INFLUENCE OF POLYBENZIMIDAZOLE NANOFILLER IN PINEAPPLE FIBER-BASED EPOXY COMPOSITES: TRIBOLOGICAL AND OPTIMIZATION ANALYSES

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In the present work, the epoxy matrix was reinforced with pineapple fiber and polybenzimidazole (PBI) filler as secondary reinforcement. The composites were manufactured by the hand lay-up process. Wear characteristics were studied utilizing two-body abrasive wear tests. The input characteristics chosen for the study were: (i) polybenzimidazole content (wt%), (ii) load (N), and (iii) sliding distance (m). The resulting parameters assessed were: specific wear rate (SWR) and coefficient of friction (COF). A scanning electron microscope was utilized to study the worn surface of the abraded surfaces. The output of the experiments revealed that the addition of PBI filler to the pineapple fiber-based epoxy composite resulted in an increase in wear resistance. Finally, the output of the experiments was optimized by multi-criteria decision methods, such as Additive Ratio Assessment, Vise Kriterijumska Optimizacija Kompromisno Reseneje, and Weighted Aggregated Sum Product Assessment methods.

Keywords: abrasive wear, pineapple fiber, optimization, polybenzimidazole filler, tribology

INTRODUCTION

In the present global scenario, the disposal of wastes, especially of plastics, has stirred significant concerns, because of the environmental issues it causes.[1] A possible solution to mitigate plastic pollution is using natural, biodegradable materials to replace plastics. Various fibers, such as banana, jute, hemp, flax, pineapple fibers and others, have been investigated in the development of composite materials, which could reduce pollution-related problems.[2] Natural fibers have excellent properties that recommend them for several lightweight medium-load applications, and thus they could replace non-biodegradable fibers, such as glass and carbon fibers.[3] Their lower cost and wide availability also support their use in various applications. However, the properties of the natural fibers vary as a function of the conditions in which they are grown, the part of the plant they are extracted from (bast, root, leaf)[4] and the extraction procedure used.[5]

Epoxy is one of the most commonly used matrices for composites, being known for its high strength and excellent bonding characteristics.[6] Its major limitations consist in its low durability and its brittle nature. Adding fillers to the epoxy matrix can help overcome these limitations.[7] A good dispersion of the filler leads to an improvement in the properties of the epoxy.[8] Researchers have investigated various fibers to reinforce epoxy based composites. For example, Mylsamy and Rajendran[13] used agave fibre in different lengths in the epoxy matrix and studied the tribological properties of the composites.

They concluded that there is an increase in wear resistance when the fibre length is increased. Jenish *et al.*[14] investigated the dry sliding wear of *Cissus quadrangularis* stem fiber/epoxy resin composite, reinforced with red mud particulate filler composites, and found out that when the loading of the red mud filler was increased, the wear rate was reduced. El-Tayeb[15] observed that the wear resistance of composites reinforced with chopped sugarcane enhances with the fiber loading at the fiber dimension of 5 mm. Another potential filler to consider is pineapple fiber.[9] The leaves of pineapple (*Ananas comosus*) are usually considered as waste products.[10] However, they could be used to extract fibers. The composition of the pineapple fibre (cellulose content of 72.15%, hemicelluloses of 4.86%, lignin of 13.55%),[11] and their robustness and stiffness,[12] could make them good candidates for reinforcing composite materials.

The Taguchi technique is an approach for optimization studies, which is based on three fundamental concepts: orthogonal arrays, quality loss function, and the signal-to-noise (S/N) ratio. The S/N ratio is employed to evaluate the quality of a product or process by analyzing the ratio between the desired signal and the undesirable noise.[16] Orthogonal arrays are used to develop experiments that efficiently identify the optimal combination of design parameters with fewer trials. The Taguchi methodology has proven highly beneficial in diverse areas, including automation and manufacturing. Its efficacy has been demonstrated through numerous studies reported in the literature.[17,18] Optimizing process parameters increases efficiency and reduces cost.[19] Within the Taguchi method, the multi-criteria decision-making (MCDM) model is a critical problem-solving approach that seeks to identify the optimal choice by evaluating multiple criteria during selection. MCDM offers a variety of tools and strategies that can be utilized across various sectors, including design engineering.[20] Some mathematical tools that support MCDM include: WASPAS (Weighted Aggregates Sum Product Assessment), VIKOR (Vlsekriterijumska Optimizacija i Kompromisno Resenje – in Serbian) and ARAS (Additive Ratio Assessment), which have been used in various research areas.[21,22,23,24,25,26] The VIKOR technique focuses on establishing priorities and choosing from a set of options, while evaluating a solution that maximizes the benefit for the majority and minimizes regret for the minority. ARAS is an MCDM tool that simplifies ordering a small number of choice alternatives by evaluating them simultaneously based on different decision criteria without requiring intricate calculations.

The present work explores the friction and wear characteristics of hybrid composites reinforced with pineapple fiber and polybenzimidazole (PBI). First, the study involved manufacturing pineapple/PBI composites at various weight percentages. Once manufactured, the samples were cut for tribological characterization, in terms of two-body abrasive wear. The experiments were designed according to Taguchi L16 optimization, and the output was optimized using ARAS, WASPAS, and VIKOR methods. Finally, the worn surface morphology of the abraded surfaces was studied.

EXPERIMENTAL

Materials

Araldite LY556 grade epoxy was selected as the matrix material for the present study, due to its superior resistance to chemicals, compliance with every stage of production, and accessibility. Araldite HY 951 epoxy hardener was chosen due to its compatibility with LY556, excellent curing features, and resistance to chemicals. The hardener and resin were both produced by the Huntsman Company.

