Artificial Neural Network Modeling of Abrasion Loss and Surface Roughness of Crab Carapace Impregnated Coir Vinyl Ester Composites

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Abstract

Roughness plays an important role in determining how an object would be related with its environment. In tribology, rough surfaces easily obtain wear more quickly and have higher friction coefficients than smooth surfaces. Roughness is often a good analyzer of the performance of a mechanical component. This investigation is aimed to study the abrasion loss and surface roughness behaviors in crab carapace-filled coir fiber reinforced vinyl ester composites. The development of filler-impregnated fiber-polymer composites in recent years necessitated the evaluation and prediction of tribological behaviors in fiber reinforced composites. The composite fabrication was planned by varying the three fabrication parameters with three levels such as fiber length (10 mm, 30 mm, and 50 mm), fiber diameter (0.1 mm, 0.18 mm, and 0.25 mm), and content of crab carapace fillers (0%, 2%, and 4%) as per Design of Experiments (DOEs) in this current investigation. Low velocity integrated wear loss tests on composite samples were carried out, and also the average surface roughness is measured in the fabricated composites. Nonlinear regression equations were developed to study the correlation between tribological behaviors and fabrication parameters. The interaction effect of fabrication parameters was studied using ANOVA two-tail test and validated using response surface plots. In order to forecast abrasion loss and surface roughness behaviors, artificial neural network (ANN) models were constructed, and it was discovered that the produced ANN models effectively predicted the abrasion loss as well as surface roughness behavior within the given ranges.

1. Introduction

Composites are materials that are made up of a strong load-bearing element (known as reinforcement) contained in a weaker substance (known as matrix material). Reinforcement contributes to the strength and rigidity of a structure, allowing it to withstand structural loads. The matrix or binder (organic or inorganic) is responsible for keeping the reinforcement in its proper location and orientation. Despite the fact that the constituents of the composites maintain their separate characteristics, such as physical as well as chemical properties, they work together to produce a mix of
traits that would be impossible for any one of the constituents to produce alone. Fiber-reinforced composites (FRCs) are created by mixing fibers and polymer resin, and they are also known as fiber composites (FRCs). Fiber reinforced composites are made up of fibers that are excellent in strength, lightweight, and toughness, and they are placed in a matrix that has unique interfaces between the fibers. Traditional materials such as steel and aluminum are isotropic in nature, whereas fiber reinforced composites exhibit anisotropic behavior. The majority of composites currently in use in the industry are composed of polymer matrices. The term “polymer” refers to a long-chain molecule that is composed of a huge number of repeating units with the same structural characteristics as one another [1]. The role of the matrix is to distribute the load to the fibers and also give a barrier towards an adverse environment as well as to protect the surface of the fibers against mechanical wear. Fillers are used in natural fiber reinforced composites to generate the required mould shape in sheet mould compounds (SMCs) and also to decrease the manufacturing costs of the composites. Fillers are used in natural fiber reinforced composites to produce significant mould shapes in sheet mould compounds (SMCs) and to decrease the manufacturing costs of the composites [2]. Despite the presence of filler, the mechanical characteristics of the coir/epoxy micro-composites are not significantly altered after their formation. When compared with NEU and NE, the NET exhibits a significant increase in flexural strength and flexural modulus. Despite the presence of filler, the mechanical characteristics of such coir/epoxy micro-composites are really not significantly altered after their formation. Tensile and fatigue tests were used to examine the material [3]. The surfaces of the fractured samples were investigated in order to evaluate the fracture mechanisms. Results reported a reduction in fatigue life of composites when imposed larger stress because of bonding interfacial, which was not acceptable. Most of the works in natural fiber reinforced polymer composites were concentrated on the characterization of composites, and the predictive modeling of behaviors was limited in literature [4]. In several of the production experiments on glass fiber reinforced composites, response surface methodology and neural network technologies were utilized in conjunction with each other [5]. Shukla and Tambe evaluated the surface roughness and kerf widths in abrasive water jet cutting of Kevlar composites utilizing the neural network. The result reveals that the that NN model was able to effectively forecast the two kerf widths as well as the surface roughness, with the predicted values closely matching the observed values in the experimental data [6]. Antil et al. demonstrated that the S form woven glass fibers reinforced polymer matrix composites (PMCs) can be used to investigate bonding behavior between reinforcement and matrix when subjected to the natural abrasive slurry. For the purpose of determining the effect of different erosion variables on erosion resistance, the response surface methodology is used. Compared with other techniques, response surface methodology (RSM), as well as artificial neural network (ANN) simulations, demonstrates good conformity with the erosion behavior of polymer matrix composites strengthened with glass fiber [7]. Subhrajit et al. analyzed the erosion performance of glass-epoxy composites loaded with marble waste with the help of an artificial neural network. The rate of erosion wear in composites lowers as the amount of filler in the composites increases. It was found that the results of the predictive model, which is based on artificial neural networks, are in good agreement with the values of the practical model [8]. In another prevailing study, Zain et al. used artificial neural network to predict surface roughness by end milling machining operations. They concluded that by varying the amount of layers as well as nodes in the hidden layers of the ANN network structure, the framework for surface roughness in the milling process could be enhanced, especially for estimating the value of the surface roughness efficiency measure, which is important in the manufacturing process [9].

