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DAMAGE MECHANISM IDENTIFICATION OF GLASS FIBER-REINFORCED POLYMER COMPOSITES BASED ON ACOUSTIC EMISSION AND UNSUPERVISED LEARNING ALGORITHMS

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ABSTRACT

Glass fiber-reinforced polymer composites (GFRPC) have reached a high level of maturity and are therefore a viable option for a range of industrial and engineering applications. Low specific mass and high specific mechanical properties are some of the appealing features of GFRPC. However, identifying and categorizing damage mechanisms for these kinds of materials remains challenging. Numerous scientific studies have examined GFRPC failure mechanisms using a variety of approaches, including non-destructive methods and different types of learning algorithms. Nonetheless, research is still needed to increase confidence in identifying damage mechanisms in GFRPC. Therefore, to discover damage mechanisms in GFRPC during tensile testing, the current work explores the use of non-destructive testing in conjunction with unsupervised learning algorithms. In the present work, NDT with an acoustic emission (AE) approach was employed to characterize the waveforms of various failure mechanisms during testing. In this context, unsupervised learning algorithms such as principal component analysis (PCA) and a k-means algorithm were used for waveform classification. The most suitable and appropriate AE descriptors were chosen using the PCA approach to distinguish between the different damage mechanisms, while a failure mechanism clustering analysis and classification were carried out by the k-means algorithm. Some of the failure mechanisms of GFRPC investigated in the present work are fiber-matrix debonding, matrix cracking, delamination, and fiber breakage. Scanning electron microscopic images of the failures are presented to validate the results.

1 INTRODUCTION

Glass-fiber-reinforced-polymer-composite (GFRPC) materials are extensively utilized in various technical and industrial applications. The attractiveness of these materials in engineering design is attributed to their low specific mass and outstanding mechanical properties, including stiffness and strength, which surpass those of neat polymers and other engineering materials [1]. Nevertheless, the process of discovering and evaluating damage and failure processes is a multifaceted and demanding endeavor, particularly when employing destructive methodologies in tandem with mechanical testing. Consequently, non-destructive methods have been employed to facilitate the examination of specimens in a given environment during experimental procedures. One of the non-destructive procedures commonly utilized in conjunction with material testing, such as tensile tests, is acoustic emission (AE). The AE methodology can provide important information for identifying the different damage mechanisms of GFRPCs with a big dataset. However, for determining the suitable AE features it is important to combine this methodology with other types of algorithms to create an efficient approach. Recently, different research works have developed techniques involving AE in conjunction with unsupervised learning algorithms. For example, Harizi et al. [2] developed a coupling method between three multivariable analysis techniques (principal component analysis (PCA), k-means and Kohonen Self-Organizing Map) applied to AE data on GFRPC materials to monitor and identify their damage mechanisms, i.e., matrix cracking, fiber/matrix debonding, delamination and fiber breakage. They also combined AE with DIC to monitor the damage to the composites. Other scientists, such as Rubio-Gonzales et al. [3], provided a combination of AE and self-sensing capability by integrating carbon nanotube networks for damage progression monitoring of GFRPCs under flexural loading. The acoustic signals recorded during the tests were analyzed by a classification methodology consisting of the k-means method and PCA, which allowed the identification of the various damage.

The identification and assessment of the damage mechanisms in short GFRPC materials using an AE method in conjunction with unsupervised and supervised learning algorithms is still an ongoing field that requires more analysis and research. Therefore, the current study involves the collection of AE data during tensile testing on a short (GFRPC) material in order to identify and analyze the mechanisms of damage that occur during loading. The failure mechanisms encompass matrix cracking, delamination, fragmentation of the matrix/fiber link, and fiber fracture. The AE dataset includes a total of ten parameters, including duration (DURATION), absolute energy (ABS-ENERGY), signal strength (SIG-STRENGHT), rise time (RISE), counts (COUNT), amplitude (AMP), energy (ENER), counts to peak (PCNTS), centroid frequency (C-FRQ), and peak frequency (P-FRQ). The AE approach integrates PCA and the k-means algorithm to identify and ascertain the AE parameters that hold the greatest significance in the experiments. Scanning electron microscopy (SEM) images were used to correlate the AE data obtained from the experiments to the corresponding failure mechanisms. The acquired data from the most relevant AE features was also compared with AE data from the technical literature pertaining to the above-mentioned damage mechanisms.