The natural fiber selected for the present study was pineapple fiber. The fibers were obtained by the water retting process. Initially, the pineapple leaves were kept in a closed water basin, to avoid direct sunlight. The basin was opened every four days, and the water was replaced. This process was carried out for 20 days. After 20 days, the fibers were separated from the remaining material, cleaned with metal brushes and then washed with distilled water. The clean fibers were dried and woven according to requirements.[27]

The PBI nanoparticle reinforcement, with sizes in the range of 90–120 nm and a glass transition temperature of 485 °C, was provided by Merck, India, under the trade name GAZOLE™ 5000.

Manufacturing of composites

The composites were produced by employing the hand lay-up technique. The epoxy matrix was reinforced with four variations of weight percentages (0, 2.5, 5 and 7.5 wt%) of PBI. A mold release agent was initially applied to the surface to facilitate the easy removal of the manufactured composites from the surface. PBI at the required proportion was mixed with an epoxy-hardener solution using a magnetic stirrer. Then, degassing was performed to remove the entrapped air bubbles. After that, it was supplemented with an epoxy-hardener-PBI solution. Each layer of pineapple fiber was kept at the die surface, and the epoxy hardener and the mixture of epoxy-hardener-

PBI reinforcement were applied between the pineapple fibers. This was done until the stacking sequence was completed. The sample denotation of the manufactured composites is shown in Table 1.

Abrasive wear tests

The optimization of process parameters is time-consuming, particularly as the number of parameters rises. The Taguchi method utilizes orthogonal arrays to mitigate these limitations by reducing the number of required tests.

The friction and wear properties of the produced composites were studied through two-body abrasive wear experiments, involving 320-grit abrasive paper attached to a steel disc. The tests utilized Taguchi L'16 design with input parameters including PBI (wt%), applied load (N), and sliding distance (m). Factors such as specific wear rate and coefficient of friction are considered in the output. The process parameters and their levels are shown in Table 2.

The abraded surface of the sample was then analyzed using a scanning electron microscope. The samples were prepared for SEM by cutting them to dimensions of 10 mm x 10 mm, sputtering them with gold to enhance surface conductivity and ensure clear capture of SEM images.

Table 1
Sample formulations used in the study

Sl. No.	Epoxy and hardener (wt%)	Pineapple fiber (wt%)
1	100	0
2	97.5	2.5
3	95	5
4	92.5	7.5

Table 2
Control factors and their levels for abrasive wear tests

Control factors	Levels			
	1	2	3	4
PBI (wt%)	0	1	3	5
Applied load (N)	10	15	20	25
Sliding distance (m)	75	150	225	300

RESULTS AND DISCUSSION

Two-body abrasive wear experiments were conducted using the L16 orthogonal array. Table 3 presents the values of coefficient of friction (COF) and specific wear rate (SWR) for the input parameters.

Specific wear rate

The effect of process parameters on SWR is shown in Figure 1. In the case of sliding distance, the SWR values declined with an increasing sliding distance. High initial SWR values were observed when the sliding distance was set to 75 meters, which exposed the outermost layer of the manufactured composites. In the initial stages, the wear track is not formed; a thin layer forms on the abrasive surface, acting as a lubricant. When the sliding distance was increased, the material slid on the same lubricating surface, which reduced the SWR values.

Similarly, when the load increases, the SWR values decrease. At higher levels of load conditions, PBI powder is exposed as the outer layer gets removed due to the formation of heat at the counter face. When the PBI filler particles are exposed, there is a decrease in SWR values. Due to the exposure, a thin film of lubricant forms, resulting in lower values of SWR. Thus, at higher loads, SWR values are reduced. When no PBI was used as reinforcement along the pineapple fiber, the SWR was higher, and when the PBI powder was added, the SWR values decreased, as shown in Figure 1. The proper bonding and the interaction between the fiber and filler led to a decrease in SWR values. When the amount of the filler dispersed was higher (5 wt%), a decline in SWR was noted. Thus, it can be concluded that when 5 wt% PBI led to increased wear resistance. The obtained results match those reported by Pogacni *et al*.[28]

Coefficient of friction

The effects of process parameters on the evolution of the coefficient of friction (COF) are shown in Figure 2. During the experiments, it was noted that COF was maximum when no PBI was added besides the pineapple fiber. With the addition of PBI to the pineapple fiber, the COF values started decreasing. The addition of PBI increased the resistance to wear, as discussed above, which was the main reason for the decrease in SWR values. Similarly, the COF values were minimal in the case of the addition of PBI at 5 wt%.

COF values as a function of the load are shown in Figure 2. It can be noted that the COF values decreased as the load increased from 10 N to 25 N. At the maximum applied load of 25 N, a thin lubricant on the surface formed, which facilitated the decrease in COF values. The heat generation on the counter face was the major reason for the formation of the lubrication surface.

