DAMAGE IDENTIFICATION OF FIBER-REINFORCED COMPOSITES DURING THREE-POINT BEND TESTS BASED ON ACOUSTIC EMISSION AND UNSUPERVISED LEARNING METHODS

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Abstract— Advancements in composite materials design have rendered fiber-reinforced polymer composite (FRPC) materials an effective candidate for various engineering and industrial applications. A low specific mass and high specific mechanical stiffness and strength are attractive characteristics of FRPCs. However, studies to reliably identify mechanical failures in FRPCs is an ongoing endeavor. Therefore, in the present work, an acoustic emission (AE) technique combined with unsupervised learning methods was used to detect the damage mechanisms and progress in glass FRPC panels during three-point bend tests. The classification of the waveform for AE presented in this study was based on principal component analysis and the k-means method. The two most significant AE features were selected: peak frequency and amplitude. Frequency bands were obtained and compared to AE data from the technical literature associated with specific failure mechanisms, such as matrix cracking, fiber-matrix debonding, delamination, and fiber breakage. Amplitude values along with computed stress were analyzed as a function of time.

Keywords—Fiber reinforced polymer composite; acoustic emission; unsupervised learning; principal component analysis; k-means method

I. INTRODUCTION

Fiber reinforced polymer composite (FRPC) materials are widely used in many engineering and industrial applications. Their low specific mass and high mechanical properties, such as stiffness and strength, make them an attractive option in engineering design over neat polymers and other engineering materials [1]. However, the identification and assessment of damage and failure mechanisms is a complex and challenging task, especially when relying on destructive techniques in conjunction with mechanical testing. Therefore, non-destructive techniques have been used to enable in-situ interrogation of specimens during the experimental tests. One of these non-destructive techniques is acoustic emission (AE), which is frequently employed in tandem with material testing, such as three-point bend tests. For example, Ereifej et al. [2] investigated the fracture resistance of polymer composites using three-point bending testing and AE analysis. The specimens were loaded to failure in a universal testing machine while an AE system was used to detect acoustic signals. The authors found that monitoring acoustic signals revealed important information regarding the fracture process. They further ascertained that fracture resistance improved with the addition of fiber reinforcements to the base polymer material.

In another study, Mouzakis and Dimogianopoulos [3] investigated the effects of exposing high-performance carbon composite materials for structural applications in aviation to aging-inducing environmental conditions, such as varying temperature, humidity, and ultraviolet radiation. The authors assessed the impact on the composites’ mechanical response by employing AE analysis. They collected signals from three-point bending testing of pristine specimens, thermally shocked, and environmentally aged ones. In a recent study, Nazaripoor et al. [4] used an AE technique to investigate the damage progress in short glass fiber-reinforced composite panels during three-point bend tests. Their methodology detected damage accumulation during flexure for composite panels with various sizes and fiber volume content. Their work used an innovative approach by recording AE data using different timing parameters and two different transducer types. The AE waveform classification was based on peak frequency distribution. The frequency bands could be associated with specific failure mechanisms. The authors found that cumulative signal strength and cumulative rise time versus peak amplitude ratio as AE output parameters was an effective means for integrity assessment for the employed complex material system.

AE is a technique that can be combined with other types of algorithms to create a more efficient approach for determining different failure mechanisms in composite materials. For example, Pushmforoush et al. [5] proposed integrating the k-means algorithm and genetic algorithm to cluster AE events of glass/epoxy composite during the three-point bending test.
They obtained three clusters with separate frequency ranges, each representing a distinct damage mechanism. The frequency ranges of the components were compared with k-means genetic algorithm outputs, and scanning electron microscopy was utilized to validate their findings. Other researchers, including Barile et al. [6], presented a deep convolutional neural network for image-based AE waveform classification for different damage modes of carbon fiber-reinforced polymers. They used AE waveforms associated with different damage modes, i.e., matrix cracking, delamination, debonding, and fiber breakage. Recently, Ma et al. [7] used AE and X-ray micro-computed tomography in conjunction with digital image correlation measurements to investigate the mechanical behavior of 3D printed continuous fiber-reinforced composites in three-point bending. They ascertained that parameters such as frequency, amplitude, and amplitude ratio were closely associated with the damage process of different specimens using the cross-validation results of cluster analysis (k-means), K-Nearest Neighbor and principal component analysis.

