International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Annales de Chimie - Science des Matériaux
Vol. 46, No. 1, February, 2022, pp. 9-17
Journal homepage: http://iieta.org/journals/acsm

Effectiveness of Shannon Entropy Weight Method on Wear Behaviour of Polyester/Carbon Fibre Composites Using GRA

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https://doi.org/10.18280/acsm.460102

Received: 26 January 2022
Accepted: 15 February 2022

Keywords:
Taguchi method, GRA, entropy weight method, polyester composites

ABSTRACT

In recent past conventional monolithic materials are replaced with fiber reinforced polymer composite materials due to their high specific strength. The current study focused on dry-sliding wear behaviour of carbon fiber reinforced polyester (CFRP) composites using a pin-on-disc tribometer. The two output responses selected were rate of wear and frictional force with respect to controlled variables using the Taguchi L16 OA (Orthogonal Array). In order to assess the best optimal conditions GRA technique has been used in the study. The effectiveness of entropy weights on the optimal result has been carried out in support with ANOVA studies. In GRA analysis, the combined effect of wear and frictional force is considered and the optimal conditional identified in two ways namely equal weightage method (EWM) and entropy based weightage method (EBWM). While considering EWM method the optimal condition obtained is S1 L4 D3 R4 whereas in EBWM the optimal solution obtained is S1 L4 D1 R4. This shows because of the uneven weights generated by EBWM method there is a change in optimal solution in comparison with EWM method.

1. INTRODUCTION

Over the last few decades world has changed a lot so as the demands for composite materials in a variety of domains. Polymers have dominated as new materials alongside composite materials and ceramics. Because of their unique properties like high stiffness and strength-to-weight ratio, the number of applications for composites has steadily increased. Demand for polymeric composite materials, which are used in a variety of automotive applications such as chassis frames and wheels, has increased. Polyester development has progressed significantly to specific composites for aerospace and other applications. Improved mechanical properties extend the life of commercial polymers [1]. A side from their desirable mechanical properties, resistance towards corrosion is an appealing consideration for the use of such composites in a variety of applications. Because polyester is sensitive to UV rays, humidity, and moist conditions, good environmental maintenance primes to an upsurge in their durability [2, 3]. Polyesters are widely used for matrix purposes, primarily reinforced with glass fibers and many more reinforced materials [4-6].

To achieve aesthetic balance of good weight, mechanical properties along with strength to weight ratio carbon fiber is one of the preeminent option available for engineers now days. It has been proved as one of the reinforcement material in aluminium and titanium alloys allowing them to dislodge the traditional materials in several structural applications [7, 8]. Niedermann et al. [9] reported the effect of jute fiber and Carbon fibre reinforcement in epoxy resin for aircraft applications. Davim et al. [10] reported that the usage of PEEK (Poly-Ether-Ether-Ketone) reinforced with carbon fibres for orthopedic applications thereby they investigated the effect of reinforcement on diverse parameters like frictional behaviour, sliding velocity and so on. Kumar and Sai Ram [11] made an attempt by reinforcing the carbon fibres in polyester resin. They reported that carbon fibres have good homogeneity up to 6% by weight beyond this threshold value a lot of clusters are observed dropping the wear resistance. In order to select the most suitable and optimal parameters for better tribological properties, numerous decision-making techniques such as AHP (Analytic Hierarchy method) and GRA (Grey Relational Analysis) are used for numerous applications by various researchers [12]. With simple steps and automating the overall process to save time, made Taguchi-GRA combinatorial approach as a foster technology in the field of composites. This Taguchi-GRA combinatorial approach was applied for various machining operations, milling, grinding, drilling, and turning to evaluate multi-objective optimization machining parameters [13-15].

In Multi objective decision-making weights to the responses plays a prominent role and influence the optimization process. Geeth et al. [16] conducted a series of experiments based on Taguchi orthogonal array on Polyester reinforced with carbon fibres they reported the GRA technique with equal weight consideration. However suitable techniques have to be implemented for effective consideration of weights rather than by equal weights. So, entropy method is one of the popular technique which determines the weights based on the difference of lowest to highest parameters in the particular set.

Therefore, an attempt is made here to apply entropy based weight method (EBWM) to calculate the weights and to report the effect of these methods on the multi objective optimization and wear behaviour of polyester/Carbon fiber reinforcements in different weight fractions.

This paper report experimental details in section 2 which involves materials used, fabrication and testing methods, methodology in section 3 followed by results and discussions. Conclusions have been reported at the end of the paper.

