Sliding Wear Behavior of CSPE Composites Using Taguchi and Neural Network Approach

G H Manjunatha Chary[1], K Sabeel Ahmed[2]

Abstract - Coconut shell particle reinforced epoxy (CSPE) composite has been developed and the effect of particle volume fraction on dry sliding wear behavior of the developed composite was investigated using Taguchi and Neural Network Approach. Planning of experiments was based on L_{27} orthogonal array with four control parameters namely, sliding velocity (3, 4 & 5 m/s), normal load (20, 40 & 60 N), particle volume fractions (40, 50 & 60 %) and sliding distance (1500, 1800 & 2100 m) at three different levels. Regression equation relating the control parameters and wear rate was established by analysis of variance and is validated by confirmation experiments. FFB Neural network tool in MATLAB was also used to predict the dependence of wear rate on selected control factors beyond the experimentation. The predicted results are found to be in good agreement with the results of Taguchi experiments. The tests confirmed that coconut shell particles (0.25mm size) reinforced epoxy composite with 40% particle volume fraction exhibited better wear resistance. Worn surface morphology of CSPE composites was examined using scanning electron microscopy (SEM).

Keywords: Coconut shell particles, FFB Neural Network. Particle volume fraction, Taguchi analysis,

1 INTRODUCTION

In the recent years, research interest has been budging from synthetic and ceramic materials to natural particles in polymer composites. The particulate composites made of synthetic and ceramic materials have dominated in various engineering applications, such as aerospace[1,2], automotive[3], construction[4,5] and sports[6] industries. However, the drawbacks of these materials such as non-renewability, non-recyclability and non-degradability etc., have made the researchers to divert towards the use of natural particles as reinforcement in the composites. Though mechanical properties of natural particles are inferior to synthetic and ceramic particles, their specific properties and stiffness are analogous because of their low density. Although enormous amount of work was carried out on wear behavior of polymer matrix composites using natural reinforcement material in fiber form, the same in the particulate form has not been much noticed in the literature. Aurrekoetxea et al.[7] compared the wear rate and wear micro mechanism of pine wood reinforced polypropylene composite (WPC). 5% of maleated polypropylene (PP) has been added as a coupling agent, and the pine wood has been treated in *N*-2-aminoetil–3-aminopropiltrimetoxisilane solution. Results of the study revealed that WPC and pine wood showed similar co-efficient of friction, where as PP revealed higher value. The wear of WPC is 10 times lesser compared to these two materials. A study on friction co-efficient and specific wear property of phenol reinforced rice husk (RH) ceramic composite was carried out by Dugarjav et al.[8] The results illustrated that composite exhibited superior properties such as, very low friction coefficient and low specific wear rate under dry condition due to the formation of the transferred film, consisting mainly from amorphous silica on the counterpart surfaces. Shicheng et al.[9] addressed the usage of 0 – 14.6 vol % NaOH treated walnut shell particles (WSPs) as particle in the proposed eco-friendly brake friction materials. Five non-asbestos friction material samples containing WSP and jute fibers were prepared. Based on the test results, the composite sample with 5.6 vol% WSP was considered as the formulation best, with respect to both the COF and the wear rate. Asuke et al.[10] studied the effect of applied load on the wear behavior of carbonized bone particles (CBp) reinforced with polypropylene (PP) matrix in different weight fractions of CBp (0, 5, 10, and 15 wt%). The test results reveal that the composite with 15wt% CBp loaded at 5 N showed minimum wear rate of 6.16×10^{-3} g/ min. Finally, the author has concluded that wear rate increases with increase in applied load and decrease with the increase of CBp. Experiments to investigate the effect of particle volume fraction of the phenol composites filled with carbonized rice husk porous particles on the wear behavior were conducted by Morimoto et al.[11] Tests were conducted using block-on-ring type machine under multi-pass condition to examine the wear behavior of the composite against a metal ring. Finally, the author concluded that the wear rate of the composite decrease with the increase in the volume fraction of particle. Several articles have explored the dry slide wear analysis using Taguchi design of experiment approach and

