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Assessment of Tribological Behaviour of Flax/Bagasse Composites Using GRA Based Statistical Studies

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Abstract: A combined Taguchi-grey Relational Analysis (GRA) has been used to improve the wear resistance of Flax, Bagasse and Epoxy F-B-E composites that have been treated with NaOH. The study investigates Dry sliding wear behaviour using Taguchi's L27 orthogonal array experimental design in compliance with ASTM G99 standards. Additionally, this study assesses the influence of independent variables such as usual load (2N,3N,4N), Sliding velocity (1m/s,2m/s,3m/s) and proportion of fibers (F75-B25, F50-B50, F25-B75) on the wear behaviour of epoxy resin reinforced with flax and bagasse powder composites, adopting a statistical methodology. Composite samples were made by hand layup technique using an epoxy resin mixed with flax fiber and bagasse powder. Dry sliding wear tests were done in a pin-on-disc setup, with adherence to Taguchi's experimental design L27. This means scheming the "Signal-to-noise" (S/N) ratio and performing analysis of variances (ANOVA) to identify the optimal factors to minimize the wear rate to 98.30%. A better wear resistance rating was obtained from a composite material created by epoxy reinforced with 25% flax and 75% bagasse. Regression analysis's multi-response rate was 98.57%. The results showed that A1 (Load), B1 (Sliding Velocity), and C3 (Fibre Content Percentage) produced the best outcomes for wear rate and co-efficient of friction. The observed composite specimens were the primary variable influencing the wear rate, with sliding velocity and normal load also being major factors. ANOVA on the grey relational grade (GRG) showed that sliding velocity was the most important factor affecting how well the F-B-E composites resist wear.

Keywords: Flax, Bagasse, Epoxy, NaOH, Wear Behaviour, Taguchi method, ANOVA, GRA

1. Introduction

The advancement of human culture to its current position has rendered composite materials essential in numerous aspects of our existence. Composites consist of two or more constituent materials that exhibit different forms, chemical compositions, and physical or chemical properties, which do not dissolve in each other. As a result, composites are being engineered as alternatives to conventional materials to improve mechanical properties, such as increased fracture toughness, high specific strength, resistance to cold, moisture, and heat, and ease of production. [1-4] Wear study and characterisation is a fundamental aspect of tribology that involves the examination of how materials and their constituents deteriorate under different loads and environmental conditions [5]. In many tribological applications, the consideration of minimizing size is taken into account within the goal of minimizing wear rates and achieving nominal material loss. The various physical and chemical forms of physical surface modification, which are more effective than others, as they can produce a modified pinion interface which strengthens the interaction of the fibres in the composite materials and the matrix. Gang D, et al. describe recognized chemical alteration procedures alkali, silane, acid, and peroxide treatments that can enhance the interfacial interactions between the fiber and matrix by creating an additional strengthening effect. It is essential to identify the tribological properties of the natural fibre composites before use in a tribological application [6]. The experimental study conducted by Liu Y, Xie J, Wu N et al demonstrated the mechanical and tribological properties of the corn stalk composite were greatly improved with the silane treatment of the fibres to improve the fibre-matrix bonding [7]. Rajesh Kumar G et al concluded that treating Phoenix sp. fibre with a 15% NaOH solution has enhanced the shape and wear resistance of the fibre and its composites [8].

This work highlights of tribological behaviour of F-B-E composites with NaOH treatment under different weight percentages and loading conditions. A novel effort has been undertaken to ascertain the wear behaviour of F-B-E composites by statistical methodologies. The research makes a way for the young researchers to develop sustainable projects in manufacturing automotive sector. The section 2 describes the material preparation while the section three 3 furnish about Taguchi methodology while a section four focusses on results and discussion followed by derived conclusions.

2. Materials Preparation

2.1 Preparation of Fibers

The preparation of materials is Flax serves as a matrix material, while bagasse acts as a reinforcement; the addition of epoxy functions as a hardening agent, resulting in a liquid with increased viscosity. This experiment utilised the hand layup method to fabricate the flax bagasse fiber-reinforced composite. The composite laminates were manufactured and cured. The cured laminates were cut to create wear test specimens following ASTM G99 criteria [9]. Table 1 delineates the parameters of the fabricated composite specimens.

Table 1. Composite Characteristics

S.no	Specimens	Composite
1	A	Flax75/Bagasse25
2	B	Flax50/Bagasse50
3	C	Flax25/Bagasse75

2.2 Preparation of Composites

Flax served as the matrix material, and bagasse and epoxy hardener served as reinforcement in the preparation of the wear test specimens. Flax-bagasse fibers treated with NaOH were stacked using a simple hand layup technique. The fiber layers were then evenly covered with a pre-mixed epoxy and hardener mixture. Applying weights to the layup allowed for efficient resin penetration and consolidation. To optimize mechanical qualities, the laminates were post-cured after a 24-hour initial curing period at room temperature. Composite sheets were carefully removed once they had fully dried, and examples were then cut to the proper sizes for wear tests.

2.3 Test Setup and Wear Runs

The wear properties of the specimens were analysed via a pin-on-disc wear testing device, in compliance with the ASTM G99 standard. The experiments were conducted using weights of 2N, 3N, and 4N. Figure 1(a) illustrates the DUCOM TR20LE pin-on-disc testing apparatus. The specimens consisted of round cylindrical pieces adhered with glue to a 30-mm-long composite specimen pin. This preserved the contact surface in alignment with the plane of the laminate, as illustrated in Figure. 1(b). This study aimed to assess how engineered composite materials wear under different conditions, such as sliding speeds of 1 m/s, 2 m/s, and 3 m/s; weights of 2 N, 3 N, and 4 N; and different material mixes. The fibre composition was modified across three formulations: Flax 75% - Bagasse 25%, Flax 50% - Bagasse 50%, and Flax 25% - Bagasse 75%. The experiment aimed to determine the influence of these characteristics on Dry sliding wear rate and co-efficient of friction (COF).

2.4 Plan of Experiments

This research employed an L27 orthogonal array to systematically analyze the impact of these three variables, conducting 27 tests with three variables at three levels each.

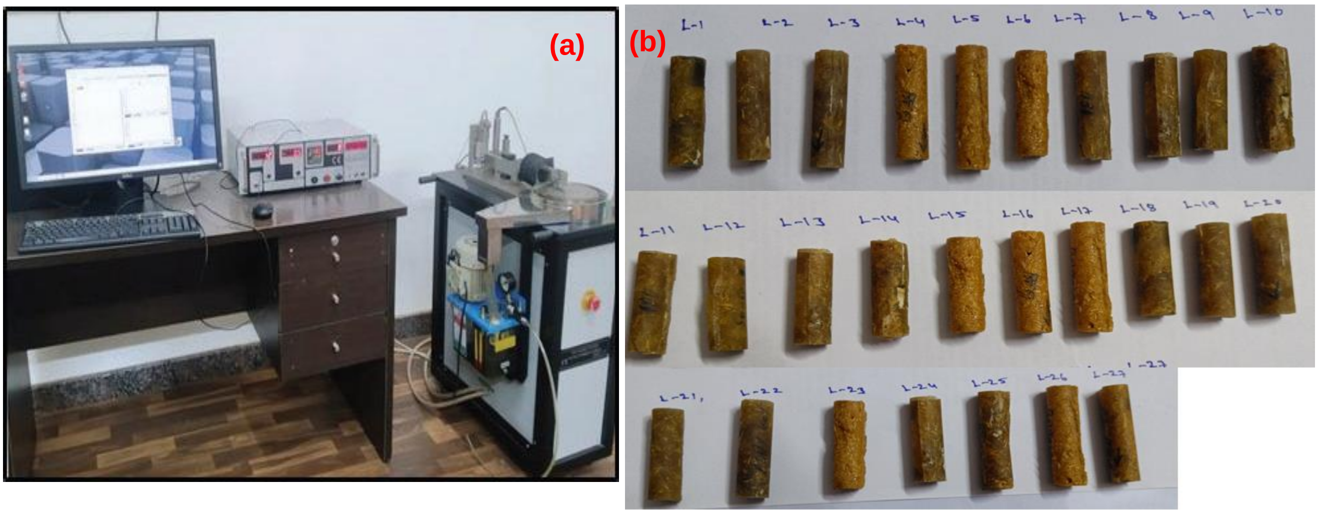

Figure1 (a) Wear Experimental Setup, **(b)** Wear Specimens

The impact of material type, applied stress, and sliding velocity on wear rate and coefficient of friction was investigated by quantitative approaches, including Taguchi optimisation and ANOVA analysis. The "Smaller is better" methodology was employed to determine the optimal parameters for minimising wear rates and friction.