As regards the effects of sliding distance, initially COF increased with increasing sliding distance to 150 m, and then further increases led to a decrease in COF. When the sliding distance is set at higher values, wear debris get clogged on the wear track. This clogging of materials acted as a barrier to wear, which increased the wear rate. The reduced efficiency due to the clogging was a vital reason for the decrease in wear rate. The results obtained are in correlation with the experimental results of Gupta and Srivatsa.[29]

Table 3
Experimental results for coefficient of friction, weight loss and specific wear rate at 0.5 m/s sliding velocity

Sl. No.	Percentage of nanofiller (wt%)	Applied load (N)	Sliding distance (m)	Coefficient of friction (μ)	Specific wear rate (mm^3/Nm)
1	0	10	100	0.279897	7.77036
2	0	15	150	0.274261	7.41455
3	0	20	200	0.253598	4.960345
4	0	25	250	0.230116	3.25975
5	1	10	150	0.251748	7.7572
6	1	15	100	0.240101	6.6
7	1	20	250	0.224871	3.96
8	1	25	200	0.223079	2.9975
9	3	10	200	0.204395	5.0512968
10	3	15	250	0.200241	4.45096
11	3	20	100	0.198579	5.45514
12	3	25	150	0.204395	4.17956
13	5	10	250	0.19488	4.291248
14	5	15	200	0.189266	3.25864
15	5	20	150	0.193276	3.813032
16	5	25	100	0.183652	3.608838

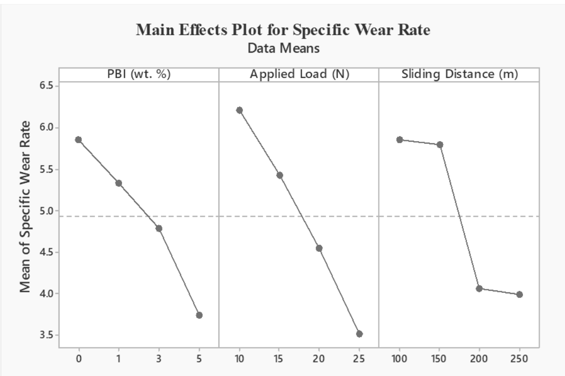

Figure 1: Main effect plots for specific wear rate

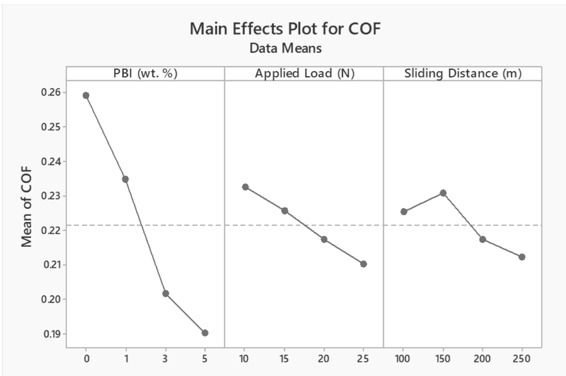

Figure 2: Main effect plots for coefficient of friction

A NOVA

By examining the interrelationships among the input parameters (PBI (wt%), sliding distance (m), and applied load (N)), the ANOVA determines the impact of these parameters on the output variables (COF, SWR). The objective of the ANOVA is to determine which abrasive wear characteristics impact the output statistically.

Using Minitab V 16.0, SWR and COF were analyzed in this investigation, and the lower the values obtained, the better. Tables 4 and 5 contain the ANOVA data for SWR and COF, respectively, statistically analyzed with a 95% confidence level.

PBI (wt%), load (N), and sliding distance (m) were identified as significant variables based on the fact that the F values obtained from statistical calculations for SWR and COF were more important than the F values obtained from other statistical calculations. For SWR, the dominant factors were applied load (40.91%), followed by sliding distance (32.50%) and percentage of nanofiller (24.52%). For COF, the dominant factors were the percentage of nanofiller (62.44%), followed by applied load (22.62%) and sliding distance (11.39%).

Table 4
ANOVA for SWR

Source	DOF	Adj. SS	Adj. MS	F_{table}	F_{cal}	% Contribution
Percentage of nanofiller (wt%)	3	9.7519	3.2506	4.76	23.83	24.52
Applied load (N)	3	16.2708	5.4236	4.76	39.75	40.91
Sliding distance (m)	3	12.9250	4.3083	4.76	31.58	32.50
Error	6	0.8186	0.1364	-	-	2.07
Total	15	39.7662	-	-	-	100

DOF – degrees of freedom, Adj. SS – adjacent sum of squares, MS – mean sum of squares

Table 5
ANOVA for COF

Source	DOF	Adj. SS	Adj. MS	F_{table}	F_{cal}	% Contribution
Percentage of nanofiller (wt%)	3	0.004366	0.001455	35.35	0	62.44
Applied load (N)	3	0.001582	0.000527	12.81	0.005	22.62
Sliding distance (m)	3	0.000797	0.000266	6.46	0.026	11.39
Error	6	0.000247	0.000041			3.53
Total	15	0.006992				100

DOF – degrees of freedom, Adj. SS – adjacent sum of squares, MS – mean sum of squares

Optimization of process parameters

The entropy approach was utilized to determine the weights for Multiple Criteria Decision Making (MCDM) situations when the data in the decision matrix is available. The three major weighting techniques are subjective, objective, and integral. Objective entropy weighting was used for calculating weights in Multiple Criteria Decision Making (MCDM) situations. MCDM approaches were used to establish the best process parameters by ranking alternatives based on their performance or output responses. Equations 1-3, as shown in Table 6, were used for calculating entropy weights. The weights obtained using the equations are 0.937 for SWR and 0.063 for COF.