2. METHODOLOGY

2.1 Materials and methods

In this work, polyester resin is cured with addition of carbon fibres of size 85 µm in a mild steel mould of dimensions Ø1.5cm ×15cm in height. Figure 1 portrays the research methodology for fabrication and optimization of CFRP composites.

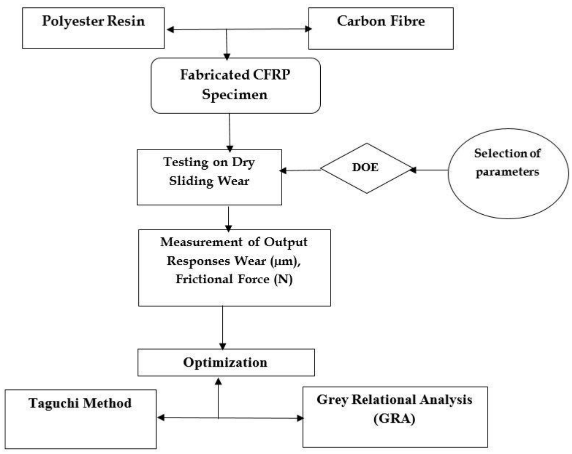

Figure 1. Methodology of current research

2.2 Composite fabrication

Due to addition of hardeners Methyl Ethyl Ketone Peroxide (MEKP) and Cobalt octoate (CO) unsaturated polyester resin is cured with carbon fiber of 85 µm in size. Table 1 depicts the composition of various composites. Before pouring the resin into the mould the releasing agent is applied. For better yield of the casting semi solid state mixture is held for 24 hours at ambient conditions. After 24 hours specimens are withdrawn from the mould and are machined to 8 mm diameter at RVR & JC College of engineering and specimens were polished for wear tests in a calibrated machine.

Table 1. The composition of various composites

Sl. no	Identification of Composite	Wt% of Carbon fiber	Wt% of Polyester resin	Wt% of Hardener (MEKP+CO)
1.	100% Pure Polyester	0	200	2
2.	2Wt% CF + 98% Polyester	2	200	4
3.	4Wt% CF + 96% Polyester	4	200	6
4.	6Wt% CF + 94% Polyester	6	200	8

2.3 Dry-sliding wear test

Based on the literature available wear tests were conducted using pin-on-disc tribometer as per ASTM G99-95 standards [17]. Figure 2 depicts the pin on disc tribometer in which wear pins are prepared with dimensions Ø0.8 cm×5 cm in height. The load was imparted on to the pin against its counterpart on an EN32 steel disc during the test. After running over a sliding distance, the pins were removed, gutted with acetone, dried out, and weighted to know the wear due to loss of weight. The loss of wear is determined by difference in weight measured pre and post experimentation. The wear (W in µm) and frictional force (FF in N) of prepared CFRP composites were investigated as a function of normal loads (L), percent of reinforcement (R), sliding velocity (S), and sliding distance (D).

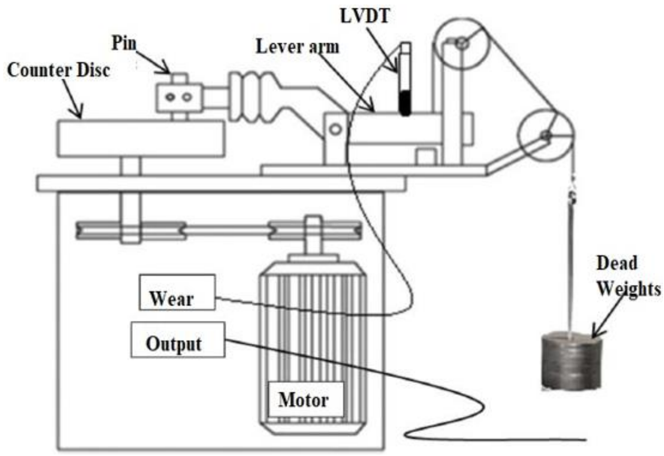

Figure 2. Pin-on-disc tribometer [18]

2.4 Taguchi's design of experiments (DOE)

Table 2. Control factors and their levels

Control Factors	Levels				Units
	1	2	3	4	
S	2	4	6	8	m/s
L	5	10	15	20	N
D	1000	2000	3000	4000	m
R	0	2	4	6	%

Taguchi experimental design is a versatile method for finding the impacts of multiple parameter effect on response variables. The most critical step in the DOE is picking the monitoring factors that influence the output readings. Initially various factors are taken into account, out of those less significant factors affecting are nullified, leaving only the more significant aspects. In the experimentation of sliding wear, four major factors are taken into account, as shown in Table 2. At room temperature with reference to L16 OA four levels are opted namely load (L), sliding distance (D), sliding velocity (S), and percent of fibre reinforcement (R) and experimentation is conducted. The number of Experiments was decreased from 256 conventional runs to just 16 runs using Taguchi L16 OA, saving both time and money (Table 3). These tests results are converted into signal-to-noise ratios (SNR). To convert S/N ratio logarithmic function is used as shown in Eq. (1) [19-21].

