

# Pattern Recognition of Acoustic Emission signal During the Mode I Fracture Mechanisms in Carbon- Epoxy Composite

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## Abstract

The aim of the paper is to use Acoustic Emission technique to distinguish the micro/macro failure mechanisms of carbon-epoxy composite laminates during Double Cantilever Beam (DCB) tests. In order to recognize and detect different damage mechanisms, Self-Organizing Map (SOM) method has been used to cluster the AE signals according with the fracture mode that originated them. In addition, most significant learning vector quantization (LVQ) program has been applied to verify the signals. Five AE features were selected as main parameters: Rise-time, Counts, Energy, Duration and Amplitude. The results highlighted that different signals can be recognized and classified related to their origin. The failure mechanisms detected are Matrix cracking, delamination, and fiber breakage. Scanning Electron Microscopy (SEM) images validate the results.

Mathematics data and experimental results confirmed a good converging of AE data.

**Keywords:** Acoustic emission, micro-failure mechanisms, Carbon-epoxy composite, SOM, LVQ

## 1. Introduction

Carbon fiber composites have many applications in the aerospace industries (military and defense industry), vehicles, new energy, pressure tubes, piping, electrical sources of wind energy, and all of these are due to the high strength and stiffness of composites compared with their weight. So knowing the micro-mechanisms of failure mechanisms during the different loading are necessary and vital. Delamination is one of the important failure mechanisms. It is an interfacial failure mechanism and cause bifurcation of the material and finally complete disrepair, so it is important to recognize and understand this kind of failure [1, 2].

Acoustic Emission (AE) signals are the ultrasonic waves (ultrasonic) that are produced when the material undergoes to the stress. Acoustic emission method can be used to distinguish different types of failures, during the loading of the materials. In order to, the main problem is to distinguish the relationship between the signals from different sources of acoustic emission and failure mechanisms. So, classification of the data is an important tool for inspection and interpretation of the data. There are two methods for classification that includes: Non-supervised and supervised techniques [3].

Johnson et al. [4] Studied the principal component analyzing of acoustic emission signals during the tensile test for glass/epoxy laminates. The obtained signals from failure mechanisms i.e. matrix cracking and local delamination, were investigated separately.

Godin et al. [5] are used the Kohonen map of neuron combined with the k-means as a non-supervised algorithm, imposed. Finally, they were able to detrition of the micro-mechanism of failures, such as: separation of fibers from the matrix, separation of the composite plates, the failures to identify the fiber matrix and fiber breakage.

Marec et al. [6], by using the PCA method and fuzzy c-means clustering (FCM) recognized the failure mechanisms in polymer based composite material.

Arumugam et al. [7], by using of the Fast Fourier Transform (FFT) and Short Time Fast Fourier Transform (STFFT) analyzes the acoustic emission signals. Then by non-supervised approach of FCM, investigated the failure process in the glass-epoxy composite like: matrix cracking, delamination and fiber breakage.

For considering of the failure mechanisms, the understanding of the relationship between the features of AE signals and failure mechanisms are necessary. To do this, several ways to identify and classify types of signal are present [4, 8]. There are a set of numerical modeling to evaluate micro-mechanism failure that suggested by researchers.

Moëvus et al. [9] used unsupervised k-means and time domain analysis of acoustic emission signal for detecting different kind of failure mechanisms. They recognized different kind of cracks in Sic/[Si-B-C] composite.