An orthogonal array was formed following the identification of control parameters, their levels, and responses, as illustrated in Table 2. Three factors are being assessed at three distinct levels. This study performed a Taguchi experiment employing an L27 orthogonal array, including 27 trials, 3 factors, and 3 levels [10].

Table 2. Control factors and their levels

Control Factors	Level 1	Level 2	Level 3
Load N (A)	2	3	4
Sliding Velocity m/s (B)	1	2	3
Fiber Percentages % (C)	Flax 75% Bagasse 25%	Flax 50% Bagasse 50%	Flax 25% Bagasse 75%

Table 3. Standard Orthogonal Array L27 (33) of Taguchi for Wear

Runs	Control Factors		
	Load, N	Sliding Velocity m/s	Fiber Content wt.%
1	2	1	25
2	2	1	50
3	2	1	75
4	2	2	25
5	2	2	50
6	2	2	75
7	2	3	25
8	2	3	50
9	2	3	75
10	3	1	25
11	3	1	50
12	3	1	75
13	3	2	25
14	3	2	50
15	3	2	75
16	3	3	25
17	3	3	50
18	3	3	75
19	4	1	25
20	4	1	50
21	4	1	75
22	4	2	25
23	4	2	50
24	4	2	75
25	4	3	25
26	4	3	50
27	4	3	75

The tests conformed to the typical orthogonal array. The orthogonal array was selected based on the criterion that its degrees of freedom must be more than or equal to the sum of the wear parameters. This study employed an L27 orthogonal array comprising 27 rows and three columns, as depicted in Table 3.

2.5 Taguchi Technique

The Taguchi technique is an effective methodology for creating high-quality systems through a systematic approach to data collection, analysis, and interpretation to achieve study objectives [11-13]. These strategies facilitate a methodical approach to experimental design, enabling the integration of the most pertinent information while minimising experimentation. Taguchi parameter design identifies the important performance characteristics to eliminate design factors that are expected to have negative effects from unknown sources of variation. [13-14]. In contrast to conventional experimental design or parameter design, Taguchi's methods allow for the least number of trials while studying selected combinations of variables. Furthermore, the Taguchi method can efficiently create controlled data while eliminating the need to analyze the complicated and often unknown functions of the process variables. An essential and frequently problematic element of experimental planning is identifying the relevant elements. To this problem, Taguchi came up with standard orthogonal arrays whereby the experimenter can determine several factors on an ultimate desired product or outcome and organize the experimental plan systematically.

Analysing the experimental data using analysis of variance and means allows one to investigate the influence of factors.

The Signal-to-Noise (S/N) ratio formula used in wear behaviors studies, particularly within the context of Taguchi experiments, is:

$$S/N = -10 * log10((1/n) * \Sigma(yi\text{^}2)) \qquad (1)$$

3. Results and Discussions

The experiments aimed to establish the correlation between sliding speed (S), applied load (L), and displacement distance (D) in relation to the dry sliding wear of the two composites under investigation. The outcomes of dry sliding wear for each distinct combination of parameters were gathered from experiments utilising the orthogonal array method and are displayed in Table 4.

3.1 Taguchi Analsis of Dry Sliding Wear Parameters

Minitab 18 software was utilised for the statistical analysis of the experimental results. Table 4 displays the experimental results for wear, frictional force, and their corresponding S/N ratios [15].

Figure. 2 presents a graph depicting the influence of load (N), sliding velocity (m/s), and fibre content (wt%) on system performance, measured by signal-to-noise ratios, with the target of minimising the response ("smaller is better").

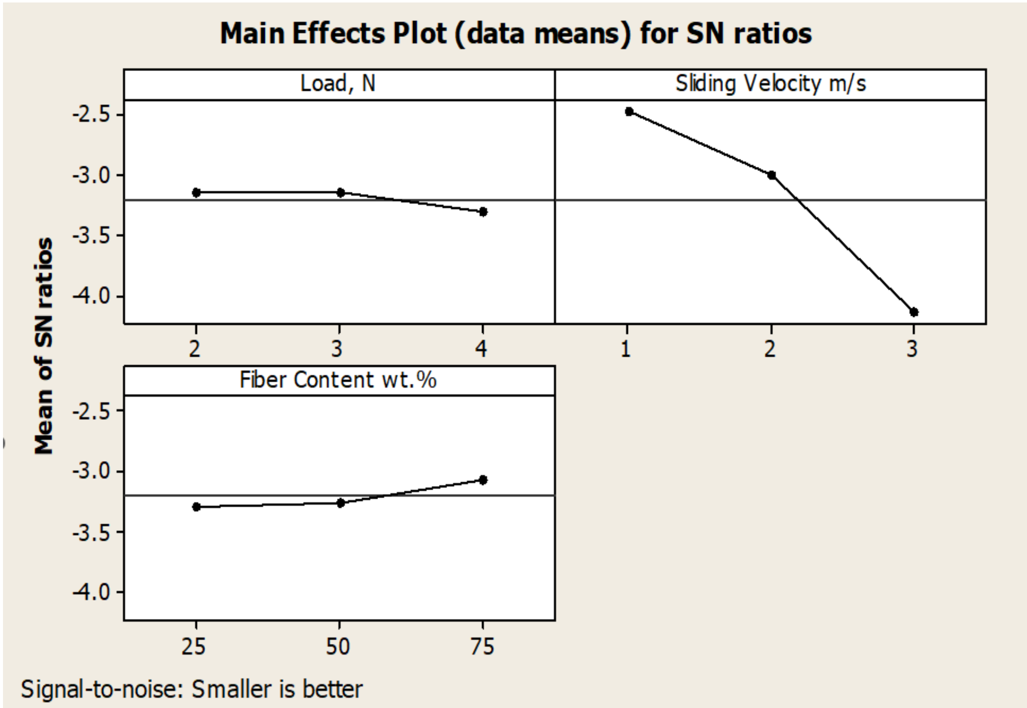

Figure 2. Wear rate Main effects Plot for S/N Ratio

Table 4. Experimental Design for sliding wear using L-27 OAs along with its output response characteristics