"Smaller-the-Better",

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

where, n represents number of runs (n=16) and y represents to the output parameters (y=2).

Table 3. L16 OA based on Taguchi approach

Runs	Independent Factors			
	S	L	D	R
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	2	1	2	3
6	2	2	1	4
7	2	3	4	1
8	2	4	3	2
9	3	1	3	4
10	3	2	4	3
11	3	3	1	2
12	3	4	2	1
13	4	1	4	2
14	4	2	3	1
15	4	3	2	4
16	4	4	1	3

2.5 Grey Relational analysis (GRA)

To enhance the process parameter in view of single objective Taguchi's experimental design is enough. When there are two or more responses with different objectives, to optimize them GRA is applied. GRA [22, 23] can also be used to assess the familiarity of unknown data. Due to this reason for multi-objective optimization to evaluate wear parameters GRA approach is used. The ANOVA method identifies important factor that are influencing the wear behaviour. Taguchi GRA combinatorial approach is evaluated using as follows [24, 25]:

Step-I: Wear and frictional force values are normalized based on "Smaller-the-Better" criteria, using Eq. (2).

$$y_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - min x_i(k)} \quad (2)$$

In Eq. (2), i=1, 2, 3, 4, 5 … 16 (no. of records), k=1, 2 (no. of output parameters), x_i (k) is empirical value, max xi(k) equals to maximum value of xi(k) and min xi(k) equals to minimum value of xi(k).

Step-II: For all process variables using Eq. (3) the deviation sequence determined.

$$\Delta_{oi}(k) = |x_o(k) - x_i(k)| \quad (3)$$

where, Δoik is the base for both xok & the comparability sequence xik and it is known as deviation sequence.

Step-III: To calculate the GRC (Grey Relational Coefficients) Eq. (3) is used.

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\,\Delta_{max}}{\Delta_{oi}(k) + \zeta\,\Delta_{max}} \quad (4)$$

In Eq. (4), ζ is distinguishing coefficient and its value is calculated in two ways namely equal weights and unequal weights. In equal weight method all the parameters are affecting considered to be equally weighed and its value is 0.5 each. But in real world equal weights are not suggestable and entire scenario changes so the allocation of weights to parameters are done by entropy method.

Step-IV: The main step in employing equation is to anticipate the GRG (Grey Relational Grade) by taking the mean of all GRC values using Eq. (5).

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad (5)$$

where, γ_i ranges from 0-1 and 'n'=number of output readings.

2.6 Entropy method

Shannon Entropy method is used to calculating weights for the various parameters considered i.e., Distinguishing coefficient(ζ). The following method is employed to find the weightage of individual parameters affecting the process.

Step 1: Normalization of the arrays of decision matrix to acquire the project outcomes p_{ij}

$$\mathrm{p_{ij}} = \frac{\mathrm{x_{ij}}}{\sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{x_{ij}}} \quad (6)$$

Step 2: Computation of the entropy measure of project outcomes using the following equation:

$$E_j = -K\sum_{i=1}^{m} p_{ij}\, log_e\, p_{ij} \quad (7)$$

where, $K = \frac{1}{log_e m}$.

Step 3: Defining the objective weight based on the entropy concept

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n}(1 - E_j)} \quad (8)$$

3. RESULTS AND DISCUSSION

3.1 Implementation of Taguchi method

3.1.1 Calculation of S/N ratio

To perform statistical analysis of the experimental records Minitab 19 software was used. Table 4 forecasts wear and frictional force experimental data, as well as the corresponding S/N ratios, whereas Table 5 illustrate S/N ratio responses for wear (W) and frictional force (FF). Figures 3 and 4 depict how the S/N ratio is altered by controlling both the parameters i.e., W & FF. An optimal control factor setting for greater performance can be accomplished by evaluating the lowest S/N ratios values. The lowest S/N ratios are shown in bold in Table 5. Figure 3 and Table 5 illustrate that percent of reinforcement (R) has an impact on wear (W), whereas Figure 4 and Table 5 show that load (L) has an impact on frictional force (FF). Based on S/N ratios, Minitab software throws a combination of parameters to get least wear as shown in Figure 3 and Table 5. Due to amalgamation of parameters least wear is obtained at S1 L2 D2 R4 whereas for minimum frictional force S1 L4 D3 R3 is the optimal condition as in Figure 4 and Table 5.

