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Characterisation of fatigue damage in composites using an Acoustic Emission Parameter Correction Technique

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ABSTRACT

In industrial applications of composite materials, accurate characterisation of damage is vital. Acoustic Emission (AE) can be utilised to achieve this, however, in large-scale complex geometry components, traditional AE approaches have limitations. In this study a large carbon fibre specimen was used to generate different damage mechanisms under fatigue loading. The Delta T Mapping technique was used to locate damage and signal features were corrected using the Parameter Correction Technique (PCT). A comparison between results obtained using traditional signal features and those obtained using PCT is given. The results are validated using C-scanning and computed tomography. Matrix cracking and delamination were successfully identified using the PCT approach and improved location accuracy was achieved.

1. Introduction

Fibre reinforced composite materials are extensively used in large-scale applications for infrastructure and transport, (aerospace, energy, automotive and marine), thanks to their high strength to weight ratio. As a result, there is a need to ensure that structural integrity is maintained which requires a deeper understanding of mechanical behaviour, damage mechanisms and remaining life to failure under static and fatigue load regimes. Many Non-Destructive Evaluation (NDE) techniques can contribute to this and one such technique is Acoustic Emission (AE) which is the passive monitoring of stress waves in a structure [1]. The stress waves originate in materials when strain energy is released during damage growth. If suitable sensors are used, such as piezoelectric transducers, the released energy can be detected. This feature can be usefully exploited for the real time monitoring of a structure and enables the provision of feedback about the structures integrity and damage evolution and hence can increase the time periods between inspections. This is particularly useful in order to reduce cost of inspection especially on hard to access structures such as off-shore wind turbines. Moreover, the use of AE allows the determination of damage locations within a structure and the identification of the damage mechanisms present by consideration of the detected AE signal features. This enables the AE technique to be used very effectively to investigate the integrity of composite structures [2]. Many studies have been conducted on different composite systems using the AE technique for monitoring real-time damage evolution and identifying different types of damage due to its high sensitivity to various damage modes [3,4].

Despite some success, full-scale damage identification using AE remains a significant challenge and is a non-trivial task. Damage characterisation using AE is well established for small isotropic components where the attenuation effects are low, but the use of AE to investigate failure mechanisms in large-scale components has been limited by the effects of propagation. Furthermore, many traditional Non-Destructive Testing (NDT) techniques do not perform well in composite materials due to their anisotropic properties. Most composite materials have a distinct anisotropic mechanical behaviour which leads to complex wave propagation and scattering phenomena. Large-scale structures also often contain geometric features such as holes, curvatures and thickness changes, which further interrupt signal propagation paths. A further challenge faced in signal classification is the variation of sensor transfer function between different sensors. To eliminate these effects the best practice for signal classification is to only consider signals recorded by a single sensor. However, large structures require the use of multiple sensors to achieve full coverage and this is particularly so in composite structures where attenuation is commonly high. The variation between sensor transfer functions can therefore have a significant effect on classification accuracy.

Hence careful consideration of AE data is required in order to

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maximise subtle differences and increase characterisation accuracy of composite damage mechanisms. It is understood that even in a similar test with permanent test conditions each sensor can record different AE signals due to sensor characteristics, sensor location, signal attenuation and superposition as a result of signal reflections from specimen edges [5–7]. Thus, it is very challenging to achieve reliable damage identification using the conventional AE approaches based on the standard recorded AE data directly. Overcoming these intrinsic limitations will improve the reliability of the AE damage characterisation technique and provide much improved SHM capabilities.

Several studies have focussed on the use of AE to identify damage mechanisms in composite materials under different loading regimes. Clustering AE signals exhibiting similarities in to groups based on conventional AE analysis has been the main target of these studies by plotting traditional AE descriptors such as amplitude, count, duration, etc. versus load or number of cycles. The correlation between two or more AE descriptors using classification techniques, both unsupervised and supervised has also been investigated [1].