Runs	Control Factors			Response Variables		S/N Ratio	
	Load, N	Sliding Velocity m/s	Fiber Content wt.%	Specific wear rate × 10^{-13} mm3 /N-m	Co-Efficient of Friction	Specific wear rate × 10^{-13} mm3 /N-m	Co-Efficient of Friction
1	2	1	25	1.326	0.332	-2.45	9.577
2	2	1	50	1.311	0.317	-2.349	9.987
3	2	1	75	1.307	0.293	-2.327	10.654
4	2	2	25	1.428	0.433	-3.094	7.264
5	2	2	50	1.405	0.413	-2.955	7.675
6	2	2	75	1.387	0.393	-2.844	8.106
7	2	3	25	1.616	0.623	-4.169	4.114
8	2	3	50	1.609	0.615	-4.129	4.227
9	2	3	75	1.594	0.6	-4.049	4.437
10	3	1	25	1.336	0.343	-2.519	9.307
11	3	1	50	1.313	0.31	-2.362	10.173
12	3	1	75	1.272	0.3	-2.091	10.458
13	3	2	25	1.427	0.43	-3.09	7.331
14	3	2	50	1.405	0.415	-2.955	7.639
15	3	2	75	1.386	0.4	-2.836	7.959
16	3	3	25	1.642	0.655	-4.305	3.675
17	3	3	50	1.602	0.643	-4.095	3.843
18	3	3	75	1.603	0.61	-4.099	4.293
19	4	1	25	1.373	0.38	-2.753	8.404
20	4	1	50	1.373	0.368	-2.75	8.683
21	4	1	75	1.358	0.36	-2.658	8.874
22	4	2	25	1.403	0.448	-2.94	6.974
23	4	2	50	1.476	0.44	-3.383	7.131
24	4	2	75	1.403	0.436	-2.938	7.21
25	4	3	25	1.643	0.649	-4.311	3.758
26	4	3	50	1.642	0.648	-4.307	3.768
27	4	3	75	1.542	0.636	-3.763	3.931

Table 5. Mean S/N Ratios for Wear rate

Level	Load, N	Sliding Velocity (m/s)	Fiber Content (wt. %)
1	-3.152	-2.474	-3.293
2	-3.15	-3.003	-3.255
3	-3.312	-4.137	-3.067
Delta	0.163	1.663	0.226
Rank	3	1	2

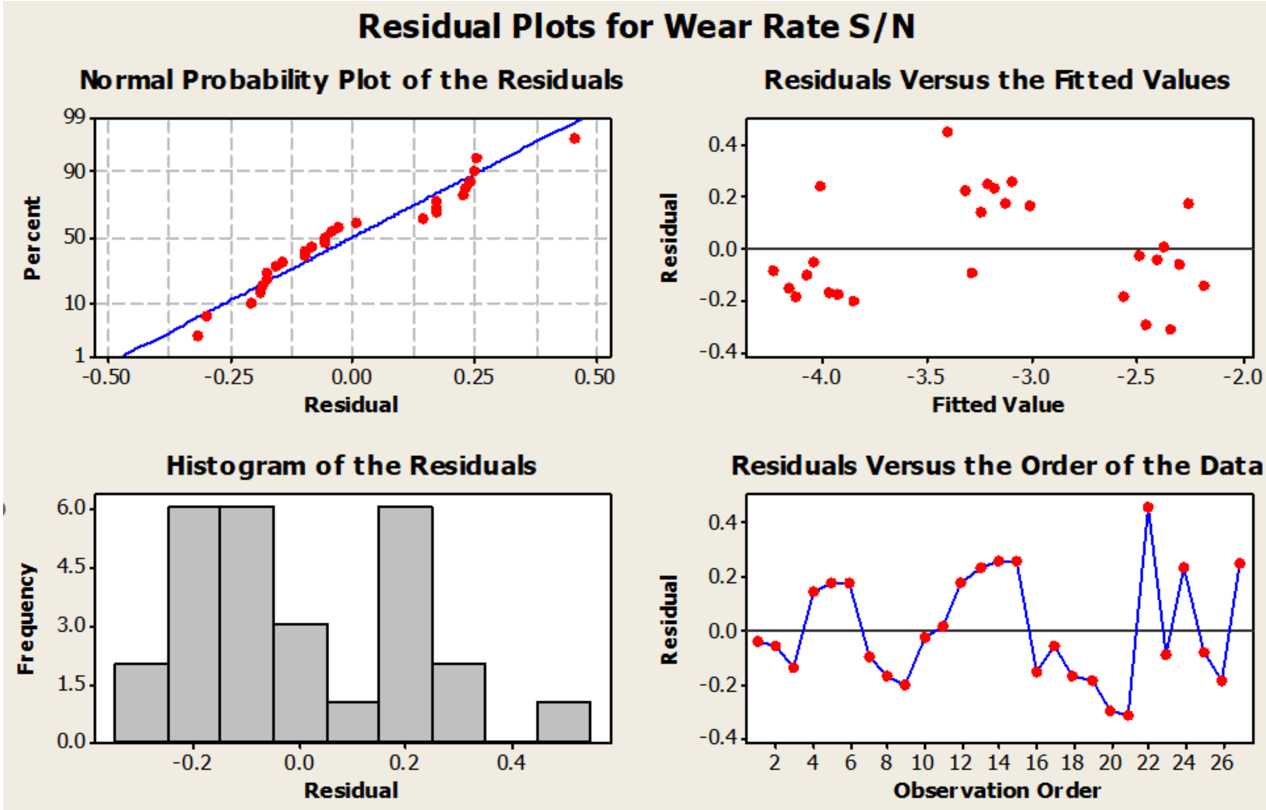

Figure 3. Residual Plots for Wear rate S/N

The load graph demonstrates a minor decline in the average signal-to-noise ratio as the load escalates from 2 N to 4 N, suggesting a negligible adverse impact [16]. The load plot demonstrates a marginal decrease in the mean S/N ratio as the load escalates from 2N to 4N, suggesting a modest adverse effect. Conversely, sliding velocity exerts a more pronounced influence; the S/N ratio declines markedly with elevated velocity, underscoring that increased sliding speeds substantially impair performance. On the other hand, fiber content shows a slight upward trend, indicating improved performance at higher fiber levels, particularly between 50% and 75%. Of the three parameters, sliding velocity is the most significant, but increased fiber content seems advantageous. So, to improve performance, we need to use lower sliding velocities and more fiber content, while the load has very little effect.

The Table 5 displays the mean S/N ratios for three components across various levels. Reduced S/N levels signify inferior performance. The S/N ratio for sliding velocity decreases markedly from level 1 to level 3, exhibiting the greatest delta of 1.663, so establishing it as the most relevant factor (Rank 1). The fiber content exhibits substantial variability (delta = 0.226), ranking second in significance. The load has the least influence, showing negligible change (delta = 0.163), and ranks third. The findings indicate that reducing sliding velocity significantly enhances performance, followed by an increase in fiber content, but load exerts a relatively minor influence.

The regression equation for Wear Rate = - 1.53 - 0.0802 Load, N - 0.831 Sliding Velocity m/s + 0.00452 Fiber Content wt. %

$$S = 0.214483 \quad R-Sq = 92.4\% \quad R-Sq\ (adj) = 91.4\% \tag{2}$$

Figure. 3 shows the leftover plots for the wear rate signal-to-noise ratio analysis, which is used to check if the regression model is good enough. The normal probability plot indicates that the residuals approximate a normal distribution, as the points closely align with the straight line. The residuals shown against the fitted values are spread out randomly without any clear patterns, which suggests that the variance is stable and the model fits well. The histogram of the residuals displays a nearly symmetric distribution centred at zero, thereby supporting the assumption of normality. The plot of residuals against the order of data shows oscillation without a clear trend or systematic pattern, suggesting that the residuals are independent and not influenced by the sequence of data collection. The analysis of the residuals shows that the model meets the assumptions of normality, independence, and homoscedasticity, which means the regression model is appropriate and reliable for studying the wear rate S/N ratio.

3.1.1 Analysis of Variance for Wear rate

Analysis of Variance (ANOVA) is a statistical method used to determine if significant differences exist among the means of multiple groups. In wear rate analysis, ANOVA assesses the influence of factors including material type, load, speed, and lubrication on wear performance.

S = 0.147813 R-Sq = 96.84% R-Sq(adj) = 95.90%

Seq SS: sequential sum of squares; DF: degrees of freedom.

Adj MS: adjusted mean squares: Adj SS: adjusted sum of squares.

