A Grey-based Taguchi Method for Wear Assesment of Red Mud Filled Polyester Composites

Siba Sankar Mahapatra and Saurav Datta

Abstract—**Recent studies reveal that polyster matrix composites reinforced by ceramic fillers have significantly better characteristics such as super wear resistance, high strength and low density than unreinforced materials. However, prohibitive costs and stability of properties pose challenge for the researchers in the process of development of composites. To address these issues, composites are being developed using waste materials as reinforcement for effective utilization of industrial wastes. The present investigation aims to develop redmud filled polyster composites with different weight fraction and characterize mechanical and tribological properties. The engineering application of composites demands that it should have high wear resistance, low density and high tensile strength. In order to assess the behavior of composites satisfying multiple performance measures, a grey-based Taguchi approach has been adopted. After thorough analysis of factors and their interactions, optimal factor settings have been suggested to improve multiple responses viz., specific wear rate, density and tensile strength. The responses have been predicted using both artificial neural network (ANN) and Taguchi method so that a comparative evaluation can be made.**

Index Terms—**grey-based Taguchi method, neural networks, sliding wear, red mud, polyester.**

I. Introduction

In the last decade, research activities in the area of thermoplastic composites have shifted to the development of 'cost-performance' engineering composites from 'high-performance' advanced composites. Polymers find wide engineering applications due to their low density, reasonably good strength and wear resistance as compared to monolithic metal alloys. For weight sensitive uses, undoubtedly they are the most suitable materials but prohibitive costs and stability of properties pose challenge for the researches in the process of development of composites. In order to bring down the cost, low cost and easily available fillers are a viable option. However, mechanical properties of the composites should not be degraded in the attempt of reducing the cost. Therefore, purpose of use of fillers is twofold: first, to improve the mechanical, thermal or tribological properties, and second, to reduce the cost of the component. Specifically, in polymers, a large number of materials such as minerals and inorganic oxides (alumina and silica) are mixed with thermoplastics like polypropelene and polyethylene [1,2,3,5]. Through judicious control of reinforcing solid particulate phase, selection of matrix and suitable processing technique, composites can be prepared to tailor the properties needed for specific application. The properties exhibited by the tailored composites may be comparable or even better than those of conventional metallic materials [6]. In order to enhance the wear resistance of the composites around two or three times, hard particulate fillers consisting of ceramic or metal particles and fiber fillers made of glass are being used [7]. The improved performance of polymers and their composites in industrial and structural applications by the addition of particulate fillers has been the subject of considerable interest to the researchers. Polymers and polymer-matrix composites reinforced with metal particles have a wide industrial applications such as heaters, electrodes, composites thermally durable at elevated temperature etc. [8,9]. In past two decades, ceramic filled polymer composites have emerged as a subject of extensive research. Extensive literature review suggests that great potential exists for utilization of cheap materials like industrial wastes in preparing particle-reinforced polymer composites. Normally, huge quantity (55-65%) of redmud, a waste material, is generated during extraction of alumina from bauxite by Bayer's process. Redmud is being accumulating at an increasing rate throughout the world (nearly 30 million tons per year). Therefore, redmud can be used as particulate filler in polymers for developing composites to obtain low cost, light weight, high strength, and wear resistant composites. Red mud is brick red in color and slimy with an average particle size of about 80 mm. It is alkaline, thixotropic, and possesses high surface area in the range of 13-16 m^2/g with a density of 3.30 g/cm^3. The physical and chemical properties of red mud largely depend on bauxite used and the manner in which the bauxite is processed. Residues from different bauxite have a wide range of composition: Fe_2O_3 20–60%, Al_2O_3 10–30%, SiO_2 2–20%, Na_2O 2–10%, CaO 2–8%, TiO_2 traces 2–8%. Detailed characterization of red mud generated from NALCO aluminum refinery at Damanjodi, India is reported by Mahapatra et al. [10] and some other sources by various authors [11-13]. The low-cost ceramic particle filler has been used with different polymer matrices such as polypropylene and nylon to study relation between the mechanical properties (tension and compression) with particle size and particle volume fraction [14-16]. For designing of proper composites satisfying various functional requirements needs that a large number of criteria must be satisfied simultaneously. The filer (redmud) content largely influences the density, tensile strength and wear characteristics of the composites. The density of the