Additive ratio assessment (ARAS) method

MCDM concerns pertain to the allocation of rankings to alternative decision-making processes. Utilizing the ARAS method, the utility function value is ascertained. The utility value, derived from the output parameter with weight criteria chosen, ascertains the optimum or possible alternative. The initial phase of the ARAS method involves the formulation of the decision matrix. The decision matrix must be initialized to tackle any discrete optimization problem using MCDM. The sequential process utilized for computations throughout the ARAS technique is outlined in Table 7.[30]

The normalized decision matrix, the weighted normalized matrix for all the experiments, is estimated by Equations 1, 2 and 3 in Table 6. Normalized weighted criteria were calculated by Equations 4, 5 and 6, and the optimality function was calculated by Equation 7 in Table 7. The utility degree with ranking is estimated by Equation 8 in Table 7. From the experimental values, fourteen experiments exhibited a higher utility value of 0.9887 as the optimum condition evaluated by ARAS methodology, exhibiting a 3.258 SWR and COF value of 0.189, showing the improved machining performance as shown in Table 9. The alternative values were ranked based on the utility degree achieved by the ARAS method. The ranking of alternatives, according to the values of utility degree, is A2<A3<A7<A15<A14<A4<A11<A16<A6<A8<A5<A10<A9<A1<A12<A13. Therefore, A14 is the best optimal parameter corresponding to the utility degree of ARAS methodology.

Table 6
Entropy weighting

Steps count	Formula used	Symbols used	Eq. No.
1	Entropy weighted method: (i) Normalization of the arrays of a decision matrix to obtain project outcome P_{ij} $P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$	P_{ij} - decision matrix	(1)
	(ii) Computation of the entropy measure of project outcomes $E_j = -k \sum_{i=1}^{m} P_{ij} \times \ln P_{ij}$ $k = \frac{1}{\ln(m)}$		(2)
	(iii) Defining the objective weight based on the entropy concept $W_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)}$ $\vartheta_{ij} = w_j \times r_{ij}$, i=1,2,….,n; j=1,2..,n	ϑ_{ij} - weighted normalized matrix w_j - weighted values	(3)

Table 7
ARAS MCDM methodology

Steps count	Formula used	Symbols used	Eq. No.
1	Construction of decision matrix $X = \begin{bmatrix} x_0 & x_{0j} & \cdots & x_{0n} \\ x_{i1} & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{mj} & \cdots & x_{mn} \end{bmatrix}, i = \overline{0,m}; j = \overline{1,n}$ If j criterion, optimal value is unknown $x_{0j} = \max_i x_{ij}$, if $\max_i x_{ij}$ is preferable; $x_{0j} = \min_i x^*_{ij}$, if $\min_i x^*_{ij}$ is preferable.	i=1,m, j=1,n (n - criteria and m - alternatives)	(1)
2	Normalizing the initial values of all criteria and defining the normalised decision matrix $\bar{x}_{ij}$ $\bar{X} = \begin{bmatrix} \bar{x}_{01} & \cdots & \bar{x}_{0j} & \cdots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix}; = \overline{0,m}; j = \overline{1,n}$	X_{0j} – j[th] criterion optimal value, where x_{ij} - values of performances and the w_j - weights criteria	(2)
3	Normalized maximum preferable criteria (for beneficial attributes) $\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}$	X_{ij} – i[th] alternative in terms of j[th] criterion performance value	(3)

4	Minimum preferable criteria values (for non-beneficial attributes) are normalized in two stages $x_{ij} = \frac{1}{x_{ij}^{*}}; \overline{x_{ij}} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}$	The summation of all the weights is equal to 1; w_j - weight criterion for j^{th} alternative, w_j is the criterion of weights lies in-between from 0 to 1	(4)
5	Normalizes weighted matrix used to estimate the weight for the criteria, the weightage value lies between from 0 to 1 (*i.e.* $0 < w_j < 1$). The sum of all weights criteria must be equal to (w_j=1), which is expressed as follows: $\sum_{j=1}^{n} W_j = 1$ $\hat{X} = \begin{bmatrix} \hat{x}_{01} & \cdots & \hat{x}_{0j} & \cdots & \hat{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{i1} & \cdots & \hat{x}_{ij} & \cdots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mj} & \cdots & \hat{x}_{mn} \end{bmatrix}; i = \overline{0, m}; j = \overline{1, n}.$	λ value is assumed to be 0.5; Q_i considered as aggregate comparative significance value	(5)
6	Weighted normalized values of all criteria $\widehat{x_{ij}} = \overline{x_{ij}} w_j; i = 0, m$	$\overline{x_{ij}}$ is the normalized value of the j criterion; W_j is the weight of the j criterion	(6)
7	To determine the optimality function by $S_i = \sum_{j=1}^{n} \widehat{x_{ij}}; i = \overline{0, m},$	where S_i is the i^{th} alternative optimality function	(7)
8	The utility degree K_i is obtained by $K_i = \frac{S_i}{S_o}$	S_i and S_0 are the optimality criteria	(8)

WASPAS (weighted aggregated sum product assessment) method

Zavadskas *et al*. proposed a mathematical theory to assess the MCDM problems based on ranking the alternative methodology. This theory combines the weighted sum method (WSM) proposed by MacCrimmon *et al*. and the weight product method (WPM). The equation shown in Table 10 is used to compute the WASPAS methodology.[31]

The objective entropy weights for output characteristics, like SWR and COF are 0.967 and 0.063, respectively, evaluated by the entropy weights equation. Equation 1 shows the decision matrix initialization. Equation 2 shows the decision matrix normalization for beneficial and non-beneficial criteria for SWR and COF. Equation 3 allows the estimation of aggregate, with comparative significance based on the WSM method. Equation 4 makes the estimation of aggregate, with comparative relevance based on the WPM method. Equation 5 shows the estimation of the aggregate, with comparative significance alternative score; the highest score was considered the best optimum value. From the experimental values, fourteen experiments exhibited a higher WASPAS - aggregate, comparative significance alternative score of 0.6359 as the optimum condition evaluated by WASPAS methodology, exhibiting 3.254 SWR and COF value of 0.189, showing the improved machining performance.