Table 6 of the ANOVA illustrates the statistical significance and impact of each factor affecting the wear rate (S/N ratio). Sliding velocity (m/s) is the primary factor, demonstrating the highest F-value (297.300) and a negligible p-value (0.000), indicating a significant influence on wear behaviour. It accounts for 93.8% of the overall variation. The fiber content (wt. %) is the subsequent influential element, exhibiting a significant p-value (0.009) and a contribution of 1.9%. Load (N) exerts a minor but statistically significant effect (p = 0.047), accounting for merely 1.1% of the variance. The error constitutes a minor fraction of the overall variation, suggesting the model is appropriately fitted [17]. In summary, sliding velocity has the greatest impact on the wear rate, followed by fibre content and load. The low p-values confirm that all components are statistically significant at a 95% confidence level, justifying their inclusion in the model.

3.2 Co-efficient Friction

The coefficient of friction (COF) is crucial in wear behaviour, influencing material degradation. A high COF increases frictional heat and wear, while a low COF reduces surface damage. Factors like load, speed, lubrication, and material properties affect COF. Optimizing COF helps enhance durability and efficiency in mechanical applications [18].

Figure 4 illustrates a main effects figure for signal-to-noise (S/N) ratios employed to assess the influence of three input factors: load (N), sliding velocity (m/s), and fibre content (wt%) on wear performance. The analysis employs the "Smaller is Better" criterion, signifying that a diminished wear rate is advantageous, which corresponds with an increased S/N ratio.

Table 6. Analysis of variance for wear rate

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% of Contribution
Load, N	2	0.156	0.156	0.078	3.580	0.047	0.011
Sliding Velocity (m/s)	2	12.991	12.991	6.496	297.300	0.000	0.938
Fiber Content (wt.%)	2	0.263	0.263	0.132	6.020	0.009	0.019
Error	20	0.437	0.437	0.022			
Total	26	13.848					

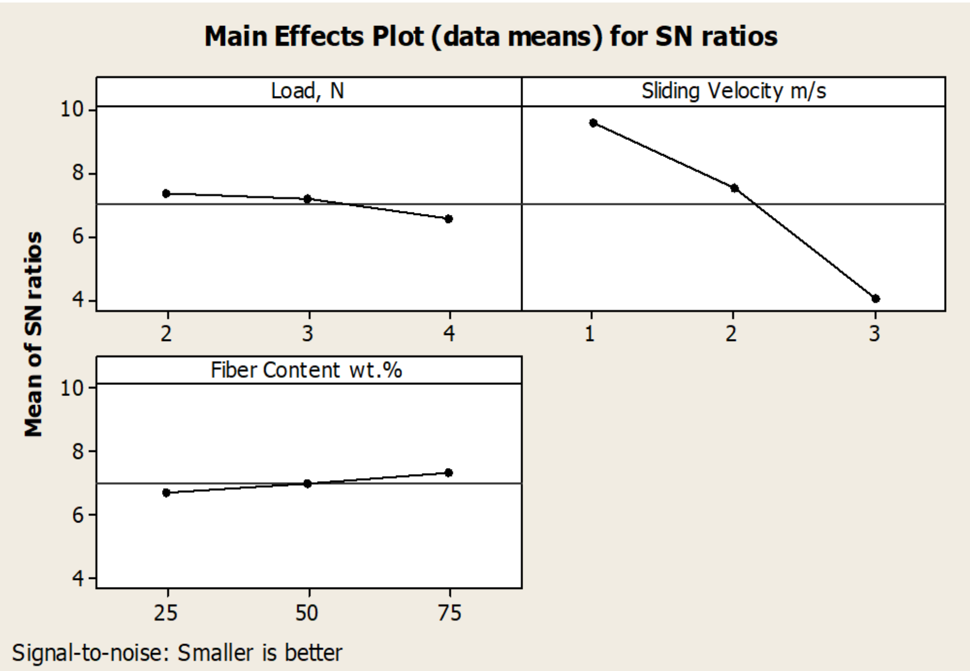

Figure 4. COF Main effects plot for S/N Ratio

Table 7. Response Table for Coefficient of Friction

Level	Load (N)	Velocity (m/s)	Fiber Content (wt. %)
1	7.339	9.567	6.71
2	7.184	7.479	7.012
3	6.526	4.003	7.326
Delta	0.813	5.564	0.616
Rank	2	1	3

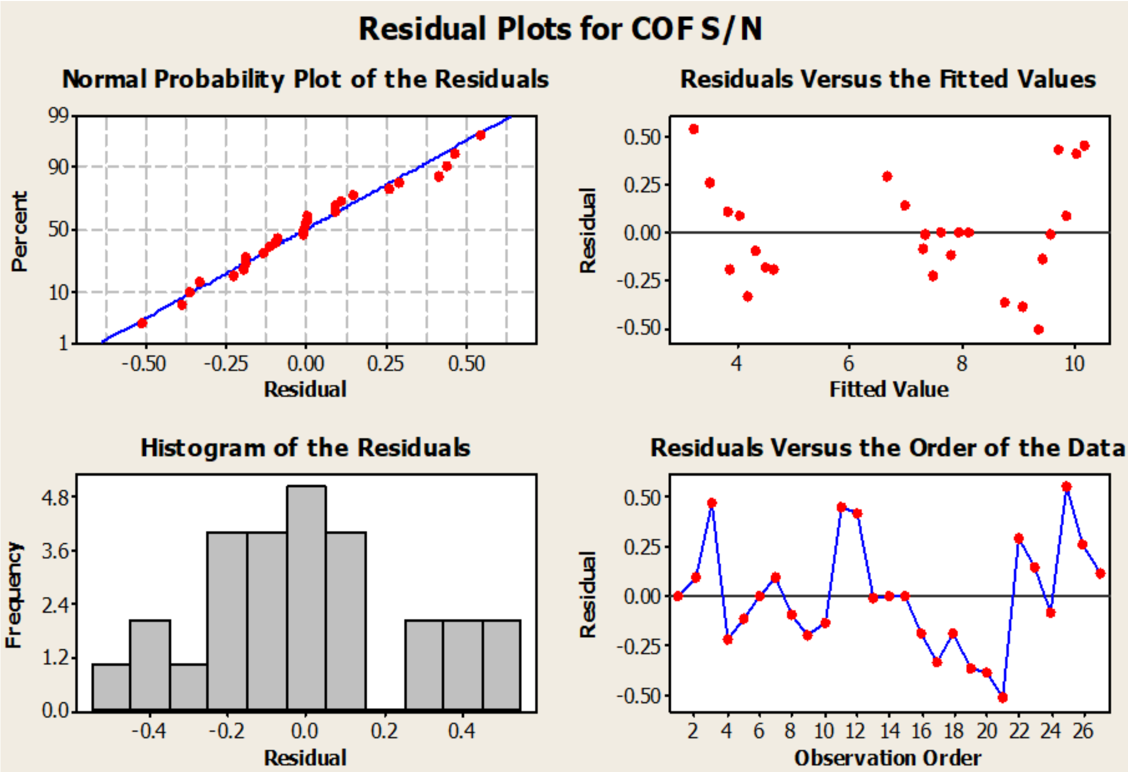

Figure 5. Residual Plots for COF S/N

The data clearly indicates that sliding velocity has the most substantial impact on the wear rate. As the velocity increases from 1 to 3 m/s, the signal-to-noise ratio significantly decreases, suggesting a rapid increase in wear. Therefore, decreasing slide velocity is crucial for minimising material wear.

The load parameter exhibits a marginal decline in the S/N ratio as load levels increase. This trend indicates that increased loads result in slightly greater wear, albeit the impact is not as significant as that of sliding velocity.