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artificial neural network prediction approach. The uses of these approaches have reduced the considerable time and cost of the analysis [12-15]. Jiang et al.[12] applied an artificial neural network (ANN) tool to predict the wear and mechanical properties of short fiber reinforced polyamide 4.6 composites. Based on the experimental data, the specific wear rate, frictional coefficients were calculated successfully by a well-trained ANN. The results are found to be in good agreement with experimental data. Wear performance of pine wood dust reinforced epoxy composites was analyzed by Kranthi et al.[13]. Composites were prepared using three different compositions of pine wood dust (0, 5 and 10 wt. %) in epoxy resin. The results elucidated that composite with 10wt% pine wood dust slided with a velocity of 42 cm/s and normal load of 15 N showed minimum wear rate. The artificial neural network (ANN) approach was also implemented to analyze the wear performance of the composite and found that the results are in good agreement with the experimental data. The wear properties of unreinforced A356 aluminium alloy and composites produced by reinforcing the carbide compounds like boron carbide, silicon carbide etc, with A356 alloy as matrix was investigated. Results of the investigation elucidated that, addition carbide compounds upto 15- 20 vol % increased the wear resistance of composites[14]. Dry sliding wear behavior of rice husk filled epoxy composites with different particle weight fractions (5, 10, 15 and 20 wt %) using Taguchi orthogonal array and artificial neural network (ANN) techniques was carried out by Arun et al.[15]. The results of Taguchi analysis showed that a composite with 20 wt% particle when slided under the velocity of 100 cm/sec with a normal load of 15 N and sliding distance of 2000 m gave minimum wear rate under dry sliding conditions. The result of ANN was in good agreement with Taguchi results. Sandeep et al.[16] examined the tribological behavior of $CaCO_3$ and $CaSO_4$ filled vinyl ester composites. Tests were carried out with different sliding velocity (1.57, 2.62 and 3.67 m/sec.), normal load (20, 40 and 60 N), filler content (0, 10 and 20 wt. %) and sliding distance (1000, 3000 and 5000 m). The plan of experiments based on the Taguchi technique was performed to acquire data in a controlled way. The results show that coefficient of friction (cof) and specific wear rate (swr) for $CaCO_3$ filled vinyl ester composites decreases with the increase of filler content. Whereas, in $CaSO_4$ filled vinyl ester composites both cof and swr decrease at 10 wt. % and then increase at 20 wt. %. The review of literature revealed that, despite many advantages of natural particles, their use for tribological applications is scanty. In this work, an attempt is made to investigate the dry sliding wear behavior of CSPE composites in different particle volume fractions using the Taguchi design of experiment and neural network approach.

2 DEVELOPMENT OF COMPOSITE

2.1 Material Details

Fully matured coconut shells bought from southern part of India were cleaned and crushed into smaller grains of 0.25 mm size for use as particles as shown in Figure 1. Epoxy resin LY 556 and hardener HY 951 was used as matrix material in the ratio of 10:1 respectively. 5% of melamine based on volume of the epoxy was also mixed to increase the rate of curing, bonding strength and to improve the surface finish of developed composites. The epoxy resin, hardener, and melamine were purchased from M/s Insulation house, Bangalore, India.

2.2 Fabrication of Composites

The CSPE composite boards were fabricated with 0.25mm particles in three different particle (coconut shell particle) volume fractions viz., 40%, 50% and 60%, using open mould process. Continuous stirring was carried out during curing process to ensure uniform dispersion of particles in matrix as presented in Figure 2.

Figure 1. 0.25 mm size Coconut shell particles

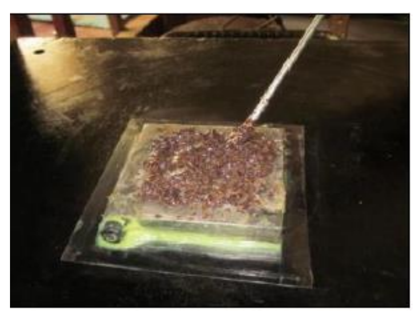

Figure 2. CSPE mixture stirred for uniform dispersion

3 DESIGN OF EXPERIMENT

The experimental plan was formulated considering four control factors and three levels based on the Taguchi recommendation. The four independent variables and their levels considered for this study are given in Table 1.