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Siba Sankar Mahapatra and Saurav Datta, Department of Mechanical Engineering National Institute of Technology Rourkela 769008 India. Phone: 91-0661-2462512 FAX: 91-0661-2472926
email:mahapatrass2003@yahoo.com ,sdattaju@gmail.com

composite increases with the increase in filler content whereas tensile strength decreases. The wear characteristics of the composites are not only dictated by filler content but also on operating conditions. In such situation, it is really a challenging task for the composite engineers to design a proper composite satisfying all functional requirements. These engineering composites are desired to have characteristics like ease of fabrication, low cost and high corrosion resistance. It should also possess desirable properties such low density, high tensile strength, and high wear resistance [17,18]. In order to study and design the composite meeting the multiple desirable performance criteria, a methodology must be evolved. The performance of the composite is heavily dependent on its compositions in different weight fractions and the environmental variables under which it has to perform. Taguchi's parameter design is capable of analyzing the impact of more than one parameter and their interactions with less number of experimental runs. Such an approach has been successfully applied for parametric appraisal in the wire electrical discharge machining (WEDM) process, drilling of metal matrix composites, and erosion behavior of polymer-matrix composites [19-21]. The major limitation of Taguchi approach lies on the fact that it can establish optimal parameter settings for one response only. As the industrial application needs multiple criteria to be satisfied simultaneously, a grey-based Taguchi approach has been proposed in this work. As a post Taguchi experimental analysis, often regression equations using sample experimental data are developed and optimization techniques adopted to find optimal setting beyond experimental domain. The optimal settings beyond the experimental domain possess theoretical implications rather than practical utility. This drawback can be easily overcome with the use of grey-based Taguchi approach. Finally, prediction of responses using both artificial neural network (ANN) and Taguchi method has been compared.

II. Experimental Details

A. Specimen Preparation

Red mud collected from NALCO aluminum refinery at Damanjodi, India is sieved to obtain a particle size in the range 70–90 mm. These particles are reinforced in unsaturated isophthalic polyester resin (modulus 3.25 GPa, density 1.35 gm/cm^3) to prepare the composites. Two percent (2%) cobalt nephthalate (as accelerator) is mixed thoroughly in isophthalic polyester resin followed by 2% methyl-ethyl-ketone-peroxide (MEKP) as hardener resin prior to reinforcement. The dough (polyester resin mixed with red mud) is then slowly decanted into the glass tubes, coated beforehand with uniform thin film of silicone-releasing agent. The composites are cast by conventional hand-lay-up technique in glass tubes so as to get cylindrical specimens (Φ 9mm, length 120 mm). Composites of three different compositions (10, 20, and 30wt% red mud filling) are made. The castings are left to cure at room temperature for about 24 hrs after which the tubes are broken and samples are released. Specimens of suitable dimension are cut using a diamond cutter for further physical characterization and wear test.

B. Assessment of Mechanical Properties and sliding wear

Micro-hardness measurement is done using a Leitz micro-hardness tester. A diamond indenter, in the form of a right pyramid with a square base and an angle 136^0 between opposite faces, is forced into the material under a load F. The two diagonals X and Y of the indentation left on the surface of the material after removal of the load are measured and their arithmetic mean L is calculated. In the present study, the load considered F = 24.54N and Vickers hardness number is calculated using the following equation.

$$H_V = 0.1889 \frac{F}{L^2} \quad .(1)$$

$$\text{and} \quad L = \frac{X+Y}{2}$$

where F is the applied load (N), L is the diagonal of square impression (mm), X is the horizontal length (mm) and Y is the vertical length (mm). The micro-hardness values recorded in Vickers' scale for the composites are 54, 59, and 62 Hv respectively. It is found to be increasing with the red mud content in the composites.

The theoretical density of composite materials in terms of weight fraction can easily be obtained as for the following equations given by Agarwal and Broutman [22]. The composites under this investigation consists of two components namely matrix and particulate filler. Hence, the expression for the density of the composite can be written as

$$\rho_{ct} = \frac{1}{(W_m/\rho_m)+(W_p/\rho_p)} \quad (2)$$

where W and ρ represent the weight fraction and density respectively. The suffix *m, p* and *ct* stand for the matrix, particulate filler materials and the composite materials respectively. The actual density of the composite, however, can be determined experimentally by simple water immersion technique. With inclusion of red mud particles in the polymer matrix, the density of the composite is found to be increasing. The densities of the three different samples (with 10, 20, and 30wt% of red mud) are measured as 1.67, 1.81, and 1.93 g/cm^3 respectively. The improvement in density is obvious as the true density of red mud is about 2.5 times that of neat polyester.

The tensile test is generally performed on flat specimens. The commonly used specimens for tensile test are the dog-bone type and the straight side type with end tabs. During the test a uniaxial load is applied through both the ends of the specimen. The ASTM standard test method for tensile properties of fiber resin composites has the designation D 638 M91. The length of the test section should be 180 mm. The tensile test is performed in the universal testing machine (UTM) Instron 1195. It is seen that in all the samples the tensile strength of the composites decrease with increase in filler content. The neat polyester has a strength of 174MPa in tension and it is seen that this value drops to 162.3MPa with the inclusion of 10wt% of red mud. The tensile strength of the composite further drops to 156.7 and 151.3MPa in the case of the other two composites with 20 and 30wt% of red mud, respectively. There can be two reasons for this decline in strength; one possibility is that the chemical reaction at the interface between the filler particles and the matrix may be too weak to transfer the tensile stress; the other is that the corner points of the irregular-shaped particulates result in stress concentration in the polyester matrix. These two factors are responsible for reducing the tensile strengths of the composites so significantly.