2 Experimental setup

The GFRPC panel coupons consisted of a resin matrix containing 30% short E-glass fibers arranged randomly. The length, width, and thickness of the specimen were 250 mm, 25 mm, and 5 mm, respectively. Figure 1 depicts a diagram with the experimental procedure and schematic of the tensile loading and data acquisition system for AE technique. Regarding tensile tests, these experiments were conducted over a gauge length of 150 mm using a universal testing machine (type 810, MTS Systems, Eden Prairie, MN, USA) equipped with a 100 kN load cell. The stroke rate prescribed for these tests was 5.0 mm/min, in accordance the ASTM D638-14 standard [4].

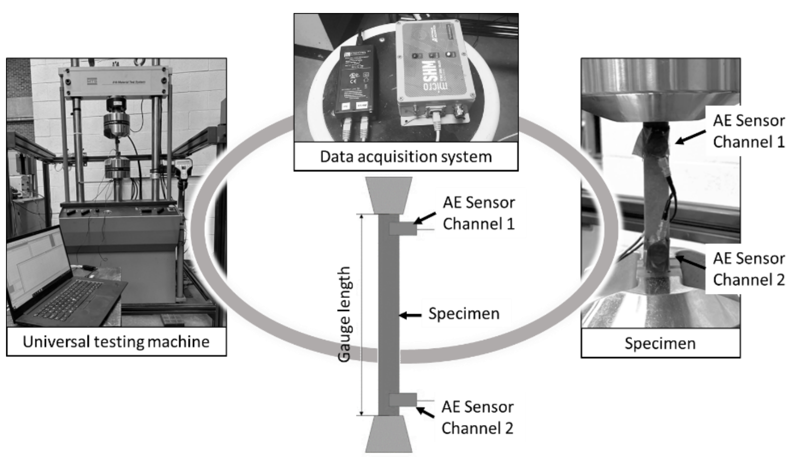

Figure 1. Schematic of experimental setup for tensile loading and data acquisition using acoustic emission technique.

In the context of the AE system, the measurement and analysis of AE signals were conducted using a Micro-SHM AE monitoring system in conjunction with the AEWin Software, developed by Physical Acoustics (West Windsor Township, NJ, USA). The piezoelectric sensor types employed in this study consisted of the PK15I sensor (Physical Acoustics), a medium frequency, resonant adaptive electrode (AE) sensor. The sensor type comprises an inbuilt 26 dB preamplifier that exhibits ultralow noise, low power consumption and filtration. The threshold for threshold-based AE event detection was established at a minimum value of 35 dB. The AE data underwent post-processing using MATLAB computational environment (MathWorks, Natick, MA, USA). The experiment involved the use of specific timing parameters, namely a peak detection time (PDT) of 50 seconds, a hit detection time (HDT) of 50 seconds, and a hit lock time (HLT) of 100 seconds.

3 UNSUPERVISED LEARNING ALGORITHMS

3.1 Principal component analysis

The fundamental principles behind classification algorithms in clustering analysis are rooted in the concepts of vectors and Euclidean distance calculations. The matrix $[X]$ is used to represent experiment data, with n rows and m columns, see Eq.(1).

$$[X] = \begin{bmatrix} x_1^1 & \cdots & x_1^m \\ \vdots & \ddots & \vdots \\ x_n^1 & \cdots & x_n^m \end{bmatrix} \tag{1}$$

The dataset consists of rows representing the observation numbers and columns representing the parameter numbers that describe each observation x_{ij}, where i ranges from 1 to m and j ranges from 1 to n. In order to transform the data into reduced centered variables, it is necessary for each column to consist of a mean of zero and a standard deviation of unity. Thus, the Euclidean distance between two observations can be calculated using Eq.(2).

$$d\left(x_1^i, x_2^i\right) = \sqrt{\sum\nolimits_{i=1}^{m} \left(x_1^i - x_2^i\right)^2}\ . \tag{2}$$

Using the Euclidean distance, it is possible to visualize all the AE data by replacing a group of connected variables with a new variable called principal component. In this way, for each component, the input variables of matrix $[X]$ are linearly concatenated. Consequently, the primary constituents exhibit orthogonality, devoid of any redundancy in information.