Ultimately, fiber content exhibits a modest yet continuous enhancement in the signal-to-noise ratio as fiber percentages increase. This evidence indicates that increased fiber reinforcing contributes to improved wear resistance.

The Table 7 presents data for three distinct levels of sliding fiber testing. It encompasses the applied stress (in Newtons), sliding fiber velocity (in meters per second), and fiber content (in weight percentage). Level 1 exhibits the maximum load and velocity, while Level 3 contains the highest fiber content. The Delta row denotes the variation in results between Level 1 and Level 3, highlighting the most significant disparity in fiber velocity (5.564 m/s). The Rank row indicates the performance ranking according to these criteria, with Level 2 achieving the greatest rank for fiber velocity and Level 3 for fiber content.

The regression equation of Co-efficient of friction= 13.2 - 0.407 Load, N - 2.78 Sliding Velocity m/s + 0.0123 Fiber Content wt.%

$$S = 0.476332 \text{ R-Sq} = 96.5\% \text{ R-Sq(adj)} = 96.0\% \qquad (3)$$

The Figure 5 presents the residual plots for the coefficient of friction signal-to-noise ratio, providing a comprehensive assessment of the regression model's appropriateness. The normal probability map (top-left) indicates that the residuals adhere to a normal distribution, as the points closely align with the straight line. The Residuals vs. Fitted Values Plot (top right) displays a random distribution, signifying consistent variance and the lack of identifiable patterns, hence confirming model validity. The residual histogram (bottom left) exhibits near-symmetry around zero, upholding the normality assumption. The Residuals vs. Observation Order Plot (bottom-right) graphically illustrates randomness of residuals vs. time and implies no autocorrelation. These plots together affirm that the regression assumptions are well met: the residuals are normally distributed, exhibit constant variance, and demonstrate no autocorrelation. This evidence confirms the dependability of the fitted model in predicting the coefficient of friction S/N ratio under the experimental conditions.

3.2.1 Analysis of Variance for COF S/N

Table 8 presents an ANOVA analysis examining the influence of three process parameters load (N), sliding velocity (m/s), and fibre content (wt %) on a measured response using the "smaller is better" signal-to-noise ratio approach.

S = 0.312480 R-Sq = 98.69% R-Sq(adj) = 98.30%

The Load (N) exhibits a Sequential Sum of Squares (Seq SS) of 3.357, an F-value of 17.19, and a p-value of 0, demonstrating statistical significance. Nonetheless, its percentage contribution to the total variation is merely 2.2%, indicating that while it exerts a measurable effect, it is not the primary factor [23].

This study finds sliding velocity (m/s) as the essential component. The Seq SS is 142.196, with a substantial F-value of 728.14 and a p-value of 0, signifying that this factor explains 95.3% of the entire variability. This evidence indicates that alterations in sliding velocity substantially affect the response variable.

The fibre content (wt.%) exhibits statistical significance (p = 0.002) with an F-value of 8.75, accounting for 1.1% of the overall variation. While its impact is less pronounced than that of sliding velocity, it remains a crucial aspect. The error term, indicative of the unexplained variability, has a total of squares amounting to 1.953. In summary, sliding velocity is the foremost factor, followed by load and fibre content in evaluating performance based on the "smaller is better" criterion.

3.3 Multi Response

The wear behaviour is influenced by several factors, such as load, sliding velocity, material composition, and lubrication conditions. A lower wear rate and coefficient of friction are generally preferred, as they indicate enhanced tribological performance [19]. A multi-response methodology of wear behaviour analysis is necessary for overall comprehension that goes beyond minimization of material loss. Reducing wear rates can unintentionally increase friction, generate excessive heat, or roughen surfaces, leading to system failure. By considering multiple variables such as wear rate, friction coefficient, surface finish, and temperature as a whole, multi-response optimization determines balanced operating parameters. This leads to more efficient solutions for tribological systems.

Sliding velocity is frequently the paramount factor influencing wear, as elevated speeds produce greater heat and exacerbate material degradation. Load significantly influences wear, as high force hastens deterioration via plastic deformation and material loss. Additionally, the fiber content in composite materials can enhance wear resistance by fortifying the matrix structure.

Residual and main effects figs assist in assessing the impact of each parameter. If residuals exhibit a normal distribution without trends, the model is deemed valid for prediction. Table 9 shown the multi-response analysis looks at all of these things at the same time to improve wear performance. The process involves analysing multiple output variables, including wear rate, coefficient of friction (COF), and surface roughness.

Table 9 Experimental design for sliding wear using L-27 OAs along with its output response characteristics for Multi responses.

Figure 6 presents the primary effects plot for signal-to-noise ratios, utilising the "smaller is better" criterion, which is suitable for evaluating wear rate.

Table 8. Analysis of variance for Co-efficient of Friction

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% of Contribution
Load, N	2	3.357	3.357	1.679	17.19	0	0.022
Sliding Velocity (m/s)	2	142.196	142.196	71.098	728.14	0	0.953
Fiber Content (wt.%)	2	1.708	1.708	0.854	8.75	0.002	0.011
Error	20	1.953	1.953	0.098			
Total	26	149.215					

Table 9. Experimental Design for sliding wear using L-27 OAs along with its output response characteristics

Runs	Control Factors			Response Variables		Multi Response value
	Load, N	Sliding Velocity m/s	Fiber Content wt.%	Specific wear rate × 10^{-13} mm3 /N-m	Co-Efficient of Friction	
1	2	1	25	1.326	0.332	1.658
2	2	1	50	1.311	0.317	1.627
3	2	1	75	1.307	0.293	1.601
4	2	2	25	1.428	0.433	1.861
5	2	2	50	1.405	0.413	1.819
6	2	2	75	1.387	0.393	1.781
7	2	3	25	1.616	0.623	2.239
8	2	3	50	1.609	0.615	2.223
9	2	3	75	1.594	0.600	2.194
10	3	1	25	1.336	0.343	1.679
11	3	1	50	1.313	0.310	1.623
12	3	1	75	1.272	0.300	1.572
13	3	2	25	1.427	0.430	1.857
14	3	2	50	1.405	0.415	1.820
15	3	2	75	1.386	0.400	1.786
16	3	3	25	1.642	0.655	2.297
17	3	3	50	1.602	0.643	2.245
18	3	3	75	1.603	0.610	2.213
19	4	1	25	1.373	0.380	1.753
20	4	1	50	1.373	0.368	1.741
21	4	1	75	1.358	0.360	1.718
22	4	2	25	1.403	0.448	1.851
23	4	2	50	1.476	0.440	1.916
24	4	2	75	1.403	0.436	1.839
25	4	3	25	1.643	0.649	2.292
26	4	3	50	1.642	0.648	2.290
27	4	3	75	1.542	0.636	2.178

The small graphs illustrate the variations in the average signal-to-noise (S/N) ratio as influenced by several factors: load (N), sliding velocity (m/s), and fibre composition (wt. %).

The load Figure 6 demonstrates a modest reduction in the S/N ratio from level 2 to 4 N, suggesting a marginal increase in wear with elevated load. The sliding velocity graph indicates a pronounced decrease in the S/N ratio from 1 to 3 m/s, implying that the wear rate markedly escalates with velocity, rendering it the most critical factor. The fiber content plot indicates a modest yet steady rise in the S/N ratio from 25% to 75%, signifying a tiny reduction in wear as fiber content escalates.

In summary, sliding velocity exerts the most significant influence on wear, whereas load and fiber content have comparatively negligible effects on the wear rate.

