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Supervised and non-supervised AE data classification of nanomodified CFRP during DCB tests

Aim of the paper is to use acoustic emissions to study the effect of electrospun nylon 6,6 Nanofibrous mat on carbon-epoxy composites during Double Cantilever beam (DCB) tests. In order to recognize the effect of the nanofibres and to detect different damage mechanisms, k-means clustering of acoustic emission signals applied to rise time, count, energy, duration and amplitude of the events is used. Supervised neural network (NN) is then applied to verify clustered signals. Results showed that clustered acoustic emission signals are a reliable tool to detect different damage mechanisms; neural network showed the method has a 99% of accuracy.

Keywords: Acoustic emissions, Carbon-epoxy composites, Electrospinning, K-means, Artificial Neural Network.

1. INTRODUCTION

Since the early 1960s, carbon fibre composites have been used because of their high strength and stiffness, high resistance to corrosion and fatigue coupled with low weight in comparison with traditional materials [1].

Delamination is one of the critical failure modes for composite structures, which may lead to the separation of plies and eventually to the failure of the component; it is therefore necessary to strengthen the interlaminar fracture toughness for highly reliable composite materials and structures. As some of the authors have already demonstrated, interleaving small diameter fibres between one or more interfaces improves strength, toughness and delamination resistance of composites without reducing the in-plane properties or adding weight [2-7].

An important aspect when designing for composite components is the knowledge of failure mechanisms, and acoustic emissions (AE) have been already successfully applied for the purpose [8-14]. The main advantages of AE are their real-time operation and the capability to distinguish damage mechanisms. AE signals can be analysed in time, frequency, and time-frequency domains. Time domain analysis, which is the most common analysing method for AE, uses certain features extracted from signals such as amplitude, energy, count, rise time and duration, as shown in Figure 1.

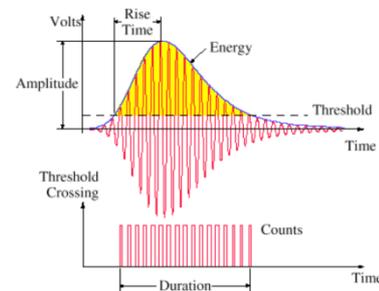


Fig.1. Acoustic emission feature [15]

Some researchers analysed different types of failure modes using Acoustic Emission in composites by supervised and non-supervised methods [16-27]. In supervised learning the categories, data is assigned to be known before computation. So they are used to teach the method the parameters significant for those Clusters. In unsupervised learning datasets are assigned to segments, without the clusters being known.

As mentioned before, one of the main advantages of using AE is that they are capable of recognizing different damage mechanisms.

de Oliveira et al. [18] used artificial neural networks with acoustic emission signals gathered from cross-ply glass-fibre/polyester laminate under tensile test, and identified damage sequence from the modal nature of the AE waves.

Refahi et al. [20] studied the effect of different fibre orientation in Double Cantilever Beam (DCB) tests of glass/polyester composites using non-supervised methods (principal component analysis and fuzzy c-means) to classify AE signals gathered from tests, showing good agreement between clusters and failure mechanisms. By frequency analysis of acoustic emission signals, it has been found that the lowest frequency range is related to the matrix cracking (100-250 kHz) and the highest to the fibre failure (400-500 kHz). Also, the debonding frequency range was between matrix cracking and fibre failure (250-350 kHz).

McCrary et al. [27] investigated the use of AE to locate and classify the type of damage occurring in

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carbon fibre panel during buckling comparing Artificial Neural Network (ANN), Unsupervised Waveform Clustering (UWC) and Corrected Measured Amplitude Ratio (MAR) techniques. They showed that a cross-correlation between techniques has the potential to be the key to developing a reliable Structural Health Monitoring (SHM) system.

Present paper uses non-supervised clustering k-means and supervised pattern recognition neural network (NN) techniques applied on the features of acoustic emission signals to discriminate different kinds of failure mechanisms. AE here considered have been recorded during the experimental campaign performed in [2]: DCB tests on carbon fibre reinforced plastic (CFRP) laminates with and without nanofibrous interleaving. Aim of the study is to investigate and explain the effect of interleaving polymeric nanofibers into CFRPs.

To date only few works have been conducted on the topic. Kostopoulos et al [28] investigated the influence of carbon nanofibers and/or piezoelectric particles on the fracture behaviour of carbon fibre reinforced polymer laminates using AE. Chen et al. [29] showed that it is possible to use the nanofibers themselves as sensor for AE for structural health monitoring purposes.

