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Grey Based Taguchi Optimization Method for Abrasive Wear Appraisal of Fibre-Reinforced PTFE Composites

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Abstract: The current study is aimed at optimizing the abrasive wear property of fibre reinforced polytetrafluoroethylene (PTFE) composites. The test was contrived based on Taguchi L_9 orthogonal array for the optimization of test trials. To appraise the abrasive wear trend of the PTFE based composites satisfying multi-objective criteria, Taguchi method combined with grey relational analysis (GRA) has been used. Abrasive wear test was performed using pin-on-disc configuration as per ASTM G99 standard involving four process parameters. Analysis of variance was used to establish significant parameters which influence the abrasive wear of reinforced PTFE composites. Observation revealed that grit size has the most significant effect on abrasive wear of reinforced PTFE composites. After exhaustive investigation of parameters, optimum combination of parameters was established. Linear regression model was built to predict the optimized conditions. The model as well as the optimum parameter values could be used by the abrasion industries for reduction in the time and cost expanded on wear test thus increasing productivity.

Keywords: PTFE, glass, carbon, abrasive wear, Taguchi, grey relational analysis

1. Introduction

Polymer matrix composites (PMCs) have been gaining attention as materials for structural application because of their exceptional features including ease of manufacture and high specific stiffness and strength. Thus, they are largely employed in applications needing abrasion resistance. Usual applications are clutches, brakes, vanes, pumps handling industrial fluids, gears, conveyor aids, bushes, seals in mining and agricultural hardware [1-2]. To design and develop PMCs suitable for aforesaid applications, polytetrafluoroethylene (PTFE) is commonly chosen owing to its thermal stability, chemical inertness, anti-friction and indentation. Similarly, fibres are added to polymers as a means of increasing their load bearing ability [3–5]. In abrasive conditions, inclusion of fibres into polymer lead to dual effect of either improvement or deterioration [6]. According to the work of Harsha and Tewari, it was found that the abrasive performance of polymeric polysulfone deteriorated when 20 wt.% and 30 wt.% glass fibre was added to it [7]. However, Suresha et al. reported improvement on the abrasive wear performance of epoxy reinforced with carbon fabric and addition of 5 wt. % and 10 wt. % graphite fillers into the epoxy-carbon fabric composites [8]. Similarly, Suresha et al. and Suresha and Kumar reported that there was an enhancement of abrasive wear performance of vinyl ester and P66/PP polymers when glass and carbon fibres and nano-clay and discontinuous carbon fibre were introduced into the polymers [9-10], respectively. The effect of various factors on abrasive wear of composites is depicted in Figure 1.

In addition to natural characteristics of materials, wear of materials relies on operating conditions as well as environments [12-13]. To better comprehend the wear rate of materials in abrasive environment, components of the materials and the operating conditions are important. Abrasive wear of materials such as PMCs have been modelled using several kinds of equations as reported in [14-15]. The equations expressed wear rate as a function of mechanical

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properties, for example hardness of reinforcements and operating conditions such as applied load. In order to advance the understanding of wear, different authors experimentally studied wear rate of various PMCs [16–[21]. In these experiments it was found that the wear rate of PMCs was influenced by the operating conditions such as load, sliding distance and grit size. Therefore, abrasive wear is a phenomenon influenced by operating conditions. The problem of the wear equations and experiments is inadequate information on the effect operating parameters influencing the abrasive wear of PMCs.