The alternative values were ranked based on the aggregate comparative significance alternative score from the WASPAS method: A16<A14<A12<A3<A15<A13<A6<A2<A10<A9<A11<A7<A8<A1<A5<A4. Therefore, A14 is the optimal parameter for the aggregate comparative significance alternative score.

Vise kriterijumska optimizacija kompromisno reseneje (VIKOR) optimization methodology

The VIKOR method is a discrete decision-making approach that utilizes multi-criteria decision-making to address issues involving non-commensurable criteria. The approach prioritizes ranking and selecting alternates from a given set to identify compromise solutions for problems involving conflicting criteria. These compromise solutions can assist decision-makers in arriving at the final solutions. The methodology utilized throughout the VIKOR methodology is detailed in Table 11.[32]

Table 8
Output from ARAS methodology

Sl. No.	PBI (wt%)	Load (N)	Sliding distance (m)	Beneficial criteria	Non-beneficial criteria	Initial decision matrix		Normalised decision matrix		Weighted normalised decision matrix		S_i	K_i	Ranking
				SWR	COF	SWR	COF	SWR	COF	SWR	COF			
1	1	10	75	7.77036	0.279897	7.7704	3.3345	0.0897	0.0493	0.0841	0.0031	0.0872	0.9880	2
2	1	20	150	7.41455	0.274261	7.4146	3.3983	0.0856	0.0502	0.0802	0.0032	0.0834	0.9450	3
3	1	30	225	4.960345	0.253598	4.9603	3.6550	0.0573	0.0540	0.0537	0.0034	0.0571	0.6468	7
4	1	40	300	3.25975	0.230116	3.2598	3.9981	0.0376	0.0591	0.0353	0.0037	0.0390	0.4419	15
5	2	10	150	7.7572	0.251748	3.2586	4.1794	0.0376	0.0618	0.0353	0.0039	0.0392	0.4437	14
6	2	20	75	6.6	0.240101	6.6000	3.8447	0.0762	0.0568	0.0714	0.0036	0.0750	0.8499	4
7	2	30	300	3.96	0.224871	3.9600	3.9236	0.0457	0.0580	0.0428	0.0037	0.0465	0.5270	11
8	2	40	225	2.9975	0.223079	2.9975	4.1139	0.0346	0.0608	0.0324	0.0038	0.0363	0.4110	16
9	3	10	225	5.0512968	0.204395	5.0513	4.0917	0.0583	0.0605	0.0547	0.0038	0.0585	0.6626	6
10	3	20	300	4.45096	0.200241	4.4510	4.1625	0.0514	0.0615	0.0482	0.0039	0.0520	0.5897	8
11	3	30	75	5.45514	0.198579	5.4551	4.1915	0.0630	0.0619	0.0590	0.0039	0.0629	0.7132	5
12	3	40	150	4.17956	0.204395	4.1796	4.0917	0.0483	0.0605	0.0452	0.0038	0.0490	0.5557	10
13	4	10	300	4.291248	0.19488	4.2912	4.0836	0.0496	0.0603	0.0464	0.0038	0.0502	0.5693	9
14	4	20	225	3.25864	0.189266	7.7572	3.5493	0.0896	0.0524	0.0839	0.0033	0.0872	0.9887	1
15	4	30	150	3.813032	0.193276	3.8130	4.1106	0.0440	0.0607	0.0413	0.0038	0.0451	0.5110	12
16	4	40	75	3.608838	0.183652	3.6088	4.4712	0.0417	0.0661	0.0390	0.0042	0.0432	0.4897	13

Table 9
WASPAS MCDM methodology

Steps count	Formula used	Symbols used	Eq. No.
1	Initializing the decision-making matrix (X) for solving the selection of problem $X - [x_{ij}]_{nXm} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{n=1} \end{bmatrix}$ X_{ij} ($X_{ij} \geq 0$); ($i \in \{1,2,\ldots n\}$, ($j \in \{1,2,\ldots m\}$);	where X_{ij} - of i^{th} attribute on j^{th} criterion performance value	(1)
2	Decision Matrix Normalization $n_{ij} = \begin{cases} \frac{x_{ij}}{\max_i x_{ij}} & \text{if } j \in N_b \\ \frac{\min_i x_{ij}}{x_{ij}} & \text{if } j \in N_{nb} \end{cases}$	N_b - beneficial criterion, N_{nb} – non-beneficial criterion	(2)
3	Estimation of Aggregate comparative significance based on WSM method $Q_i^{(1)} = \sum_{j=1}^{n} x_{ij} \cdot w_j$ ($\sum_{j=1}^{m} w_j = 1$)		(3)
4	Estimation of Aggregate comparative significance based on WPM method $Q_i^{(2)} = \prod_{j=1}^{n} x_{ij} w_j$ ($\prod_{j=1}^{n} w_j = 1$)	The summation of all the weights is equal to 1; w_j - weight criterion for j^{th} alternative, w_j is the criterion of weights lies in-between from 0 to 1	(4)
5	Estimation of Aggregate comparative significance of alternatives $Q_i = \lambda \cdot Q_i^{(1)} + (1-\lambda) \cdot Q_i^{(2)}$	λ value is assumed to be 0.5; Q_i considered as Aggregate comparative significance value	(5)