3.1.2 Analysis of variance

The key control parameters that influence wear and frictional force response values were identified using ANOVA (Analysis of Variance). The significant importance of factors is calculated using the overall sum of squared value. The bigger the total of squared values, the more important it is to manage the response values. These data are used to regulate the percentage contribution on the individual parameters [26]. The study is carried out with a 95% level of confidence and a significance level of 5%. The ANOVA results for wear and frictional force are shown in Tables 6 and 7, respectively. According to Table 6, the most important factor impacting wear is R which contributes for 65.61%, followed by L, S, and D, which contribute for 12.34%, 7.71%, and 5.35%, respectively. According to Table 7, the most important factor dominating frictional force is L which contributes about 43.85%, followed by S which contributes 31.71%, R which contributes 9.18%, and D which contributes almost 9.00%. A high F-value signifies those factors selected as a major influencing on the performance of the process [27, 28].

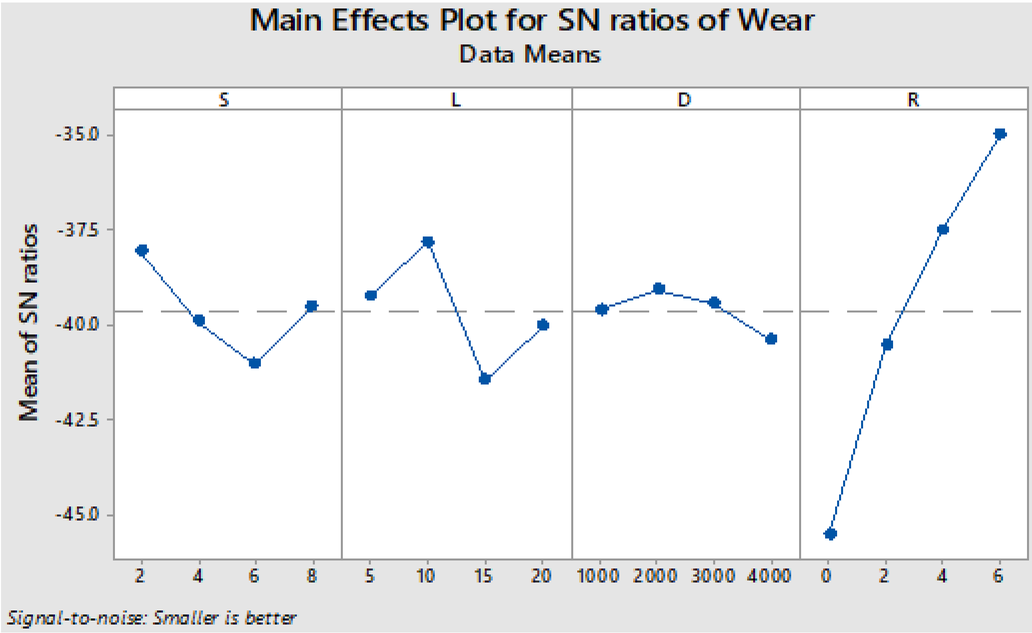

Figure 3. Main effect of wear for the *S/N* ratio plots

Table 4. Multi-response outputs along with *S/N* ratio for Taguchi L16 OA

Runs	Control Factors				Response variables		*S/N* Ratios	
	S (m/s)	L (N)	D (m)	R (%)	W (µm)	FF (N)	W (dB)	FF (dB)
1	2	5	1000	0	162	10.5	-44.1903	-20.4238
2	2	10	2000	2	83	7.25	-38.3816	-17.2068
3	2	15	3000	4	63	5.12	-35.9868	-14.1854
4	2	20	4000	6	48	4.11	-33.6248	-12.2768
5	4	5	2000	4	62	16.3	-35.8478	-24.2438
6	4	10	1000	6	39	11.03	-31.8213	-20.8515
7	4	15	4000	0	325	19.25	-50.2377	-25.6886
8	4	20	3000	2	121	4.39	-41.6557	-12.8493
9	6	5	3000	6	76	12.91	-37.6163	-22.2185
10	6	10	4000	4	84	12.36	-38.4856	-21.8404
11	6	15	1000	2	138	15.25	-42.7976	-23.6654
12	6	20	2000	0	184	9.32	-45.2964	-19.3883
13	8	5	4000	2	92	12.76	-39.2758	-22.1170
14	8	10	3000	0	133	11.37	-42.4770	-21.1152
15	8	15	2000	6	69	9.1	-36.7770	-19.1808
16	8	20	1000	4	95	4.83	-39.5545	-13.6789