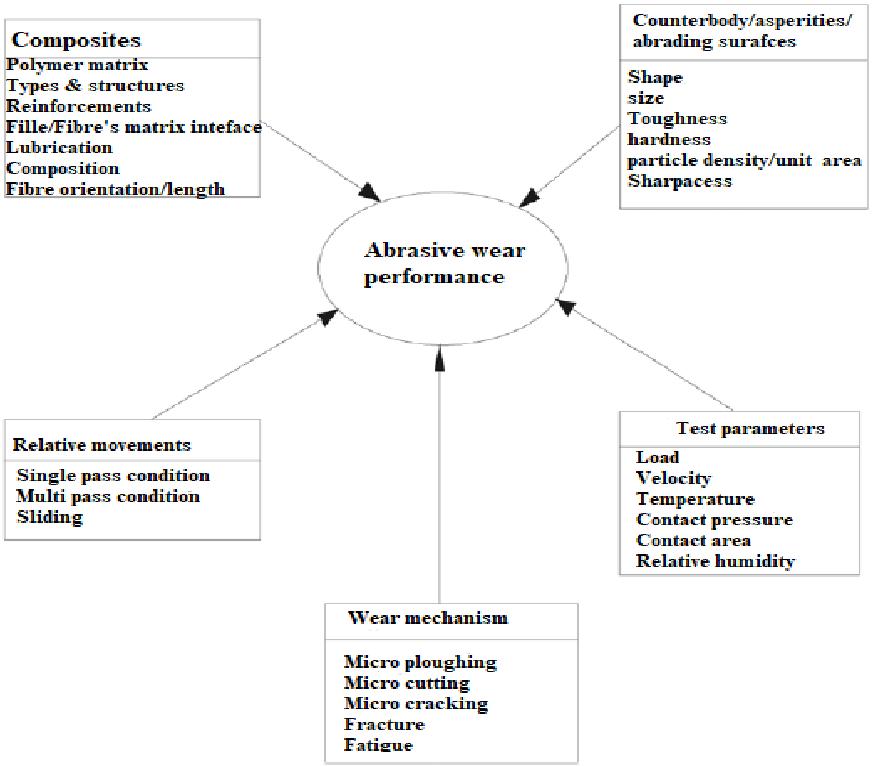

Fig. 1 - Effect of different parameters on the abrasive wear of composites [11]

In order to study the effect of process parameters for optimization of single outputs, traditional and Taguchi approaches are used. However, in wear problem of PMCs several parameters and responses are involved. The above approaches consume time and cost due to individual computation of each response and the overall determination of optimized settings are based on researcher's experience. This method is handicapped especially when dealing with problems of several responses due to likelihood of erroneous judgment [22-23]. As panacea to this problem, grey based Taguchi optimization method has been proposed for multi-objective outputs. Grey relational analysis (GRA) gives an inclusive pointer, grey relational grade (GRG), to depict the performance of all responses. Grey based Taguchi approach is used in addressing optimization problems involving multiple responses in several fields as in dimple geometry optimization of stainless steel (SS36L), machining parameters to drill hybrid aluminium metal matrix composites [24], thin-film sputtering process with many quality characteristics in colour filter manufacturing [25], submerged arc welding process parameters in hard facing [26], turning operations with multiple performance characteristics [27] and flank milling parameters [28].

Therefore, this study is aimed at optimizing parameters affecting the abrasive property of PTFE matrix reinforced with 25 wt. % glass and 25 wt. % carbon fibres composites (GF25 and CF25) as shown in Table 1 . The study is thus formulated into an optimization problem using grey based Taguchi approach so that the optimum parameter settings for multiple responses of volume loss (V_L) as well as specific wear rate (K_s) of the PTFE matrix composites are estimated.

2. Materials and Method

2.1 Materials

The wear property of PTFE matrix composites sliding against silicon carbide (SiC) abrasive paper on toughened disc under non-lubricated conditions is investigated through a bi-directional pin-on-disc configuration. Reinforcements used are glass and carbon fibres in 25 wt. %. For the glass-PTFE composite, E-glass milled fibre whose nominative diameter of 13 µm, nominal length of 0.8 mm and aspect ratio of 10 was used. Whereas for carbon-PTFE composite, amorphous petroleum-coke having particle size <75 µm and purity of 99 % was utilized. Names, codes and some properties of the materials used in the study are displayed in Table 1. Polymer Chemical Industry Ltd. (Polikim A.Ş., Gebze/Turkiye) in Turkey provides the materials in the form of plates. Produced using the compression molding process, the materials in rectangular forms were supplied by Polymer Chemical Industry Ltd., (Gebze, Turkey). At present, these materials are used in the automotive and aerospace industries. The materials, their codes, and some selected properties are shown in Table 1. Computer numerical water jet machining was used to cut samples for the tests from the rectangular plates, whose dimensions were 500 mm × 500 mm × 6 mm. Thereafter, the samples were cleaned before the experiments. SiC particles of sizes in the range of 150, 400, and 1000 meshes were used as abrasives.

Table 1 - Physical property of materials used in the study

Samples	Code	Color	ρ (gcm^{-3})
Glass–PTFE composite	GF25	Grey	2.30
Carbon–PTFE composite	CF25	Black	2.15
Polytetrafluoroethylene	PTFE	White	2.20

2.2 Method

2.2.1 Taguchi Experimental Design

Classically, parameter optimization is intricate and difficult to use when the number of factors keep increasing leading to several experiments. This drawback is solved by Taguchi approach using exclusive orthogonal arrays (OAs) to investigate the whole parameters with small number of tests at lowered cost and time. In this study, parameters affecting the wear rate of PTFE matrix composites such as load (L), girt size (G), sliding distance (D) and sliding speed (S) were treated as control parameters affecting the process. In the OA, four control parameters and each at three settings were taken. Coded and uncoded values of the control parameters are shown in Table 2. The OA has nine rows and four columns as depicted in Table 3. Each parameter was allocated to a column. The tests were randomly arranged in order to minimize errors associated with experiments. Responses are the outputs of the experiments. The current study was aimed at minimizing V_L as well as K_s. Therefore, V_L and K_s were regarded as responses. The results of the experiments based on the Taguchi were transformed into signal noise ratios (SNRs) as tabulated in Table 4. A design parameter with a huge variation in the SNRs from one parameter level to another signifies that the parameter is an important contributor to the performance characteristic. The final phase in the design of the experiment is prediction as well as verification using optimum settings of parameters. Several SNRs functions exist but here the smaller the better characteristic was selected and can be computed as logarithmic transformation of the loss function using equation (1).

$$SNRs_{(STB)} = -10\log 10\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (1)$$

Where n = number of experimental trials, y_i = output value of the i^{th} experiment.