Table 10
Optimization by entropy weights incorporated with WASPAS MCDM methodology

Sl. No.	PBI (wt%)	Load (N)	Sliding distance (m)	Normalized matrix		Weighted normalised matrix		Qi	EQN 4 Q2 (π)		Q2	QI	Ranking
				SWR	COF	SWR	COF		SWR	COF			
1	1	10	75	0.3858	0.7458	0.0634	0.0956	0.1591	0.8550	0.9631	0.8235	0.4913	16
2	1	20	150	0.4043	0.7600	0.0665	0.0975	0.1639	0.8617	0.9654	0.8319	0.4979	14
3	1	30	225	0.6043	0.8174	0.0993	0.1048	0.2042	0.9205	0.9745	0.8970	0.5506	12
4	1	40	300	0.9195	0.8942	0.1512	0.1147	0.2658	0.9863	0.9858	0.9723	0.6191	3
5	2	10	150	0.3864	0.7938	0.0635	0.1018	0.1653	0.8553	0.9708	0.8303	0.4978	15
6	2	20	75	0.4542	0.8599	0.0747	0.1103	0.1849	0.8783	0.9808	0.8615	0.5232	13
7	2	30	300	0.7569	0.8775	0.1244	0.1125	0.2370	0.9553	0.9834	0.9394	0.5882	6
8	2	40	225	0.9199	0.9347	0.1512	0.1199	0.2711	0.9864	0.9914	0.9779	0.6245	2
9	3	10	225	0.5934	0.9151	0.0976	0.1174	0.2149	0.9178	0.9887	0.9074	0.5612	10
10	3	20	300	0.6735	0.9309	0.1107	0.1194	0.2301	0.9371	0.9909	0.9285	0.5793	9
11	3	30	75	0.5495	0.9374	0.0903	0.1202	0.2106	0.9063	0.9917	0.8988	0.5547	11
12	3	40	150	0.7172	0.9151	0.1179	0.1174	0.2353	0.9468	0.9887	0.9361	0.5857	7
13	4	10	300	0.6985	0.9133	0.1148	0.1171	0.2320	0.9427	0.9884	0.9318	0.5819	8
14	4	20	225	1.0000	0.9201	0.1644	0.1180	0.2824	1.0000	0.9894	0.9894	0.6359	1
15	4	30	150	0.7861	0.9193	0.1292	0.1179	0.2471	0.9612	0.9893	0.9509	0.5990	5
16	4	40	75	0.8306	1.0000	0.1366	0.1282	0.2648	0.9699	1.0000	0.9699	0.6174	4

Table 11
VIKOR MCDM methodology

Steps count	Formula used	Symbols used	Equation No.
1	Decision matrix (x_{ij}) construction $X = [x_{ij}]_{nXm} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{n=1} \end{bmatrix}$	where Xij (Xij ≥ 0), (i ϵ {1,2, ... n} and (j ϵ {1,2, ... m} indicates the performance value of i^{th} attribute on j^{th} decisive factor	(1)
2	Estimation of linear normalized decision matrix performance values $f_{ij} = \frac{I_i^j}{\sqrt{\sum_{i=1}^{m} (I_i^j)^2}}$	i=1,2,....m, j=1,2,....n	(2)
3	Determination of utility assess (Si) and regret assess (Ri) $S_j = \sum_{i=1}^{n} w_i (f_i^* - f_{ij})/(f_i^* - f_i^-)$ For beneficial attributes $S_j = \sum_{i=1}^{n} w_i (f_i^* - f_{ij})/(f_i^* - f_i^-)$ for non-beneficial attributes $R_j = \max_i [w_i (f_i^* - f_{ij})/(f_i^* - f_i)]$ for beneficial attributes $R_j = \max_i [w_i (f_i^* - f_{ij})/(f_i^* - f_i)]$ for non-beneficial attributes		(3)
4	To calculate the value of Qi $Q_j = V * \frac{(S_i - S^*)}{S^- - S^*} + (1 - v)\frac{(R_i - R^*)}{R^- - R^*}$	V values lie between 0 to 1, as we take 0.5	(4)

Table 12
Optimization by entropy weights incorporated with VIKOR MCDM methodology

Sl. No.	PBI (wt%)	Load (N)	Sliding distance	Utility assess (Si)	Regret assess (Ri)	S_i	R_i	Q_i	Ranking
1	1	10	75	0.0000	0.0000	0.0000	0.0000	0.0000	16
2	1	20	150	0.0488	0.0015	0.0503	0.0488	0.0748	14
3	1	30	225	0.3853	0.0070	0.3923	0.3853	0.5873	10
4	1	40	300	0.6185	0.0133	0.6317	0.6185	0.9443	3
5	2	10	150	0.0018	0.0048	0.0066	0.0048	0.0086	15
6	2	20	75	0.1605	0.0106	0.1711	0.1605	0.2504	13
7	2	30	300	0.5224	0.0120	0.5344	0.5224	0.7983	6
8	2	40	225	0.6186	0.0161	0.6348	0.6186	0.9467	2
9	3	10	225	0.3728	0.0148	0.3876	0.3728	0.5743	11
10	3	20	300	0.4551	0.0159	0.4710	0.4551	0.6995	9
11	3	30	75	0.3174	0.0163	0.3338	0.3174	0.4918	12
12	3	40	150	0.4923	0.0148	0.5071	0.4923	0.7549	7
13	4	10	300	0.4770	0.0146	0.4917	0.4770	0.7316	8
14	4	20	225	0.6544	0.0151	0.6695	0.6544	1.0000	1
15	4	30	150	0.5426	0.0151	0.5577	0.5426	0.8310	5
16	4	40	75	0.5706	0.0203	0.5909	0.5706	0.8772	4

Responses with the highest appraisal score were determined to be the optimal ones for each experiment. It is evident from the VIKOR appraisal score that the parameter exhibits

favourable yield characteristics. The fourteenth experiment, as determined by the VIKOR methodology, demonstrates the highest VIKOR appraisal score of 1.0000, the most favourable and optimal parameter in the evaluation, as shown in Table 12. The alternatives were ranked as per their appraisal score values based on the evaluation as follows:
A16<A14<A10<A3<A15<A13<A6<A2<A11 <A9<A12<A7<A8<A1<A5<A4.