Present paper has the double purpose of (i) demonstrating the feasibility of AE as powerful and reliable structural health monitoring technique for composite material, and (ii) investigating the mechanical effect that a nanofibrous interleave has on the behaviour of CFRP laminates subjected to DCB loads.

2. MATERIALS AND METHODS

DCB tests have been performed on 20-ply woven prepreg carbon fibre/epoxy resin samples. Two different configurations were considered: (i) specimens made only with prepreg (henceforth named "Virgin" configuration), and (ii) specimens in which a nanofibrous layer made of Nylon 6,6 electrospun nanofibers has been interleaved in the pre-delaminated interface (henceforth named "Nanomodified" configuration) for delamination reinforcement. During the tests force-displacement curves and acoustic emissions were recorded. Mechanical parameters have been used in [2] to prove the effectiveness of the nanoreinforcement. In this paper AE features such as count, rise time, energy and amplitude, are used for investigating failure mechanisms. For a more detailed description of the experiments, reader is referred to [2].

Two data analysis techniques have been employed here: unsupervised k-means clustering and supervised artificial neural network.

2.1 Unsupervised K-means clustering algorithm

Data clustering method is the recognition method for discriminating the similarity and dissimilarity of data. In k-means method, k is the number of clusters that the data are classified in. K-means is one of the classification methods based on the similarity that

simultaneously shows the minimum distance to the centre of each cluster with the highest similarity. Each cluster is known by a point called centre: it is that point which sum of distances from all signals in that cluster is minimized. In this paper, Euclidean distance was used to cluster the signals of acoustic emission.

2.2 Supervised Artificial Neural Network (ANN)

ANNs are an alternative to congenital programmed computing and take inspiration from brain neural network. An ANN mimics the structure and functionality of a biological nervous system, and it runs a parallel distributed processing made of computation. It is capable of taking decision based on incomplete, noisy, and messy information, and can generalize rules from those cases it is trained for, applying these rules to new stimuli. Neural network architecture is a promising implicit modelling scheme based on learning a set of factors (weights), aimed at replacing the traditional explicit constitutive equations used to describe material behaviour [30].

3. RESULTS AND DISCUSSION

Mechanical results in [2] showed that virgin laminates exhibited a 12.3% higher maximum load than the nanomodified ones, while nanomodified specimens showed 23.2% and 4.9% increase in energy absorbed and GIC compared to virgin specimens respectively.

Figure 2 shows the cumulative of acoustic energy and the mechanical results. Whenever the crack propagates, force drops and AE energy rises. Furthermore Figure 2 shows that in a nanomodified interface, the energy of each AE event is smaller than the energy of each event released by the virgin interface and it is because of the nanolayer which absorbs the energy.

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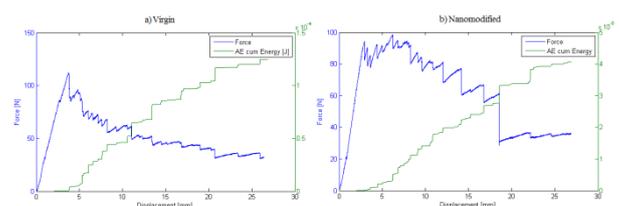


Fig.2. Force and AE cum energy versus Displacement (a) virgin and (b) nanomodified

The curves also show that AEs are very sensitive to crack propagation and, therefore, are a robust tool to monitor the condition of structure under load.

3.1 AE data clustering

Acoustic emission signals acquired during DCB tests are clustered using k-means algorithm. Rise time, count, energy, amplitude and duration are used as inputs for the k-means algorithm, and should be first normalized, meaning that they have to be mapped to the range from zero to one by using equation (1) [31]:

$$AE \text{ normal} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X is a generic AE parameter and X_{min} and X_{max} its minimum and maximum value respectively.

The classes of the algorithm represent the damage mechanisms, and therefore k, the number of classes, is set to 3: matrix cracking, fibre breakage and delamination. The failure mechanisms detected from acoustic emission signals in reference virgin and nanomodified specimens are presented in Table 1 and Table 2 respectively.