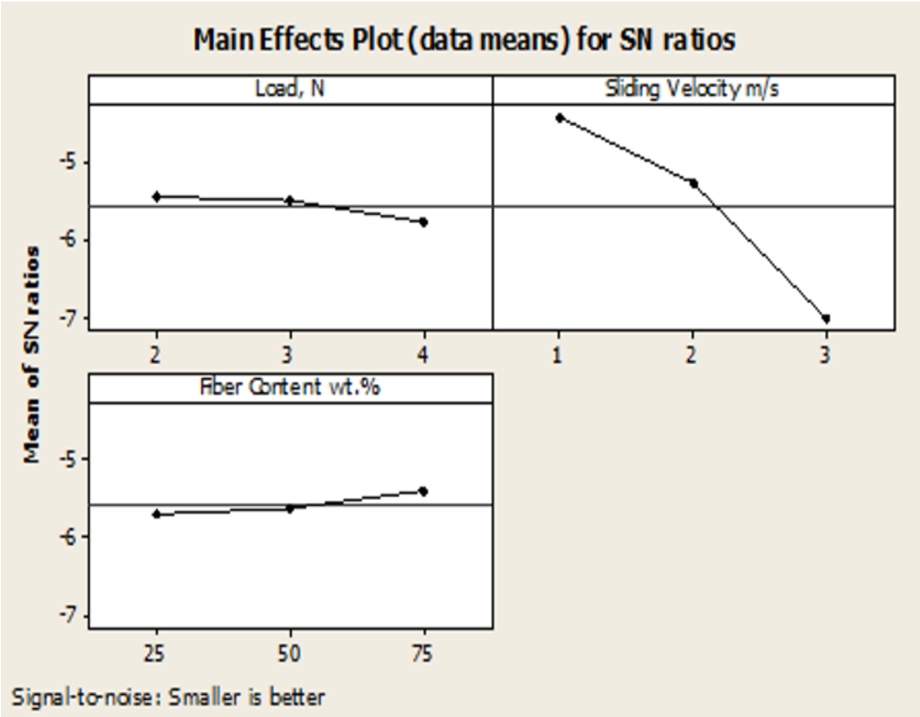

Figure 6. Main effects plot for S/N ratio

Table 10. Multi Response Table for S/N ratio

Level	Load (N)	Sliding Velocity (m/s)	Fiber Content (wt.%)
1	-5.452	-4.414	-5.701
2	-5.489	-5.278	-5.606
3	-5.76	-7.008	-5.394
Delta	0.307	2.593	0.308
Rank	3	1	2

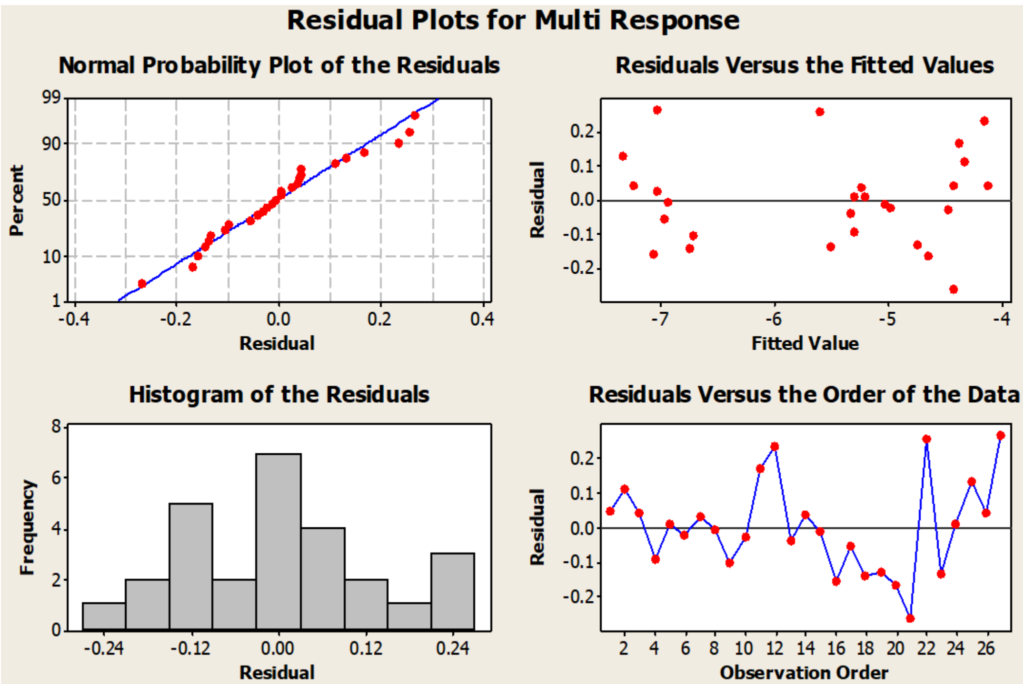

Figure 7. Residual plots for Multi response

The response Table 10 shows the signal-to-noise (S/N) ratio data for three different levels of load, sliding speed, and fiber content in a composite material experiment. Lower (more negative) signal-to-noise ratios indicate worse performance. Reduced (more negative) signal-to-noise ratios signify inferior performance. Sliding Velocity exhibits the largest delta value (2.593), indicating it exerts the most substantial influence on the output, hence ranking first.

Fiber content is ranked second with a moderate influence (Delta = 0.308), while load is ranked third with the least impact (Delta = 0.307). This analysis prioritizes control parameters, demonstrating that optimizing sliding velocity is crucial for enhancing performance response.

The regression equation of Multi response= -2.82 - 0.154 Load, N - 1.30 Sliding Velocity m/s + 0.00616 Fiber Content wt. %

$$S = 0.271321 \ \mathrm{R-Sq} = 94.8\% \ \mathrm{R-Sq\ (adj)} = 94.2\% \quad (4)$$

This Figure 7 displays four residual plots for the regression model titled "Multi response S/N." These plots are crucial for assessing the model's appropriateness by analyzing the properties of its residuals (the discrepancies between actual and predicted values).

The normal probability plot of the residuals evaluates their adhesion to a normal distribution. The data points predominantly cluster near the straight blue line, indicating that the normalcy assumption is adequately satisfied. The Residuals Versus Fitted Values plot assists in assessing constant variance. The residuals are spread out randomly around zero, showing no clear patterns or shapes, which suggests that the variance is probably consistent across the range of fitted values [26]. The histogram of the residuals offers a visual depiction of their' distribution. The histogram displays a nearly bell-shaped distribution centered at zero, so reinforcing the assumption of normality. The Residuals Versus the Order of the Data graphic examines potential patterns related to the order of observations. The apparent random distribution of points around the zero line indicates that the residuals are independent of the data's sequence.

The residual plots show that the "Wear rate + Co-efficient of friction S/N" regression model is suitable because it meets the key requirements of normality, consistent variance of the residuals, and independence from the order of data collection.

3.3.1 Analysis of Variance for Multi responses

The ANOVA Table 11 looks at how load, sliding velocity, and fiber content affect a performance measure by using signal-to-noise ratios.

S = 0.152696 R-Sq = 98.58% R-Sq(adj) = 98.15%

Sliding velocity has the greatest influence, accounting for 95.7% of the overall variation, evidenced by its highest F-value (673.17) and p-value (0.000), which denote robust statistical significance. A robust multi-response optimization framework is proposed for simultaneously optimizing multiple conflicting quality characteristics. [27-28]. Load and fiber content considerably influence the output, evidenced by F-values of 10.87 and 9.58 and p-values of 0.001, affirming their significance. Nonetheless, their contributions are rather minimal, at 1.5% and 1.4%, respectively. The minimal error percentage indicates a strong model fit, emphasizing sliding velocity as the primary variable.

3.4 Grey Relational Analysis

Grey Relational Analysis (GRA) is a method used to optimize process parameters by correlating multiple responses and their influence on wear behaviour.

