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Multi-Attribute Decision-Making Parametric Optimization in Abrasive Wear of Polytetrafluoroethylene Matrix Composites Using Grey Relational Analysis

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ABSTRACT

Abrasive wear of polymer matrix composites (PMCs) with appropriate levels of process parameters is still challenging and a burning issue in the automobile and aerospace industries. There are pressing demands for abrasive wear-resistant PMCs in these industries. Consequently, this study uses multi-objective optimization of mass loss (M_L) and coefficient of friction (μ) of abrasive wear of polytetrafluoroethylene matrix composites via Taguchi-grey relational analysis (GRA). Parameters considered are grit size (G), speed (S), distance (D) and load (L). The abrasive wear data is obtained in a controlled manner based on the Taguchi L_9 orthogonal array. Analysis of variance (ANOVA) is performed to isolate significant parameters from the insignificant ones. The minimum M_L and μ were found at optimized parameters of 9 μm, 25 m, 3 N and 0.04 ms^{-1} and 9 μm, 9 N, 90 m and 0.04 ms^{-1}, respectively. Taguchi-grey relational analysis revealed G of 9 μm, S of 0.04 ms^{-1}, L of 9 N and D of 25 m as the optimal process parameters. ANOVA results revealed G as the most significant parameter having 77.27 % contribution to the wear. Confirmation results obtained using the optimal parameters showed improvement of 44.03 % in GR grade. Taguchi's GRA approach is efficient in tackling multi-attribute decision-making problems in the abrasive wear of PMCs.

Keywords: *Mass Loss · Coefficient of Friction · Taguchi Method · Grey Relational Analysis · PTFE Composites*

1. Introduction

Polymer matrix composites (PMCs) are emerging as viable substitute materials to metals and their alloys in several advanced engineering applications. Due to their high specific strength and modulus, PMCs have been used in automotive parts such as brake linings, hood, fenders and bumpers [1]. They have also been used as conveyor aids, mining, agriculture, chute liners and other areas where wear performance in dry condition is an important factor for the choice of materials. PMCs are exposed to abrasive wear in several environments [2]. Abrasive wear is a type of wear in which hard particles on one surface move against a

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softer one under the action of load, penetrate the softer surface thereby leaving grooves [3]. Most of abrasive wear problems happens in earth moving equipment, mining and in chute liners in power plants. Common matrices are epoxy, vinyl ester polyetheretherketone, polytetrafluoroethylene (PTFE) and others. PTFE indicates low wear resistance and in order to improve the wear resistance it is reinforced with glass, carbon, aramid fibres [4]. Therefore, fibre reinforced materials are very promising materials as sliding elements materials requiring low friction and wear for instance brakes or clutches [5]. Wear and coefficient of friction are not materials properties but rely upon the system where the materials operate [6]. It has been shown that polymer reinforced with fibres tend to have better wear properties [7], [8]. Thus due to their exceptional wear properties PMCs are being increasingly used in the automotive, aerospace and sports sectors.

In order to optimize multiple responses related to wear properties of composites, several decision making techniques like data envelopment analysis (DEA), analytic hierarchy process (AHP) and grey relational analysis (GRA) have been used. Of these GRA introduced by Deng in 1989 is the most commonly when the nature of the information is uncertain and incomplete [9]. Ramesha & Sureshab, (2014) used Taguchi-GRA to find the optimal settings of abrasive performance of carbon-epoxy hybrid composites. It was found that grit size and filler loading were most influential parameters [10]. Subbaya et al., (2012) optimized the multiple responses of hardness, wear coefficient and wear rate of silicon carbide reinforced epoxy composites using the Taguchi-GRA method. Taguchi L_9 orthogonal array of experiment was adapted for four parameter (silicon content, grit size, load and sliding distance) and at three levels for silicon content (0, 5 and 10 wt. %), grit size (80, 150 and 320 meshes), load (5, 10 and 15 N) and sliding distance (25, 50 and 75 m). Optimal combination parameter settings for the multi-responses was obtained at silicon content of 10 wt. %, grit size of 320 meshes, load of 10 N and distance of 75 m. It was concluded that silicon carbide content was the most influencing factor affecting the grey relational grade having a contribution of 70.09 % [11]. Dharmalingam, Subramanian & Kok, (2013) combined Taguchi with GRA to determine the optimal parameter settings of multiple responses of abrasive wear aluminium hybrid metal composites. Optimal parameters were found to be load of 20 N, sliding speed of 1.5 ms-1 and amount of molybdenum disulphide at of 2 wt. % [12]. An integrated Taguchi with GRA has been adopted for optimization of friction coefficient and wear rate of co-long composite by Sylajakumar, Ramakrishnasamy & Palaniappan, (2018). Results of the Taguchi GRA revealed the best combination of parameter levels for desirable wear properties as 60 N, 1 ms-1 and 1000 m for load, sliding speed and sliding distance, respectively. It was concluded that an improvement of 35.25 % in GRA was found [13]. Ikubanni et al., (2021) obtained combination of process parameters of hybrid reinforced Al metal matrix composite using Taguchi grey relational analysis with load, amount of reinforcement and speed as control factors. The amount of reinforcement for palm kernel shell was in the range of 0-6 wt. %, silicon carbide 2 wt. %, and load of 250, 500, 750 and 1000 g and speed of 250, 500, 750 and 1000 rpm. Based on multi-response optimization, it was found that the optimal combination of parameters was found to be load at 250 g, speed at 250 rpm and amount of reinforcement at 2 and 6 wt. % for volume loss and wear index, respectively [13]. Joseph, Kaisan and Sanusi (2023) optimized the wear properties of blended SAE 40 lubricant through Taguchi grey relational technique. The parameters studied were load and sliding speed on coefficient of friction and wear loss. They lowest coefficient of friction (1×10^{-3}) and minimum wear rate (7×10-3 mm3N-1m-1) were obtained at optimum conditions parameters of 8 N and 0.05 ms^{-1} [14].