3.2 k-means algorithm

The k-means algorithm is an iterative technique used to partition data by reducing the variance within each group of variables x_{ij}. The group centers' coordinates are either randomly or manually initialized. In this process, the assignment of each input vector x_{ij} to the nearest group is determined based on the Euclidean distance between the input entity x_{ij} and the centers of the respective groups. Therefore, this process is iterated by adjusting the coordinates of the centers in a random manner until the algorithm reaches convergence, indicating that no more changes in the center coordinates are needed [2].

4 RESULTS AND DISCUSSION

4.1 Selection of the suitable AE descriptors through PCA

Before applying PCA, each AE descriptor carries equal significance. Hence, the AE parameters can be transformed into a two-dimensional space that corresponds to the initial two principle components. The selection of principal components is based on the criteria of selecting components that exhibit the biggest variances. However, first, it is important to notice that each AE signal, i.e., hit, in the data is associated with distinct descriptors or parameters. As previously stated, the ten AE descriptors mentioned above were used for the description of each hit. The initial step in pre-processing the AE data was verifying that the features exhibit Gaussian distributions [5]. Nevertheless, certain characteristics, such as DURATION, demonstrate exponential distributions, necessitating the conversion of their values into logarithmic values for subsequent processing. The AE data had to be normalized using the '*normalize'* function in the MATLAB computing environment for this process. In the present work, the first two principal components were selected to perform the clustering analysis, with variances equal to 64.4% and 20.4%. Note that it was not necessary to include a third or more components in the linear combination of the AE data, as their variance values do not have a statistically significant impact with values of 10.1% and 3.9% for a third and fourth component. In order to identify the most important significant AE parameters after applying PCA, two criteria were employed according to the methodology outlined in [2]. Firstly, removing the AE parameter would lead to a loss of information. Secondly, the vector associated with a significant AE parameter must be different in terms of length and direction from the previously chosen vectors used to represent principal components. Figure 2(a) and (b) shows the projection of the AE descriptors into the first two principal components after the application of PCA. When adopting the two conditions for selecting the most significant AE features discussed above, it is necessary to maintain the same quantity of clusters for the k-means algorithm. The number of clusters was determined based on Davis and Bouldin (DB) index [6] selecting the index with the lowest values as is shown in Figure 2(c). Therefore, in this study, the number of clusters for k-means algorithm was determined to be four. As a result of combining PCA and k-means algorithm, four AE descriptors were chosen: rise time, amplitude, energy, and peak frequency. These descriptors are indicated in red in Figure 2(a) and (b) and exhibit no correlation and have been chosen in an objective manner.