TABLE 1

Control factors and their levels

Control Factors	Symbols	Levels		
		I	II	III
Sliding Velocity (m/s)	A	3	4	5
Normal Load (N)	B	20	40	60
Particle Volume Fraction (%)	C	40	50	60
Sliding Distance (m)	D	1500	1800	2100

Standard L_{27} (3^{13}) orthogonal array was selected for conducting the experiment which consists of 27 rows and 13 columns. The conventional full factorial experimental design require 81 (3^4) test runs to study the selected four control factors at three levels each. Whereas, Taguchi experimental design reduces the number of test runs to 27. The response is the specific wear rate with the objective as smaller is the best, which was calculated as logarithmic transformation of loss function (equation 1).

$$S/N = -10\log\left(1/n\right)\times\left(\sum y_i^2\right) \qquad \text{........ (1)}$$

Where 'n' is the number of observations, y_i is the calculated value of specific wear rate. It is suggested that quality characteristics are optimized when S/N response is as smaller as possible. The experimental design consists of 27 test runs assigned with four control parameters. The first column was assigned to sliding velocity (A), second column to normal load (B), fifth column to particle volume fraction (C) and ninth column was assigned to sliding distance (D). The third and fourth columns were assigned to $(A\times B)_1$ and $(A\times B)_2$ respectively to estimate interaction between sliding velocity (A) and the normal load (B), sixth and seventh columns were assigned to $(B\times C)_1$ and $(B\times C)_2$ respectively to estimate the interaction between the normal load (B) and the particle volume fraction (C). Similarly, eighth and eleventh columns were assigned to $(A\times C)_1$ and $(A\times C)_2$.[16] The remaining columns were assigned to estimate the experimental error.

4 WEAR TEST

The samples required for wear tests were cut from the composite board using diamond point cutter, and accurately finished to the dimensions of 6 mm × 6 mm × 50 mm using abrasive grinder. The contact surfaces (6mm × 6mm) of the samples were further polished with 800 grade grit paper to ensure uniform surface contact with the rotating disc of wear testing machine. Series of wear tests were conducted using a pin-on-disc machine (Model: Wear & Friction Monitor TR-20LE) supplied by DUCOM Instruments, Bangalore, as per ASTM G99. The parameters considered for the tests are illustrated in Table 1. The sample was held against the counter face of the rotating disc (EN32 steel disc) with a track radius of 80mm. The pin was loaded against the disc through a dead weight loading system. The contact surface was cleaned with acetone after each test. The specimens were weighed to an accuracy of 0.0001 gm using digital electronic weighing machine prior to and after each test and specific wear rate was then determined using equation 2.

$$K_s = \frac{\Delta m}{\rho\times L\times F_n} \qquad \text{........ (2)}$$

Where, Δm represents the measured wear loss in gm, ρ is the density of the specimen in gm/mm^3, L is the sliding distance in meters and F_n is the normal load in Newton's.

5 NEURAL NETWORK APPROACH

Neural network is used as one of the computational tool in Matlab software that provides algorithms and functions to create, train, simulate the network and predict the input – output evolutions. Neural network is a technology which can solve complex non-linear, multi dimensional problems as it has the capability to think like human being. It is composed of interconnected and interacting components called nodes or neurons. The neural network usually consists of three layers, namely, input layer, hidden layer and output layer. The input layer receives the input (coarse) information and sends it to hidden layer, where the information will be processed, then exports the results through output layer.[13]

6 MICROSCOPY

Scanning electron microscopic (SEM) study was carried out to analyze the wear mechanism using a computer interfaced scanning electron microscope (JEOL 6360) operated at 20 kV. SEM samples were sputter coated with a thin layer of gold to minimize the charging problem and then kept under microscope for scanning.