From the foregoing, it was noted that Taguchi grey relational analysis (T-GRA) has been employed to optimize tribological properties of composite materials. However, little or no study that uses T-GRA to optimize abrasive wear of carbon and glass fibres reinforced PTFE composites was reported. Therefore, in this article Taguchi L9 orthogonal array (OA) experimental design and GRA was used to optimize the responses of dry sliding performance of abrasive wear experiment performed by varying the control parameters namely: grit size, load, sliding distance and sliding speed. Analysis of variance (ANOVA) was used to determine the contribution of each parameter on the abrasive performance of the composites of interest.

2. Materials and Methods

2.1 Materials

The wear properties of PTFE matrix composites sliding against protuberances on steel under dry conditions were investigated on a pin-on-disc machine. For glass reinforced PTFE composite, E-glass fibre having a nominal radius of 6.5 μm, length of 8×10^{-1} mm as well as aspect ratio of approximately 10 was used. Regarding the carbon fibre reinforced PTFE composite, non-crystalline petroleum coke with a purity of 99 % C and particle size of 75 μm was used. Therefore, in this study three materials namely PTFE, glass reinforced PTFE composite with 25 wt. % glass fibre (GF25) and 75 wt. % PTFE and carbon-reinforced PTFE composite having 25 wt. % carbon fibre (CF25) and 75 wt. % PTFE were tested. Properties of the reinforced PTFE composites were indicated in Table 1. Polymer Chemical Industry Ltd (Polikm A.Ş., Gebze/Turkiye) supplies the materials in the form of rectangular plates of dimensions (100 × 100 × 6) mm. This is because of the unavailability of equipment to manufacture the materials. Computer Numerical Control (CNC) water jet machining was used to cut samples of square size (25 × 25) mm from the plate for the abrasion experiment. Figure 1 shows the pictures of the materials used in this work.

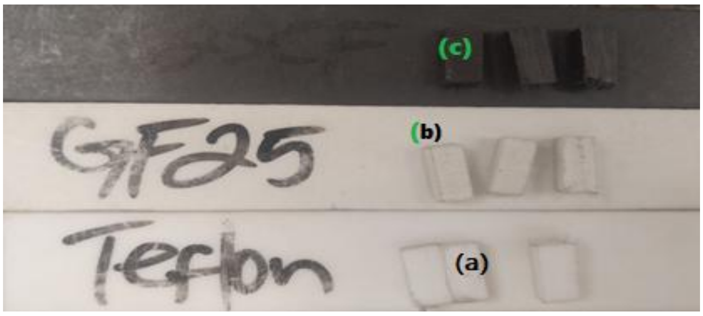

Figure 1. Materials used (a) PTFE, (b) Glass fibre reinforced PTFE composites and (c) carbon fibre reinforced PTFE composites

2.2 Methods

2.2.1 Experimental design (DOE)

In order to appraise the abrasive wear performance of the reinforced PTFE composites, four control factors viz load, (L, N), distance (D, m), grit size (G, μm) and speed (S, m/s) each at three (3) levels, were chosen as illustrated in Table 2. The levels of these parameters were selected based on the capacity of the tribometer: maximum load 10 N, maximum sliding speed 0.15 m/s, maximum sliding distance 100 m. Taguchi L_9 orthogonal array (OA) was contrived with nine runs to perform the abrasive wear tests as per ASTM G99. Silicon carbide as abrasives was glued to a rotating disc. The pins were bolted to a fixture and then inserted to arm of the pin-on-disc tribometer. Masses before and after abrasive tests were measured using a digital weighing balance with 10^{-3} g sensitiveness. The abrasive wear performance was evaluated using two responses: mass loss (M_L) as well as coefficient of friction (μ). The M_L was calculated as mass before experiment minus mass after experiment while μ as ratio of frictional force (Ff) to normal load (F) as shown in equations 1 and 2, respectively.

$$M_L = W_A - W_B \quad (1)$$

$$\mu = \frac{F_f}{F} \quad (2)$$

Where M_L = mass loss (g), W_A = mass before experiment and W_B = mass after the experiment.