Table 2 - Process parameters and their levels

Symbol	Parameter	Unit	Level 1	Level 2	Level 3
L	Load	N	3	6	9
G	Grit size	mesh	1000	400	150
D	Sliding distance	m	25	45	55
S	Sliding speed	ms^{-1}	0.04	0.08	0.14

Table 3 - Standard Taguchi L_9 experimental design

Run	Parameter L	Parameter G	Parameter D	Parameter S
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

2.2.2 Wear Experiment

Pin-on-disc configuration (according to ASTM: G99 standard) was applied for the abrasive tribological experiments tribometer machine. Rectangular surface of (20 × 20 × 6) mm composite samples were fixed to a fixture specially fabricated to hold the composite samples before putting the composite samples to the lever of the tribometer. The waterproof silicon carbide (SiC) abrasive papers glued to a rotating disc which come in contact with the composite samples. Prior to experimentation, the samples were polished against SiC paper of 1000 mesh to establish good contact with the counter face. The surface finish of 0.12 µm centre line average was maintained for each sample to ensure good contact. Samples' surfaces were cleaned with acetone and completely dried before experimentation. From the first to the last of the experimentation, samples were maintained along the same wear path and for each sample a new SiC abrasive paper was applied. Prior to performing multi-faceted optimization, prelude trials were conducted so that an adequate insight into the effect of parameters upon V_L and K_S. These analyses not only give insight into the characteristic trends of each parameter but also assist in putting the parameter levels in order. Experiments concerning grey relational analysis were carried out as parameters depicted in Table 2. The mass losses of the samples were recorded using digital weighing balance (Ohaus: accuracy 0.001 g). The difference between the mass before testing and mass after testing of the samples gives the amount of the wear loss. At least two sets of experiments were performed for each run and average data reported and used for final analysis. The abrasive wear loss was quantified by loss in mass which was then transformed into volume loss via density data. The volume loss (V_L) and the specific wear rate (K_S) were determined based on equations (2) and (3), respectively.

$$VL = \frac{\Delta M}{\rho} \qquad (2)$$

$$K_S = \frac{\Delta M}{\rho L D} \qquad (3)$$

where ΔM = change in mass (g), VL = volume loss (mm^3), ρ = (gcm^{-3}), L = load (N), D = sliding distance (m) and S sliding distance (ms^{-1}).

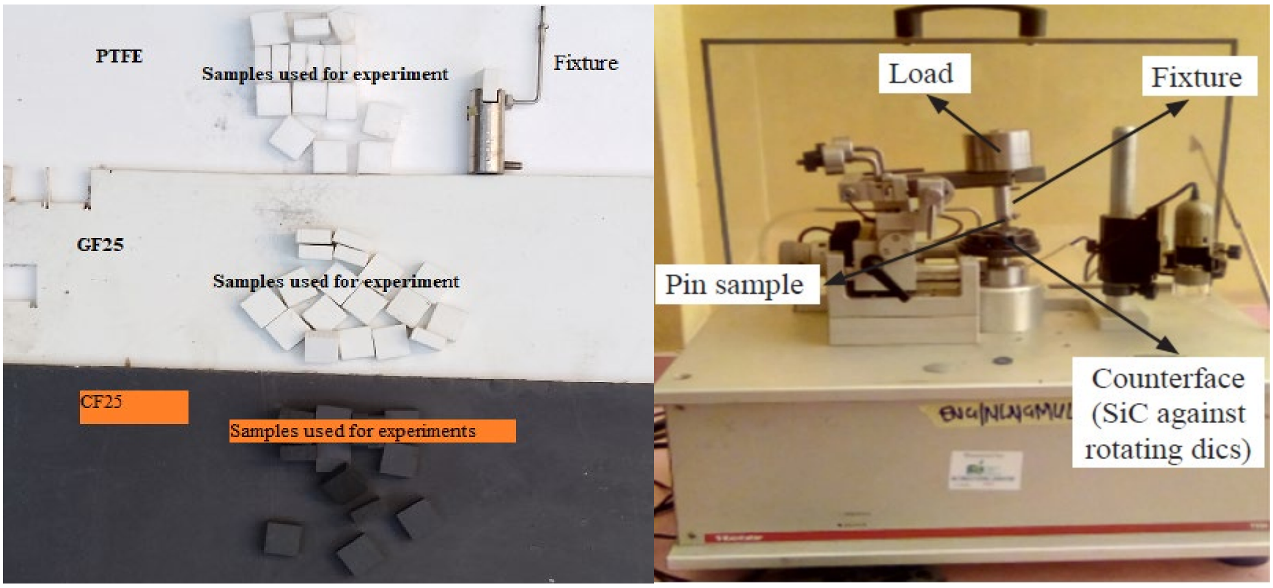

Fig. 2 - The rectangular plates, samples of materials used and experimental set-up of the abrasive experiment