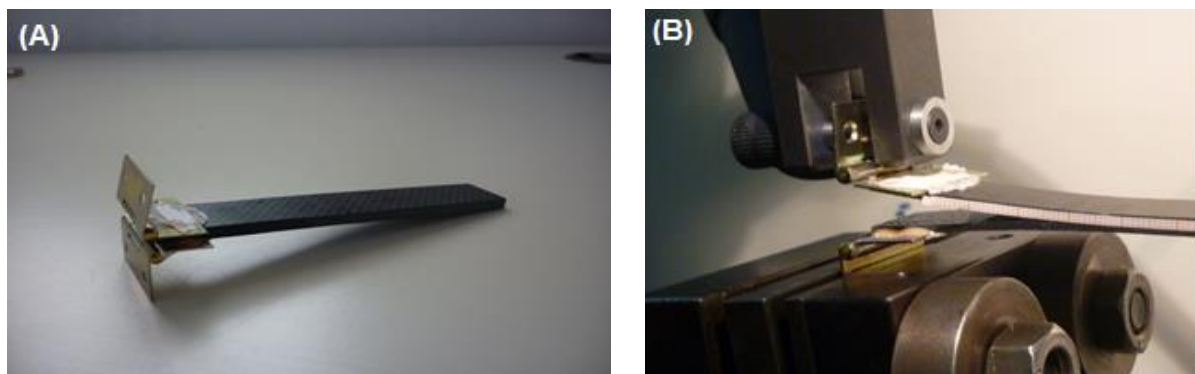
Godin et al. [3] collected acoustic emission signals during the tensile test of glass-polyester composites. They were recognized and classified failure mechanisms by k-means as an unsupervised and K-Nearest Neighbor (KNN) as a supervised method. The features which used in their study were count, average-frequency and duration.

In the present study, the specimens of epoxy as a matrix / carbon fiber which is used as a mode I test. During the test, the acoustic emission signals radiated from the material under load were recorded and eventually by using pattern recognition, signals were classified and analyzed. In this study, self-organizing map is used as a non-supervised (SOM) for clustering the acoustic emission signals during loading mode I was using. Then, by using learning vector quantization (LVQ) the accuracy of the method to be discussed.

## 2. Materials and methods of construction

### 2.1 Material

DCB tests have been performed on 20–plies woven prepreg carbon fiber\epoxy resin samples. specimens made only with prepreg configuration. During the tests force-displacement curves and acoustic emissions were recorded.



**Fig. 1.** (A) DCB specimen and (B) DCB test

### 2.1.1 DCB test

Double Cantilever Beam test Mode I fracture test was performed according to ASTM D5528[10]: 130 mm \_ 20 mm \_ 4 mm Double Cantilever Beam (DCB) specimens were manufactured as shown in Fig. 1A. Initial delamination was provided by Teflon sheet, 25 mm in length,

That was placed in the mid-interface at one of the edges of the specimens.

Experimental tests were performed under displacement control condition at constant crosshead rate of 1.5 mm/min in a servo hydraulic universal testing machine Instron 8033, Fig. 1B, with a Force capacity in the range 5–250 kN. Load and crosshead displacement were recorded 10 times per second during the test, while crack length was measured by visual inspection. Energy release Rate for Mode I fracture testing is given by the Mixed Mode Theory

Considered in the ASTM standard [10]:

$$G_{IC} = \frac{3P\delta}{2b(a+\Delta l)} \cdot \frac{F}{N} \quad (1)$$

where P and d are applied load and opening displacement respectively, b and a are specimen width and crack length respectively;  $\delta$  is determined experimentally by generating a least squares plot of the cube root of compliance,  $C^{1/3}$ , as a function of a; F and N are correction factors in order to account for the presence of the end hinges and large opening displacement.

According to the theory of linear fracture mechanics, fracture toughness  $G_{IC}$  for the crack extension can be obtained by substituting to P, in Eq. (1), the critical load  $P_c$  which is the maximum load when the delamination extends from the initial point.

### 2.2 Acoustic emission monitoring

Acoustic emission (AE) technique was used in order to monitor the material damage onset and progression. Acoustic emission data acquisition system (PAC) PCI-2 with a maximum sampling rate of 40 MHz was used to record AE events. A broadband, resonant type, single-crystal piezoelectric transducer from Physical Acoustics Corporation (PAC), called PAC R15, was used as the AE sensor. The surface of the sensor was covered with grease in order to provide good acoustic coupling between the specimen and the sensor. The signal was detected by the sensor and enhanced by a PAC pre-amplifier. The gain selector of the pre-amplifier was set to 40 dB. The test sampling rate was 10 MHz. prior to the damage check; the data acquisition system was calibrated for each kind of specimen, according to a pencil lead break procedure. The pencil lead break procedure enables the generation of waves at the specimen surface that were used for device calibration. At the same time, the velocity and attenuation of the AE waves were measured. After the calibration step, AE signals were recorded during mechanical testing. The AE data analysis were performed by a parametric approach, considering the main AE events features (hits, counts, amplitude, frequency and energy) and in particular the AE events energy was used for a detailed discussion of test results.