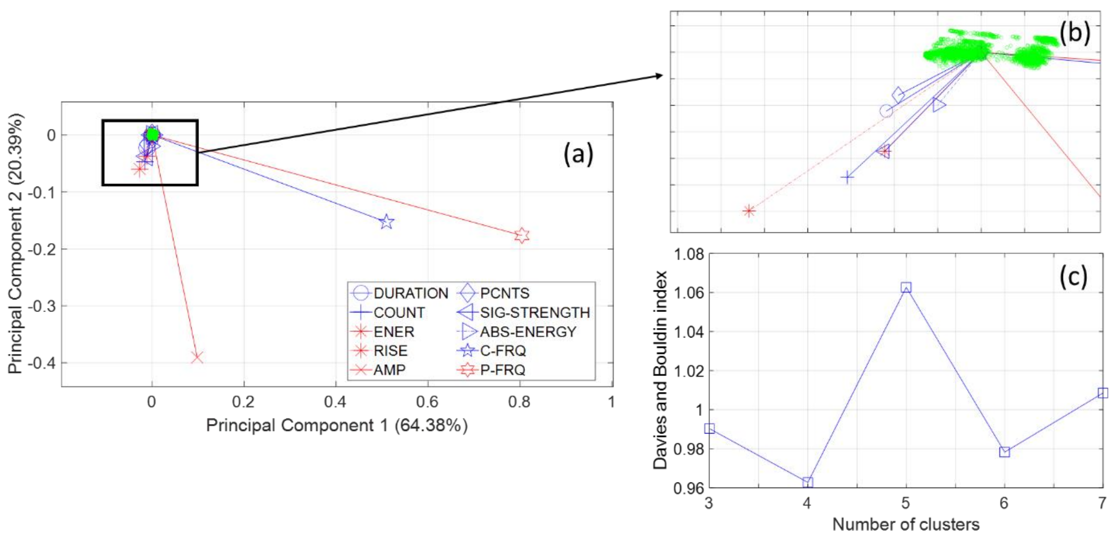

Figure 2. (a) and (b) AE features projected onto principal components 1 and 2, and (c) Davies Bouldin index for AE features.

4.2 Identification of damage mechanisms by clustering of AE features

PCA facilitates dimensionality reduction by lowering the initial set of ten AE features to a final set of four, hence enabling the use of the k-means algorithm. Figure 3(a) shows the stress values of the GFRPC material and the normalized cumulative hits of each damage mechanism: matrix cracking, fiber/matrix debonding, delamination and fiber breakage. The damage mechanisms of the GFRPC sample also exhibited a specific sequence throughout time, as in other works [3, 7], showing matrix cracking as the first damage in appearance, followed by matrix/fiber debonding and delamination, and finally fiber breakage. It can be also noticed that matrix cracking is the most dominant damage due to the fragility of the resin having 40% of total cumulative hits, while fiber breaking is the last damage failure in appearance having 15% of total cumulative hits. However, in terms of AE energy, fiber breaking is the most dominant damage mechanism with 80% of the total energy, while matrix cracking is the least dominant with 3% of total energy as shown in Figure 3(b), see also [7]. In the case of matrix/fiber debonding, the AE energy represents 10%, while for delamination this value is 6%. Another efficient method to analyze the AE feature for clustering analysis during tensile loading and shearing events is the RA value, defined as the ratio of rise time to peak amplitude [8]. In the present work, RA value units are $\mu\mathrm{sec}/\mathrm{dB}$ and the clusters for the damage modes can be observed in Figure 3(c). It may be inferred that AE hits with RA values below unity are linked to tension damage modes in the GFRPC material, such as matrix cracking and fiber breaking. Conversely, AE hits with RA values beyond unity are attributed to fiber matrix debonding and delamination. The appearance of each damage mode can also be confirmed with the different RA values as shown in Figure 3(c). Finally, Figure 3(d) illustrates SEM images obtained from a test specimen in which all the damage mechanisms can be appreciated and correlated with the findings in clustering of the AE data. Table 1 shows the frequency bands of the current work compared with those for GFRPC materials available in the technical literature. Notably, each damage mode can be associated with distinct frequency bands, see [9, 10], such as matrix cracking in a frequency band of 87-137kHz, which is similar to 62.5-137 kHz in [9], and fiber breaking in a frequency band of 350-445 kHz, which is similar to 380-430 kHz in [10].

