Fault Characteristics of CFRC Unidirectional Laminated Plate Based on Acoustic Emission

W X Lu, J J Tang, F L Chu

Department of Mechanical Engineering, Tsinghua University, Beijing 100084, China
luwenxiu@mail.tsinghua.edu.cn

Abstract. Carbon fiber reinforced composites (CFRC) are increasingly being used as raw materials of important components in the industrial production owing to its characteristics of lightweight, high-strength and corrosion resistant performance. And acoustic emission technology, as a new nondestructive testing technology, is widely applied in the fault diagnosis of CFRC laminated plates. In this paper, the tensile failure test of unidirectional laminates is carried out. The acoustic emission technology is applied to analyze the typical faults, matrix cracking and fiber-matrix debonding. Based on principal component analysis and fuzzy c-means clustering, the two faults are identified, and the acoustic emission characteristics of CFRC laminated plates in the whole failure process are obtained, which may be helpful for actual fault diagnosis.

1. Introduction

As a dynamic non-destructive testing technology, acoustic emission (AE) has been widely used in health monitoring and fault diagnosis of various components in recent years. Composite materials are important industrial materials in the future for a long period of time, and the fault diagnosis has far-reaching significance. For composite components, AE technology can detect the initial micro-defects and defect development that cannot be detected by conventional nondestructive testing methods. At the same time, important information such as damage location, damage level and life expectancy can be given in real time to achieve the purpose of health monitoring of the whole component. Therefore, acoustic emission fault diagnosis of composite materials has always been the most important subject in the field of acoustic emission technology.

Since the end of the twentieth century, a lot of research has been done on acoustic emission fault diagnosis of composite materials. The research methods can be summarized into three categories: single parameter analysis, multi-parameter analysis and waveform analysis. The fault types of composite materials are generally attributed to matrix cracking, fiber-matrix debonding, delamination and fiber fracture [1]. Peter [2] obtained AE signals of different failure modes by tension of six different CFRC plate samples. Four failure modes were distinguished by different signal frequencies. The results show that the AE signal frequency of matrix failure is about 100 KHz, while the frequency of fiber fracture is over 300 KHz. Ativitavas [3], Siron [4] and Bourchak [5] found that the damage mode was related to the acoustic emission amplitude through different experiments. They found that the lower amplitude corresponds to the matrix microcrack, the medium amplitude corresponds to the matrix crack and the delamination, and the higher amplitude corresponds to the fiber fracture. In addition to the common parameter identification, the acoustic emission fault diagnosis of composite materials using neural network is also a hotspot in recent years. Huguet [6] used Kohonen self-organizing neural network to carry out the fault diagnosis experiment of composite materials. Six
parameters of acoustic emission signal were input into the neural network as input vectors, and the matrix cracking and fiber-matrix debonding were successfully distinguished. Dirk Aljets et al. [7] have successfully separated matrix cracking and delamination failure modes by using similar methods, using the average frequency, duration and maximum amplitude of acoustic emission parameters as inputs of the neural network. For laminated composites, the research of delamination failure is an important branch of fault diagnosis. Oskouei [8], Yeum [9], Fotouhi [10] and others have studied the delamination failure of laminated composites and classified the delamination failure into 1-type delamination, 2-type delamination and their mixed delamination failure. The delamination failure is related to energy release rate, and then the failure can be described by AE characteristics parameters.

In summary, fault identification technology has always been the most important topic in the field of acoustic emission technology. In the field of acoustic emission fault identification of composite materials, the complexity of fault signal limits the application of acoustic emission technology. Therefore, it is of great significance to study the acoustic emission fault identification technology of composite materials and apply this technology to engineering practice.

In this paper, a unidirectional laminates is made and the tensile failure test of unidirectional laminates is carried out. The tensile direction of the unidirectional plate is perpendicular to the direction of the fibers to obtain the two failure modes: matrix cracking and fiber-matrix debonding. The acoustic emission technology is applied to analyze the faults. Based on principal component analysis and fuzzy c-means clustering, the two faults are identified, and the acoustic emission characteristics of CFRC laminated plates in the whole failure process are obtained, which may be helpful for actual fault diagnosis.