In this paper AE features such as count, rise time, energy, duration and amplitude, are used for investigating failure mechanisms. For a more detailed description of the experiments, reader shall refer to [1].

Two data analysis techniques have been here employed: unsupervised self-organizing map clustering and supervised learning vector quantization artificial neural network.

### **2.3 Unsupervised Self-Organizing Map clustering algorithm**

Data clustering method is the recognition method for discriminating the similarity and dissimilarity of data. This method uses the neighborhood function to preserve the map of properties from the input data space. This approach difficult issues and non-linear and high dimensional data, such as mining results and classification algorithms were used to solve. Also, this method is the most common model of true biological function of the brain.

Self-organizing map by clustering together at the same time can reduce data size and a complicated nonlinear project data with smaller dimensions and with the best possible showcase. Become self-organizing maps of one or two-dimensional input signals to be displayed on a map.

The target includes an array of two-dimensional network of cells is  $l = m \times n$ . Each cell by the unit vector  $j$   $w_j = [w_{j1}, w_{j2}, \dots, w_{jb}]$  is shown. The map is based on data from compatible unit vectors and set the unit vectors are expressed in the form of two-dimensional.

Self-organizing map method can be carried out according to the following steps:

- (1) All weights are selected for a random number between 0 and 1.
- (2) the input vector  $X$  is randomly selected and output using a quadratic function of distance is calculated as follows:

$$d_j = \|X - w_j\|^2 = \sum_{i=1}^n (w_{ij} - x_i)^2 \quad (2)$$

$n$  is the number of input vectors

- (3) Select the output neurons with minimal  $d_j$  as neurons win the closest vector input vector  $j^*$  is defined as the coefficient of winning neurons, resulting in at least the output is displayed as follows:

$$d_{j^*} = \min \|X - w_j\|^2 \quad j \in (1, \dots, m) \quad (3)$$

Here  $m$  is the number of neurons:

- (4) at the end of weights based on the winning neurons, the incidence is dumped

$$w_{ij^*} \times (k + 1) = w_{ij^*} * (k) + +\beta(k) [x_i(k) - w_{ij^*} * (k)] \quad (4)$$

### **2.4 Supervised Learning vector quantization neural network**

ANNs are an alternative to congenital programmed computing and are 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 behavior [30].

Learning vector of the dual-layer (input-output) was formed in 1981 by Kohonen[11] were raised. This method of classification problems that existed in neural networks, identify stems. Supervised learning vector is used to solve problems.

This method has the same structure but with the difference that the SOM network is monitored. A number of classifications which is performed on the data, given that the neural network function is true or false debate and ultimately decide the-move. There are various types of vectors are learning here has been a learning vector which is used by Kohonen.

Discussed variables using non-supervised SOM were clustered at first, and then learning vector classification vectors are compared to each class numbers that have already been defined, does. Input and output layers, dimensions  $n \times m$ , which are connected to each other by means of links. Each of the connectors are  $x$  weight. Cluster centers were randomly selected. First, once the vector input to output vector is introduced, and by comparing the weight of the connection each time winner neurons were changed and updated. Here the square root of the sum of squares as differentiation factor (the same) is used as the Euclidean distance between nearest neighbor (NNC) is. The weight of each node connections winner is calculated using the following equation:

$$\Delta w_i = \mu(t) d_i \quad (5)$$

Here  $\mu(t)$  is the learning rate decreases with time, and:  $0 < \mu(t) < 1$  is. Number input is  $i = 1, \dots, n$ ,  $t$  counting reps and  $d_i$  and  $i$ 'th coordinates distinction between reference and input vectors the vectors. Here it is the learning rate, which is obtained as follows:

$$\mu(t) = \gamma \left(1 - \frac{t}{10000}\right) \quad t=1, 2, \dots, z \quad 500 \leq z \leq 10000 \quad (6)$$

$\gamma$  constant learning rate, defined. In equation (6) can be seen Repeat Counter:  $t$ .