Table 1. Some properties of PTFE matrix composites

Samples	Colour	Code	CS (Kgcm^{-2})	Impact resistance (Kjm^{-2})	Density (gcm^{-3})
Polytetrafluoroethylene	White	PTFE	50	16.5	2.2
Glass reinforced Polytetrafluoroethylene	Grey	GF25	70	15	2.25
Carbon reinforced Polytetrafluoroethylene	Black	CF25	110	9	2.15

Table 2. Control factors of abrasive wear and their levels

Symbol	Process variables	Unit	Level 1	Level 2	Level 3
S	Sliding speed	m/s	0.04	0.08	0.14
D	Sliding distance	m	25	75	90
L	Load	N	3	6	9
G	Grit size	μm	9	23	89

2.2.2 Signal Noise Ratio (SNR)

For a high quality system based OA experiment, a most useful and powerful tool called Taguchi technique [13] is often applied. The Taguchi technique uses OA to minimize variance and optimize process variables. In the Taguchi technique, SNR is employed as a performance characteristic to quantify process robustness and to appraise deviation from required values. The SNR which is a logarithmic function is determined by appraising the amount of signal (mean) to the noise (standard deviation). There are three kinds of SNR which nominal-the-best, higher-the-better and smaller-the-better. With respect to study of abrasive wear, smaller material loss and coefficient of friction is desired thus the smaller-the-better SNR (equation 3) was chosen in this study [15].

$$SNR = -log10\frac{1}{n}(\sum_{i=0}^{n}(y_i)^2) \quad (3)$$

Where n = number of observations and y_i = observed data.

2.2.3 Optimization Technique by Grey Relational Analysis (GRA)

In several-response problem, the effect and correlation between various parameters are intricate and unclear. This is referred to as grey meaning poor and uncertain information. The grey relational analysis investigates this intricate uncertainty among several outputs in a given system and optimizes the system with the aid of grey relational grade. Consequently, a several-response optimization challenge is minimized to one response optimization known as grey relational grade (GRG).

Step-1

To minimize variability and avoid different units, the data is normalized as a first step. It is necessarily needed as the variation of one data varies from another data. This normalization is between 0 and 1. Generally, it is a technique of changing actual data to a comparable data. In this study, the target is to minimize mass loss and coefficient of friction and thus smaller-the-better option was chosen to scale the data into acceptable range using equation (4) given below.

$$X_k^*(k) = \frac{MaxX_i(k) - X_i(k)}{MaxX_i(k) - MinX_i(k)} \quad (4)$$

Where i = 1, 2, 3, … m; k = 1, 2, 3, … n. m = test data and n = number of responses or outputs, $X_i(k)$ = actual sequence, $X_k^*(k)$ = sequence after data normalization, $MaxX_i(k)$ = biggest value of $X_i(k)$, $MinX_i(k)$ = lowest value of $X_i(k)$ and X = required value.

Step-2

Here the grey relational coefficient ($\xi_i(k)$ is computed from the reference sequence using equation (5) as shown below.

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \quad (5)$$

Where Δ_{oi} = is deviation sequence of the reference sequence as well as the comparability sequence and is expressed as (equation 6).

$$\Delta_{oi}(k) = |X_0(k) - X_i(k)| \quad (6)$$

Where $X_0(k)$ = the reference sequence and $X_i(k)$ = the comparability sequence. Δ_{min} and Δ_{max} = minimum and maximum values of the absolute differences (Δ_{oi}) of all comparing sequences. ζ = distinguishing or identification coefficient and the range is between 0 to 1. Usually, the value of $\zeta = \frac{1}{2}$.

Step-3

Here the grey relational grade (GRG) is computed using equation (7) provided below.

$$\gamma_i = \frac{1}{n}\sum_{i=1}^{n} \xi_i(k) \qquad (7)$$

Where γ_i = GRG obtained for ith test run, n = summation count of performance attributes. The GRG depicts the level of correlation between the reference sequence and the comparability sequence and is the overall representative of all the quality characteristics. Thus the multi-response optimization problem is converted into single response optimization problem through grey relational analysis coupled with Taguchi approach.

