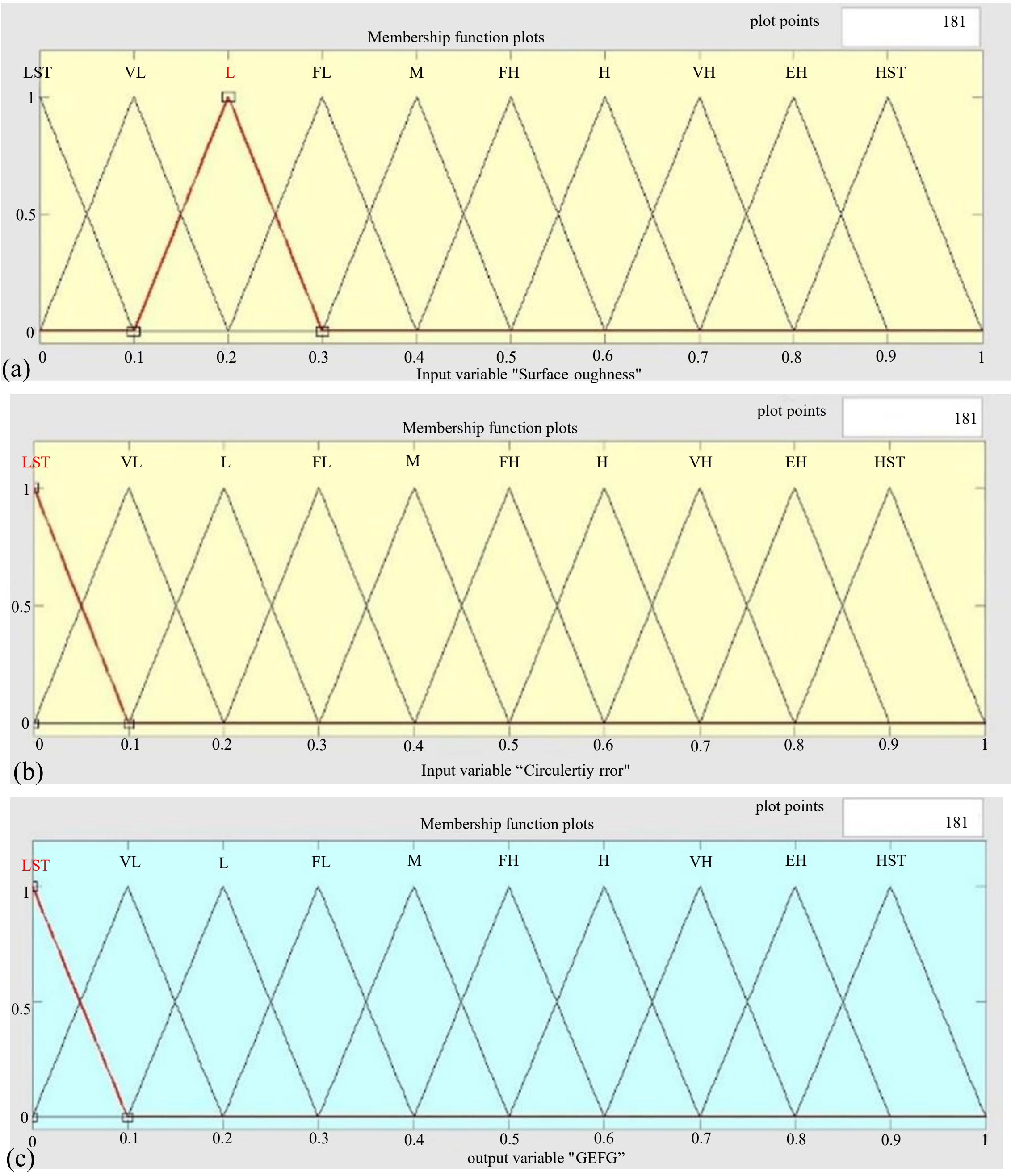

Figure 6. (a)&(b) Input membership function (c) output membership function.

Defuzzification

The knowledge base of FIS returns a qualitative output variable of GEG, which needs to be defuzzified to generate F-GEG in the form of crisp values. The fuzzy linguistic variable is fed as an input to the defuzzification interface module which then transforms the output in the form of crisp values, which denotes the fuzzy GEG. The crisp values of fuzzy GEG gives the prioritization level. Mamdani fuzzy inference model is used to convert the linguistic rules to a quantitative result. Moreover, centroid method is used as a defuzzification technique which returns the central point of the area under the fuzzy set, which is a crisp value. Figure 8 shows the rule viewer which provides the crisp value of GEG. The crisp values of fuzzy-GEG are shown in Table 4.