Worn surface morphology

Worn surface morphology is widely used to study the wear mechanism that is predominant during wear testing. The worn surface images corresponding to experiment 4 and experiment 16 are shown in Figures 3 and 4. From Figure 3, it can be seen that there is extensive damage to the fiber, which can be explained by insufficient loading of nanofiller in the manufactured composites. From Figure 4, it can be seen that the exposed filler particles prevented deep matrix damage. As the damage is less significant, there is a decrease in wear resistance of the samples. PBI particle patches can be seen, which increased the wear resistance. Thus, the damage on the surface is lower than in the other samples. Therefore, the worn surface analysis results correlated with the experimental values.

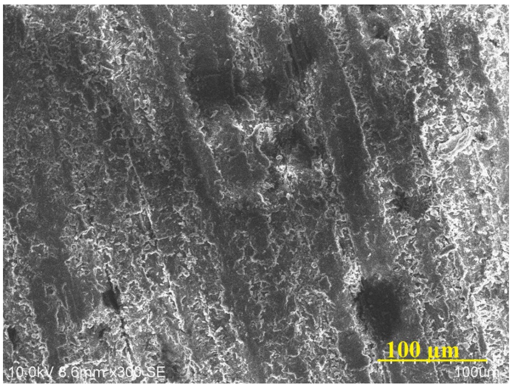

Figure 3: Worn surface image corresponding to Experiment No 4

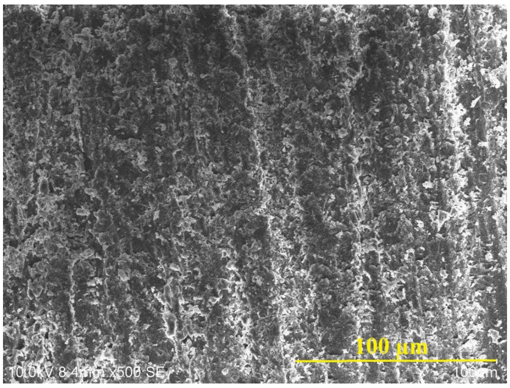

Figure 4: Worn surface image corresponding to Experiment No 16

CONCLUSION

Pineapple fiber reinforced composites incorporating with a PBI filler were manufactured using the hand lay-up method. The output of the experiments was optimized using techniques like VIKOR, WASPAS, and VIKOR methodology. The following conclusions were drawn from the study.

It was confirmed through abrasive wear tests that the incorporation of additives enhanced the manufactured samples' resistance to wear. When SWR was considered, it was minimum when PBI was reinforced at 5 wt%, at a load of 20 N, and sliding distance of 250 m. The presence of PBI in the epoxy matrix increased wear resistance. When COF was considered, it was maximum in the absence of PBI, at a load of 5 N, and sliding distance of 75 m. The absence of the nanofiller was the main reason for the increase in wear. ANOVA studies revealed that the load (40.91%) is the dominating factor for SWR, and for COF, PBI (62.44%) is the dominating factor. An increase in PBI in the matrix results in a corresponding increase in wear resistance, as determined by worn surface morphology. The presence of PBI increased wear resistance. The output of the optimization techniques revealed that experiment number 14 resulted in the best combination among the experiments.

REFERENCES

[1] M. L. Rinawa, K. Singh, V. Chaudhary, N. Ahamad, P. P. Das *et al*., *Mater. Today Proc*., **56**, 2640 (2022), https://doi.org/10.1016/j.matpr.2021.09.184

[2] R. Vijay, D. L. Singaravelu, A. Vinod, M. R. Sanjay, S. Siengchin *et al*., *Int. J. Biol. Macromol*., **125**, 99 (2019), https://doi.org/10.1016/j.ijbiomac.2018.12.109

[3] R. Venkatesh, S. Ballal, A. Mohana Krishnan, S. Prabagaran, S. Mohankumar *et al*., *Heliyon*, **9**, 1 (2023), https://doi.org/10.1016/j.heliyon.2023.e15934

[4] B. T. Parthasarathi, S. Arunachalam, N. K. Jawaharlal and M. C. R. Balasundaram, *Cellulose Chem. Technol*., **58**, 349 (2024), https://doi.org/10.35812/CelluloseChemTechnol.2024.58.34