Shaikh et al. investigated the manufacturing, characterization, statistical analysis, and application of rice husk ash strengthened aluminium matrix composites. Based on the comparison of experimental and anticipated outcomes, it can be concluded that a properly trained ANN model is an effective tool for forecasting tribological behavior [10]. Recently, artificial intelligence-based models have emerged as the favored trend, and most academics are utilizing these models to construct a model for near-optimal machining settings [11–15]. Vinod et al. studied thermo-mechanical characterization of Calotropis gigantea added in jute fiber reinforced epoxy composites. It was shown that 10 weight percentages of filler improved the mechanical properties such as ultimate tensile, ultimate flexural, and ultimate compressive strengths compared with unfilled ones [16]. Vijay et al. evaluated spent *Camellia sinensis* seed and *Azadirachta indica* seed powders as bio-fillers in the jute epoxy composites. The results showed that the morphological and physical properties of the fillers play a major role in improving the thermal and mechanical properties of the composites [17]. Dinesh et al. found that Rosewood dust and Padauk wood dust were used as fillers in the jute fiber epoxy composites. They have analyzed for mechanical, thermal, water absorption, and biodegradation characteristics. It was found that Padauk wood dust filler had improved the ultimate tensile strength, ultimate flexural strength, ultimate compressive strength, impact strength, and hardness properties to compare Rosewood dust filler composites [18]. Hayajneh et al. investigated thermo-mechanical characteristics of treated and untreated *Portunus sanguinolentus* shell filler used in jute fiber reinforced epoxy composites. The result showed that 10 wt% treated filler powder improved tensile, flexural, compressive, shear, impact, and hardness properties. Through the establishment of an expert system, it is also considered to be an effective strategy for modeling the machining process in order to anticipate performance measurements in the manufacturing process [19]. It is an expert system when a computer program performs expert-like functions in the context of solving some certain type of problem employing a knowledge base, inference engine, and user interface. A model based on artificial neural networks
(ANNs) is capable of learning, adapting to changes, and mimicking the human thought process with minimal human input [16–20]. The FL model operates on linguistic variables instead of on discrete values, as opposed to the conventional approach [10, 21, 22]. In this study, the abrasion loss and surface roughness in crab carapace-coir vinyl ester composites and predicting model create using the regression model and artificial neural network.

2. Materials and Methods

2.1. Materials. Crab carapace has been selected as filler material because it is abundantly available and being wasted as sea dumps. After removing their flesh, the obtained crab shells were washed with sodium hydroxide solution for numerous times to remove impurities, protein residues, and so on. The pigment constituents were removed by quenching the crude shells in the pure ethanol for 6 h at room temperature, followed by filtration and washing. The obtained crab shells were then dried at 100°C to remove the external water and then grinded via a ball-milled using a ball grinding mill. The grounded particles were used as filler for coir vinyl ester composites. The major compositions of crab carapace were carbon 37.77%, oxygen 29.86%, and calcium 32.37% [23].

2.2. Design of Experiments. A factorial design may also be called a fully crossed design. Such an experiment allows studying the effect of each factor on the response variable, as well as the effects of interactions between factors on the response variable. A 3³ factorial design with a total of 27 experimental was carried out. Composites of filler-impregnated coir and vinyl ester were constructed using three-level full factorial designs of fiber characteristics, including fiber length, diameter, and filler loading. The composites were prepared for a maximum thickness of three millimeters (mm). Table 1 lists the fiber properties as well as the levels that were chosen for them.