To evaluate the performance of these composites under dry sliding condition, wear tests are carried out in a pin-on-disc type friction and wear monitoring test rig (supplied by DUCOM) as per ASTM G 99. The counter body is a disc made of hardened ground steel (EN-32, hardness 72 HRC, surface roughness 0.6 μ Ra). The chemical composition of the steel disc in weight % is 0.1 C, 0.6 Mn, 0.15 Si, 0.035 P and 0.035 S. The equipment has flexibility to vary normal load, rotational speed and wear track diameter. With electronic sensors, friction force and rotational speed can be monitored time to time. During the tests, the end of the pin (specimen) is pressed against the steel disc. The pin is held by a collect attached to the lever which in turn is connected to the loading arrangement. Loading ranging from 0-200 N can be applied through the arrangement to press the pin against the disc. The specifications for test apparatus is shown in Table 1. The specimen is held stationary and the disc is rotated while a normal force is applied through a lever mechanism. A series of tests are conducted with three sliding velocities of 100, 200, and 300 cm/s under three different normal loadings of 10, 15, and 20 N. The material loss from the composite surface is measured using a precision electronic balance with accuracy ±0.1mg. The specific wear rate (mm^3/N-m) defined as the volume loss of the specimen per unit sliding distance per unit applied normal load. The volumetric wear rate Wv of the composite relating to density (ρ) and the abrading time (t) is expressed as, Wv = Δm / ρt where Δm is the mass loss. Then, specific wear rate (Ws) can be calculated using Ws = Wv / Vs Fn where Vs is the sliding velocity and Fn is the applied load. The wear test set up is shown in Figure. 1.

TABLE 1. SPECIFICATIONS FOR WEAR MONITORING TEST RIG

Pin Diameter	15 mm
Disc Size	250 ϕ and thickness 20mm
Wear track diameter	50mm-220mm
Disc rotational speed	100 to 1100 rpm continuously variable with digital tachometer.
Drive	1.1 kw DC motor, constant torque
Motor controller	Thyrister converter with full motor protection
Normal load	200 N (maximum)
Frictional force	0-200 N Digital display
Power	230V line +/- 5%, 15 amp single phase, 50Hz AC

Figure 1. Sliding Wear Test Set up

C. Experimental Design

In this study, Taguchi method, a powerful tool for parameter design of the performance characteristics has been used to determine optimal parameters settings for minimization of specific wear rate. Based on Taguchi's Orthogonal Array design, the experimental data needs to be transformed into a signal-to-noise (S/N) ratio for analysis. The characteristic that higher value represents desired response, such as tensile strength, 'higher-the-better, HB and the characteristic that lower value represents desired response, such as specific wear rate and density 'lower-the-better', LB are used. Therefore, HB for the tensile strength, LB for the density and specific wear rate has been selected for obtaining optimum performance characteristics. The loss function (L) for objective of HB and LB is defined as follows:

$$L_{HB} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_{ts}^2} \tag{3}$$

$$L_{LB} = \frac{1}{n}\sum_{i=1}^{n} y_d^2 \tag{4}$$

$$L_{LB} = \frac{1}{n}\sum_{i=1}^{n} y_{sw}^2 \tag{5}$$

where y_{ts} , y_d and y_{sw} represent response for tensile strength, density and specific wear rate and n denotes the number of experiments.

The S/N ratio can be calculated as a logarithmic transformation of the loss function as shown below.

S/N ratio for tensile strength = -10log $_{10}$(L_{HB}) (6)

S/N ratio for density = -10log $_{10}$ (L_{LB}) (7)

S/N ratio for specific wear rate = -10log $_{10}$ (L_{LB}) (8)

In order to study the effect of various variables (factors) such as redmud content (wt%) in the composite, applied load and sliding velocity and their interactions on specific wear rate of the composite, a L_{27} (3^{13}) orthogonal array is chosen. Table 2 indicates the factors to be studied and the corresponding levels of factors. Using linear graph shown in Figure. 2, the factors are assigned to columns of the OA array. The first column is assigned to sliding velocity (A), the second column assigned to red mud content (B) and fifth column assigned to the normal load (C). The third and fourth column is assigned to the interaction of sliding velocity and red mud content (AxB), the sixth and seventh column to the interaction of redmud content and sliding velocity (BxC) and the eight and eleven column assigned to the interaction of sliding velocity and normal load (AxC) [23]. The response (specific wear rate) is transformed into signal to noise (S/N) ratio using lower-the-better condition. An analysis of variance (ANOVA) was performed to establish statistically significant parameters for a 95% confidence level.