### 3. Results and discussion

The results of DCB mechanical samples are shown in Figure 2. Force-displacement divided on width for normalized and at the same time AE energy and displacement are shown. At the first stage, the relation between the force and displacements are linear at the beginning stage until 3.3 mm in displacement. It shows that at the first because of the elasticity of the material there is not any visual crack until to the first drops and also it refers to the creation of micro crack in the matrix and continue until reach to the macro. At the same time, the AE energy released by the matrix and during the loading.

DCB results showed in table. 1. Where the maximum load, the mechanical energy calculated at the 14 mm of displacement, and  $G_{IC}$  are summarized.

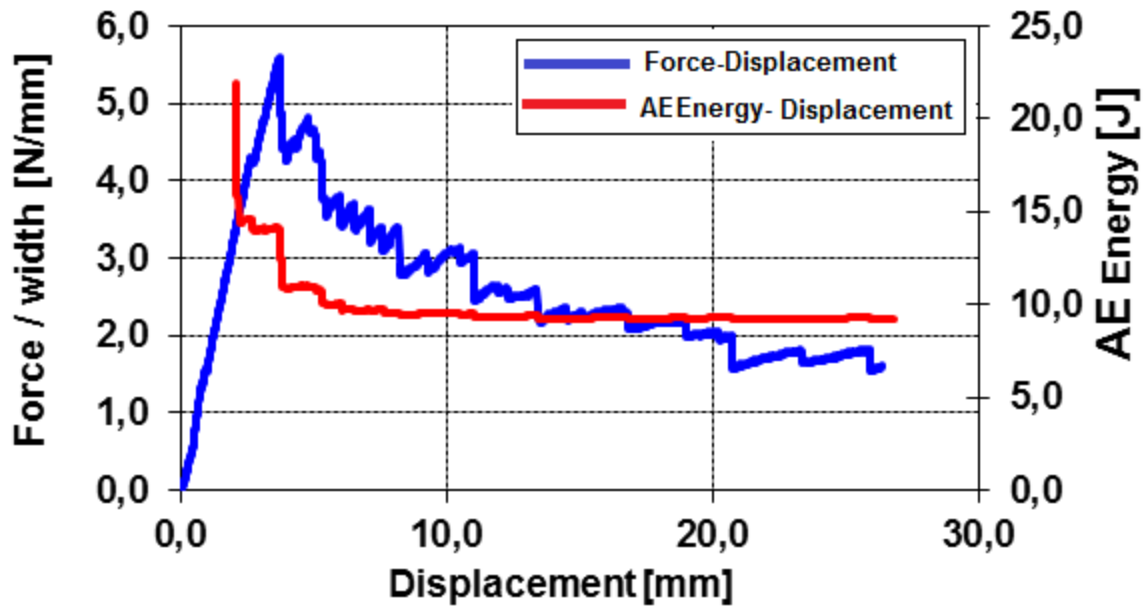


Fig. 2. Force-Displacement and AE-energy-Displacement

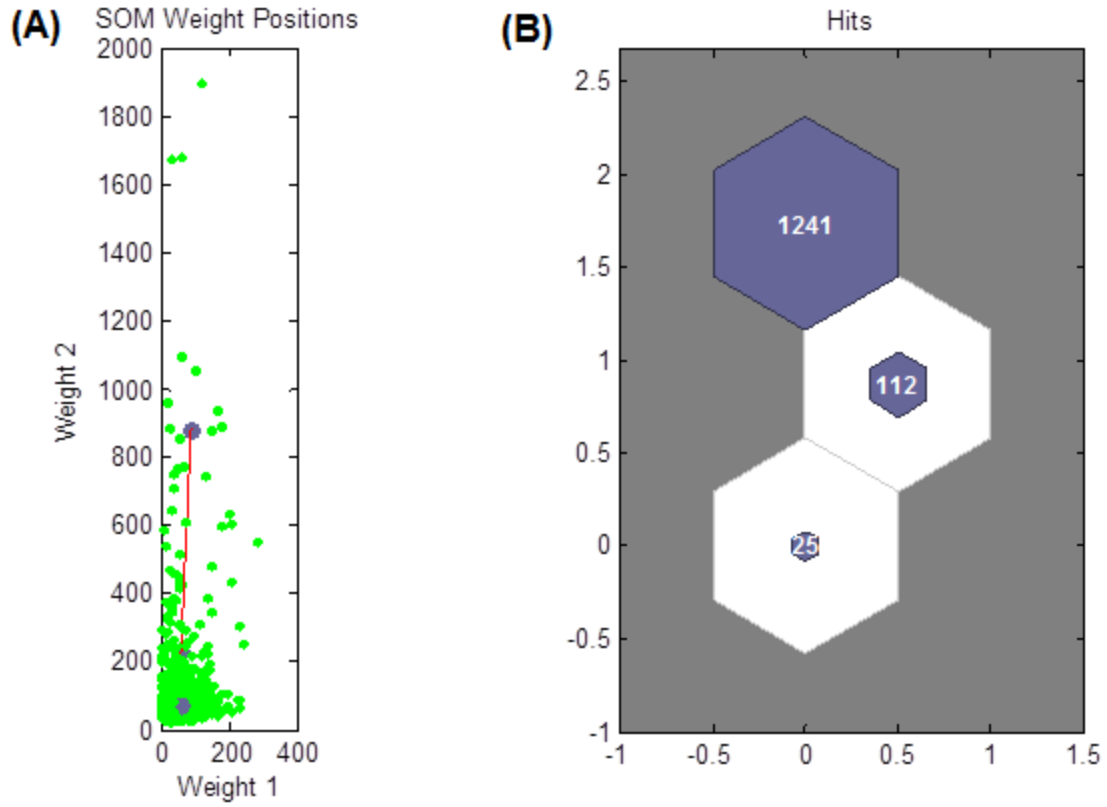
Table. 1. DCB mechanical results