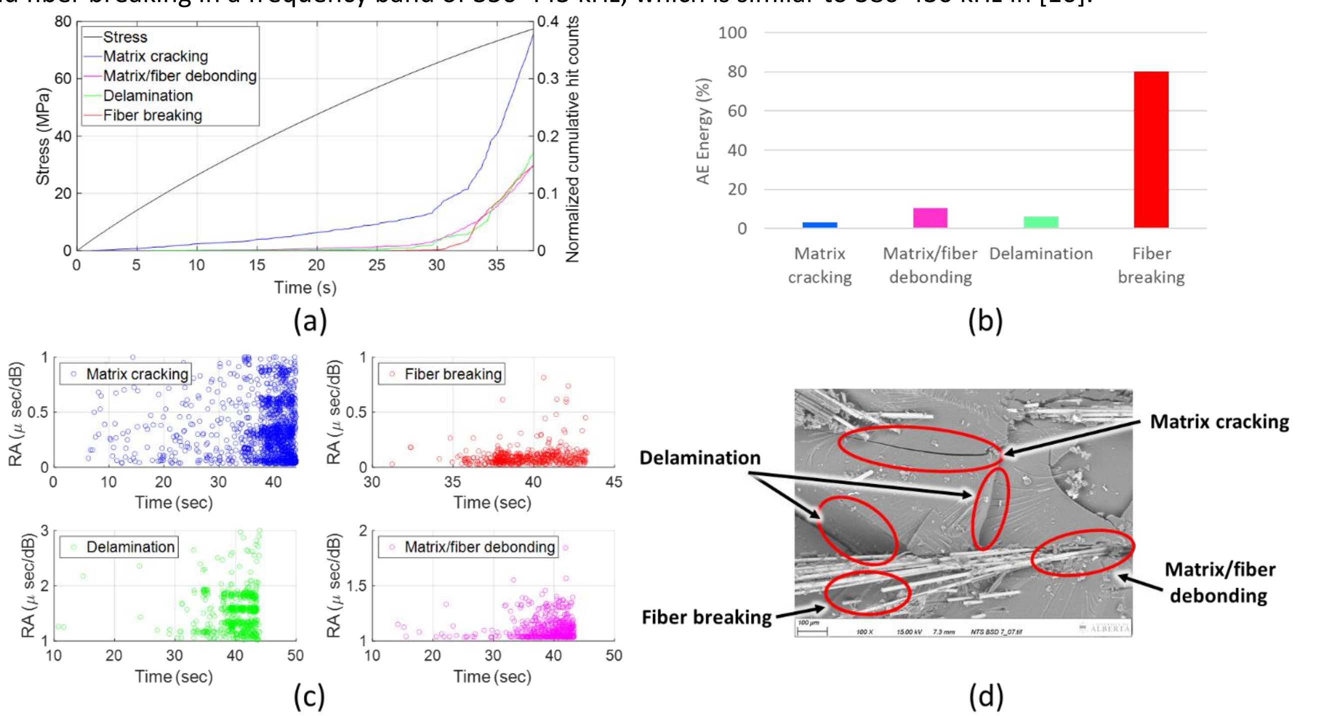

Figure 3. (a) Stress applied to specimen and normalized cumulative hit of damage modes as function of time; (b) AE energy of damage mechanisms, (c) RA values of damage mechanisms, and (d) SEM images of specimen damage.

Table 1. Comparison of frequency bands for damage modes of GFRPC materials with data from technical literature [kHz].

Ref	Matrix/Fiber	Matrix cracking	Matrix/fiber debonding	Delamination	Fiber breaking
Current work	Epoxy/Gf	87-137	146-180	192-332	350-445
[9]	Epoxy/Gf	62.5-125	125-187.5	-	187.5-250
[10]	Epoxy/Gf	<60	-	200-320	380-430

5 CONCLUSION

In the present study, AE was combined with PCA and the k-means algorithm as a non-destructive tool for damage mechanism identification of GFRPC materials. The selection of AE features included four out of ten descriptors that represented the most suitable for clustering the damage modes. These AE features were rise time, amplitude, energy, and peak frequency. The most dominant damage mechanism was matrix cracking in terms of AE hits and first in appearance, while fiber breaking was the less dominant and last in appearance. However, fiber breaking represented 80% of the total AE energy while matrix cracking just 3%. The other damage modes present in the failure of the GFRPC specimen were matrix/fiber debonding and delamination. Another interesting method investigated was the RA values defined as the ratio of rise time to the peak amplitude. The RA values provided important information during the tensile loading of GFRPC specimen, having values below unity related to matrix cracking and fiber breaking with low rise time, while RA values greater than unity were related to delamination and matrix/fiber debonding. Peak frequency was also used to compare with AE data from the technical literature pertaining to the above-mentioned damage modes. Therefore, the integration of machine learning methodologies with complementary AE features may be deemed suitable for the purpose of identifying damage modes in GFRPC materials. The present findings yielded valuable insights into the damage modes associated with these materials.

6 REFERENCES

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