TABLE 2. LEVELS OF THE VARIABLE USED IN THE EXPERIMENT

Control factor	Level			
	I	II	III	Units
Sliding velocity (A)	100	200	300	cm/s
Red mud content (B)	10	20	30	wt%
Normal load (C)	10	15	20	N

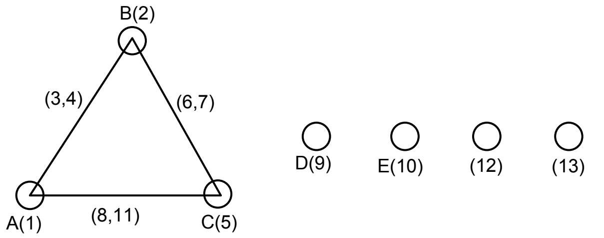

Figure 2 Linear Graph for L_{27} Orthogonal Array

D. Grey-Based Taguchi Method

However, traditional Taguchi method can optimize a single response at a time but not multi-responses simultaneously. So, specific wear rate, density and tensile strength can be optimized individually by using this Taguchi technique. But, it may so happen that, the optimal setting for a response hardly ensures best settings for other responses. So, it is desirable to go for an optimal parameter setting that optimizes all the responses (maximum tensile strength, minimum density and minimum specific wear rate) simultaneously. These have been aimed to achieve using grey based Taguchi method [24]. This method can convert several responses into an equivalent single response function (representative of all desired response characteristics of the product/process), which would be maximized next.

In grey relational analysis, experimental data are first normalized ranging from zero to one. The process is known as grey relational generation. Next, based on normalized experimental data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. This approach converts a multiple response process optimization problem into a single response optimization situation with the objective function is overall grey relational grade. The optimal parametric combination is then evaluated which would result highest grey relational grade. The optimal factor setting for maximizing overall grey relational grade can be performed by Taguchi method.

In grey relational generation, the normalized data i.e. density and specific wear rate corresponding to lower-the-better (LB) criterion can be expressed as:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{9}$$

Tensile Streghth should follow higher-the-better criterion (HB), which can be expressed as:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{10}$$

where $x_i(k)$ is the value after grey relational generation, $\min y_i(k)$ is the smallest value of $y_i(k)$ for the k^{th} response, and $\max y_i(k)$ is the largest value of $y_i(k)$ for the k^{th} response. An ideal sequence is $x_0(k)\ (k = 1,2,3,.......,27)$ for the responses. The definition of grey relational grade in the course of grey relational analysis is to reveal the degree of relation between the 27 sequences $x_0(k)$ *and* $x_i(k),\ (k = 1,2,3,.......,27)$. The grey relational coefficient $\xi_i(k)$ can be calculated as:

$$\xi_i(k) = \frac{\Delta_{\min} + \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \tag{11}$$

where $\Delta_{0i} = \left\| x_0(k) - x_i(k) \right\|$ = difference of absolute value $x_0(k)$ and $x_i(k)$; ψ is the distinguishing coefficient $0 \le \psi \le 1$; $\Delta_{\min} = \forall j^{\min} \in i \forall k^{\min} \left\| x_0(k) - xj(k) \right\|$ = the smallest value of Δ_{0i} ;

and $\Delta_{\max} = \forall j^{\max} \in i \forall k^{\max} \left\| x_0(k) - xj(k) \right\|$ = the largest value of Δ_{0i} .

After averaging the grey relational coefficients, the grey relational grade γ_i can be computed as:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k), \tag{12}$$

where n is the number of process responses.

The higher value of grey relational grade corresponds to intense relational degree between the reference sequence $x_0(k)$ and the given sequence $x_i(k)$. The reference sequence $x_0(k)$ represents the best process sequence; therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal. The mean response for the grey relational grade with its grand mean and the main effect plot of grey relational grade are very important because optimal process condition can be evaluated from this plot.

III. RESULTS AND DISCUSSIONS

The data on responses viz., specific wear arte, density and tensile strength are collected for 27 experimental runs as per combination of sliding wear process parameters. The experimental data on specific wear rate, density and tensile strength are converted into S/N ratios using equations 6-8. The data are shown in Table 3. Taguchi method is adopted to analyze the effect of various process parameters viz., A, B, and C on specific wear rate. The analyses are made using the popular software specifically used for design of experiment applications known as MINITAB 14. Figure 3 shows graphically the effect of the three control factors on specific wear rate.