Step-4

Then an optimal level of process parameters is determined using higher grey relational grade that indicates the better product quality. To obtain this, average grade values for each level of process parameter is to be find out which can be shown as mean response table. From, mean response table, higher values of average grade values is chosen as optimal parametric combination for multi-responses.

Step-5

After obtaining the best combination of parameter settings, the next method is analysis of variance (ANOVA) for determining the significant parameters influencing the multi-responses at 95% confidence level and thus providing useful information about the test data. Taguchi technique cannot appraise the influence of each control factor on multi-responses [16], [17]. Consequently, ANOVA is applied to ascertain the percentage of contribution of each factor. The ANOVA separates out the total variability of the response into each parameter contributions and error. The P-value (probability of significance) is in general computed according to F value or Fisher's F- ratio to obtain the information of importance on the chosen response if its value is < 0.05. The degree of freedom (DF) is desired to determine the mean square (MS) and measure the availability of independent information to find the sum of squares (SS). In an ANOVA, mean square deviation and F-value is computed by MS = SS/DF and F = MS for a source parameter/MS for the error.

Step-6

After optimal combination of process parameters are found out, the next step is very the improvement of grey relational grade through conducting confirmatory experiment. The predicted value of GRG for optimal level can be obtained as follows,

$$\vartheta_{Predicted} = \vartheta_T + \sum_{i=1}^{0}(\vartheta_{im} - \vartheta_T) \qquad (8)$$

Where ϑ_T = total mean GRG, ϑ_{im} = mean of GRG at optimal setting of each parameter, and 0 = number of significant process parameter. Figure 2 shows the schematic representation of the TGRA adapted in this study.

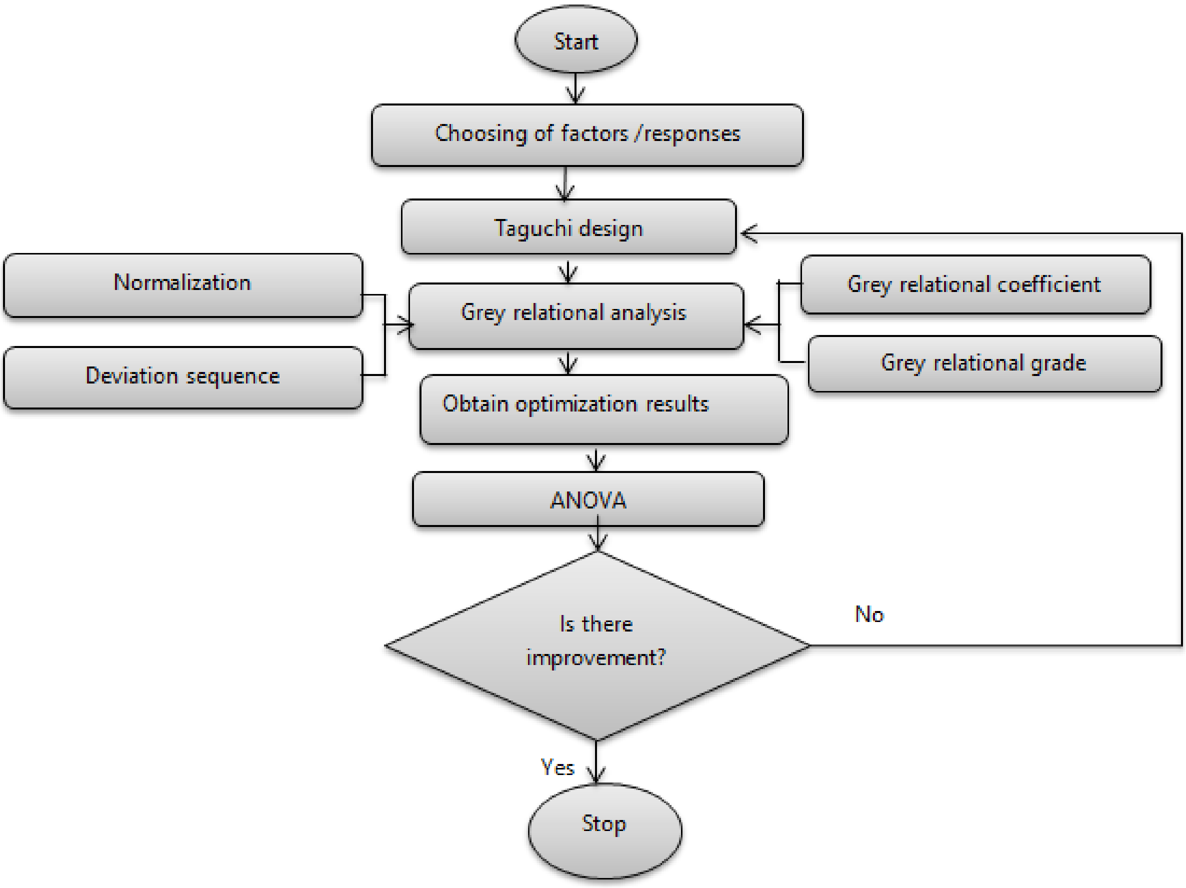

Figure 2. Schematic representation of the Taguchi grey relational analysis methodology adapted for this study (Authors' computation)

3. Results and Discussion

The experimental results of the abrasive wear tests are presented in Table 3 as per the Taguchi L_9 OA.