	Max load/width (N/mm)			Mech energy*/width (J/m)			$G_{IC}$ (J/m <sup>2</sup> )		
	M.V.	S.D.	$\Delta\%$	M.V.	S.D.	$\Delta\%$	M.V.	S.D.	$\Delta\%$
Carbon-epoxy composite	5.61	0.42	-12.3	43.6	2.3	+23.2	473	12	+4.9

\*Mechanical energy has been calculated at the displacement of 14 mm

### 3.1 Clustering of the AE signals

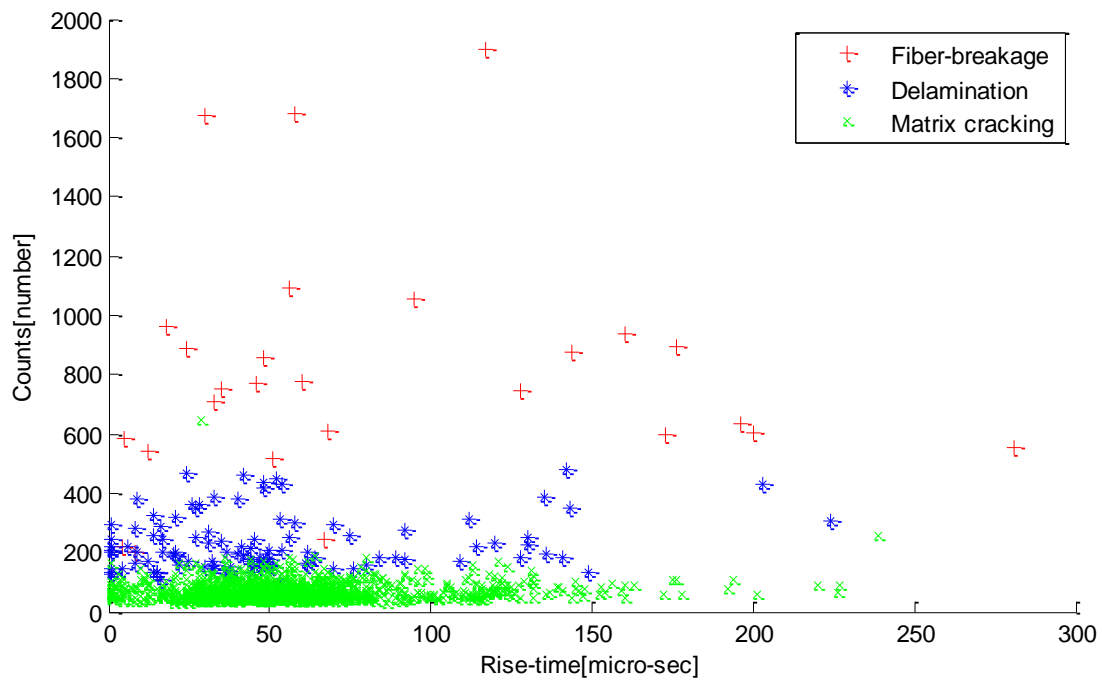
Clustering of the Acoustic emission was done by self-organizing map. The SOM network using as a neural network with  $1 \times 3$  in dimensions (Figure 3). Three classes shown by the weight of each element as SOM weight position (Fig. 3A). All the 1376 signals that were collected during the test referred to the three classes. The first class with 1241 signals is related to the matrix cracking because during the test at the first stage until the end, matrix cracking happens. The second class is delamination with 112 signals and the last 25 AE signals refers to the fiber breakage (Fig. 3B).