Figure 3 clearly shows that specific wear rate is highly sensitive to sliding velocity (factor A). Concrete visualization of impact of various factors and their interactions can be easily made with the help analysis of variance (ANOVA). ANOVA table is shown in Table 4. This analysis is undertaken for a level of confidence of significance of 5%. The last column of the table indicates the order of significance among factors and interactions. It can be observed that the sliding velocity, factor A (p=0.000) and normal load, factor C (p-0.003) have great influence on specific wear rate. The interaction of sliding velocity, factor A and normal load, factor C (p=0.209) and red mud content, factor B and normal load, factor C (p=0.454) shows significant contribution on the specific wear rate. But, interaction between sliding velocity, factor A and red mud content, factor B (p=0.461) exhibits less significant contribution on specific wear rate. The interaction plots are shown in Figure 4. Analysis of factors and their interactions helps to set the optimal process parameters for minimum wear rate as $A_3B_1C_1$.

TABLE 3. THE EXPERIMENTAL DATA

L_{27} (3^{13})	Sliding Velocity (cm/s) A	Red mud content (wt %) B	Normal Load (N) C	Specific Wear (mm^2/N-m)	Density (gm/cm^3)	Tensile Strength (MPa)
1	100	10	10	3.19	1.67	162.3
2	100	10	15	3.61	1.67	162.3
3	100	10	20	3.82	1.67	162.3
4	100	20	10	3.20	1.81	156.7
5	100	20	15	3.62	1.81	156.7
6	100	20	20	3.82	1.81	156.7
7	100	30	10	3.21	1.93	151.3
8	100	30	15	3.62	1.93	151.3
9	100	30	20	3.83	1.93	151.3
10	200	10	10	1.84	1.67	162.3
11	200	10	15	2.20	1.67	162.3
12	200	10	20	2.74	1.67	162.3
13	200	20	10	1.87	1.81	156.7
14	200	20	15	2.23	1.81	156.7
15	200	20	20	2.76	1.81	156.7
16	200	30	10	2.90	1.93	151.3
17	200	30	15	2.26	1.93	151.3
18	200	30	20	2.76	1.93	151.3
19	300	10	10	1.47	1.67	162.3
20	300	10	15	1.53	1.67	162.3
21	300	10	20	1.67	1.67	162.3
22	300	20	10	1.51	1.81	156.7
23	300	20	15	1.57	1.81	156.7
24	300	20	20	1.70	1.81	156.7
25	300	30	10	1.54	1.93	151.3
26	300	30	15	1.61	1.93	151.3
27	300	30	20	1.73	1.93	151.3

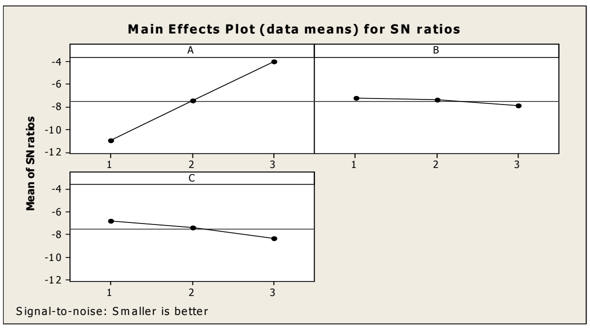

Figure 3. Effect of control factors on specific wear rate

TABLE 4. ANOVA FOR THE RESPONSE SPECIFIC WEAR RATE

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Rank
A	2	17.3708	17.3708	8.6854	227.41	0.000	1
B	2	0.1248	0.1248	0.0624	1.63	0.254	3
C	2	0.9547	0.9547	0.4773	12.50	0.003	2
A*B	4	0.1528	0.1528	0.0382	1.00	0.461	3
B*C	4	0.1552	0.1552	0.0388	1.02	0.454	2
A*C	4	0.2855	0.2855	0.0714	1.87	0.209	1
Error	8	0.3055	0.3055	0.0382			
Total	26	19.3493					

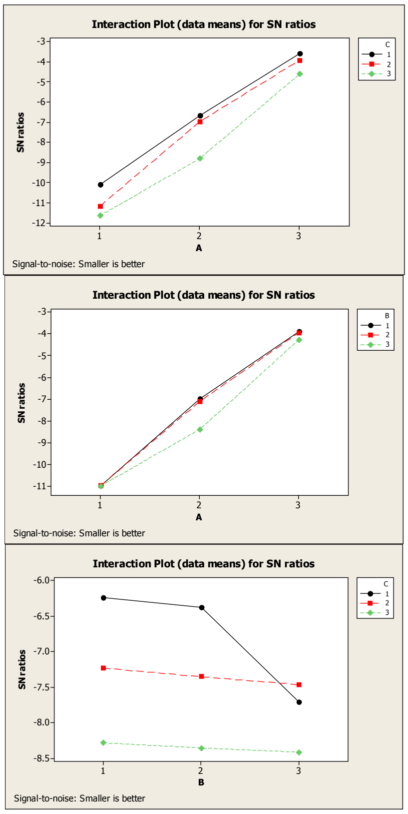

Figure 4. The Interaction Effects

After analyzing the factor and interaction effects and setting optimal process parameter levels, it is customary to develop a linear predictive equation for confirmation and verification tests. Therefore, the predictive equation for optimal factor settings, $A_3B_1C_1$ can be represented as follows:

$$\hat{\eta} = \overline{T} + (\overline{A}_3 - \overline{T}) + (\overline{B}_1 - \overline{T}) + [(\overline{A}_3\overline{B}_1 - \overline{T}) - (\overline{A}_3 - \overline{T}) - (\overline{B}_1 - \overline{T})] + (\overline{C}_1 - \overline{T}) + [(\overline{A}_3\overline{C}_1 - \overline{T}) - (\overline{A}_3 - \overline{T}) - (\overline{C}_1 - \overline{T})] + [(\overline{B}_1\overline{C}_1 - \overline{T}) - (\overline{B}_1 - \overline{T}) - (\overline{C}_1 - \overline{T})] \quad (13)$$

$\hat{\eta}$ - Predicted response

$\overline{T}$ - Overall experimental mean

$\overline{A}_3, \overline{B}_1, \overline{A}_3\overline{B}_1, \overline{C}_1, \overline{A}_3\overline{C}_1, \overline{B}_1\overline{C}_1$ - Mean values of factors and interactions at designated level.

TABLE 5. COMPARISON OF NEURAL NETWORK AND TAGUCHI PREDICTION

L_{27} (3^{13})	Neural Network prediction for Specific Wear	Taguchi prediction for Specific Wear
1	3.18	3.10
2	3.64	3.67
3	3.80	3.84
4	3.20	3.13
5	3.59	3.64
6	3.85	3.87
7	3.21	3.35
8	3.63	3.55
9	3.82	3.75
10	1.83	1.97
11	2.22	2.14
12	2.73	2.65
13	1.90	2.03
14	2.20	2.14
15	2.78	2.70
16	2.89	2.60
17	2.27	2.40
18	2.76	2.91
19	1.49	1.40
20	1.55	1.59
21	1.66	1.69
22	1.48	1.42
23	1.57	1.57
24	1.68	1.73
25	1.56	1.70
26	1.60	1.54
27	1.75	1.66

Similar equations can be developed for different levels of factor combination and prediction of specific wear rate can be made. Such a prediction is known as Taguchi prediction. Taguchi prediction for all 27 runs of the experiment is shown in column 2 of Table 5. It can be observed that maximum error between experimental data and Taguchi prediction is around 15%. In order to predict the specific wear rate correctly, a neural network model based on back propagation algorithm has been implemented. The network architecture has three neurons at the input layer to feed the normalized data of process parameters such as sliding velocity, redmud content and normal load. The output layer contains only one node to predict the normalized specific wear rate. The number of neurons at the hidden layer, the momentum and learning parameters are varied until the network converges to minimum root mean square (RMS) error. Out of 27 experimental data, fifteen are used for training and twelve are tested. The momentum and learning parameters are set at 0.15 and 0.20 respectively. Number of neurons at the hidden layer is 5. The number of epochs needed for training is 288220 when RMS error is 0.02. The popular neural network software Neunet Pro 2.3 is used for neural network implementation. The neural network prediction is shown in column number 1 of Table 5. It is evident that the error between experimental data and neural network prediction is around 3%. Therefore, it can be concluded that neural network prediction is superior to Taguchi prediction. The reason for this discrepancy is attributed to the fact that superior characteristic of neural networks in predicting output when functional relation between the inputs and outputs are completely unknown or any nonlinear relation among inputs and outputs exists. However, error is amplified in Taguchi prediction because linear relation between output and inputs are assumed which may not be the case in real practice.

The preceding discussions analyses the effect of various process parameters on minimization of specific wear rate and redmud content of the composite on density and tensile strength. However, design of composites should emphasize on lower density, high tensile strength and minimum specific wear rate. Taguchi method breaks down to estimate optimal process parameters when multiple desired responses are achieved simultaneously. Therefore, a grey-based Taguchi technique is adopted to achieve more than one performance criteria. The experimental data of L_{27} orthogonal array shown in Table 3 are used. The results of grey relational generation using equations 9 and 10 is shown in Table 6.