In the present work, AE data was recorded during three-point bend testing for a short glass fiber-reinforced polymer composite material to detect and identify the damage mechanisms during loading. These failure mechanisms include matrix cracking, delamination, debonding, and fiber breakage. The recorded AE data comprises 15 parameters, i.e., rise time, counts, counts to peak, duration, amplitude, energy, absolute energy, average frequency, root mean square, reverberation frequency, signal strength, centroid frequency, peak frequency and average signal level. To select and determine the AE parameters most significant to experimental tests, the chosen AE approach combines principal component analysis and the K-means method. Frequency bands related to damage mechanisms obtained in the present work were compared to data obtained from the technical literature. In addition, amplitude values were contrasted with computed stress for the given composite material.

II. UNSUPERVISED ANALYSIS METHODS

Classification methods for clustering analysis are mainly based on the concept of vectors and the calculation of the Euclidean distance. Once the descriptors are selected, experimental data is represented in the form of vectors forming a matrix \([X]\) of \(n\) rows and \(m\) columns as follows [8]:

\[
[X] = \begin{bmatrix}
\begin{array}{cccc}
x_1^1 & x_1^2 & \cdots & x_1^m \\
x_2^1 & x_2^2 & \cdots & x_2^m \\
\vdots & \vdots & \ddots & \vdots \\
x_n^1 & x_n^2 & \cdots & x_n^m 
\end{array}
\end{bmatrix}
\]  

(1)

where the rows are the observation numbers, and the columns are the parameter numbers describing each observation \(x_j^i\) in which \(i = 1, \ldots, m\) and \(j = 1, \ldots, n\). Then, the data needs to be transformed into reduced centered variables so that each column has a mean equal to zero and a standard deviation equal to one. Thus, the Euclidean distance between two observations (i.e. \(x_j^i\) and \(x_j^j\)) can be calculated as follows [8]:

\[
m(x_j^i, x_j^j) = \sqrt{\sum_{i=1}^{m} (x_j^i - x_j^j)^2}
\]  

(2)

Pertinent analysis methods are detailed to provide a basis for the clustering analysis in the following subsections.

A. Principal component analysis

Principal component analysis (PCA) is a quantitative method to visualize multidimensional data by replacing a group of linked variables with a new variable called the principal component. Each component is a linear combination of the input variables from the matrix \([X]\). Therefore, the principal components are orthogonal, with no information redundancy. The covariance matrix \([C]\) of \([X]\) can be calculated as follows [8]:

\[
[C] = [XX^T].
\]  

(3)

B. k-means method

k-means is an iterative method of partitioning data by minimizing intra-group variance [9]. The coordinates of the group centers are initialized randomly or manually. Then, each input vector \(x_j^i\) is assigned to the nearest group, depending on the Euclidean distance between the input entity \(x_j^i\) and the group centers. Thus, this procedure is repeated by randomly changing the coordinates of the centers until the method converges, which means no change in the coordinates of the centers is reported [8].

III. MATERIAL AND EXPERIMENTAL PROCEDURE

A universal testing machine (type 810, MTS Systems, Eden Prairie, MN, USA) with a 100 kN load cell was utilized to conduct three-point bend tests over a support span of 152.4 mm by prescribing a stroke rate of 2.0 mm/min. Regarding the AE systems, a Micro-SHM AE monitoring system was used along with the AEWin Software (both Physical Acoustics, West Windsor Township, NJ, USA) to record and analyze the AE signals. Post-processing of the AE data was performed using the MATLAB computing environment (MathWorks, Natick, MA, USA). The labels ‘Ch1’ and ‘Ch2’ indicate the two sensor channels. The following timing parameters were applied: a peak detection time (PDT) of 50 \(\mu\)sec, a hit detection time (HDT) of 50 \(\mu\)sec (Ch1) or 100 \(\mu\)sec (Ch2), and a hit lock time (HLT) of 100 \(\mu\)sec. Figure 1 shows a schematic and a picture of the experimental setup. The specimen dimensions were 304 mm in length, 76.2 mm in width and 10 mm in thickness. The sandwich panel coupon was composed of a polyester matrix with short E-glass fibers with random orientation. Note that the exact material composition is proprietary.
third condition was included, i.e., (3) the relative importance of the AE feature in the principal component.

When PCA is applied, the AE features are projected in the first two principal components, as shown in Figure 2. Implementing the three conditions can be repeated as necessary throughout the analysis.

![Figure 2. Acoustic emission features projected onto principal components 1 and 2.](image)

The selection of the principal components is based on the variance of each component. The original data can be projected into a new two-dimensional space by considering the components with the highest variance. Table I shows the variance for the principal components. In the present work, selecting the first two principal components, corresponding to variances of 43.61% and 27.27%, are necessary to perform the clustering analysis. A third or more components are not required because their variance values do not represent a major effect in the linear combination of the AE data.