Table 1. Different ranges of acoustic emission feature by k-means for Virgin reference specimen

	Amplitude (dB)	Duration (μs)	Energy	Count (number)	Rise Time (μs)
Class 1: Matrix Cracking	56-68	204-3200	10-116	25-433	1-227
Class 2: Delamination	68-81	298-3184	13-189	34-379	1-220
Class 3: Fiber Breackage	79-91	476-9800	68-3766	62-1898	1-281

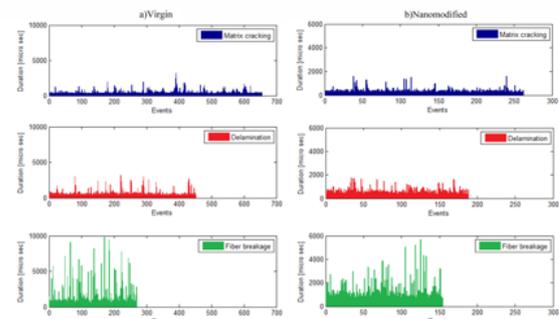
Table 2. Different ranges of acoustic emission feature by k-means for nanomodified reference specimens

	Amplitude (dB)	Duration (μs)	Energy	Count (number)	Rise Time (μs)
Class 1: Matrix Cracking	60-71	228-16200	10-48	27-167	1-200
Class 2: Delamination	71-84	268-1732	22-170	43-233	1-208
Class 3: Fiber Breackage	83-92	631-5670	113-3573	75-695	1-243

Tables 1 and 2 give individually useful information on the failure modes of the laminates, but also, combined, represent a useful tool to investigate the effect of the nanointerleave into the laminates. Tables show that the acoustic events in virgin composite, for all the three failure modes, are longer than those in nanomodified sample, due to the crack arresting mechanism played by the nanofibers. During the tests, in virgin samples the crack propagates for longer steps than the nanomodified specimens, because of the resistance offered by the nanointerleave. For the better

clarification of the duration, for both virgin and nanomodified specimen, these parameter are plotted in Fig. 3.

Figure 3: Duration vs. number of counts (a) virgin and (b) nanomodified



Comparing Table 1 and Table 2 also suggests that the range count of signals registered for virgin specimens is more than the double of the events than those registered for nanomodified specimens, suggesting that nanofibers not only reduce the propagation step but also reduce the total number of steps.

Figure 4 shows the ranges of AE energy versus amplitude for both (a) virgin and (b) nanomodified specimens.

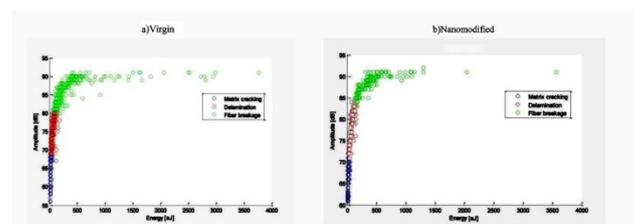


Figure 4: Amplitude vs. Energy of: (a) virgin and (b) Nanomodified

Figure shows that the lowest amounts of amplitude and energy are related to the matrix cracking, the moderate values to delamination, and the highest amount to fibre breakage, showing good agreement with results of other studies [32,33].

3.2 Supervised AE clustering by neural network

In this section, the results from k-means algorithm were investigated by NN as a pattern recognition technique. By analysing the data recorded during the DCB tests, the failure mechanisms in the composite can be predicted. By using acoustic emission signals with the NN, the relationship between different damage modes of composite and signals can be investigated. Input data includes normalized AE features such as rise-time, count, energy, duration and amplitude and output are associated classes to each signal.

By employing NN method, the input data and results are linked to each other with a connection weight. The weights are assigned to other input parameters to predict the unknown results. Matlab NN toolbox was used for solving the pattern recognition classification problem.

In this method three sections are involved: training, validation and testing. The training part is based on finding the relationship between input and output data [34].

Neural network solves a pattern-recognition classification problem by using a two-layer feed-forward network with sigmoid output neurons. The neuron is the simplest kind of node, and maps an input vector $x \in \mathfrak{R}^n$ to a scalar output $f(x;w, \theta)$ via:

$$f(x; w, \theta) = \theta + \sum_{i=1}^n w_i x_i$$

where θ are 'bias' and w_i are 'weights' of the i -th variables in the input vector x which include n variables. We will focus mainly on a 3-layer feed-forward ANN, which consists of a hidden layer and an output layer as shown in Figure 5. The default number of hidden neurons is set to 10. The number of output neurons is set to 3, equal to the number of elements in the target vector, equal to the failure modes.

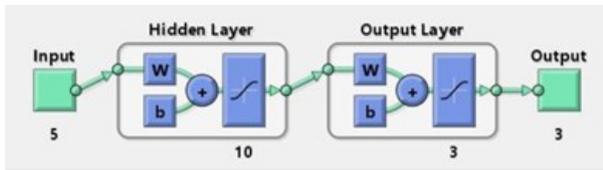


Fig.5. Schematic artificial neural network with 5input variables, 10 hidden layers and 3 output layers

The input vectors x and target vectors t is randomly divided into three sets:

- 70% allocated for training set, used for computing the gradient and updating the network weights and biases;
- 15% allocated for validation in generalizing and stopping training before over-fitting;
- 15% allocated for a completely independent test of network generalization.