Table 3. Experimental results of mass loss and μ according to Taguchi L_9 OA design

Run	Materials	L (N)	G (μm)	D (m)	S (m/s)	M_L	μ	M_L SNR (dB)	μ SNRs (dB)
1	PTFE	3	9	25	0.04	0.00135	0.11	57.3933	19.0545
2	CF25	3	23	45	0.08	0.00625	0.28	44.0824	11.0879
3	GF25	3	89	55	0.14	0.00920	0.53	40.7242	5.4655
4	PTFE	6	9	45	0.14	0.00265	0.27	51.5351	11.2609
5	CF25	6	23	55	0.04	0.00455	0.13	46.8398	17.9582
6	GF25	6	89	25	0.08	0.00895	0.45	40.9635	6.9841
7*	CF25	9	9	55	0.08	0.00295	0.03	50.6036	29.4991
8	PTFE	9	23	25	0.14	0.00450	0.09	46.9357	21.3607
9	GF25	9	89	45	0.04	0.01285	0.31	37.8219	10.2431

*Initial design run

3.1 Effect of the Parameters of Mass Loss (M_L) and coefficient of Friction (μ)

The main effect plots (Figure 3 (a) and (b)), shows the effect of the parameters on the M_L and μ of the materials.

As the load increases the M_L increases while the μ decreases. The loss in M_L due to increasing load is associated with the contact between the materials and the SiC counter-face increased thereby increasing the contact pressure. More so, the load breaks the layer which separates the materials and the SiC paper. For decrease in μ due to increasing load, it is because of the formation of layer by the fibres acting as lubricant.

These findings were in agreement with literature data [18]. It is seen in Figure 2 (a) and (b) that decrease in grit is accompanied by decrease in M_L and μ. This phenomenon is explained on the basis that smaller grit size is attributed to smoothness of the SiC particles leading to the formation of protective layer (lubricant) at the contact surface, preventing direct contact of the materials with the abrasive surfaces. This finding agrees with the finding of [19] when bronze and carbon filled PTFE was studied. With respect to the effect of sliding distance on the M_L and μ, it can be observed that as the sliding distance increases the both M_L and the μ decreases. This is related to the sliding distance behaving as lubrication to the contact surfaces thus separating the materials from the abrasive counter-face. Also, mass debris is transferred from the matrix leading to lower. Similar findings were reported by [20] when nylon 6 was reinforced with glass fibre at varied amounts. Increase in sliding speed leads to decrease in M_L but increase in μ as depicted in Figure 3 (a, b). In the former, increasing the speed causes oxidization ad change in temperature at the contacting surfaces thus forming of a mechanically mixed and rough coating which is laid on the parts. While in the latter, there is no oxidation and formation of oxide layer thus raising the μ

As both M_L and μ are of equal importance, abrasive wear influences PMCs to a greater degree. Hence, simultaneous optimization of M_L and μ is importantly needed to extract decision on abrasive performance of PMCs.