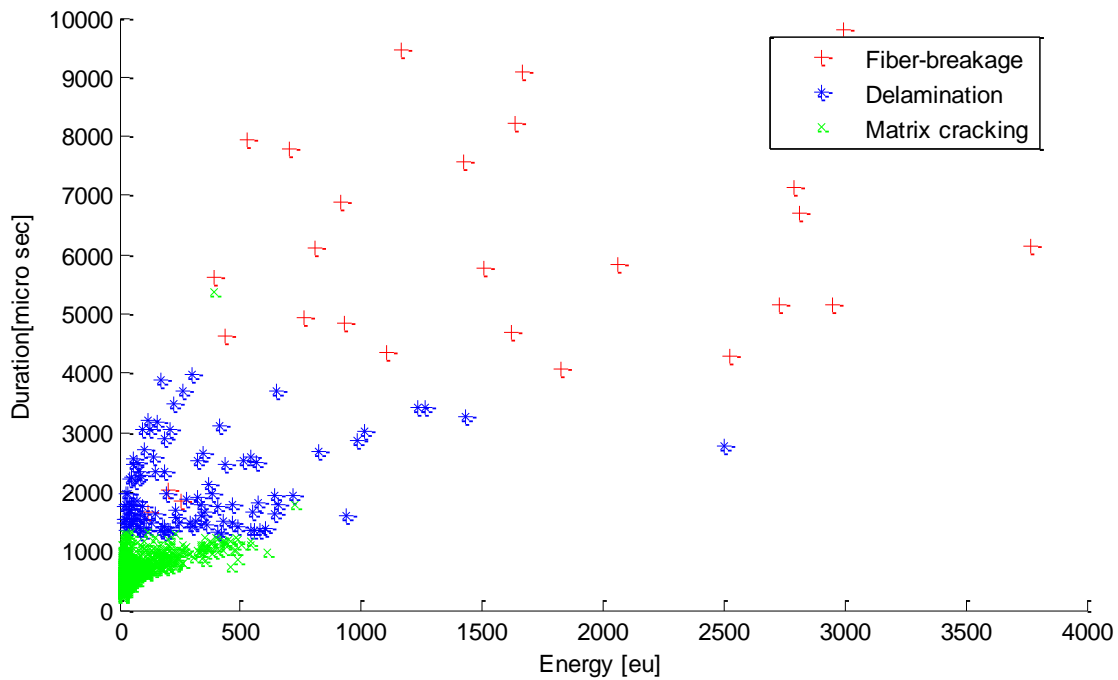
**Fig. 3.** (A) SOM weight position (B) Number of hits for each classes

**Table. 2.** Groups of acoustic parameters for any damage micro mechanism shown in

Type of failures	Rise-time	Counts	Energy	Duration	Amplitude
Matrix cracking	1-239	25-647	10-726	204-5360	56-68
Delamination	1-224	105-480	16-2500	1288-3964	68-81
Fiber breakage	4-281	201-1898	117-3766	1661-9800	79-91



**Fig. 4.** Rise time vs. counts for three different classes of failure



**Fig. 5.** Energy vs. duration for three different classes of failure



According to Table 2 and Fig. 4, the highest amount of counts (25-647) are related to the matrix cracking and also the number of counts (signal) is much more than delamination and fiber breakage.