2.2.3 Grey Relational Analysis (GRA)

Proposed by Deng, grey system theory is helpful in dealing with poor, uncertain as well as insufficient data. GRA is according to this theory and is related to Taguchi approach presents a method of optimization of parameters affecting tribological rate involving many performance objectives. In GRA, results gotten from the experiments were first normalized ranging from 0 to 1[29]. This operation is referred to as grey relational generation (GRGr). In GRGr, the normal values of V_L as well as K_s correspond to the smaller the better-quality characteristic which was given by the following equation:

$$X_i^*(k) = \frac{max\varphi_i(k) - \varphi_i(k)}{max\varphi_i(k) - min\varphi_i(k)} \tag{4}$$

Where $X_i^*(k)$ is the value after normalization, $\varphi_i(k)$ is the comparability sequence, k = 1 and 2 for V_L and K_s, i = 1, 2, 3… for 1-9 experiments, max$\varphi_i(k)$ = maximum value of $\varphi_i(k)$ and min$\varphi_i(k)$ = minimum value of$\varphi_i(k)$.

Secondly, the deviation sequence of the normalized data which is the difference of the absolute value of $X_0^*(k)$ can be computed using equation (5).

$$\Delta_{oi}(k) = \left| X_0^*(k) - X_i^*(k) \right| \tag{5}$$

Where $\Delta_{oi}(k)$ stands for deviation, $X_0^*(k)$ denotes the normalized data, and $X_i^*(k)$ refers to the comparability sequence. Table 7 shows the reference and deviation sequences of the study. Thirdly, grey relational grade (GRG) that depicts the relationship between reference sequence and the real normalized test results can be estimated through equation (6):

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \tag{6}$$

Where $\xi_i(k)$ = grey relational coefficient (GRC) of response variable, Δ_{min} and Δ_{max} are the minimum and the maximum deviations of the individual target factor, respectively. The identification coefficient is characterized by ζ and is held in the range of $\zeta \epsilon [0,1]$. This is commonly placed at 0.5 to give equal weights to every variable. In the fourth stage of GRA, GRG is obtained by finding the average of the GRG of individual response according to equation (7):

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

where γ_i presents the GRG whereas n stands for number of multiple responses. Table 8 depicts the GRG computed for the data. Finally, prediction and confirmation of the best conditions using the optimum combination of parameters was performed. The predicted results are achieved using equation (8) given below.

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{q} \gamma_0 - \gamma_m \tag{8}$$

where γ_0 = biggest mean of GRG at best operating conditions, γ_m = average GRG. q = parameter that exhibits the parameters which affect the responses.

2.2.4 Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) is traditionally applied to find out the effect of independent variables on dependent variables. Percentage contribution (%C) of each factor is used as a criterion for establishing the effect of each independent variable on the dependent variable. A large %C signifies an independent variable (parameter) exerting a significant influence on the dependent variable (response).

3. Results and Discussion

3.1 Effect of the Process Parameters on V_L

The results of V_L in Table 4 were transformed into SNRs using Mintab 2007 software. The most influential parameters were established using the maximum-minimum i.e. delta (max-min) values in the table of response for SNRs provided (Table 5). Ranks are assigned to the parameters based on the max-min value. Max-min with highest value is assigned the first rank and max-min with lowest value the last rank and named the most and least influential process parameter affecting the V_L. Therefore, the process parameters are ranked in the following order as G (1st) D

(2nd), S (3rd) and L (4th) as seen in Table 5. Desired parameter levels were bolded to make understanding easier in all tables shown in the study.