Table 5. Response table for wear and frictional force based on *S/N* ratio

	Wear				Frictional force			
Level	**S**	**L**	**D**	**R**	**S**	**L**	**D**	**R**
1	**-38.05**	-39.23	-39.59	-45.55	**-16.02**	-22.25	-19.65	-21.65
2	-39.89	**-37.79**	**-39.08**	-40.53	-20.91	-20.25	-20	-18.96
3	-41.05	-41.45	-39.43	-37.47	-21.78	-20.68	**-17.59**	**-18.49**
4	-39.52	-40.03	-40.41	**-34.96**	-19.02	**-14.55**	-20.48	-18.63
Delta	3	3.66	1.33	10.59	5.75	7.7	2.89	3.17
Rank	3	2	4	1	2	1	4	3

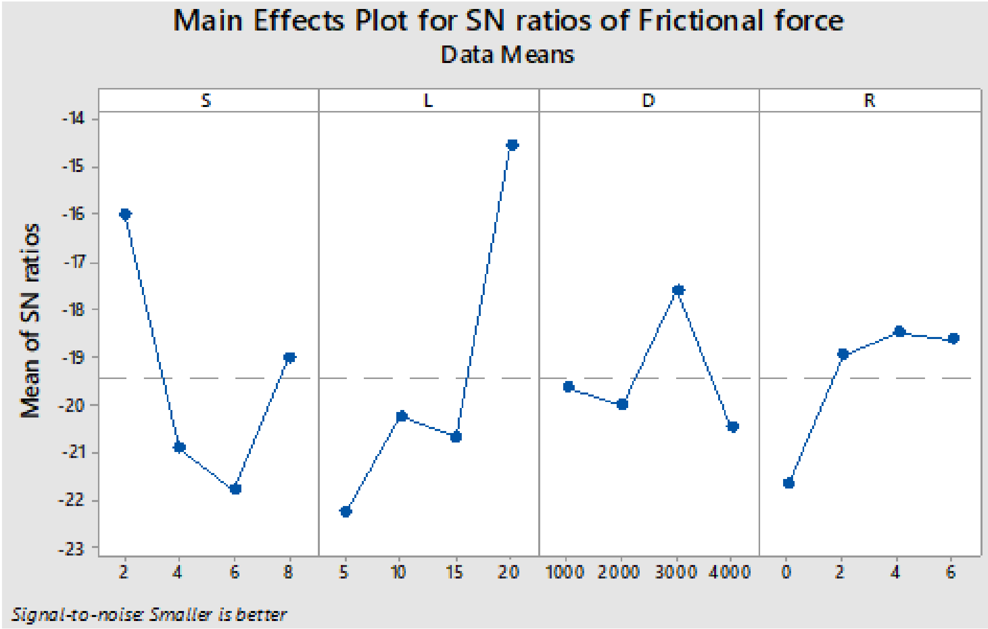

Figure 4. Main effect of frictional force for the *S/N* ratio plots

Table 6. ANOVA table for the *S/N* ratio of wear

Source	SS [a]	DF [b]	MS [c]	F-value	P-value	Contribution %
S	5705	3	1902	0.86	0.549	7.71
L	9136	3	3045	1.37	0.4	12.34
D	3960	3	1320	0.6	0.66	5.35
R	48561	3	16187	7.3	0.068	65.61
Error	6653	3	2218			8.99
Total	74016	15				100.00
S=47.09, R^2=91.01%, R^2_{adj}=55.06%						

Table 7. ANOVA table for the *S/N* ratio of frictional force

Source	SS [a]	DF [b]	MS [c]	F-value	P-value	Contribution %
S	95.47	3	31.825	5.07	0.108	31.71
L	132.01	3	44.004	7.01	0.072	43.85
D	27.1	3	9.033	1.44	0.386	9.00
R	27.65	3	9.218	1.47	0.38	9.18
Error	18.82	3	6.275			6.25
Total	301.06	15				100.00
S=2.50, R^2=93.75%, R^2_{adj}=68.74%						

[a] Sum of Squares. [b] Degrees of Freedom. [c] Mean squares.

Table 6 depicts that % reinforcement is the major contributing factor change in wear. Similarly, in Table 7 load is the major factor affecting change in frictional force. From Table 6 and 7 based on the R2 (i.e., coefficient of correlation) one may predict that the model as good linear fit with less error [29, 30].

3.2 Multi-response optimization using GRA

Wear and frictional force are two characteristics that occur simultaneously. Consequently, they need to be optimized in tandem. GRA was chosen for this purpose since it has the ability to reduce a multi-objective problem to a single-objective problem from which it can be optimized [31].