<table>
<thead>
<tr>
<th>Principal component</th>
<th>Variance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>43.61</td>
</tr>
<tr>
<td>2</td>
<td>27.27</td>
</tr>
<tr>
<td>3</td>
<td>12.15</td>
</tr>
<tr>
<td>4</td>
<td>8.32</td>
</tr>
<tr>
<td>5</td>
<td>3.56</td>
</tr>
<tr>
<td>6</td>
<td>2.18</td>
</tr>
<tr>
<td>7</td>
<td>1.39</td>
</tr>
</tbody>
</table>

The quantity of clusters for the k-means algorithm, based on the Davis and Bouldin (DB) index [14], must remain the same when implementing the three conditions for selecting the most significant AE features mentioned above. The DB index must be the lowest value to select the appropriate number of clusters. Hence, in the present work, the number of clusters for
the k-means is four based on the AE data, before and after applying the conditions, as shown in Figure 3. Thus, after coupling the k-means algorithm and PCA, two AE features were selected: amplitude and peak frequency. These features are not correlated and are selected objectively based on the methodology presented in this work.

Moreover, amplitude represents the maximum voltage value of an AE waveform, which can be used to determine different stress levels during the loading in the experiment. In the case of the peak frequency, this feature represents the maximum power point in the spectrum of the AE waveform, which can be utilized to identify different damage mechanisms during loading in the experiment. In the following subsection, an analysis of the mechanisms of failure is presented.

![Figure 3. Davies Bouldin index before and after applying conditions.](image)

**B. Clustering of acoustic emission features and damage classification**

PCA has an essential role in the present work because it improves the clustering results by reducing the noise (outliers) among the clusters and provides dimensionality reduction, having at the beginning 15 features and thus 2 features at the end for applying the k-means method. If PCA is not applied in the AE data, there would be redundant information and non-well-defined clusters. Hence, Figures 4 and 5 show a specimen's clustered AE signals for channels Ch1 and Ch2, respectively. It can be observed that the clusters are well-defined for different ranges of the peak frequency, while for amplitude the values are combined. The boundaries of these clusters are similar to other works in the technical literature. In the case of Ch1, the peak frequency ranges are from 151 kHz to 209 kHz (cluster 1), from 214 kHz to 288 kHz (cluster 2), from 292 kHz to 400 kHz (cluster 3), and from 78 kHz to 146 kHz (cluster 4). The percentage of the number of hits per cluster (as shown in Table II) is as follows: 36.57% for cluster 1, 13.79% for cluster 2, 3.96% for cluster 3, and 45.69% for cluster 4. For channel 2, the peak frequency ranges are from 131 kHz to 161 kHz (cluster 1), from 78 kHz to 126 kHz (cluster 2), from 224 kHz to 300 kHz (cluster 3), and from 166 kHz to 219 kHz (cluster 4). The number of hits per cluster in percent (as shown in Table II) is 33.92% for cluster 1, 9.93% for cluster 2, 35.36% for cluster 3, and 20.79% for cluster 4.

![Figure 4. k-means classification of channel 1 of acoustic emission parameters: amplitude and peak frequency.](image)

![Figure 5. k-means classification of channel 2 of acoustic emission parameters: amplitude and peak frequency.](image)

**TABLE II. PERCENTAGE OF HITS PER CLUSTER FOR CHANNEL 1 AND 2.**

<table>
<thead>
<tr>
<th>Cluster</th>
<th>% of hits</th>
<th>Cluster</th>
<th>% of hits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36.57</td>
<td>1</td>
<td>33.92</td>
</tr>
<tr>
<td>2</td>
<td>13.79</td>
<td>2</td>
<td>9.93</td>
</tr>
<tr>
<td>3</td>
<td>3.96</td>
<td>3</td>
<td>35.36</td>
</tr>
<tr>
<td>4</td>
<td>45.69</td>
<td>4</td>
<td>20.79</td>
</tr>
</tbody>
</table>

Table III compares the frequency bands for Ch1 and Ch2 with frequency bands for glass fiber (GF) reinforced composites obtained from the technical literature, where each band or cluster is associated with a specific failure mode, i.e., matrix cracking, fiber-matrix debonding, delamination, and fiber breakage. The matrix cracking failure mode is delineated by a frequency band of 62.5-125 kHz in [10], which compares to the frequency band for Ch2 of 78-126 kHz. In the case of Ch1, the frequency band is 78-150 kHz, which is similar to 100-150 kHz in [11] and 100-190 kHz in [12]. For fiber-matrix debonding, the frequency band for Ch1 of 156-220 kHz corresponds to 150-250 kHz in [11], while the frequency band for Ch2 of 131-161 kHz is similar to 125-187.5 kHz in [10]. For the case of delamination, the frequency band for Ch1 of 224-317 kHz compares to that of 200-320 kHz in [12] and
[13]. For fiber breakage, the frequency band for Ch1 of 322-400 kHz is similar to 380-430 kHz in [12] and [13], while the frequency band for Ch2 of 224-300 kHz compares to 187.5-250 kHz in [10]. Consequently, each failure mechanism considered in this work can be associated with distinct clusters obtained for Ch1 and Ch2 in congruence with findings presented in the technical literature.