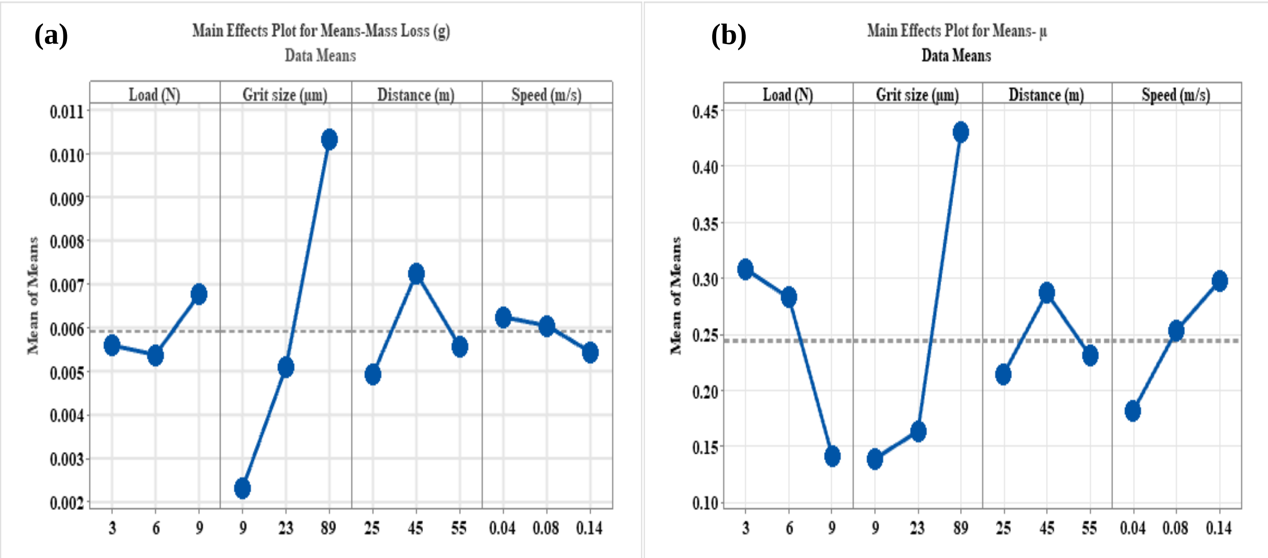

Figure 3. Main effect plot for (a) M_L and (b) μ

3.2 Optimized Settings for Minimum M_L and μ

Table 4. Response table for Signal to Noise Ratios of M_L (Smaller is better)

Level	Load (N)	Grit size (µm)	Distance (m)	Speed (m/s)
1	**47.40**	**53.18**	**48.43**	**47.35**
2	46.45	45.95	44.48	45.22
3	45.12	39.84	46.06	46.40
Delta	2.28	13.34	3.95	2.14
Rank	3	1	2	4

Table 5. Response table for Signal to Noise Ratios for (μ) Smaller is better

Level	Load (N)	Grit size(µm)	Distance (m)	Speed (m/s)
1	11.869	**19.938**	15.800	15.752
2	12.068	16.802	10.864	**15.857**
3	**20.368**	7.564	**17.641**	12.696
Delta	8.498	12.374	6.777	3.161
Rank	2	1	3	4

To obtain the optimum parameter settings for lowest M_L ad μ Tables 4 and 5 aforesaid were used. For the M_L the minimum was obtained at 9 µm, 25 m, 3 N and 0.04 ms^{-1}. This combination was ranked G1S1L1D1. For μ, the optimum combination of that would produce the lowest μ was determined to e 9 N, 9 µm, 90 m and 0.08 ms^{-1}. This combination is ranked G1L3D3S3. These values were obtained based on the maximum values (bolded) as illustrated in Tables 4 and 5.

3.3 Implementation strategy to ascertain multi-response parametric optimization

Step-1

The test data has been normalized for both mass loss and μ using equation 2 to obtain grey relational generation values as shown in Table 6.

Table 6. Grey relational generation values

Run	M_L	μ
	Smaller-the-better	Smaller-the-better
1	1.0000	0.8438
2	0.5739	0.5085
3	0.3174	0.0000
4	0.8870	0.5195
5	0.7217	0.8138
6	0.3391	0.1712
7	0.8609	1.0000
8	0.7261	0.8959
9	0.0000	0.4515

Step-2

From Table 4, GRCs have been determined via equation 3. The value of ζ is taken as $\frac{1}{2}$ as equal weighting needs to be assigned to both quality characteristics. The results are shown in Table 5.

Step-3

Next, grey relational grade (GRG) has been found out using Equation 3 from the results of GRCs. Results of GRC, GRG and ranking were provided in Table 5. Correspondingly, the GRG values were used to produce SNRs (Table 7). Higher SNRs is useful and shows that the test data lies close to the ideal normalized values of GRG. Figure 3 shows the plot of GRG versus GRG SNRs. It indicates that the seventh trial has the highest SNR. Accordingly, the seventh run was ranked first. The trailing behaviour of the GRG, above the graph of its SNRs in Figure 4 also supplements the foregoing discussion. This result is utilized for optimizing the multi-responses as it is converted to a single grade.