3.2.1 Calculation of GRG

Using Eq. (3) based on the normalized values, deviation sequences are evaluated followed by calculations of GRC and GRG for all responses. The bold values in Table 8 signify that experimental run (4) has the maximum GRG value of 1.00, thereby indicating it as the optimal value. Using Eq. (3) based on the normalized values, deviation sequences are evaluated followed by calculations of GRC and GRG for all responses. The bold values in Table 8 signify that experimental run (4) has the maximum GRG value of 1.00, thereby indicating it as the optimal value. Using the equations i.e., from Eq. (6) to Eq. (8) the entropy weights of wear and frictional force are found to be 0.217, 0.783 and based on that GRG score is evaluated and mentioned in Table 9.

For each parameter based on EWM and EBW methods, GRG responses are evaluated and are depicted in Table 10. Figure 5 and Figure 6 illustrates the main effect plots of GRG using Equal weighted method and Entropy based weight method. Based on EWM method S1 L4 D3 R4 is the optimised condition whereas for EBWM method S1 L4 D1 R4 is the optimal value obtained. The higher the GRG, the closer the product's quality is to its ideal value. As a result, a greater GRG is required for optimal performance.

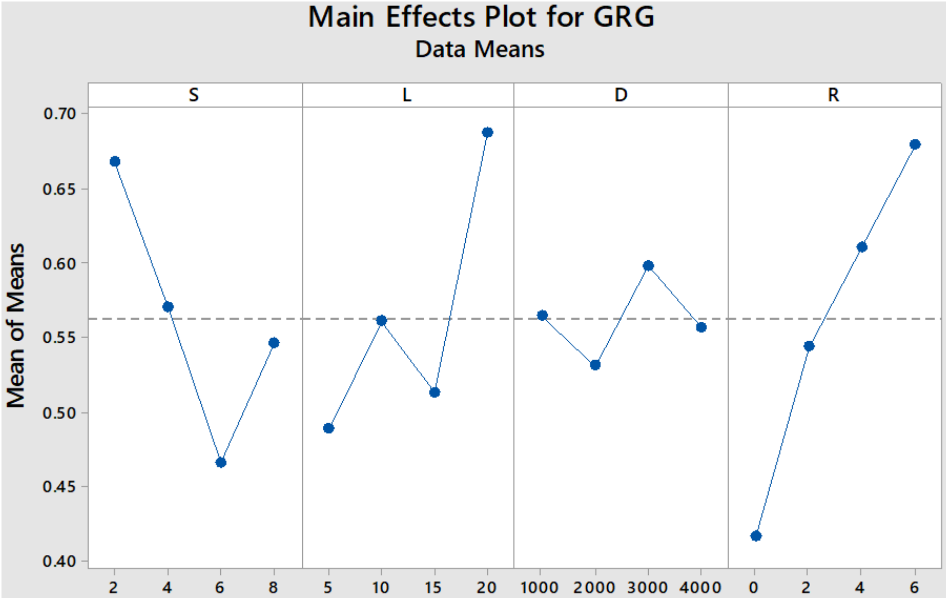

Figure 5. Main effect plots of GRG using EWM

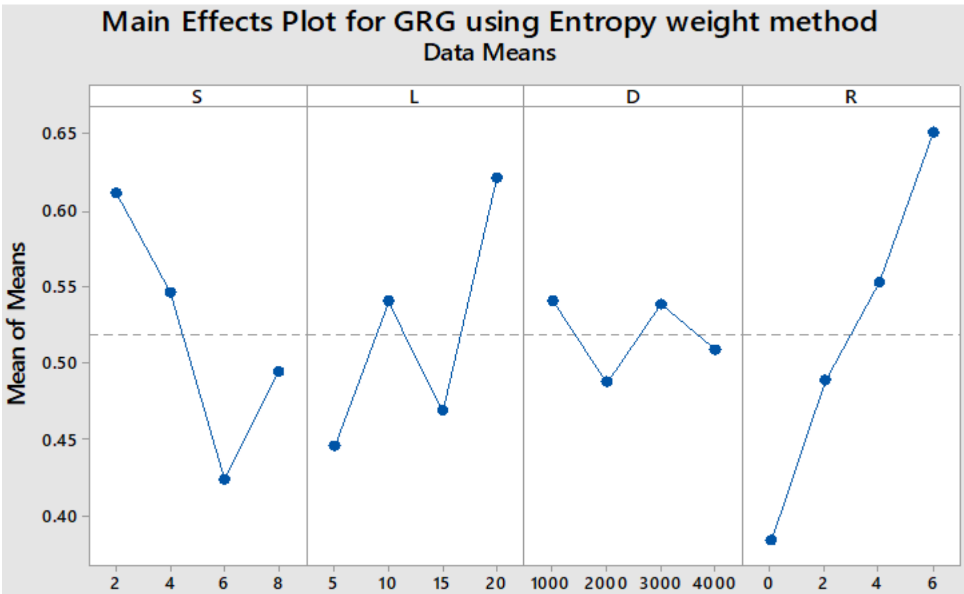

Figure 6. Main effect plots of GRG using EBWM

Table 8. Calculation of GRC and GRG for wear and frictional force based on equal weightage method (EWM)