7 RESULTS AND DISCUSSION

8 7.1 Design of experiment

Table 2 presents the results of wear tests as per the test runs along with the S/N ratios generated using statistical software MINITAB 17. The influence of controlled process parameters on wear rate was analyzed and rank was assigned based on the signal to noise response (Table 3). It is evident from Table.3 that, among these parameters, sliding velocity [A] is the most dominant influencing factor on the wear rate followed by particle volume fraction [C], normal load [B] and sliding distance [D]. The influence of process parameters on wear rate are graphically represented in Figure 3.

TABLE 2
Experimental design (L_{27} orthogonal array) with output and S/N ratio

Sliding Velocity[A] (m/s)	Normal Load [B] (N)	Particle Volume Fraction [C] (%)	Sliding Distance [D] (m)	Specific Wear Rate [mm^3/Nm]	S/N Ratio [dB]
3	20	40	1500	0.0000075	102.495
3	20	50	1800	0.0000077	102.307
3	20	60	2100	0.0000097	100.265
3	40	40	1800	0.0000054	105.370
3	40	50	2100	0.0000071	103.010
3	40	60	1500	0.0000086	101.319
3	60	40	2100	0.0000073	102.745
3	60	50	1500	0.0000077	102.278
3	60	60	1800	0.0000097	100.294
4	20	40	1500	0.0000085	101.396
4	20	50	1800	0.0000107	99.396
4	20	60	2100	0.0000105	99.584
4	40	40	1800	0.0000077	102.306
4	40	50	2100	0.0000094	100.583
4	40	60	1500	0.0000100	99.983
4	60	40	2100	0.0000088	101.110
4	60	50	1500	0.0000113	98.908
4	60	60	1800	0.0000115	98.771
5	20	40	1500	0.0000117	98.629
5	20	50	1800	0.0000097	100.274
5	20	60	2100	0.0000133	97.530
5	40	40	1800	0.0000100	100.029
5	40	50	2100	0.0000112	99.031
5	40	60	1500	0.0000106	99.486
5	60	40	2100	0.0000124	98.167
5	60	50	1500	0.0000119	98.511
5	60	60	1800	0.0000148	96.612

TABLE 3
Response table for Specific wear rate

Level	[A] (m/s)	[B] (N)	[C] (%)	[D] (m)
1	102.23	100.21	101.36	100.33
2	100.23	101.24	100.48	100.60
3	98.70	99.71	99.32	100.23
Delta	3.54	1.52	2.04	0.37
Rank	1	3	2	4

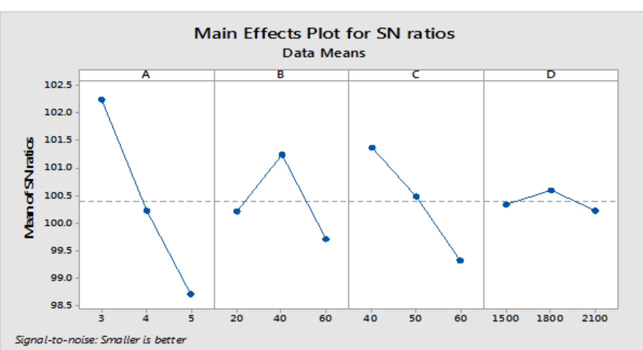

Figure 3. Influence of control factors on wear rate

7.2 Analysis of Variance (ANOVA)

ANOVA was carried out at a level of 5% significance, i.e. up to a confidence level of 95% using software MINITAB 17. In Table 4, the last column indicates the percentage contribution of each factor indicating their degree of influence on the result. It can be observed from the table that the Sliding velocity [A] has greater influence on the dry slide wear of CSPE composites (57.46%) followed by particle volume fraction [C] (19.23%), normal load [B] (11.05%), sliding distance [D] (0.12%) and interactions A×B (1.15%), B×C (1.84%), A×C (6.06%). However, the sliding distance [D] and interactions A×B, B×C does not have the much influence on the specific wear rate of CSPE composites as their contributions are smaller than the error which is 3.10%. This means that increasing the sliding velocity, particle volume fraction and normal load the specific wear rate can be reduced, i.e. wear resistance of CSPE composites can be increased.