TABLE 6. GREY RELATIONAL GENERATION

Scenario	Specific Wear Rate	Density	Tensile Strength
1	0.200	1.000	1.000
2	0.059	1.000	1.000
3	0.014	1.000	1.000
4	0.193	0.444	0.500
5	0.073	0.444	0.500
6	0.000	0.444	0.500
7	0.190	0.000	0.000
8	0.062	0.000	0.000
9	0.008	0.000	0.000
10	0. 778	1.000	1.000
11	0.576	1.000	1.000
12	0.360	1.000	1.000
13	0.739	0.444	0.500
14	0.585	0.444	0.500
15	0.341	0.444	0.500
16	0.300	0.000	0.000
17	0.553	0.000	0.000
18	0.348	0.000	0.000
19	0.993	1.000	1.000
20	0.952	1.000	1.000
21	0.880	1.000	1.000
22	1.000	0.444	0.500
23	0.938	0.444	0.500
24	0.867	0.444	0.500
25	0.945	0.000	0.000
26	0.918	0.000	0.000
27	0.825	0.000	0.000

The grey relational grade is considered as the response for multiple objective optimization case and analyzed using MINITAB 14.0. The ANOVA table is shown in Table 9. The analysis is undertaken for a level of significance of 5%. The last column of the table indicates the order of significance among factors and interactions. It can be observed that the redmud content, factor B (p=0.000) and sliding velocity, factor A (p=0.000) have great influence on grey relational grade. The interaction of red mud content, factor B and normal load, factor C (p=0.014) shows significant contribution on grey relational grade. The graphical representation of effects of factors and interaction plots are shown in Figure. 5. Analysis of factors and their interactions help to set the optimal process parameters for maximum grey relational grade as $A_3B_1C_1$. It is to be noted that the optimal factor settings for minimization of wear rate and maximization of grey relational grade is same in this case. The grey based Taguchi method can be extended by putting different weightages for various performance criteria and optimal settings may be compared.

TABLE 7. RESULTS OF GREY RELATIONAL COEFFICIENT

Scenario	Specific Wear Rate	Density	Tensile Strength
1	0.385	1.000	1.000
2	0.347	1.000	1.000
3	0.336	1.000	1.000
4	0.383	0.473	0.500
5	0.350	0.473	0.500
6	0.333	0.473	0.500
7	0.382	0.333	0.333
8	0.348	0.333	0.333
9	0.335	0.333	0.333
10	0.692	1.000	1.000
11	0.541	1.000	1.000
12	0.438	1.000	1.000
13	0.657	0.473	0.500
14	0.547	0.473	0.500
15	0.431	0.473	0.500
16	0.417	0.333	0.333
17	0.528	0.333	0.333
18	0.434	0.333	0.333
19	0.986	1.000	1.000
20	0.912	1.000	1.000
21	0.806	1.000	1.000
22	1.000	0.473	0.500
23	0.890	0.473	0.500
24	0.790	0.473	0.500
25	0.901	0.333	0.333
26	0.860	0.333	0.333
27	0.740	0.333	0.333

The grey relational coefficients using equation 11 are shown in Table 7. Using equal weightage for all the objectives, the grey relational grade using equation 12 is calculated as shown in Table 8.

The grey relational grade is considered as the response for multiple objective optimization case and analyzed using MINITAB 14.0. The ANOVA table is shown in Table 9. The analysis is undertaken for a level of significance of 5%. The last column of the table indicates the order of significance among factors and interactions. It can be observed that the redmud content, factor B (p=0.000) and sliding velocity, factor A (p=0.000) have great influence on grey relational grade. The interaction of red mud content, factor B and normal load, factor C (p=0.014) shows significant contribution on grey relational grade. The graphical representation of effects of factors and interaction plots are shown in Figure. 5. Analysis of factors and their interactions help to set the optimal process parameters for maximum grey relational grade as $A_3B_1C_1$. It is to be noted that the optimal factor settings for minimization of wear rate and maximization of grey relational grade is same in this case. The grey based Taguchi method can be extended by putting different weightages for various performance criteria and optimal settings may be compared.

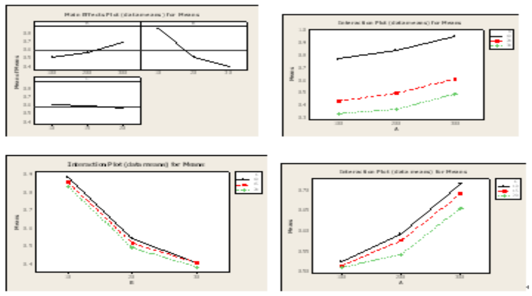

Figure 5. The factor and interaction plots

TABLE8 RESULTS OF GREY RELATIONAL COEFFICIENT

Scenario	Specific Wear Rate	Density	Tensile Strength
1	0.385	1.000	1.000
2	0.347	1.000	1.000
3	0.336	1.000	1.000
4	0.383	0.473	0.500
5	0.350	0.473	0.500
6	0.333	0.473	0.500
7	0.382	0.333	0.333
8	0.348	0.333	0.333
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24	0.790	0.473	0.500
25	0.901	0.333	0.333
26	0.860	0.333	0.333
27	0.740	0.333	0.333