Runs	Normalized data [$y_i(k)$]		Deviation sequence [$\Delta_{oi}(k)$]		GRC [$\xi_i(k)$]		GRG (γ_i)	Rank
	W	FF	W	FF	W	FF		
1	0.328	0.393	0.672	0.607	0.427	0.451	0.439	14
2	0.644	0.632	0.356	0.368	0.584	0.576	0.580	6
3	0.774	0.858	0.226	0.142	0.689	0.778	0.733	2
4	**0.902**	**1.000**	**0.098**	**0.000**	**0.836**	**1.000**	**0.918**	**1**
5	0.781	0.108	0.219	0.892	0.696	0.359	0.527	8
6	1.000	0.361	0.000	0.639	1.000	0.439	0.719	3
7	0.000	0.000	1.000	1.000	0.333	0.333	0.333	16
8	0.466	0.957	0.534	0.043	0.484	0.921	0.702	4
9	0.685	0.259	0.315	0.741	0.614	0.403	0.508	9
10	0.638	0.287	0.362	0.713	0.580	0.412	0.496	10
11	0.404	0.151	0.596	0.849	0.456	0.371	0.413	15
12	0.268	0.470	0.732	0.530	0.406	0.485	0.446	13
13	0.595	0.266	0.405	0.734	0.553	0.405	0.479	11
14	0.421	0.341	0.579	0.659	0.464	0.431	0.447	12
15	0.731	0.485	0.269	0.515	0.650	0.493	0.571	7
16	0.580	0.895	0.420	0.105	0.544	0.827	0.685	5

Table 9. Calculation of GRC and GRG for wear and frictional force based on entropy based weightage method (EBWM)

Runs	Normalized data [$y_i(k)$]		Deviation sequence [$\Delta_{oi}(k)$]		GRC [$\xi_i(k)$]		GRG	Rank
	W	FF	W	FF	W	FF	(γ_i)	
1	0.328	0.393	0.672	0.607	0.245	0.563	0.404	14
2	0.644	0.632	0.356	0.368	0.379	0.680	0.530	6
3	0.774	0.858	0.226	0.142	0.490	0.846	0.668	3
4	**0.902**	**1.000**	**0.098**	**0.000**	**0.689**	**1.000**	**0.845**	**1**
5	0.781	0.108	0.219	0.892	0.499	0.467	0.483	8
6	1.000	0.361	0.000	0.639	1.000	0.550	0.775	2
7	0.000	0.000	1.000	1.000	0.179	0.439	0.309	16
8	0.466	0.957	0.534	0.043	0.289	0.948	0.619	4
9	0.685	0.259	0.315	0.741	0.409	0.514	0.461	9
10.	0.638	0.287	0.362	0.713	0.375	0.523	0.449	10
11.	0.404	0.151	0.596	0.849	0.267	0.480	0.373	15
12.	0.268	0.470	0.732	0.530	0.229	0.596	0.413	12
13	0.595	0.266	0.405	0.734	0.349	0.516	0.433	11
14	0.421	0.341	0.579	0.659	0.273	0.543	0.408	13
15	0.731	0.485	0.269	0.515	0.447	0.603	0.525	7
16	0.580	0.895	0.420	0.105	0.341	0.882	0.612	5

Table 10. GRG response table using EWM and EBWM

	Equal weightage method (EWM)				Entropy based weightage method (EBWM)			
Level	**S**	**L**	**D**	**R**	**S**	**L**	**D**	**R**
1	**0.6677**	0.4885	0.5643	0.4164	**0.6116**	0.4451	**0.541**	0.3833
2	0.5707	0.5608	0.5312	0.5437	0.5464	0.5405	0.4876	0.4887
3	0.4659	0.5129	**0.5979**	0.6106	0.4241	0.4688	0.539	0.553
4	0.5458	**0.6879**	0.5566	**0.6793**	0.4944	**0.6219**	0.5089	**0.6515**
Delta	0.2018	0.1994	0.0668	0.2629	0.1875	0.1768	0.0534	0.2682
Rank	2	3	4	1	2	3	4	1