2. Experimental design

2.1. Manufacture of the sample for tension test
The unidirectional plate of the test sample is made as the size of the inner cavity $280 \times 220 \times 2\,\text{mm}$, the number of layers 16. The sample is pressed for 10 hours at the temperature $90^\circ\text{C}$ and the pressure about 10KN. Considering the layout space of sensors and the high strength of CFRC laminates, the pressed laminates are processed into rectangular tensile samples (the size is $280 \times 20 \times 2\,\text{mm}$) with symmetrical notches at the midpoint of the length direction of the rectangular samples. As shown in Fig.1, the width and depth of the notches are 2 mm and 5 mm, respectively. Water sputtering cutting method is adopted to avoid machining defects and maintain good smoothness of the machined surface. The clamping aluminum plate is pasted on both ends of the tensile sample to eliminate the damage of the clamping head to the tensile sample during the tensile process. As shown in Fig.1, the size of the clamping aluminum plate is $40 \times 20 \times 2\,\text{mm}$, and the high strength adhesive is used to bond the aluminum plate to the sample.

![Figure 1. Dimension diagram of laminate samples](image)

2.2. Tensile test
As shown in Fig. 2, the sample was tensioned by WDW-100/E universal testing machine (maximum load is 100KN) at room temperature. The moving speed of the clamping head is 0.1mm/min, and the
The tensile direction of the unidirectional plate is perpendicular to the direction of the fiber, so as to obtain two failure modes of matrix cracking and fiber-matrix debonding.

Acoustic emission signals are collected by PAC's integrated acquisition equipment. The sensors are WD series sensors. The two sensors are symmetrically arranged relative to the notch, 100 mm apart. The acoustic coupling between the sensor and the sample is carried out by Vaseline. The sampling frequency is 1 MHz, and the amplification factor of the preamplifier is 40 dB. The threshold of 35 dB is used for front-end filtering to eliminate noise interference in the surrounding environment. The peak definition time is set to 20 $\mu$s, the impact definition time is set to 300 $\mu$s, and the impact unlock time is set to 600 $\mu$s. Before each tensile test, the two sensors are calibrated. The calibration method is lead breaking test in the middle of the sample to obtain consistent sensor measurement results as the standard for successful calibration.

3. Experimental results and discussions

3.1. Single parameter analysis

![AE waveform schematic diagram](image)

Acoustic emission parameter analysis method is the most classical signal processing method in the field of acoustic emission signal processing, which originated in the 1950s. The basic principle is to extract the acoustic emission parameters reflecting the basic characteristics of the pulse wave through the pulse attenuation wave of the acoustic emission signal, and through the subsequent parameter analysis to realize the analysis of the acoustic emission signal, so as to achieve the purpose of fault identification. Fig. 3 is a simplified AE waveform [11]. The most commonly used AE signal characteristic parameters, including ring count, event count, amplitude, rise time, duration and energy,
such as RMS, RMS, RMV and average signal electrical equality parameters, are all transformed from basic parameters.

AE parameters (such as amplitude and frequency) have different distribution characteristics in different fault modes for fault identification of CFRC laminates, and there is a serious overlap between these distribution characteristics, therefore it is impossible to identify faults by single parameter analysis. However, since the counting of AE characteristic parameters can describe the intensity of AE activity to a certain extent, and the intensity of AE activity reflects the severity of material damage to a certain extent, the failure situation at different stages of tensile process can be described by analyzing the time history of counting and accumulative counting.

Fig. 4 describes the time history of load, event count and accumulative count in the process of unidirectional plate tensile test. It can be seen from the graph that the process of tensile failure can be roughly divided into four stages: initial failure formation, stable development of failure, rapid development of failure and explode of failure. 50-100s is the initial stage of fault formation, with less acoustic emission signals; 100-320s is the stable stage of fault development, with more stable and abundant acoustic emission signals and occasionally more intensive acoustic emission signals; 320-560s is the rapid stage of fault development, with the acoustic emission activities significantly increased and the cumulative growth rate increased; 560-577s is the explode stage of fault development, with extremely rich acoustic emission signals. However, it is not clear in the AE signals which are from matrix cracking and fiber-matrix debonding, respectively.