Table 11. Analysis of Variance for Multi response S/N

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% of Contribution
Load, N	2	0.507	0.507	0.2535	10.87	0.001	0.015
Sliding Velocity (m/s)	2	31.3916	31.3916	15.6958	673.17	0	0.957
Fiber Content (wt.%)	2	0.4468	0.4468	0.2234	9.58	0.001	0.014
Error	20	0.4663	0.4663	0.0233			
Total	26	32.8118					

Table 12. Experimental Design for sliding wear using L-27 OAs along with its output response characteristics

Experiment No	Load, N	Sliding Velocity m/s	Fiber Content wt.%	Specific wear rate × 10^{-13} mm3 /N-m	Co-Efficient of Friction	GRG
1	2	1	25	1.326	0.332	0.799
2	2	1	50	1.311	0.317	0.857
3	2	1	75	1.307	0.293	0.921
4	2	2	25	1.428	0.433	0.553
5	2	2	50	1.405	0.413	0.592
6	2	2	75	1.387	0.393	0.630
7	2	3	25	1.616	0.623	0.352
8	2	3	50	1.609	0.615	0.358
9	2	3	75	1.594	0.600	0.368
10	3	1	25	1.336	0.343	0.764
11	3	1	50	1.313	0.310	0.868
12	3	1	75	1.272	0.300	0.982
13	3	2	25	1.427	0.430	0.557
14	3	2	50	1.405	0.415	0.590
15	3	2	75	1.386	0.400	0.624
16	3	3	25	1.642	0.655	0.334
17	3	3	50	1.602	0.643	0.350
18	3	3	75	1.603	0.610	0.361
19	4	1	25	1.373	0.380	0.662
20	4	1	50	1.373	0.368	0.678
21	4	1	75	1.358	0.360	0.707
22	4	2	25	1.403	0.448	0.563
23	4	2	50	1.476	0.440	0.514
24	4	2	75	1.403	0.436	0.573
25	4	3	25	1.643	0.649	0.335
26	4	3	50	1.642	0.648	0.336
27	4	3	75	1.542	0.636	0.376

Ju-long first developed GRA in 1982, and this article elaborates on the sequential methodology associated with GRA optimization. Initially, the fig 8 shown the procedure of GRA normalizes the experimental data to a range of 0 to 1, a process referred to as gray relational generation [22, 23]

The last phase entails assessing the correlation between the desired and actual experimental data by computing the grey relational coefficient (GRC) from the normalised data. Each experiment involving several response variables is consolidated into a singular overall response objective by averaging the grey relational coefficients (GRCs) of those variables. The grey relational grade (GRG) [24] is employed to complete this assignment. This study employs analysis of variance (ANOVA) on the GRG data to identify the elements that most significantly influence the wear performance of silane-treated F-B-E composites.

Table 12 outlines a methodology for an experiment on slide wear with L-27 orthogonal arrays (OAs).

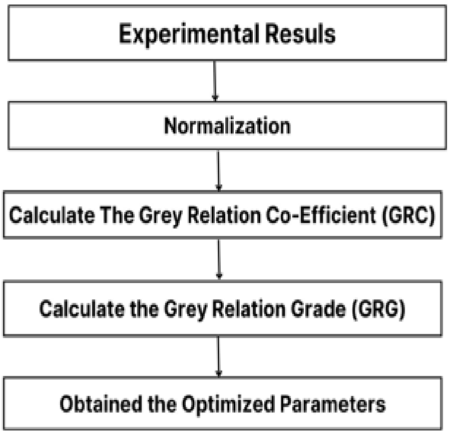

Figure 8. GRA Procedure

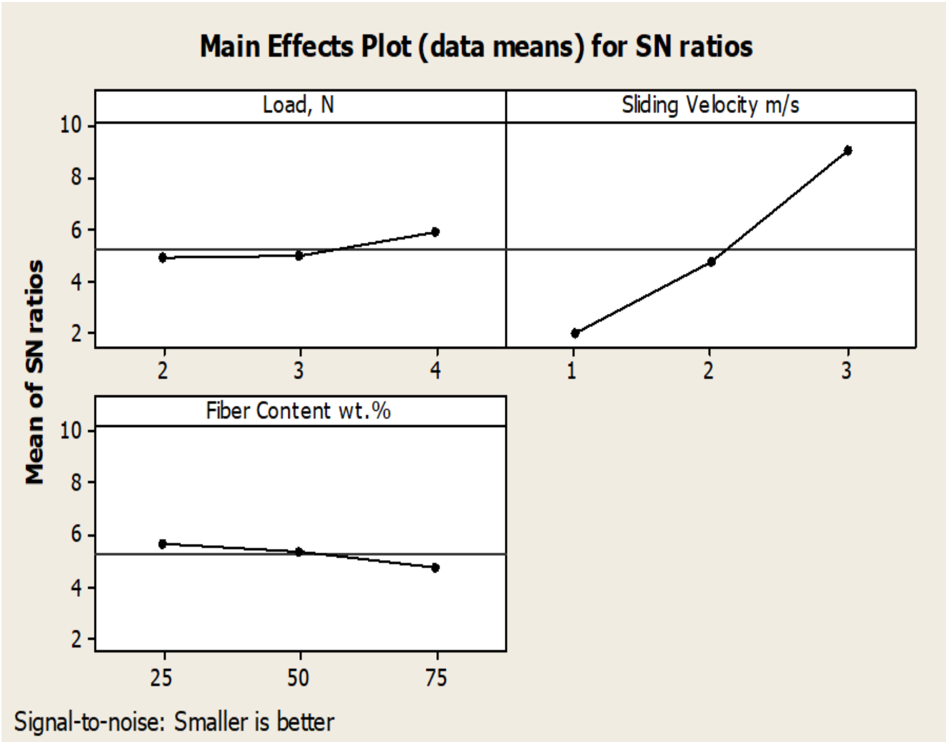

Figure 9. Gray relation grades to main effect

The objective of the experiment is to ascertain the influence of load, sliding velocity, and fibre composition on wear parameters. The input variables include load (N), sliding speed (m/s), and fibre content (wt%). The output variables are the friction coefficient and the specific wear rate $\times 10^{-33}$ $mm^3/N\text{-}m$). Furthermore, we provide normal outcomes for both responses. Elevated fibre content usually diminishes wear, whereas increased sliding velocity and load tend to intensify it. This experiment aims to enhance wear resistance in composite materials by identifying the most critical components through Taguchi's experimental design methodology.

In Grey Relational Analysis (GRA), the Grey Relation Coefficient (GRC) quantifies the similarity between empirical data and an ideal reference. It standardised replies and enhanced multi-response optimisation. A higher GRC value indicates a more robust correlation between the measured performance and the expected performance, facilitating the selection of optimal settings.

The primary consequences Figure 9 illustrates the impacts of load (N), sliding velocity (m/s), and fibre content (wt%) on signal-to-noise (SN) ratios. As the signal-to-noise ratio decreases, the outcomes improve. Increased velocities lead to worse (elevated) signal-to-noise ratios, as seen by the data, which demonstrates that sliding velocity has the most significant influence. The impact of load is substantial, whereas the effect of fibre content is minimal, suggesting a marginal enhancement in performance at 75 percent weight. The optimal parameters for minimising the S/N ratio include low sliding velocity, a low load, and high fibre content.