TABLE 4
ANOVA for Specific wear rate of CSPE composites

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P (%)
A	2	56.5817	56.5817	28.2909	55.60	57.46%
B	2	10.8771	10.8771	5.4386	10.69	11.05%
C	2	18.9320	18.9320	9.4660	18.60	19.23%
D	2	0.1134	0.1134	0.0567	0.11	0.12%
A*B	4	1.1321	1.1321	0.2830	0.56	1.15%
B*C	4	1.8150	1.8150	0.4537	0.89	1.84%
A*C	4	5.9689	5.9689	1.4922	2.93	6.06%
Error	6	3.0531	3.0531	0.5089		3.10%
Total	26	98.4733				100.00%

7.3 Multiple Linear Regression Models

The linear regression model for S/N ratio developed by the software MINTAB 17 is given by equation (3).

$$\text{S/N Ratio} = 119.47 - 3.52\ A + 0.0687\ B - 0.269\ C - 0.000204\ D - 0.0143\ (A\times B) + 0.0466\ (A\times C) - 0.00048\ (B\times C) \quad \dots (3)$$

7.4 Confirmation Tests

The confirmation experiments were performed on composites by selecting a set of specific combination of parameters shown in Table 5 to validate the statistical analysis. The comparison of results between the confirmation experiments and regression model (predicted) are also presented in Table 5.

TABLE 5
Parameters used in the Confirmation Tests and comparison of results

Test run	Optimal Control Factors	S/N Ratio (Experimental)	S/N ratio by Regression Model (Predicted)	Error (%)
1	$A_1B_1C_2D_2$	104.013	102.1548	1.79
2	$A_2B_1C_3D_1$	99.7940	99.436	0.36
3	$A_3B_1C_1D_3$	100.664	99.1216	1.53
4	$A_2B_3C_1D_2$	100.105	101.2568	1.13

From Table 5, it can be observed that S/N ratios obtained experimentally are in good agreement with those obtained from regression model (predicted) with errors less than 2%.

8 WEAR LOSS PREDICTION USING FFB NEURAL NETWORK

The wear loss of composites is considered to be a non linear problem with respect to its control factors and operating conditions. To acquire minimum wear loss, suitable combinations of control factors have to be designed. For doing this, FFB Neural network tool in MATLAB was chosen as the prediction tool for wear loss of the composites beyond the experimental domain. The FFB Neural network is a tool composed of several cross-linked simple processing units called neurons. It is a simplest type of neural network in which the information moves in only one direction, forward from the input layer to output layer through the hidden layer.

In the present work, the sliding velocity, normal load, particle volume fraction and sliding distance are considered as four input parameters. Each parameter in the input layer is characterized by one neuron. The experimental wear loss corresponding to various combinations of input parameters were used to train the network to build an understanding between input and output parameters. The minimum number of neurons in the hidden layer must be four according to equation (4).[17]

$$\text{Hidden Layer} = \text{Input Layer} + 1 \qquad \dots (4)$$

In this analysis, number of neurons in the hidden layer is optimized to 10. The output layer of the network consists of only one neuron to represent wear loss. The network structure used in this analysis is shown in Figure 4.

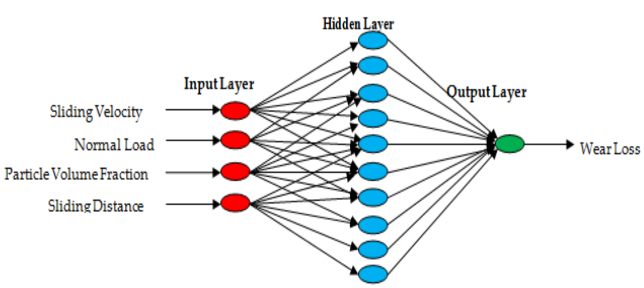

Figure 4. Three Layered Neural network structure

To train the network used in this analysis, about 80% of the data sets (Different input combinations and its output) obtained by experimentation were taken. Many network structures with varying number of neurons in the hidden layer, training function, and learning function were investigated using LOGSIG as transmission function in the input and output layer for the end results. The best network was approximated based on least error criterion as shown in Table 6. The network was trained scrupulously with many numbers of cycles. The wear loss values predicted by ANN were converted to specific wear rate using equation (2) and comparison is made with those obtained from Taguchi Experiments, in Table 7. An error in the range of 0 – 10.37% was noticed. This establishes the validation of neural network computation. However the error percent can further be decreased by increasing the training sets and by optimizing the network structure.