According to Table. 2 and Fig. 5, the highest energy (117-3766) and duration (1661-9800) are related to the fiber breakage. Also the minimum of amplitude is related to the matrix cracking. Compared with the previous experiments, Liu et al. [12] were shown that for carbon-epoxy composites, the ranges of matrix cracking are 40-60dB and Zhuang et al.[13] represented that the low amplitude (under 60dB) refers to the matrix cracking and amplitude in the range of 60-80 dB are related to the delamination, which these research have a good agreement between the present results from the carbon-epoxy composite during the DCB tests.

### ***3.2 Supervised LVQ***

In this part all the results from the SOM were analyzed by LVQ to be sure about the precision of the classification.

#### ***3.2.1 Confusion matrix***

As shown in Figure 6, the total number of signals from the carbon-epoxy is 1378 which separated in three classes that dedicated micro mechanism failure mechanisms. According to the pattern recognition self-organizing map and confusion matrix (Fig.6.) 1241 received signal are exactly related to the Matrix cracking, 112 signals related to delamination, and only 25 signals related to the fiber breakage. Finally, the confusion matrix of the LVQ method achieved to the 100% of accuracy for classifying signals.

The receiver operating characteristic diagrams (ROC) in figure 7. Shows the quality of classification. This graph by applying a certain threshold in the interval [0,1] on the outputs achieved. For each the threshold of the true positive rate (the number of output greater than or equal to the threshold, divided by the number one goal), and the proportion of false positives (less than the threshold number of output divided by the number zero target) is calculated.

As can be seen, all three classes are exact in the true positive region and it shows the good accuracy classification.

Finally, using scanning electron microscopy (SEM) failure carbon composite epoxy (Figure 8) depicted is a good agreement between the numerical results and the actual.