![Figure 4. Time history diagram of load, AE count and accumulated count in tensile process](image)

3.2. Multi-parameter analysis

Considering that the number of parameters will inevitably increase the difficulty of the study, and there is a certain correlation between the parameters, the principal component analysis method [12] was adopted to pre-process the acoustic emission data. The acoustic emission parameters used in multi-parameter analysis include five parameters: amplitude, counting, rising time, duration and energy. Fig. 5 shows the result of principal component analysis of unidirectional laminated plate. It can be seen that the contribution rate of principal component 1 (PC1) and principal component 2 (PC2) is 87%. Considering the convenience of two-dimensional signal in data visualization, the two principal components to describe acoustic emission signal.
3.3. Fuzzy C-means Clustering

After the AE signals described by PC1 and PC2 parameters are obtained, the corresponding relationship between PC1 and PC2 and fault mode are still unclear. The fuzzy C-means clustering analysis is applied to identify the failure mode using the two-dimensional data after principle component analysis.

Fuzzy C-means clustering [13] is an unsupervised modal recognition method. It determines the degree of clustering of each data in the data set by membership degree from the perspective of probability, and to achieve the effect of data classification. Assuming that there are n data vector sets \( x_j (j = 1, 2, \ldots, n) \), the clustering goal is to divide the data vector sets into k classes, with the centre of each class being \( c_i (i = 1, 2, \ldots, k) \), and the degree of the vector \( x_j \) belonging to the \( i \)th class is given by the degree of membership \( u_{ij} \). The objective of the fuzzy c-means clustering algorithm is to minimize the value function of non-similarity index by finding \( k \) clustering centres. The value function is defined as

\[
J(U, c_1, c_2, \ldots, c_k) = \sum_{j=1}^{n} \sum_{i=1}^{k} u_{ij}^p d^2(x_j, c_i)
\]  

(1)

where, \( p \) is the fuzzy constant (\( p = 2 \) in this paper), \( U \) is the membership matrix composed of membership degree, and it can be expressed as following:

\[
U = \begin{bmatrix}
  u_{11} & u_{12} & L & u_{1n} \\
u_{21} & u_{22} & L & u_{2n} \\
M & M & O & M \\
u_{k1} & u_{k2} & L & u_{kn}
\end{bmatrix}
\]  

(2)

Membership degree should to be satisfied as

\[
\sum_{i=1}^{k} u_{ij} = 1, \forall j
\]  

(3)
That is, the sum of membership degree of vector $x_i$ belonging to each class is 1. $d^2(x_i, c_i)$ represents the square of the Eulerian distance between the vector $x_i$ and the clustering centre $c_i$, i.e.

$$d^2(x_i, c_i) = (x_i - c_i)^T(x_i - c_i)$$

In order to determine the size of $k$, the following two classification index parameters are adopted:

1) Partition coefficient PC, defined as follows

$$PC(k) = \frac{1}{n} \sum_{i=1}^{k} \sum_{j=1}^{n} u^2_{ij}$$

The partition coefficient $PC$ represents the degree of overlap among clusters. The larger the $PC$ value, the smaller the overlap, the more reasonable the clustering is.

2) Partition index PI, defined as follows

$$PI(k) = \sum_{i=1}^{k} \left( \frac{\sum_{j=1}^{n} u^2_{ij} d^2(x_i, c_i)}{\sum_{q=1}^{n} d^2(c_q, c_i)} \right)$$

The partition index $PI$ represents the clustering compactness and the distance between different clustering centres. The molecules in the definition reflect the clustering compactness, and the denominator reflects the distance between different clustering centres. Obviously, the smaller the $PI$ is, the closer the clustering is, the greater the distance between clustering centres, the easier to distinguish and the more reasonable the clustering is.