Table 7. GRC, GRG and GRG signal noise ratios

	Evaluation of Δ_{0i}		GRC		GRG	Rank	GRG SNRs
Run	M_L	μ	M_L	μ			
1	0.0000	0.1562	1.0000	0.7620	0.8810	2	-1.1004
2	0.4261	0.4915	0.5399	0.5043	0.5221	6	-5.6450
3	0.6826	1.0000	0.4228	0.3333	0.3781	9	-8.4487
4	0.1130	0.4805	0.8156	0.5010	0.6628	5	-3.5726
5	0.2783	0.1862	0.6425	0.7287	0.6856	4	-3.2791
6	0.6609	0.8288	0.4307	0.3763	0.4034	8	-7.8833
7	0.1391	0.0000	0.7823	1.0000	0.8912	1	-1.0009
8	0.2739	0.1041	0.6461	0.8277	0.7369	3	-2.6522
9	1.0000	0.5485	0.3333	0.4769	0.4051	7	-7.8489

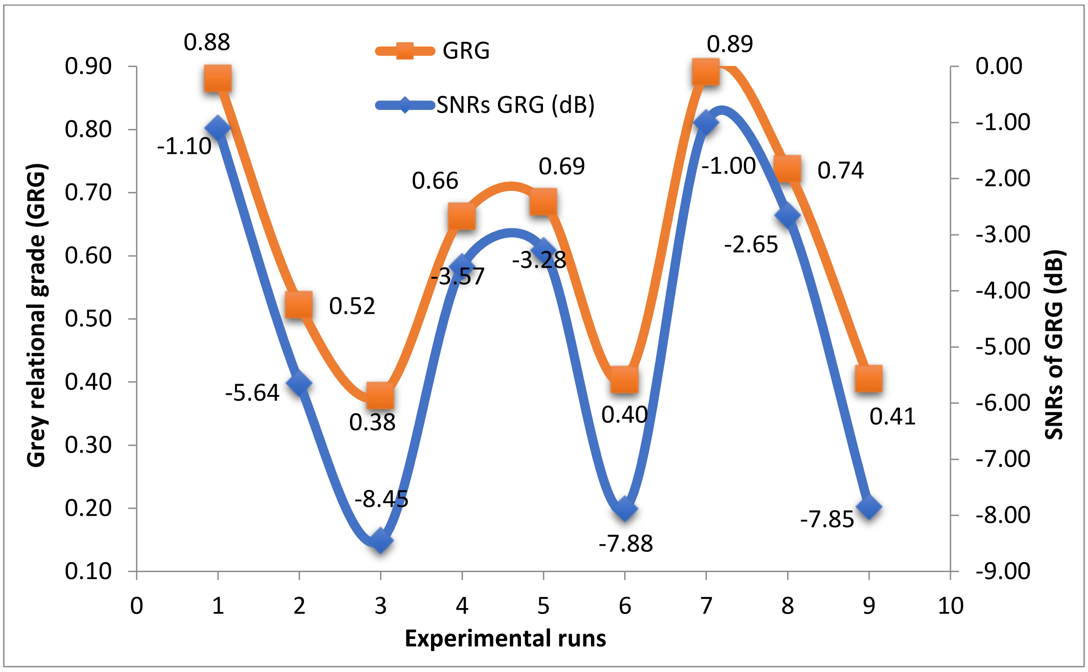

Figure 4. Plot of GRG against GRG SNRs

Step-4

From the value of GRG, the influences of each process parameter at different levels are graphed and depicted in Figure 4 and mean GRG is provided in Table 6. The optimum parametric setting combination is selected based on maximum mean GRG values as bolded in Table 6. The maximum value of GRG signifies a stronger correlation to the normalized data and effective performance. Therefore, the optimal levels for multi-responses becomes L3G1D1S1 i.e. 9 N, 9 μm. 25 m, 0.04 ms^{-1}, respectively. The maximum values of GRG (Figure 5) give the minimum values of M_L and μ. The delta values of mean GRG for abrasive parameters were as 0.0938 for load, 0.4161 for grit size, 0.1438 for distance and 0.0646 for speed (Table 8). This result shows that grit size has the most significant influence on the multi-responses compared to distance, load as well as speed. The sequence of significance of process parameters on multi-responses are grit size>distance> load>speed.