Based on the response in Table 5, the main effects graph for SNRs of V_L were produced as displayed in Figure 3 (a). The behaviour of the graph indicated that V_L is significantly influenced by variation in the SiC grit size. As observed in Table 4, the V_L increased with decrease in the SiC grit size. A possible reason for this is penetration of large grit size into the materials thereby pulling out or removing either the matrix or the fibre from the whole system of composites. The increasing behaviour in a steep manner of SNRs for V_L from 150 to 1000 mesh in Figure 3 (a) adds to the explanation that quality of responses is enhanced when the SiC grit size soars. The correlation between load and SNRs in Figure 3(a) expresses a decreasing pattern for load from 3 N to 9 N. The graph for sliding distance indicates an increasing trend from 25 m to 45 m as well as a decreasing pattern from 45 m to 55 m. However, the reverse was obtained for the relationship between sliding speed and SNRs for sliding speed. As regards SNRs analysis, irrespective of the quality characteristic, a higher SNRs signify desired values of experiments; here, a smaller V_L. According to Table 5 and the main effects graph for SNRs in Figure 3 (a) signify that L1, G1, D2 and S3 were the required parameter levels for high SNRs corresponding to desired values of V_L.

Table 4 - Taguchi L_9 OA and multi-objective responses with SNRs

	Control Factors				Response values		SNRs (dB)	
Run	L (N)	G (mesh)	D (m)	S (ms^{-1})	V_L×10^{-4} (mm^3)	K_S × 10^{-6} ($mm^3N^{-1}m^{-1}$)	V_L	K_s
1	3	1000	25	0.04	6.14	8.18	64.2418	101.743
2	3	400	45	0.08	8.70	6.44	61.2140	103.821
3	3	150	55	0.14	27.44	16.63	51.2317	95.581
4	6	1000	45	0.14	3.95	1.46	68.0604	116.688
5[1]	**6**	**400**	**55**	**0.04**	10.91	3.31	59.2442	109.615
6	6	150	25	0.08	40.47	26.98	47.8584	91.380
7	9	1000	55	0.08	13.72	2.77	57.2523	111.144
8	9	400	25	0.14	13.04	5.80	57.6921	104.736
9	9	150	45	0.04	23.41	5.78	52.6123	104.761

Table 5 - Response table for SNRs of V_L

Level	L	G	D	S
1	**58.90**	50.57	56.60	58.70
2	58.39	59.38	**60.63**	55.44
3	55.85	**63.18**	55.91	**58.99**
Delta	3.04	12.62	4.72	3.55
Rank	4	1	2	3

Table 6 - Response table for SNRs of K_s

Level	L	G	D	S
1	100.38	97.24	99.29	105.37
2	105.89	106.06	**108.42**	102.12
3	**106.88**	**109.86**	105.45	**105.67**
Delta	6.50	12.62	9.14	3.55
Rank	3	1	2	4

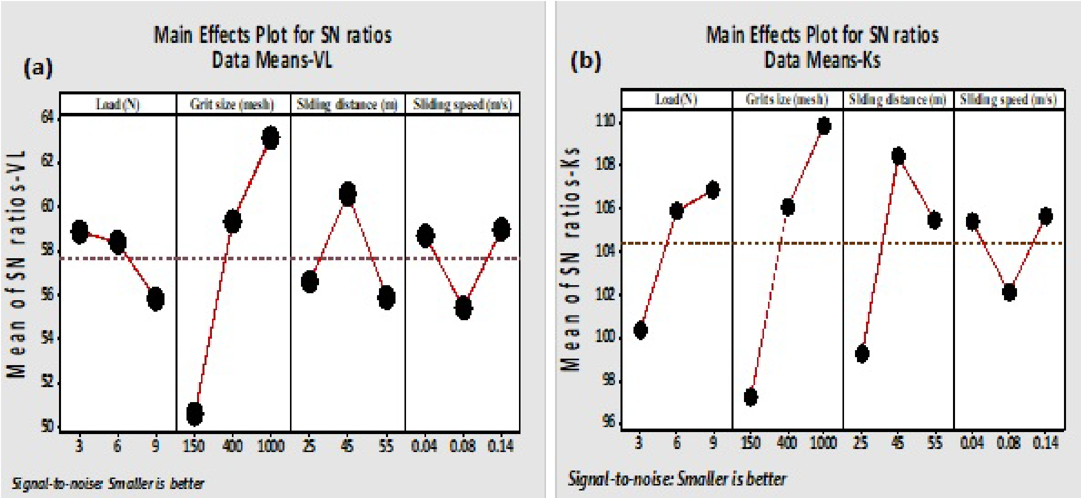

Fig. 3 - Main effects plot for SNRs of (a) V_L and; (b) K_s

3.2 Effect of the Process Parameters on K_s

To find the parameters affecting the K_S, the SNRs of the experimental data were computed (Table 4). Similarly, the smaller the better characteristic of Taguchi approach has been chosen to evaluate the parameter influences on K_S. The response table for SNRs of K_S was then generated using the same software as indicated in Table 6. The findings showed that the grit size with a max-min value of 12.62 possesses the biggest effect on K_S followed by sliding distance with max-min value 9.14, load with max-min value 6.50 and finally sliding speed with max-min value of 3.55. Table 5 was utilized to get the graph of main effects for K_S as shown in Figure 3 (b). It could be decoded that the ratios increased steeply for load and SiC grit size with increase in the load and grit size. In the case of sliding distance and speed, the ratios increased and decreased (from 25-45 m and 45-55 m) as well as decreased and increased (from 0.01-0.08 ms^{-1} and 0.08-0.14 ms^{-1}), respectively. Figure 3 (b) indicates that required values of SNRs of K_S were obtained as follows: load at level (L3), grit size at level one (G1), sliding distance at second level (D2) and finally third level of sliding speed (S3). The outcomes of SNRs in Table 6 also indicate similar findings. More so, the max-min value (Table 6) exhibit that K_s is majorly influenced by SiC grit size, coming after are distance, load as well as speed.