As the weights and biases of the network are initialized, the network is ready for training. The training process of a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function [35,36]

The default performance function (ϵ) for feed-forward networks is defined as mean squared error between the network outputs f and the target outputs t . It is defined as follows [35]:

$$\epsilon = \frac{1}{2} \sum_k (f_k - t_k)^2$$

All the three sets (training, validation and testing) were calculated, and shown in Figure 6.

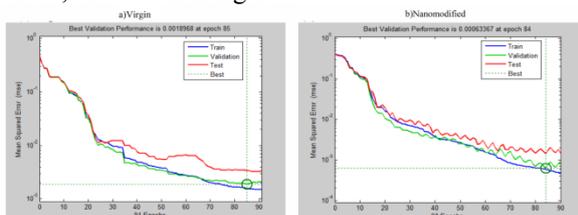


Fig.6. Performance plot: (a) Virgin and (b) Nanomodified

Depending on the network architecture, there can be millions of network weights and biases which make network training very complicated and computationally challenging. The simplest optimization algorithm -gradient descent- is used in the present study. It updates the network weights and biases in the direction in which the performance function decreases most rapidly, the negative of the gradient. The gradient will become very small as the training reaches a minimum of the performance. The iteration of this algorithm can be written as [35]:

$$x_{k+1} = x_k - a_k g_k$$

Where x_k is a vector of current weights and biases, g_k is the current gradient, and a_k is the learning rate [40]. Figures 7a and 7b show the variations of current gradient for virgin and nanomodified composites respectively.

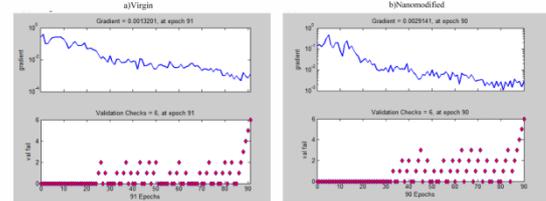


Fig.7. Training state plot: (a) Virgin and (b) Nanomodified

Thereafter a set of test signals (test matrix) is applied for the evaluation of the trained network, which will again give the confusion matrix of final output (tested data). The level of neural network training can be determined by examining the results shown in confusion matrix [36,37]. Figures 8a and 8b show the confusion matrices of virgin and nanomodified data. Confusion matrix can determine the accuracy of clustering for all training, testing, and validation data. According to the results signals are classified in three classes: the green part shows the signals correctly classified by k-means algorithm. The network's outputs are almost perfect, as can be seen from the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The diagonal [35] cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified ones. The blue cell in the bottom right depicts the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). According to the results for virgin composites 656/659 signals are related to matrix cracking, 451/452 signals are related to delamination and all fibre breakage signals have been classified correctly. Therefore 99.7% of the signals have been correctly classified. For nanomodified composite all signals have been classified correctly.



Fig.8. Confusion matrix: (a) Virgin and (b) Nanomodified

Table 3 shows the Mean Squared Error (MSE) and percent of error (%E) calculated for both virgin and nanomodified samples. Mean square error is the average squared difference between outputs and targets. Lower values show a better accuracy as zero means no error. Percent error represents the fraction of samples that are misclassified. A value of 0 means no misclassification.

Table 3. Mean squared error and percent of error in Virgin

	Samples		MSE		%E	
	Virgin	Nano	Virgin	Nano	Virgin	Nano
Training	964	422	1.57e-3	5.89e-4	0.20	0
Validation	207	91	1.90e-3	6.34e-4	0.48	0
Testing	207	91	3.37e-3	1.44e-3	0.48	0

4. CONCLUSIONS

This paper investigate the use of AE signals to monitor the fracture modes of composites with and without nanofibers, during a fracture mechanics test.

Form the analysis of the results AE revealed that nanofibers are capable of mitigating the delamination by reducing the number crack steps and their length during the tests.

k-means algorithm, an unsupervised technique, has then be used to classify AE signals rose during the DCB tests to recognize failure mechanisms such as matrix cracking, delamination and fibre breakage. Different ranges of acoustic emission features for different damage mechanism of both types of virgin and nanomodified specimens are determined. Based on the results, the lowest amplitude and energy signals are related to matrix cracking, while the highest amplitude and energy refer to fibre breakage in both specimens. Then neural network were applied as a supervised method to display the percentages of the correct classification signals: remarkably both kinds of specimens show more than 99% of accuracy.

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