Table 4. Fuzzy grey entropy grade values.

Normalized values		Deviational Sequence		Grey Relational Coefficients		GRG	Fuzzy-GEG
SR	***CE***	***SR***	***CE***	***SR***	***CE***		
0.7690	0.8454	0.2310	0.1546	0.6840	0.7638	0.7335	0.1
0.9025	0.6433	0.0975	0.3567	0.8369	0.5837	0.6799	0.092
1.0000	0.0000	0.0000	1.0000	1.0000	0.3333	0.5867	0.5
0.3685	0.9757	0.6315	0.0243	0.4419	0.9537	0.7592	0.1
0.2336	0.1625	0.7664	0.8375	0.3948	0.3738	0.3818	0.369
0.1282	0.6845	0.8718	0.3155	0.3645	0.6131	0.5187	0.242
0.2109	0.7404	0.7891	0.2596	0.3879	0.6582	0.5555	0.226
0.1015	0.4673	0.8985	0.5327	0.3575	0.4842	0.4360	0.356
0.0000	1.0000	1.0000	0.0000	0.3333	1.0000	0.7467	0.5

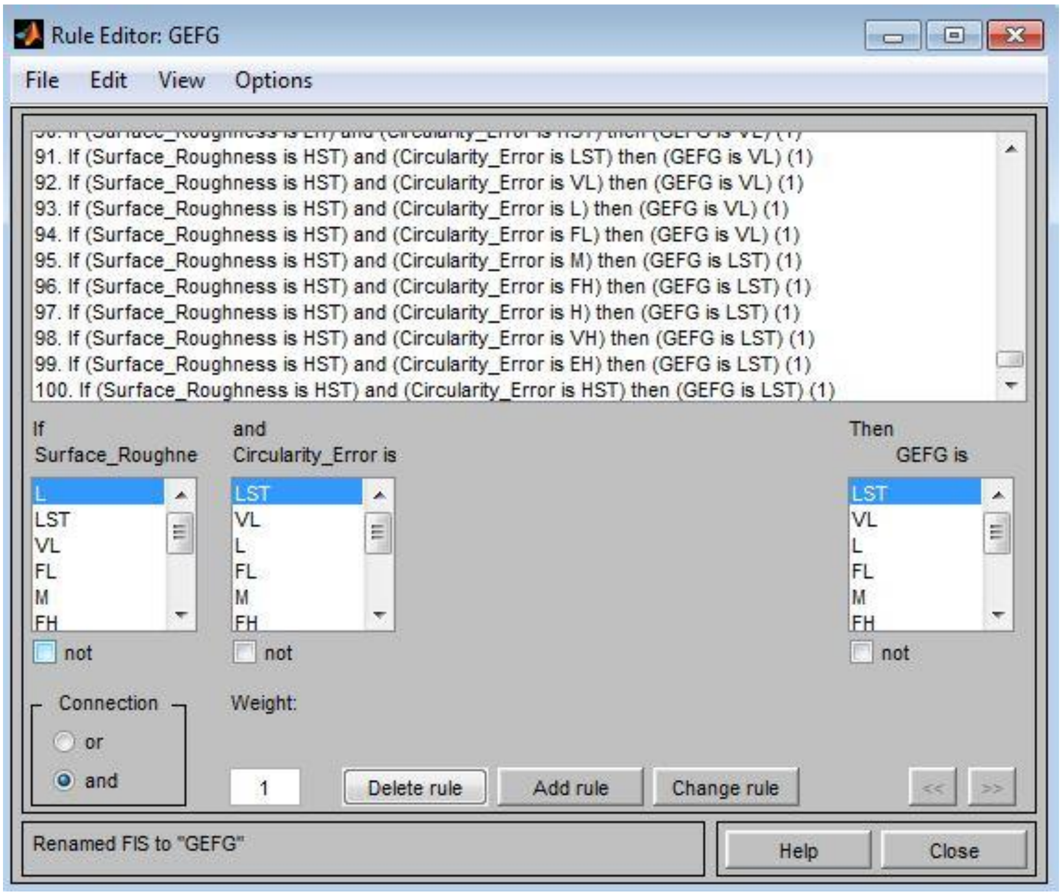

Figure 7. Rule editor.