3.3 Multi-Objective Optimization

GRG is fundamentally used to solve practical issues composed of a limited set of data. The results in Table 4 were preprocessed via grey relational generation. Reference sequence of the responses within range of 0-1 was determined through normalization (equation 4). Thereafter, deviation sequences were calculated using equation 5. Once the deviation sequences were determined the grey relational coefficient (GRC) for individual value of the output was computed via equation 6. Lastly, mean values of the GRCs were calculated to find the grey relational grade (GRG). As provided in Table 8, the calculated values of GRGs were used to generate the SNRs. A bigger magnitude of SNRs is useful and shows that the experiments are in proximity to values of GRG [30] equation 7. Figure 5 shows the graph of GRGs against the SNRs. It shows the fourth trial has the maximum SNR. Consequently, the first rank was apportioned to the fourth trial. The chasing behaviour of the GRG below the graph of SNRs (Figure 5) adds to the discussion aforesaid. As soon as the ranks have been found, the mean response table for GRG is contrived. The GRG of individual parameter at the selected setting is chosen and its average determined to produce the mean of GRG for each parameter. As an example, the parameter load was set at level 1 (L1) in the first, second and third trials of the test. The equivalent GRG values in Table 8 were used for computation as in equation (9).

$$L1 = \frac{0.7741 + 0.7566 + 0.4471}{3} = 0.6593 \qquad (9)$$

Following the above operation, Table 9 was created. The grades in the response table act as a criterion of the correlativity between reference sequence and comparability sequence of GRA. Bigger values of the average GRGs show a strong correlativity [31]. Hence, based on Table 9 it is potential to obtain optimum parameters which can maximize the whole response. Therefore, the maximum GRG live at L2, at G1, at D2 and at S1. Consequently, the optimum parameter settings for beneficial abrasive wear behaviour of filled PTFE composite are L at 6 N, G at 1000 mesh, D at 45 m as well as S at 0.04 ms^{-1}.

3.4 ANOVA

To determine the %C of each process parameter to V_L, K_S and GRG ANOVA was performed. For V_L, it was found that G having a %C of 76.25% has the maximum influence on the V_L, followed by D with 11.83%, S with 7.08% and then L with least contribution of 4.84%. With respect to K_S, it was established that G shows the maximum percentage contribution of 52.52%, followed by D of 27.22%, L of 15.38% and lastly S with the least contribution of 4.87%. Similarly, ANOVA for GRG shows that G with 76.63% is the biggest contributor, followed by D with 16.55%, S having 6.14% and then L with least %C of 1.40%. These are further depicted in Figure 4 (a, b and c) for V_L, K_S and GRG, respectively.

Table 7 - Reference as well as deviation sequences post data pre-processing

Run	$X_i^*(k)$ **V_L**	$X_i^*(k)$ **K_s**	$\Delta_{oi}(k)$ **V_L**	$\Delta_{oi}(k)$ **K_s**
1	0.9402	0.7367	0.0598	0.2633
2	0.8701	0.8049	0.1299	0.1951
3	0.3567	0.4055	0.6433	0.5945
4	1.0000	1.0000	0.0000	0.0000
5	0.8095	0.9278	0.1905	0.0722
6	0.0000	0.0000	1.0000	1.0000
7	0.7325	0.9487	0.2675	0.0513
8	0.7510	0.8302	0.2490	0.1698
9	0.4671	0.8308	0.5329	0.1692

Table 8 - Rank of GRG with SNRs

Run	$\xi_i(k)$	$\xi_i(k)$	γ_i	γ_i **SNRs(dB)**	**Rank**
1	0.8932	0.6550	0.7741	-2.22	4
2	0.7938	0.7193	0.7566	-2.42	5
3	0.4373	0.4568	0.4471	-6.99	8
4	1.0000	1.0000	1.0000	0.00	1
5	0.7241	0.8738	0.7990	-1.95	2
6	0.3333	0.3333	0.3333	-9.54	9
7	0.6515	0.9070	0.7792	-2.17	3
8	0.6676	0.7465	0.7070	-3.01	6
9	0.4841	0.7472	0.6156	-4.21	7