Fig. 6. LVQ confusion Matrix

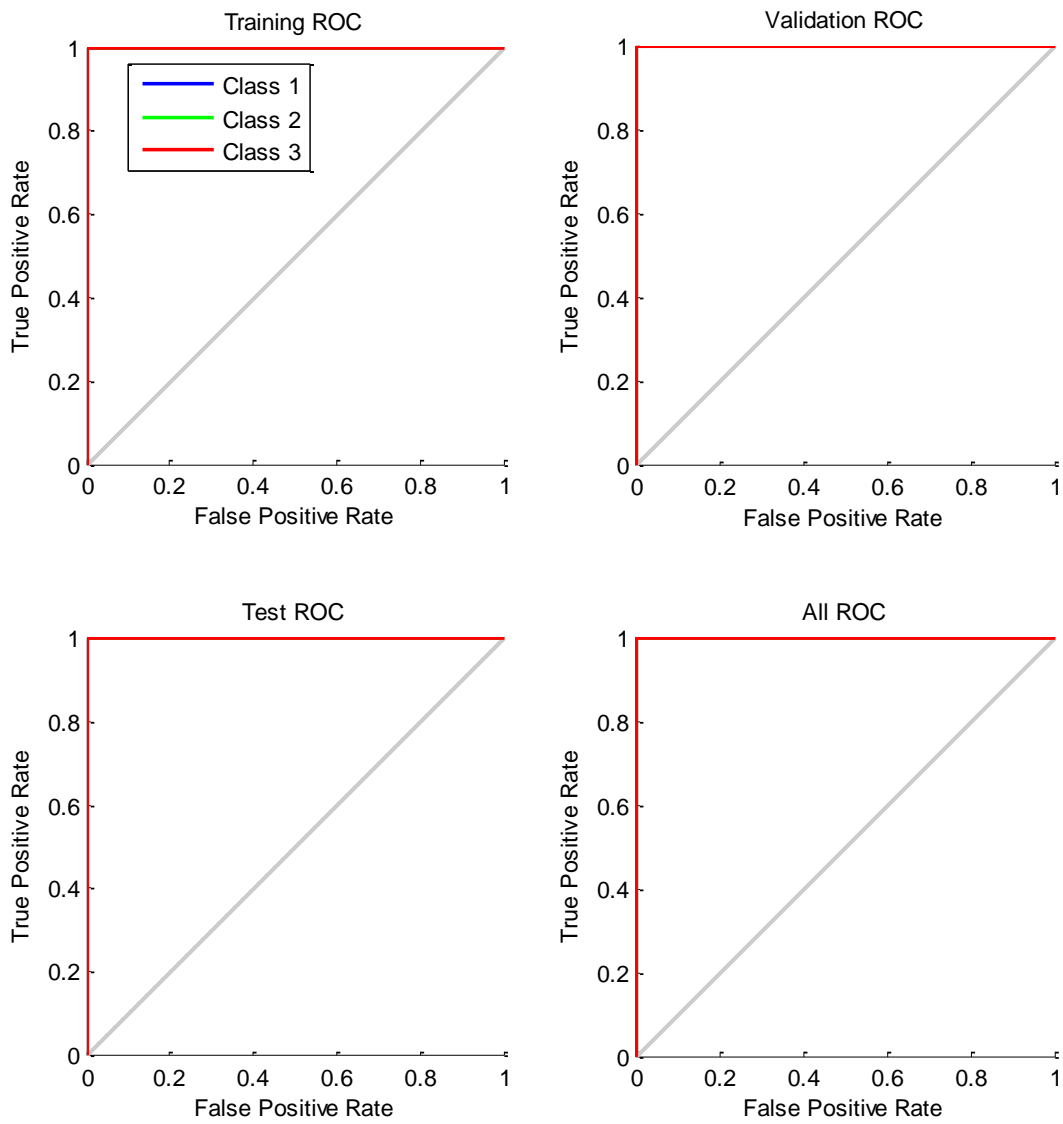


Fig. 7. ROC diagram

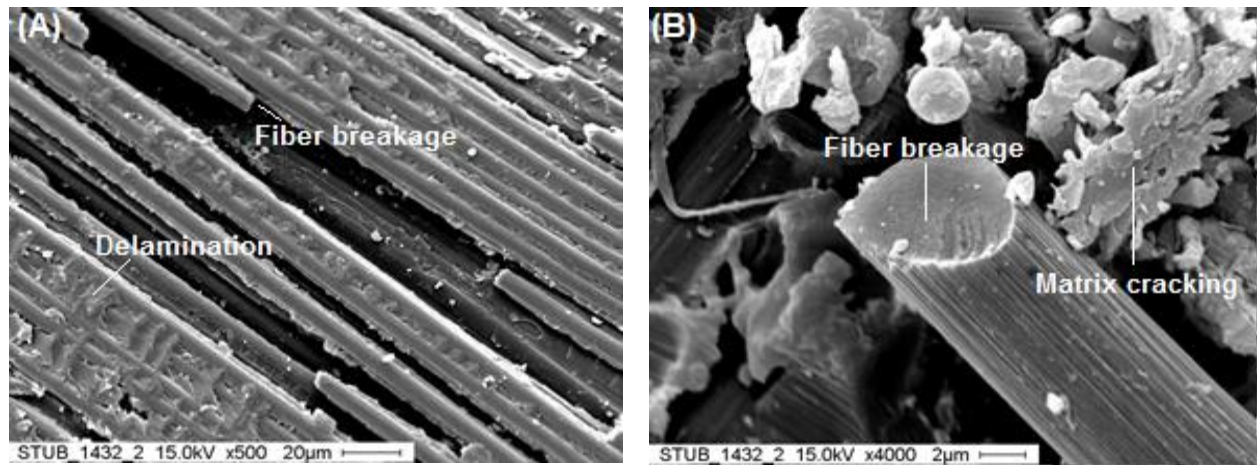


Fig. 8. SEM pictures: (A) Delamination and Fiber breakage, (B) Matrix cracking and Fiber breakage

## 4. Conclusion

This paper investigate the use of AE signals to monitor the failure mechanisms of composites during double-cantilever beam test.

Self-organizing map (SOM) algorithm used as an unsupervised technique, has then be used to classify AE signals rose during the mode I fracture to recognize failure mechanisms such as matrix cracking, delamination and fiber breakage. Different ranges of acoustic emission features for different damage mechanism carbon-epoxy 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 fiber breakage in both specimens. Then learning vector quantization (LVQ) of neural network were applied as a supervised method to display the percentages of the correct classification signals: remarkably the specimens show 100% of accuracy.

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