Table 13. Response Table for GRG

Level	Load (N)	Sliding Velocity (m/s)	Fiber Content (wt.%)
1	4.932	4.997	5.894
2	1.966	4.787	9.07
3	5.685	5.376	4.761
Delta	0.962	7.104	0.925
Rank	2	1	3

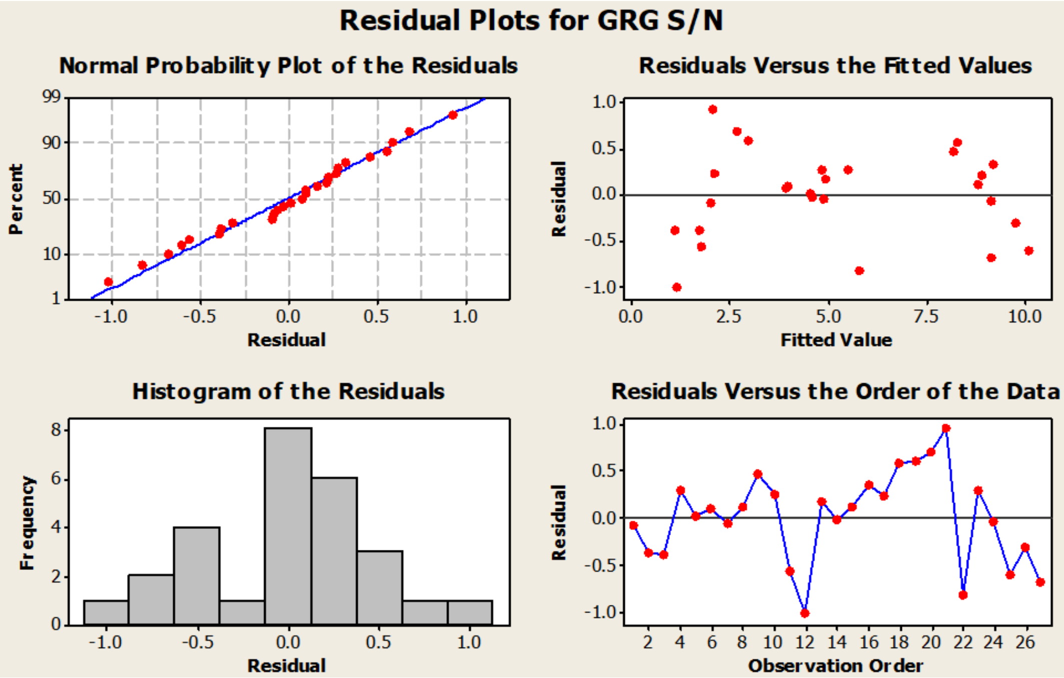

Figure 10. Residual plots for GRG

Table 14. Analysis of variance for GRG

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% of Contribution
Load, N	2	5.207	5.207	2.604	8.77	0.002	0.021
Sliding Velocity (m/s)	2	230.322	230.322	115.161	387.78	0	0.938
Fiber Content (wt.%)	2	3.988	3.988	1.994	6.71	0.006	0.016
Error	20	5.94	5.94	0.297			
Total	26	245.457					

Table 13 presents the mean response for each component level. Delta signifies the difference between the greatest and minimum averages for each factor, reflecting its magnitude of influence. Sliding velocity demonstrates the largest delta (7.104), making it the most significant (Rank 1). The load has a moderate delta of 0.962, positioning it in second place.

The fiber content exhibits the lowest delta (0.925), indicating it is the least influential (rank 3). In fact, optimizing the reaction mostly necessitates managing sliding velocity, followed by load adjustment, although variations in fiber content exert a relatively negligible influence**.**

The regression equation for GRG = - 2.35 + 0.481 Load, N + 3.55 Sliding Velocity m/s - 0.0185 Fiber Content wt.%

$$S = 0.670032 \; R-Sq = 95.8\% \; R-Sq\,(adj) = 95.2\% \tag{5}$$

The Figure 10 shows four residual plots for a general regression (GRG) model with an unknown signal-to-noise ratio. These graphs provide residual distributions (the discrepancies between observed and anticipated values) to evaluate model fit.

The residual normal probability plot checks the normal distribution. Ideally, the points should be straight, which they typically are, implying normalcy. The residuals versus fitted values plot tests homoscedasticity or constant residual variance across predicted values. The points appear randomly about zero without a pattern, suggesting continual variance.

The residual histogram shows residual distribution in another way. A somewhat bell-shaped distribution near zero supports normalcy.

Finally, the Residuals Versus the Order of the Data plot searches for patterns related to data collection order, which may show time-dependent effects. The dispersed points without a trend show that residuals are data order independent.

These residual plots show that the GRG model fits the data perfectly, meeting the assumptions of normality, constant variance, and independence from data order.

3.4.1 Analysis of Variance for GRG

This ANOVA Table 14 measures the influence of three factors on the response variable.

S = 0.544957 R-Sq = 97.58% R-Sq(adj) = 96.85%

Sliding velocity is the most important factor, making up 93.8% of the total variation (Seq SS = 230.322) and has a very high F-value (387.78, $p < 0.001$). Load makes up 2.1% (Seq SS = 5.207, F = 8.77, p = 0.002), showing a moderate but significant effect. Load accounts for 2.1% (Seq SS = 5.207, F = 8.77, p = 0.002), indicating a moderate yet significant influence. The fiber content exerts a modest but statistically significant influence, accounting for 1.6% of the variation (Seq SS = 3.988, F = 6.71, p = 0.006). The minimal residual error indicates that the model accounts for the majority of variability, affirming sliding velocity as the primary determinant [18].

4. Conclusion

The research identified A1 (Load), B1 (Sliding Velocity), and C3 (Fibre Content Percentage) as optimal settings for reducing wear rate and enhancing the coefficient of friction. Various approaches, including the Taguchi method, regression analysis, and Grey Relational Analysis (GRA), supported this finding.

- The Taguchi approach effectively determined the ideal settings for each objective function.
- The results were confirmed by regression modelling, which showed that the wear rate regression had an R^2 value of 96.1% (Adjusted R^2 = 96.5%) and that the ANOVA results for wear rate were 98.70% and 98.30%.
- The regression analysis of the coefficient of friction produced values of 92.04% and 98.30%, accompanied by ANOVA results of 96.84% and 95.90%. Multi-response regression and ANOVA demonstrated high accuracy, with values between 94.2% and 98.58%.
- The GRA technique yielded additional validation, with regression values of 93.8% and 93.0%, along with ANOVA values of 94.70% and 93.11%. Dependability and utilitarian implementation the elevated precision of multi-objective optimisation techniques substantiates a robust link between experimental and mathematical models.
- The optimisation strategies effectively enhanced the sliding- wear parameters with various response factors. The optimal wear process parameters that yielded the highest hardness in the F-B-E composite, resulting in the lowest coefficient of friction (COF) and specific wear rate (SWR), were identified as the configuration of A1, B1, and C3. The settings produced test conditions for a 2N load, a sliding velocity of 1 m/s, and a fibre content of 75 wt%.

This method is exceptionally helpful for analysing wear behaviour and offers a reliable framework for researchers and companies to enhance material performance in diverse settings.

The results provide a systematic strategy for enhancing wear resistance in fibre-reinforced composites, which is beneficial for manufacturing, material selection, and design methodologies. The study's technique can provide a basis for subsequent research and practical applications in tribology and composite materials engineering.

4.1 Future Work

This study's findings establish a robust basis for future research aimed at optimizing wear behaviour in fiber-reinforced composites. Subsequent investigations may examine the impact of varying fibre orientations, hybrid composites, and environmental factors on wear performance. Advanced optimization methods, such as machine learning and artificial intelligence, can improve prediction modeling for wear rates and friction characteristics. Furthermore, we can establish real-time wear monitoring in industrial applications to improve material durability.

Adding more types of loads, lubricated environments, and nanoscale reinforcements to this research could give the automotive, aerospace, and biomedical industries a lot of useful information for finding high-performance materials that don't wear out quickly.

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Authors Contribution Statement

Yerru Kalyana Krishna: Conceptualization, Methodology, Investigation, Validation, Data Curation, Writing original Manuscript. B. Karthikeyan: Writing, Review and Editing, Devarakonda Sameer Kumar: Writing, Review and Editing. All the authors read and approved the final version of the manuscript.

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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