Table 9 - Response table of GRGs

Level	**L**	**G**	**D**	**S**
1	0.6593	0.4654	0.6048	**0.7296**
2	**0.7108**	0.7542	**0.7907**	0.6230
3	0.7006	**0.8511**	0.6751	0.7180
Delta	0.0515	0.3858	0.1859	0.1065
Rank	4	1	2	3

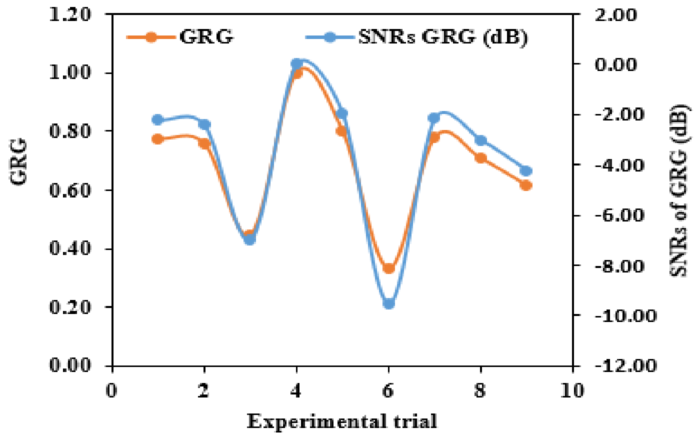

Fig. 5 - Plot of GRG against GRG SNRs

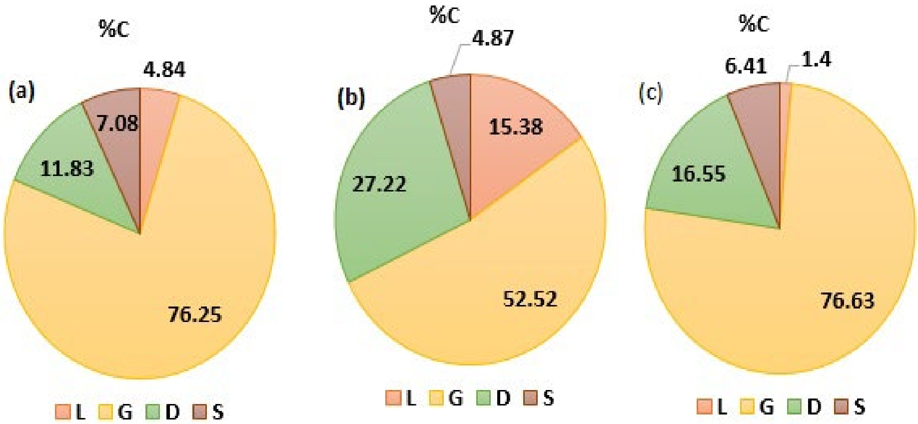

Fig. 4 - Pie chart showing the percentage contribution of each factor on (a) V_L; (b) K_s and; (c) GRG

3.5 Confirmation Tests

Prediction and validation of the performance improvement of the responses is the final phase in GRA analysis. GRA prediction was performed using equation 8. Confirmation was carried out to verify outcomes of the investigation and the average of two tests was calculated and reported. For best condition, V_L and K_S were determined to be 3.67×10^{-5} mm^3 and 4.98×10^{-6} mm^{3}N^{-1}m^{-1}, respectively. Besides, it could be inferred from Table 10 that the findings of confirmatory tests are in concord with the predicted findings. Moreover, an improvement of 21.93% in GRA was realized. This asserts the rigour of Taguchi hybridized with GRA for getting higher abrasive tribological performance of reinforced PTFE composites.

Table 10 - Results of the confirmation tests

		Optimal Parameter	
	Initial Design Parameter	**Prediction**	**Confirmation**
Level settings	L2G2D3S1	L2G1D2S1	L2G1D2S1
GRG	0.7990	1.0000	0.9742
Improvement (%)		25.16	21.93

4. Modelling of the GRG

In the current study, a mathematical model has been built based on the findings of the GRG for the reinforced PTFE composites using linear regression analysis in Minitab 2017. No transformation has been carried out on the GRG. The mathematical models for predicting the GRG as a function of load, grit size, sliding speed and sliding distance obtained from the regression analysis is provided in the following equation 10.

$$GRG = 3.01 \times 10^{-1} + 6.9 \times 10^{-3} L(N) + 4.0 \times 10^{-4} G(mesh) + 3.34 \times 10^{-3} D(m) + 2.0 \times 10^{-2} S(ms^{-1}) \quad (10)$$

The adequacy of the built model was checked by means of coefficient of determination ($R^{2.}$). $R^{2.}$ value differs from zero to unity. If the R^2 is close to unity it signifies that there exists a good fit between the independent and dependent variables otherwise bad fit exists. Assuming, $R^2 = 90\%$ then it means that the new observations were predicted with a variability of 90 %. In the current article, the mathematical model developed based on the linear regression model for GRG has $R^{2.} = 63.09$ %. The residual plot was utilized to find the importance of the coefficients in the mathematical model. When the residual plot is a straight line, it shows that the residual errors in the mathematical model are important. The residual plot achieved for the GRG was as depicted in Figure 6.