TABLE 6
Optimized Neural network Model

Algorithm	Network Structure	Training Function	Learning Function	Performance Function	Transmission Function
Feed Forward Back propagation (FFB)	4-10-1	TRAIN BR	LEARNGD	SSE	LOGSIG

TABLE 7
Comparison of experimental and Neural Network predicted wear rate

Test Run	Optimal Control Factors	Specific Wear Rate (Taguchi Experimental) [mm^3/Nm]	Specific Wear Rate (Predicted by Neural Network) [mm^3/Nm]	Error (%)
1	A1B1C1D1	0.0000075	0.000008256	9.13
2	A1B1C2D2	0.0000077	0.000007587	1.47
3	A1B1C3D3	0.0000097	0.000009445	2.62
4	A2B2C1D2	0.0000077	0.000008465	9.04
5	A2B2C2D3	0.0000094	0.000008626	8.23
6	A2B2C3D1	0.0000100	0.000009537	4.63
7	A3B3C1D3	0.0000124	0.000012121	2.25
8	A3B3C2D1	0.0000119	0.00001067	10.34
9	A3B3C3D2	0.0000148	0.00001375	7.10

Figure 5(a) shows the effect of sliding velocity and normal load on wear loss in composites with 40% particle volume fraction. It is obvious that, at lowest values of sliding velocity and normal load, the wear loss is only marginal (0.000246 gms). A maximum wear loss of 0.001374 gms was predicted for composite at highest values of sliding velocity (8 m/s) and normal load (60 N). Figure 5(b) and 5 (c) illustrates the effect of particle volume fraction on wear loss at a constant normal load of 20 N and at a constant sliding velocity of 3 m/s respectively. It is clear from the figures that, a minimum wear loss is predicted for composites with 40% particle volume fraction. This may be because of its high hardness and enhanced interfacial area of bonding compared to composites made with 50% and 60% particle volume percent. This indicates that the composite with 40 % particle volume fraction exhibits better wear resistance.