TABLE 9. ANOVA FOR GREY RELATIONAL GRADE

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Rank
A	2	0.138	0.138633	0.069317	194.89	0.000	2
B	2	1.020651	1.020651	0.510326	1434.80	0.000	1
C	2	0.000627	0.000627	0.000314	0.88	0.451	3
A*B	4	0.000991	0.000991	0.000248	0.70	0.615	2
B*C	4	0.008948	0.008948	0.002237	6.29	0.014	1
A*C	4	0.000789	0.000789	0.000197	0.55	0.702	3
Error	8	0.002845	0.002845	0.000356			
Total	26	1.173485					

The worn surfaces of the specimens are examined directly by scanning electron microscope JEOL JSM-6480LV. The worn samples are mounted on stubs with silver paste. To enhance the conductivity of the samples, a thin film of platinum is vacuum evaporated onto them before the photomicrographs are taken. The morphology of the worn surface of polyester composite with 10wt% red mud is illustrated in Figure 6. This micrograph is taken after 3 h of test duration with a sliding velocity of 200 cm/s under a normal load of 20 N. It can be seen that there is a plastic flow of the matrix material in the sliding direction which is indicated by the arrow. It is understandable that with increase in applied load and/or sliding velocity, the thermoplastic polyester softens due to frictional heat generation. As a result, the red mud particles, which are brittle in nature and have sharp edges, easily tear the matrix and gradually get aligned along the sliding direction. These particles by virtue of their size, shape, brittleness, and high harness influence modify the wear behavior of the composites. In the process, the red mud particles are dispersed and coagulated in a different manner. Longer duration of sliding results in formation of wear debris of different sizes and shapes.

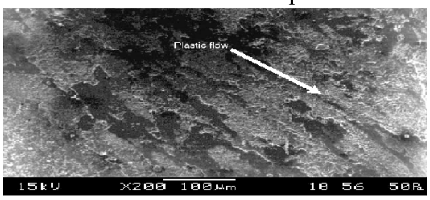

Figure 6. SEM micrograph of worn composite surface.

IV. CONCLUSIONS

This experimental investigation into the sliding wear behavior of red mud filled polyester matrix composites leads to the following conclusions.

1) As the compatibility of red mud particles with polyester resin is fairly good, it being an industrial waste can be used as a potential filler material to produce cost effective polyester matrix composites. The content of redmud in the composite determines the mechanical properties such as hardness, density and tensile strength of the composites.
2) Taguchi method, a simple, systematic, and efficient methodology for analysis of control factors and their interactions, can be conveniently used for setting optimal levels to meet the objective. It needs less number of experimental runs to study dry sliding wear characteristics of composites.
3) Factors like sliding velocity, normal load, and redmud content in order of priority are significant to minimize the specific wear rate. Although the effect of filler content is less compared to other factors, it cannot be ignored because it shows significant interaction with other factors like the normal load.
4) Since the nonlinear functional relation among input parameters and responses can be mapped easily with neural networks, neural network predicts the responses more accurately than Taguchi prediction.
5) Grey-based Taguchi method can be easily adopted when it is desired to improve simultaneously more than one performance criteria. Analysis using grey relational grade as response, factors like redmud content, sliding velocity, and normal load in order of priority become significant. Although the effect of normal load is less compared to other factors, it cannot be ignored because it shows significant interaction with other factors like the redmud content. However, the optimal factor settings are found to be same either specific wear rate or grey relational grade is treated as response. It is to be noted that three objectives viz., specific wear rate, density and tensile strength are equally weighted while calculating grey relational grade. If different weightages are considered for various objectives, the optimal settings may change.
6) The major advantage of using grey Taguchi method lies on the fact that tendency to develop regression equations using sample experimental data to be adopted in optimization techniques for finding out so called global optimal setting may be avoided. Such approaches may result in optimal settings beyond the experimental domain leading to a theoretical implications rather than practical utility.
7) Red mud is found to possess good filler characteristics as it improves the sliding wear resistance of the composite. Scanning electron microscopy suggests that particle detachment due to the tearing of the thermoplastic matrix body by the sharp edges of the filler particles is the dominant wear mechanism occurring during the contact of composite with the counter body. It leads to the conclusion that spherodized red mud particles may be preferred for filling purposes during composite making.
8) In future, this study can be extended to polymer matrix composites using other filler materials.

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Siba Sankar Mahapatra is a Professor in the Department of Mechanical Engineering, NIT Rourkela, India. He has more than 20 years of experience in teaching and research. His current area of research includes multi-criteria decision-making, quality engineering, assembly line balancing, group technology, neural networks, and non-traditional optimization and simulation. He has published more than 40 journal papers. He has written few books related to his research work. He is currently dealing with few sponsored projects.

Saurav Datta is an Assistant Professor in the Department of Mechanical Engineering, NIT Rourkela, India. He has more than five years of experience in teaching and research. His current area of research includes welding technology, manufacturing processes, multi-criteria decision-making, quality engineering, optimisation and simulation modelling.