The steps of the fuzzy $c$-means clustering algorithm are summarized as follows:

1) Initialize the membership matrix $U$ randomly so that every element in the matrix $U$ is satisfied with $u_{ij} \in [0,1]$, and the matrix $U$ is satisfied with equation (3);

2) Calculate new clustering centres $c_i$

$$c_i = \frac{\sum_{j=1}^{n} u^p_{ij} x_j}{\sum_{j=1}^{n} u^p_{ij}}, i = 1, 2, L, k$$

3) Update membership matrix

$$u_{ij} = \left( \sum_{q=1}^{k} \left[ \frac{d(x_i, c_i)}{d(c_j, c_q)} \right]^{2/(p-1)} \right)^{-1}, i = 1, 2, L, k, \quad j = 1, 2, L, n$$

Repeat steps 2) and 3) until the iteration stopping condition is satisfied:

$$\left\| U - U^{-1} \right\| < \varepsilon, 0 < \varepsilon < 1$$

The final result of iteration is to divide $n$ data vectors into reasonable $k$ categories, and use $u_{ij}$ to indicate the degree to which the vector $x_i$ belong to the $i$th category.

In order to obtain more accurate clustering analysis results, the number of clusters is not specified in advance, but through the partition coefficient PC and the partition index PI to determine the number of clusters. As shown in Fig. 6, the partition coefficient PC and the partition index PI both decrease with the increase of the number of clusters, but the decrease of PC is harmful to the rationality of clustering analysis (there is a big overlap between different classifications), while the decrease of PI is beneficial to the rationality of clustering analysis (the tightness of the same classification increases, the distance between different classifications increases). The value of PC agreed in this paper should not be less than 0.9. The value of PI should not be greater than 0.5. Then, it can be seen from Fig.6 that the
reasonable clustering number of unidirectional laminated plate is 2, corresponding to two failure modes, which is consistent with the expected number of faults in sample design.

![Partition coefficient and partition index trend with cluster number](image1.png)

**Figure 6.** Partition coefficient and partition index trend with cluster number

![Multi-parameter principal component clustering analysis](image2.png)

**Figure 7.** Multi-parameter principal component clustering analysis

According to the number of clusters determined above, the fault feature signals described by PC1 and PC2 are clustered. In the process of analysis, because the degree of membership of each pair of PC1 and PC2 is given by the degree of membership, there will be a situation that the degree of membership of one pair of PC1 and PC2 belongs to one of them is equal or similar to that of the other. In order to solve this problem, only the signal with the degree of membership of 80% or more is taken to analyze. That is, when the degree is above 80%, PC1 and PC2 are classified as Class X. Otherwise, the acoustic emission signal parameters do not belong to any class.
Assuming that the classification results of unidirectional laminated plate are marked A and B, respectively, and the results of clustering analysis are visualized as shown in Fig. 7. It can be seen that the clustering analysis method has achieved good clustering results.

![Figure 8. Amplitude distribution of clustering data](image)

However, the type of failure represented by class A and B is still unknown. The distribution of the amplitudes of acoustic emission signals corresponding to PC1 and PC2 in each classification is analyzed, and the results are shown in Fig. 8. According to the conclusion given in reference [14] (the AE amplitudes of matrix cracking and fiber-matrix debonding increase in turn), cluster A belongs to matrix cracking and cluster B belongs to fiber-matrix debonding.

![Figure 9. Accumulated AE counting diagrams for different failure modes](image)

After the corresponding categories of each failure mode are determined, the cumulative counting time histories of different types of AE signals are given as Fig. 9. It can been seen that the AE activity (cumulative counting) of matrix cracking in the two failure modes is the largest, which runs through the whole process of CFRC laminated plate failure. For unidirectional plates, the debonding failure of fibre-matrix occurs from about 180s to about 270s. When it reaches 560s, a large number of acoustic emission signals corresponding to matrix cracking and fiber-matrix debonding failure modes occur, which basically coincides with the description of fault development in 3.1.

4. Conclusions
The tensile failure experiments with designed unidirectional plate samples are carried out to obtain the
acoustic emission signals of different failure modes. The single-parameter analysis method is used to obtain a rough description of the failure situation of laminated plate at different stages. Then, five common acoustic emission parameters are used to carry out multi-parameter analysis based on principal component analysis and fuzzy c-means clustering, the two faults matrix cracking and fiber-matrix debonding are identified, and the acoustic emission characteristics of CFRC laminated plates in the whole failure process are obtained.

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