Table 11. ANOVA table for GRG using EWM

Source	SS [a]	DOF [b]	MS [c]	F-value	P-value	Contribution %
S	0.083014	3	0.027671	7.99	0.061	23.87
L	0.094656	3	0.031552	9.11	0.051	27.22
D	0.0091	3	0.003033	0.88	0.542	2.62
R	0.150627	3	0.050209	14.5	0.027	43.31
Error	0.010386	3	0.003462			2.99
Total	0.347783	15				100.00
S=0.0588, R2=97.01%, R2adj=85.07%						

Table 12. ANOVA table for GRG using EBWM

Source	SS [a]	DOF [b]	MS [c]	F-value	P-value	Contribution %
S	0.075747	3	0.025249	3.8	0.151	22.82
L	0.076122	3	0.025374	3.82	0.15	22.94
D	0.007899	3	0.002633	0.4	0.766	2.38
R	0.152201	3	0.050734	7.64	0.065	45.86
Error	0.019934	3	0.006645			6.01
Total	0.331903	15				100.00
S=0.0815, R2=93.99%, R2adj=69.97%						

a Sum of Squares. b Degrees of Freedom (DOF) c Mean squares.

3.2.2 ANOVA for GRG

Analysis of Variance (ANOVA) is used to examine aspects which have a substantial influence on an individual's performance. This is performed by dividing total GRG variability, as measured by the sum of squared deviations from the GRG's average value into contributions from each wear parameter and listing them in Table 11 and 12. For each parameter based on EWM and EBWM methods, ANNOVA analysis is performed are evaluated. The ANOVA results for EWM and EBWM methods are shown in Tables 11 and 12, respectively. According to Table 11, the most important factor affecting EWM method is R which contributes for 43.31%, followed by L, S, and D, which contribute for 27.22%, 23.87%, and 2.62%, respectively whereas Table 12 depicts the contributions of factors affecting under the influence of unequal weights (EBW method). The most important factor affecting EBWM method is R which contributes for 45.86%, followed by L, S, and D, which contribute for 22.94%, 22.82%, and 2.38%.

3.2.3 Confirmation test

A confirmation test was done to validate experimental results based on the discovery of the ideal parameter's effecting numerous replies. The projected GRG is calculated using Eq. (9). Table 13 shows that the expected and experimental results are nearly identical for both the EWM and EBW method. Thus, indicating that the study was carried out satisfactorily. The measured GRG for the optimal combo level in EWM is 0.868, while the expected GRG is 0.869 whereas for EBW method experimental value is 0.943 while the expected GRG is 0.945. The experimental and expected outcomes were very similar. As a result, the grey relation approach is useful for optimising the wear parameter when numerous attributes must be investigated at the same time [32].

$$\hat{y} = y_m + \sum_{i=1}^{q} (\overline{y_i} - y_m) \tag{9}$$

where, $\hat{y}$ means predicted grey relation grade, y_m means average value of GRG, y_i GRG at optimum levels and q equals to number of factors.

Table 13. Confirmation test readings

	Best process parameters	
	Expected	**Investigational**
Using Entropy weight method	S1 L4 D1 R4	S1 L4 D1 R4
GRG	0.869	0.868
Equal weights consideration	S1 L4 D3 R4	S1 L4 D3 R4
GRG	0.945	0.943

Both the methods have been successively applied to forecast the of wear behaviour of Polyester composite using GRA technique. The best experimental conditions have been considered and closely matched to predicted values within the margin of minimum error. EWM method calculates the GRC by considering all variables with equal importance however EBW method decides the weightages depending upon variation in larger to smaller values. Even though both methods produced satisfactory results it is up to the decision maker to choose the weightage scenario depending upon the condition and application.

4. CONCLUSIONS

Die casting technique was used to create polyester composites with carbon fiber additions rising from 2 to 6 Wt% at 2 Wt% intervals. The findings show that increasing the content of carbon fibers reduces the sliding wear dramatically.

- Using Taguchi-GRA combinatorial approach, parameters of sliding wear along with multi-response characteristics using equal and by using Shannon Entropy method weights was optimized.
- For equal weights **S1 L4 D1 R4** (S1=2m/s L4=20N D1=1000m R4=6 Wt%) was found to have optimal value of wear process parameter in reference to low wear and frictional force whereas using unequal weights the optimized condition is changed and is found to be **S1 L4 D1 R4 (**S1=2m/s L4=40N D1=1000m R4=6 Wt%).
- As the contribution of both % reinforcement, load (L) are at high end using ANOVA analysis considered as they dominate the wear performance in comparison with other parameters compared.
- The confirmation test validated that the optimal parameters determine for the multi-response characteristics were effective.

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