2.3. Experimental Procedure. It was determined that natural coir fiber would be the most effective reinforcement material in this experiment. The matrix substance was untreated vinyl ester resin, and the filler material was crab carapace, and they were both employed in the construction. The hand lay-up technique was employed to fabricate the filler-impregnated coir vinyl ester composites used in this study. Before the fabrication process began, a releasing agent made of polyvinyl acetate (PVA) was added to the surface. Previously, the coir fibers were pre-impregnated with a matrix composition comprising of unsaturated vinyl ester resin-crab carapace filler, N-dimethylaniline accelerator, methyl ethyl ketone peroxide catalyst, and cobalt naphthenate promoter in a proper ratio. A resin matrix (360 mm × 360 mm) was used to hold the impregnated layers in place before they were removed by applying a lot of pressure (1000 N). After 1 hour, the fabricated composites were removed from the mould and allowed to cure at room temperature (28 degrees Fahrenheit) for 24 hours. Figure 1 depicts a photographic view of produced carapace filler-filled coir fiber reinforced composites sheets with a coir fiber reinforcement structure [24].

2.4. Abrasion Loss Testing. Experiments on abrasion loss as well as surface roughness were carried out on specimens that were cut from the produced composite and completed to the standard size with a compact handsaw machine and emery paper. The abrasion loss test was carried out in accordance with ASTM D5963-04 (2019). The test was carried out with the help of an Abrasion Resistance Tester. Figure 2 depicts a photographic view of an abrasion test specimen under examination.

2.5. Surface Roughness Testing. Surface roughness is essential in various fields and also has significant significance in the study of surface accuracy as well as the formulation of the ISO 1997 norm for surface roughness. In accordance with the workpiece random orientation of fiber and percentage of filler material, the variation of surface roughness showed that the surface roughness fluctuated among different fiber orientations. Figure 3 shows a photograph of a surface roughness analyzer (Mitutoyo SJ-310) taken using a digital camera.

3. Results and Discussion

3.1. Impact of Fiber Parameters on Abrasion Loss of Carapace Filler-Filled Coir Vinyl Ester Composites. The relationship between fiber parameters (length, diameter, and filler content) and abrasion loss is illustrated in Figure 4 (mm ³). It was possible to get very low abrasion loss using a 50-mm fiber length, 0.18-mm fiber diameter, and a 0 percent carapace filler content, whereas the greatest abrasion loss was achieved using a 30-millimeter fiber length, 0.25-mm fiber diameter, and a 0 percent carapace filler content. The SEM images of carapace filler-filled coir vinyl ester composites after abrasion test are illustrated in Figure 5. The filler reinforced composite is characterized as being composed of fillers suspended in a matrix; it can have virtually any shape, size, or configuration. Filler is used in fiber reinforced composites to enhance the properties [25, 26].

3.2. Effect of Fiber Parameters on Surface Roughness of Carapace Filler-Filled Coir Vinyl Ester Composites. The association between fiber parameters (length, diameter, and filler content) and surface roughness (microns) is depicted in Figure 6. In 50 mm fiber length, 0.18 mm fiber diameter, 2 percent carapace filler percentage, and maximum surface roughness, the extremely low surface roughness was achieved. The fibers had a length of 30 mm, a diameter of 0.18 mm, and a filler concentration of 4% carapace filler. The
SEM images of carapace filler-filled coir vinyl ester composites after roughness test are shown in Figure 7.

Experimental results (abrasion and surface roughness) for carapace filler-filled coir vinyl ester composites are shown in Table 2.