In summary, the frequency bands for Ch1 for the different failure mechanisms, considering the percentage of hits for each cluster, are as follows: 78-150 kHz for matrix cracking with 45.69% of hits; 156-220 kHz for fiber-matrix debonding with 36.57% of hits; 224-317 kHz for delamination with 13.79% of hits; and 322-400 kHz for fiber breakage with 3.96% of hits. Similarly, for Ch2 the frequency bands and percentage of hits associated with each failure mechanism are: 78-126 kHz for matrix cracking with 35.26% of hits; 131-161 kHz for fiber-matrix debonding with 33.92% of hits; 166-220 kHz for delamination with 20.79% of hits; and 224-300 kHz for fiber breakage with 9.93% of hits.

TABLE III. COMPARISON OF FREQUENCY RANGE FOR CHANNELS 1 AND 2 WITH REF. FROM LITERATURE.

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Fiber/Matrix type</th>
<th>Matrix cracking</th>
<th>Fiber-matrix debonding</th>
<th>Delamination</th>
<th>Fiber breakage</th>
</tr>
</thead>
<tbody>
<tr>
<td>[10]</td>
<td>GF/epoxy</td>
<td>62.5-125</td>
<td>125-187.5</td>
<td></td>
<td>187.5-250</td>
</tr>
<tr>
<td>[12]</td>
<td>GF/epoxy</td>
<td>100-190</td>
<td>-</td>
<td>200-320</td>
<td>380-430</td>
</tr>
<tr>
<td>Ch1</td>
<td>GF/epoxy</td>
<td>78-150</td>
<td>156-220</td>
<td>224-317</td>
<td>322-400</td>
</tr>
<tr>
<td>Ch2</td>
<td>GF/epoxy</td>
<td>78-126</td>
<td>131-161</td>
<td>166-220</td>
<td>224-300</td>
</tr>
</tbody>
</table>

Regarding signal amplitude, Figures 6 and 7 depict a comparison of amplitude and computed stress as a function of time for Ch1 and Ch2, respectively. Figure 6 indicates an increase in amplitude values with rising stress, with a significant change in signal when it reaches approximately 65 MPa, representing 74.7% of the ultimate strength at approximately 130 seconds. In Figure 7, the values of amplitude and stress follow a similar trend, with a considerable increase in hits occurring at approximately 61 MPa, representing 70.1% of the ultimate strength at about 120 seconds. These data indicate that damage events significant to specimen failure commenced between 61 and 65 MPa. Notably, the distribution of amplitude values as a function of time differs between channels. Recall that Ch1 and Ch2 capture a HDT above 50 μsec and above 100 μsec, respectively. It is thus surmised that the timing parameters set for Ch1 are better suited for the analysis of failure modes in the composite material.

Figure 6. Amplitude values and Stress of the specimen as a function of time for Channel 1.

Figure 7. Amplitude values and Stress of the specimen as a function of time for Channel 2.

V. CONCLUSION

This study employed (AE) acoustic emission combined with unsupervised learning techniques as a non-destructive tool for integrity assessment in glass fiber-reinforced polymer composite panels subjected to three-point bending. The selection of the AE data included 15 parameters that provided diverse information during testing. The unsupervised learning techniques included the principal component analysis and k-means algorithm to determine the AE parameters most suitable for the damage analysis. The AE features preferable for damage analysis were peak frequency and amplitude.

This study also attempted damage mode identification based on peak frequency bands as defined in the technical literature. The prominent failure mode was matrix cracking, followed by fiber-matrix debonding, delamination, and fiber breakage. Regarding signal amplitude, the analysis indicated that specific timing parameters were more suitable for failure mode identification. A distinct increase in amplitude values was observed (at around 65 MPa), suggesting that damage events significant to failure started at a specific point during specimen loading. Based on the present findings, the employed AE methodology, combining machine learning techniques and involving a complement of AE features, is considered appropriate for damage mode identification in FRPC materials.
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REFERENCES