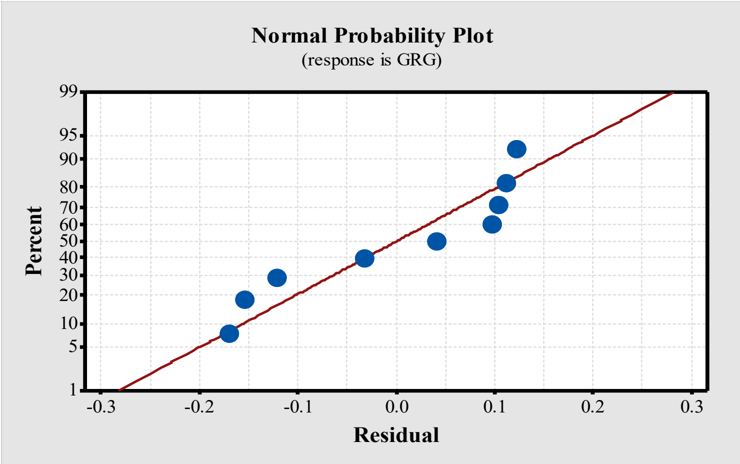

Fig. 6 - Normal probability plot of the residuals for GRG

From Figure 6, it was noticed that only a few points fell near the straight line for the GRG. This implies that the built mathematical model coefficients for predicting the GRG are insignificant. Additionally, abrasive wear is noisy, complex and non-linear phenomenon. Thus, linear regression model cannot handle these behaviours of abrasion. Using the developed mathematical model, corresponding values for the GRG were obtained and compared with the actual GRG values as presented in Figure 7. As seen from the figure, the observed values seemed to mimic the actual values but with less accuracy.

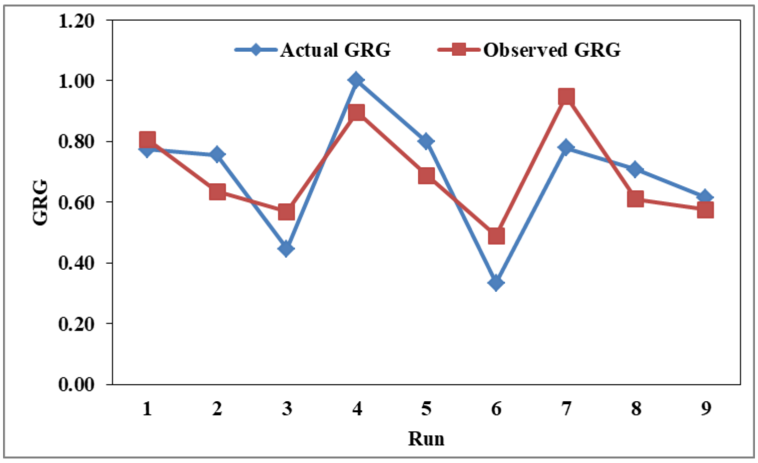

Fig. 7 - Comparison of the actual and observed GRG values

5. Conclusion

Taguchi based grey relational analysis (GRA) for multi-objective approach was used in this paper for optimization of wear rate of reinforced polytetrafluoroethylene (PTFE) composites. Findings of the study were summarized as follows: The study proposed an orthogonal array hybridized with GRA in order to optimize the multiple objectives of volume loss as well as specific wear rate of reinforced PTFE composites. Experimental findings indicated that abrasive wear rate of PTFE composites was greatly influenced by grit size, load, sliding distance as well as sliding speed. The GRA converted the multi-objectives namely volume loss and specific wear rate into a response. The optimum combination of parameters of grey relational grade (GRG) for abrasive wear rate of reinforced PTFE composites was determined to be load of 6 N, grit size of 1000 mesh, sliding distance of 45 m and sliding speed of 0.04 ms^{-1}. According to the analysis of variance of GRG, it was found that SiC grit size with 76.63% exerted the biggest impact on abrasive wear of PTFE based composites, followed by sliding distance with 16.55%, sliding speed having 6.14% and load with least exertion of 1.40%. Confirmation tests conducted revealed an improvement of 21.93 % in GRG from 0.7990 for initial design parameter combination (L2G2D3S1) to 0.9742 for the combination of optimal parameters (L2G1D2S1). The mathematical modelling of the GRG revealed a fair agreement of 63.09 % between the actual and the observed values of GRG.

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