[5] R. Vijay, J. D. Dhilip, J. Gowtham, S. Harikrishnan, B. Chandru *et al*., *J. Nat. Fibers*, **19**, 1343 (2022), https://doi.org/10.1080/15440478.2020.1764457
[6] M. Ramesh, D. J. D. James, G. Sathish Kumar, V. Vijayan, S. Raja Narayanan *et al*., *Bioorg. Chem*., **2022**, 6344179 (2022), https://doi.org/10.1155/2022/6344179
[7] S. Chandrasekaran, N. Sato, F. Tölle, R. Mülhaupt, B. Fiedler *et al*., *Compos. Sci. Technol*., **97**, 90 (2014), https://doi.org/10.1016/j.compscitech.2014.03.014
[8] K. Zhang, F. Wang, W. Liang, Z. Wang, Z. Duan *et al*., *Polymers*, **10**, 608 (2018), https://doi.org/10.3390/polym10060608
[9] K. Z. M. A. Motaleb, M. S. Islam and M. B. Hoque, *Int. J. Biomater*., **6**, 94 (2018), https://doi.org/10.3390/fib6040094
[10] R. Kannojiya, K. Gaurav, R. Ranjan, N. K. Tiyer and K. M. Pandey, *J. Environ. Res. Dev*., **7**, 1385 (2013), https://doi.org/10.1155/2015/950567
[11] V. Raghunathan, J. D. J. Dhilip, M. Ramesh, R. Kumaresan, S. Govindarajan *et al*., *J. Nat. Fibers*, **19**, 9681 (2021), https://doi.org/10.1080/15440478.2021.1990183
[12] S. M. Sapuan, A. R. Mohamed, J. P. Siregar and M. R. Ishak, in "Cellulose Fibers: Bio- and Nano-Polymer Composites: Green Chemistry and Technology", edited by S. Kalia, B. S. Kaith and I. Kaur, Springer, 2011, pp. 325-343, https://doi.org10.1007/978-3-642-17370-7_16
[13] K. Mylsamy and I. Rajendran, *Tribol. Lett*., **44**, 75 (2011), https://doi.org/10.1007/s11249-011-9829-z
[14] I. Jenish, V. C. S. Gandhi, R. E. Raj, S. Basavarajappa, S. Indran *et al*., *J. Nat. Fibers*, **19**, 3502 (2022), https://doi.org/10.1080/15440478.2020.1848709
[15] N. S. M. El-Tayeb, *Wear*, **265**, 223 (2008), https://doi.org/10.1016/j.wear.2007.10.006
[16] A. Sequeiera, D. Deepak and H. K. Sachidananda, *SN Appl. Sci*., **5**, 11 (2023), https://doi.org/10.1007/s42452-022-05249-9
[17] S. M. V. Kumar, R. Jeyakumar, N. Manikandaprabu and C. Sasikumar, *Cellulose Chem. Techno*., **58**, 833 (2024), https://doi.org/10.35812/CelluloseChemTechnol.2024.58.74
[18] D. E. Ighravwe and S. A. Oke, *Int. J. Syst. Assur. Eng. Manage*., **8**, 961 (2017), https://doi.org/10.1080/2374068X.2018.1524256
[19] M. C. Pariz, C. M. F. Carvalho, P. C. A. Rebelo and J. C. J Colmenero, *Multi-Criter. Decis. Anal*., **29**, 327 (2022), https://doi.org/10.1007/s11665-022-07082-y
[20] B. Vučijak, T. Kupusović, S. MidŽić-Kurtagić and A. Ćerić, *Int. J. Innov. Res. Adv. Stud*., **4**, 59 (2013), https://doi.org/10.4018/ijsds.2014040105
[21] D. E. Ighravwe and S. A. Oke, *Int. J. Syst. Assur. Eng. Manage*., **8**, 961 (2017), https://doi.org/10.1007/s13198-016-0554-8
[22] M. Mathew, R. K. Chakrabortty and M. J. Ryan, *Eng. Appl. Artif. Intell*., **96**, 103988 (2020), https://10.1016/j.engappai.2020.103988
[23] B. Vučijak, T. Kupusović, S. Midžić-Kurtagić and A. Ćerić, *Appl. Energ*., **101**, 267 (2012), https://doi.org/10.1016/j.apenergy.2012.05.024
[24] S. Opricovic and G.-H. Tzeng, *Eur. J. Oper. Res*., **156**, 445 (2004), https://doi.org/10.1016/S0377-2217(03)00020-1
[25] E. A. Adali and A. T. Işik, *Manas Sosyal Araştırmalar Dergisi*, **5**, 124 (2016), https://dergipark.org.tr/en/pub/mjss/issue/40504/485321
[26] S. Shubhra Goswami and D. K. Behera, *Surf. Topogr. Metrol. Prop*., **38**, 2256 (2021), https://doi.org/10.1016/j.matpr.2020.06.320
[27] F. A. Albert, D. J. D. Jafrey, G. Karthik Pandiyan, I. W. John, S. Hariharan *et al*., *J. Mater. Eng. Perform*., **32**, 82 (2023), https://doi.org/10.1007/s11665-022-07082-y
[28] A. Pogačnik, A. Kupec and M. Kalin, *Wear*, **378**, 17 (2017), https://doi.org/10.1016/j.wear.2017.01.118
[29] M. K. Gupta and R. K. Srivastava, *Indian J. Eng. Mater. Sci*., **23**, 37 (2016)
[30] J. D. J. Dhilip, K. Pandiyan Ganesan and V. Sivalingam, *J. Mater. Eng. Perform*., **33**, 5547 (2024), https://doi.org/10.1007/s11665-023-08323-4
[31] A. Perec and A. Radomska-Zalas, *Proc. Comput. Sci*., **207**, 1193 (2022), https://doi.org/10.1016/j.procs.2022.09.175
[32] S. Chakraborty, *Informatica*, **25**, 1 (2014), https://doi.org 10.15388/Informatica.2014.01