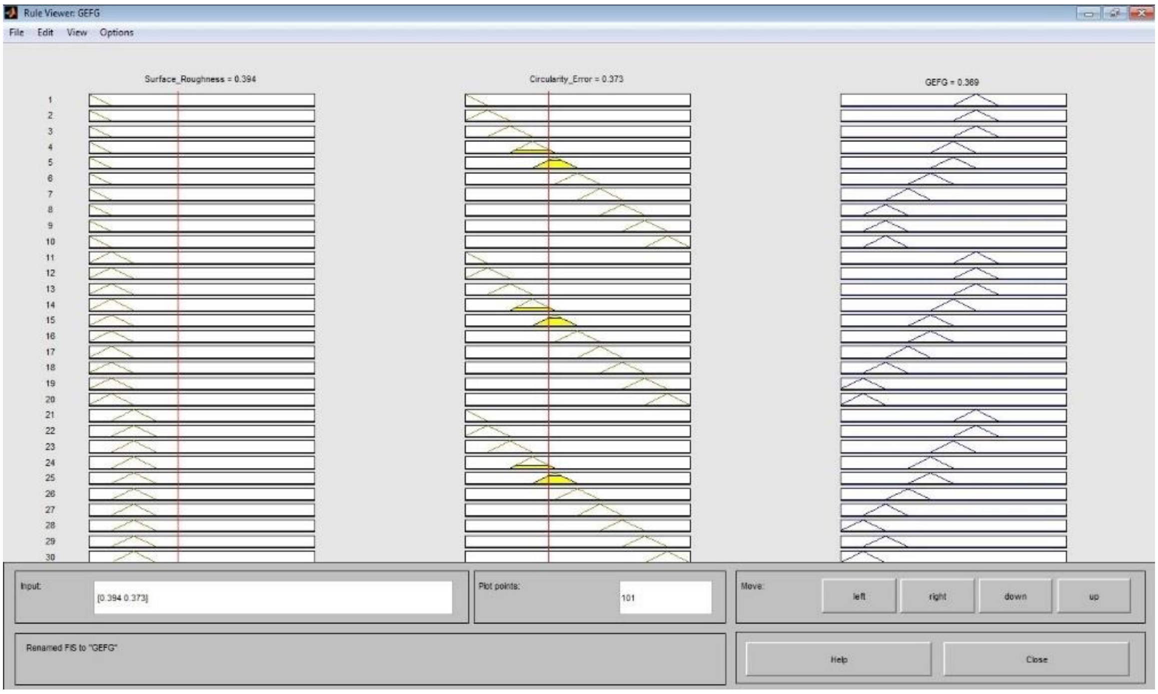

Figure 8. Defuzzification of crisp values.

CONCLUSION

This study examined the drilling performance of hybrid carbon-glass fiber reinforced epoxy (CGFR) composites using a comprehensive optimization methodology. The experimental trials, designed using the Taguchi L9 orthogonal array, explored the effects of drill diameter, spindle speed, and point angle on two critical machining responses: surface roughness (SR) and circularity error (CE). From the signal-to-noise (S/N) ratio analysis, it was observed that: Surface roughness decreased significantly with smaller drill diameters (6 mm) and larger point angles (124°), while spindle speed showed negligible influence. Circularity error was minimized with a larger drill diameter (10 mm), spindle speeds of 2000 or 3000 rpm, and a point angle of 120°.

To address the trade-offs in optimizing multiple performance characteristics, a multi-response optimization framework was developed using Grey Relational Analysis (GRA) integrated with a Fuzzy Inference System (FIS) and further enhanced with Fuzzy Grey Entropy Grade (Fuzzy-GEG) analysis.

Trials 1 and 4 recorded the lowest Fuzzy-GEG values (0.1), identifying them as the most favorable combinations for simultaneous reduction of surface roughness and circularity error. Trial 9 also ranked highly (Fuzzy-GEG = 0.5), indicating consistent performance across both response parameters. The incorporation of fuzzy grey entropy ranking adds an additional layer of decision accuracy, accounting for not only relational closeness but also the degree of information entropy between the responses. In contrast to conventional methods that focus on single-objective outcomes, this study introduces a hybrid fuzzy-grey-entropy framework that enhances the robustness of process parameter selection. The results corroborate certain established trends (e.g., higher point angles improving surface finish) while also offering new insights into composite machining trade-offs, such as the impact of drill stiffness on circularity accuracy.

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