3.3. Regression Models. Design Expert 8.0.4 statistical software was used to model the tribological phenomena, including surface roughness and abrasion loss. The letters \( f_1 \) and \( f_2 \) refer to fiber length and diameter, respectively, whereas the term \( f_3 \) refers to the amount of filler present. These are the mathematical models of surface roughness (SR) and abrasion loss (\( A_1 \)), which have been created, and are shown in equations (1) and (2).

\[
\begin{align*}
SR &= 0.34606 + 0.016024 f_1 + 5.69038 f_2 + 0.026597 f_3 - 0.013760 f_1 f_2 + 1.2437510^{-3} f_2 f_3 \\
&\quad - 0.037771 f_1 f_3 - 1.9583310^{-4} f_1^2 - 13.80688 f_2^2 + 9.0833310^{-3} f_3^2,
\end{align*}
\]

\[
\begin{align*}
A_1 &= 687 + 5.18 f_1 - 745 f_2 - 22.9 f_3 - 0.122 f_1^2 + 2492 f_2^2 + 1.59 f_3^2 - 3.28 f_1 f_2 \\
&\quad + 24.4 f_2 f_3 + 0.294 f_1 f_3.
\end{align*}
\]

3.4. Artificial Neural Network (ANN). A neural network is composed of a number of artificial neurons that are connected to one another and that process data using a connectionist technique to computation. Because the capabilities of a single neuron are restricted, complicated functions can be achieved by linking a large number of neurons.
Figure 4: Impact of fiber parameters on abrasion loss.

Figure 5: SEM images after the abrasion test.

Figure 6: Effect of fiber parameters on the surface roughness test.

Figure 7: SEM images after the surface roughness test.
neurons together in series. According to a large body of evidence, the topography of a neural network, the demonstration of data, the simplification of inputs and outputs, and the appropriate choice of activation functions all seem to have a considerable impact on the effectiveness and performance of a trained neural network.

3.5. Training the Artificial Neural Network. The training was carried out using the MATLAB software package. It is demonstrated in this paper that the ANN module can be used to estimate the abrasion loss as well as the surface roughness of carapace filler-impregnated coir vinyl ester composites. The features fiber length, fiber diameter as well as filler content are used as inputs, while the outputs are abrasion loss and surface roughness, which are used in the training of neural networks to determine the effectiveness of the network. Randomly generated weights among the input layer and the hidden layer and weights between both the hidden layers with the output layer are generated for the network topology that has been specified. An artificial neural network was trained using the feed forward back propagation technique, with a total of 27 patterns being employed in the training process. All of the ANN’s training were accomplished without the introduction of almost any permissible error. The patterns that will be used for testing and training the ANN are chosen. These carefully chosen designs were normalized such that they fall between 0 and 1 on the scale. Performance curve for abrasion loss values and roughness values is depicted in Figures 8 and 9.

![Performance curve for abrasion loss values.](image)

The normalization of the inputs and outputs is performed by

$$X_i = \frac{X_i}{X_{\text{max}}}.$$  \hspace{1cm} (3)

The difference between the value of a characteristic and its maximum value is denoted by \(X_i\) and \(X_{\text{max}}\).

3.6. Validation of Abrasion Loss Test Result. Experiments were carried out to confirm the optimal conditions for eight different sets of variables. The differences between the

<table>
<thead>
<tr>
<th>Sample specimen</th>
<th>Fiber length (mm)</th>
<th>Fiber diameter (mm)</th>
<th>Filler content (%)</th>
<th>Abrasion loss</th>
<th>Surface roughness</th>
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<td>4</td>
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</table>
Experimental and expected values are as shown in Figures 10 and 11; there is a comparison between anticipated and experimental abrasion loss as well as surface roughness values. Series 1 indicates the experimental value, Series 2 indicates the mathematical modeling value, and Series 3 indicates the predicted value.

4. Conclusion

In this experiment, the abrasion loss and surface hardness of carapace filler-filled coir vinyl ester composites were measured. Over a wide variety of situations, the regression and artificial neural network (ANN) models were constructed to forecast abrasion loss and surface roughness. Between the expected and experimental results, there was a high degree of agreement seen. The ANN-based models may be used to forecast the surface roughness as well as abrasion loss behaviors of carapace filler-coir vinyl ester composites, and they have proven to be useful. Surface roughness and abrasion loss were predicted by artificial neural network models with average absolute error percentages of 0.04 and 0.041, respectively, which are lower than the predictions made by regression models. The better abrasion loss was obtained for the fiber length of 30 mm, fiber diameter of 0.2 mm, and filler content of 2%, and high surface roughness was obtained for the fiber length of 30 mm, fiber diameter of 0.18 mm, and filler content of 4%. The result reveals that decrease in the fiber length and increase in filler content in the composites lead to reduction in the abrasion loss and surface roughness.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

This study was performed as a part of the employment of the authors.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References