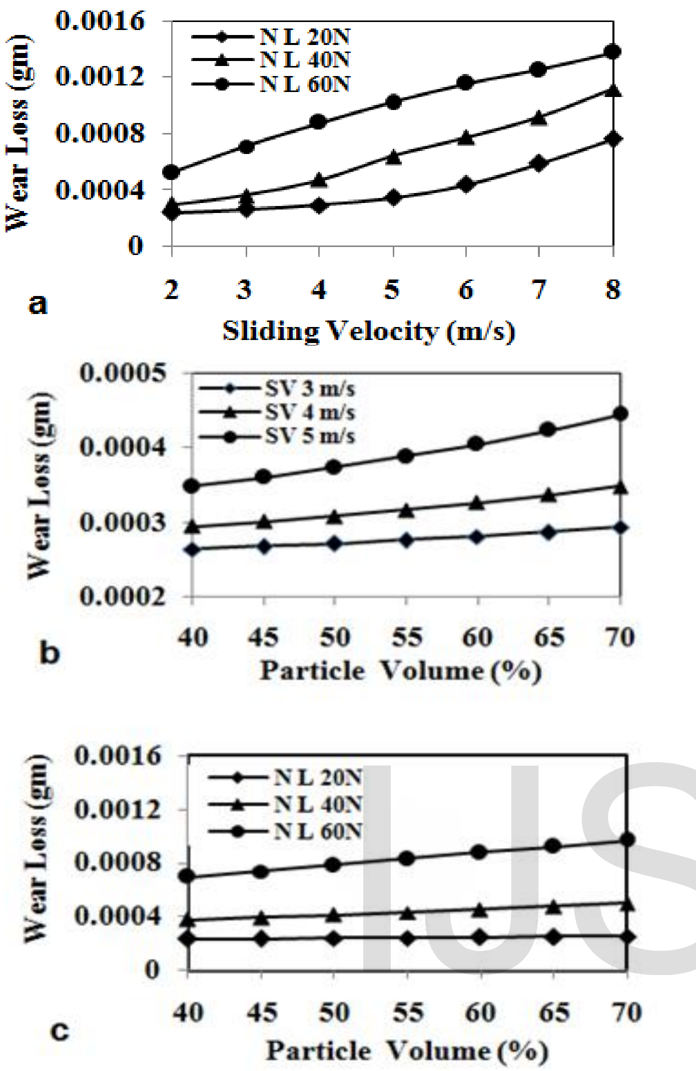

Figure 5. Variation of predicted wear loss with (a) sliding velocity for different normal loads (b) particle volume % for different sliding velocities (c)) particle volume % for different normal loads

9 MICROSCOPIC EXAMINATION

Figure 6 illustrates the micrographic images of worn surface of samples tested under maximum applied load of 60N at a sliding velocity of 4 m/s. The worn surface of a composite characterized by the plastic deformation was noticed. The increase in the applied load and sliding velocity increases the friction resulting in the heat generation which in turn softens the surface of the polymer. The CSPE samples are brittle in nature scratches the resin forming the scars and gradually get aligned along the sliding direction. Also, these particles by virtue of their size, brittleness, and high harness influence modify the wear behavior of the composites. The Long time and continuous sliding results in the formation of wear debris (Figure 6.a). As the worn surface is quite rough, the coconut shell particles protruding from the surface due to the wear away by over time exposing the particle particles, these materials worn out further and loss of the particle particles can occur, resulting in the formation of pits or voids (Figure 6.b) Brittle materials on the other hand, possesses high hardness and therefore high resistance to penetration of counter face asperities so that the effective contact area remains small. They are however, very sensitive to formation of micro cracks (Figure 6.a).

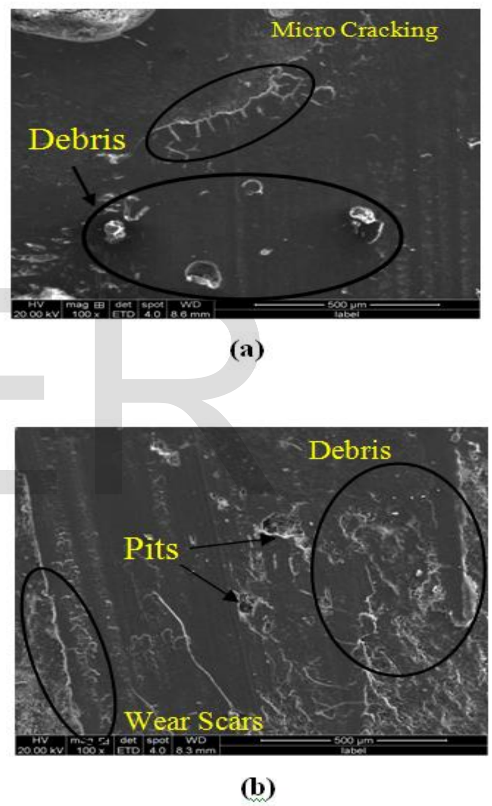

Figure 6. SEM features of CSPE composite samples

10 CONCLUSION

The effect of particle volume fraction on dry sliding wear properties of CSPE composites has been studied using Taguchi and Neural network approaches. Analysis was carried out on dry sliding wear behavior of CSPE composites with particles of size 0.25 mm in 40%, 50% and 60% particle volume fractions. The ANOVA results show that the sliding velocity has greater influence on the dry slide wear of CSPE composites. The use of FFB neural network was also found to be an efficient tool for the prediction of dry slide wear of CSPE composites within and beyond the experimental domain. The specific wear rate predicted by FFB neural network and Taguchi technique are found to be in good agreement with experimental results. SEM images of CSPE composites depicted the formation of micro cracks, debris, scars and pits. Uniform distribution of particles is also noticed. The CSPE composite with 40% particle volume fraction exhibited better wear resistance than 50% and 60% particle volume fraction CSPE composites.

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