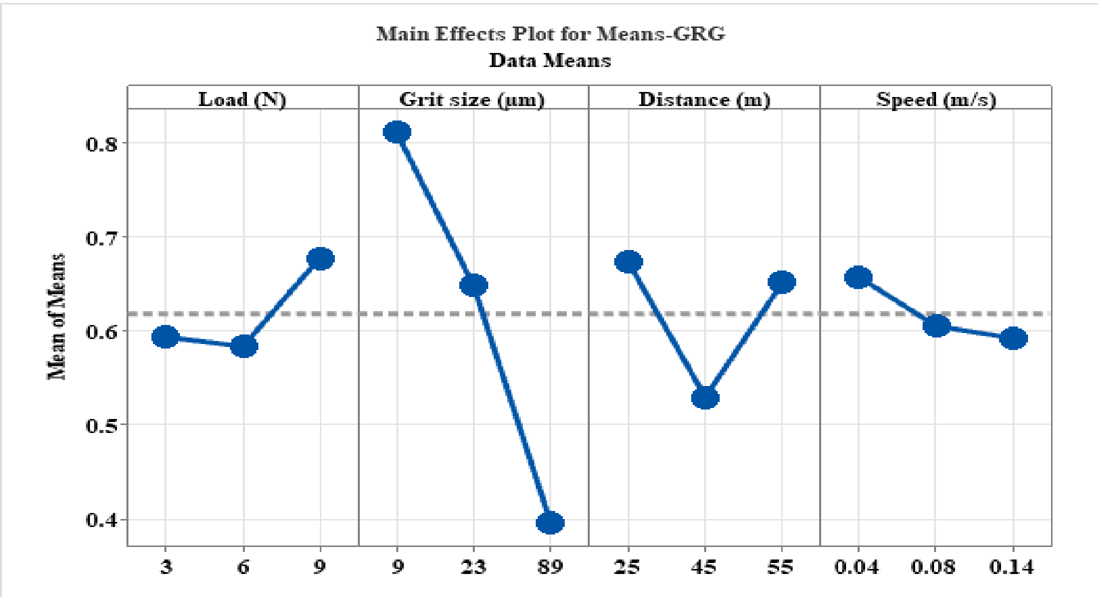

Figure 5. Main effect plot of GRG

Table 8. Main effect on mean GRG

Level	Load (N)	Grit size (μm)	Distance (m)	Speed (m/s)
1	0.5937	0.8116	0.6738	0.6572
2	0.5839	0.6482	0.5300	0.6056
3	0.6777	0.3955	0.6516	0.5926
Delta	0.0938	0.4161	0.1438	0.0646
Rank	3	1	2	4

Step-5

Next, ANOVA table is generated taking into cognizance GRG value depicted in Table 9. This table provides the importance of process parameters on multi-responses. From Table 9, it is found that grit size is the significant process parameter influencing multi-responses as its p-value is less than 0.05 i.e. p-value = 0.012 at 95 % confidence level. Load, distance and speed did not exhibit any significance on the two responses at the same time.

Table 9. ANOVA for grey relational grade

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value	Remarks
Load (N)	1	0.010580	3.28%	0.010580	0.010580	0.80	0.423	Insignificant
Grit size (μm)	1	0.249274	77.27%	0.249274	0.249274	18.75	0.012	significant
Distance (m)	1	0.003864	1.20%	0.003864	0.003864	0.29	0.618	Insignificant
Speed (m/s)	1	0.005704	1.77%	0.005704	0.005704	0.43	0.548	Insignificant
Error	4	0.053174	16.48%	0.053174	0.013293			
Total	8	0.322595	100.00%					

Step-6

Confirmation was performed to identify the improvement of GRG from initial combination of parameter levels to the combination of optimum parameter settings obtained in abrasive wear of reinforced PTFE matrix composites. The estimated GRG can be determined using equation 8. The GRG at optimal setting becomes 0.8184 which is close to predicted value (0.9650). From confirmation run (Table 10), it is revealed that the GRG of both responses such M_L and μ are significantly improved (0.4403) through setting of optimal parametric combination. This tallies with the in [21] when Taguchi-GRA was applied to optimize the reinforcement parameters of aluminium alloy composites. From the above analysis, the parameters are optimized and minimum values of M_L and μ are obtained through Taguchi-grey relational analysis technique.

Table 10. Confirmation results

	Initial parameter setting	Optimal abrasive setting	
		Prediction	Experiment
Level	L1G3D3S3	L3G1D1S1	L3G1D1S1
M_L	0.0092		0.0034
μ	0.2800		0.0400
GRG	0.3781	0.9650	0.8184
GRG improvement = 0.4403			

4. Conclusion

This study presented the results of decision making multi-criteria process optimization of parameters in abrasive wear of reinforced polytetrafluoroethylene composites via Taguchi grey relational analysis. At first, the output of varying four parameters (load, grit size, sliding speed and sliding distance) on the multi-responses of mass loss and coefficient of friction were investigated through Taguchi L9 orthogonal array and grey relational analysis strategy. Based on the response table of the grey relational grades, optimal parameter settings for better abrasive wear performance of the reinforced polytetrafluoroethylene composites were determined to be load at 9 N, sliding speed at 0.04 ms^{-1}, grit size at 9 μm and sliding distance at 25 m. Analysis of variance for the grey relational grade showed only p-value of grit size was less than 0.05 and thus the significant parameter. Lastly, confirmation experiment carried out to validate the betterment of 0.4403 in grey relational grade, from 0.3781 for the initial design control parameters (L1G3D3S3) to 0.8184 for the best parameters (L3G1D1S1). The Taguchi coupled with grey relational analysis has proven to be an efficient technique for addressing multi-attribute decision making problem in abrasive wear.

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6. References

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