To discriminate between different damage mechanisms, some authors have correlated each damage type with frequency by using the peak frequency, time-frequency or frequency-intensity data from AE signals [8–18]. Others have correlated damage with a traditional AE parameter such as amplitude of AE signals [10,15,19–21]. However, the correlation between damage type and frequency range observed by different studies is dissimilar, suggesting that it is not a reliable approach to consider the frequency extracted from the AE waveforms as a discriminating factor. This is due to the fact that the frequency is dependent on many factors such as the structural geometry, sensor response, signal propagation path and source frequency [22]. Furthermore, using burst amplitude for damage classification in complex materials is often inaccurate [23].

In efforts to achieve greater reliability, many researchers have adopted multivariate approaches to signal classification. These multidimensional analyses consider a large number of AE signal descriptors in an attempt to provide a more powerful correlation between AE data from different damage mechanisms. Many multivariate classification approaches have been investigated both individually or in combination, these include algorithms such as k-means [24–29], k-Nearest Neighbours (k-NN) [27], Fuzzy c-means [30,31], Principal Components Analysis (PCA) [25,30], Gaussian mixture distribution (GMD) [26], Artificial Neural Network (ANN) (such as the Self-Organising Map (SOM) [26–29,32–34] and Competitive Neural Networks (CNN) [26]). These normally correlate the resultant classes with observable damage mechanisms and then use a single signal parameter such as the peak frequency or amplitude to validate the classification results. Most studies are conducted using signals received by a single sensor and recorded directly by an acquisition system without removing effects of propagation, which will likely affect the reliability of the classification result.

The objective of the present work is to use the AE technique to identify damage mechanisms generated within a large-scale laminated carbon fibre composite panel under low-cycle tension-tension fatigue. An AE parameter correction methodology known as the "Parameter Correction Technique (PCT)" [35,36] is used to correct the propagation effects of AE data collected from the panel. An unsupervised classification technique, k-means, is then used to classify the AE data into suitable classes.

The PCT has been developed by the authors in order to correct for the propagation effects of as-recorded traditional AE parameters in large-scale composite structures with complex geometries. It has been previously demonstrated that this technique provides a reliable recalculation of the signal features recorded from artificial AE sources at different positions within a carbon fibre composite panel [36]. It is noteworthy that the PCT presents advantages over conventional techniques by overcoming the restriction of using data from a single sensor for analysis by utilising data from multiple sensors in the recalculation process for each signal parameter. Therefore no AE data is lost due to large source to sensor distances.

The work presented in this paper builds on two previous papers by the authors [36,37] and shares the same experimental process. The initial paper focussing on PCT [36] used artificial data, created using a wave generator and a conical transducer, to demonstrate the technique. In Ref. [37], an Artificial Neural Network classifier was used on experimental AE data to explore approaches of self-learning to identify matrix cracking and delamination signals. This paper is the first recorded use of PCT to correlate real AE damage signals in composites that are validated by both ultrasonic scanning and CT scans. The Paper is arranged as follows. First an introduction to the PCT process and cluster analysis is given in Section 2. The experimental procedure is outlined in Section 3. In Section 4 a comparison between the traditional and re-calculated data classification is made and finally conclusions are drawn in Section 5.

2. Data processing

The aim of this process is to cluster AE data into groups of similar signals using an unsupervised clustering technique. The differing classes identified will then be attributed to specific damage modes occurring during fatigue loading of a composite panel. It should be noted that it is the intention of the authors to apply this classification procedure to signals from located AE events only. That is, only AE sources with high energy which hit at least three sensors are considered as an event to be used in the analysis.

In this work four signal parameters, (Amplitude, Count, Duration and Energy), are used as input data in the clustering process. The classification procedure is performed twice, once using the traditional signal parameters and again using the re-calculated parameters from the PCT. Fig. 1 presents an overview of the procedure adopted for analysing the AE signals. Each step will be described in this section (except assigning the results which will be discussed in Section 4).

2.1. Locate AE events

In anisotropic materials, such as composites, accurate AE location is

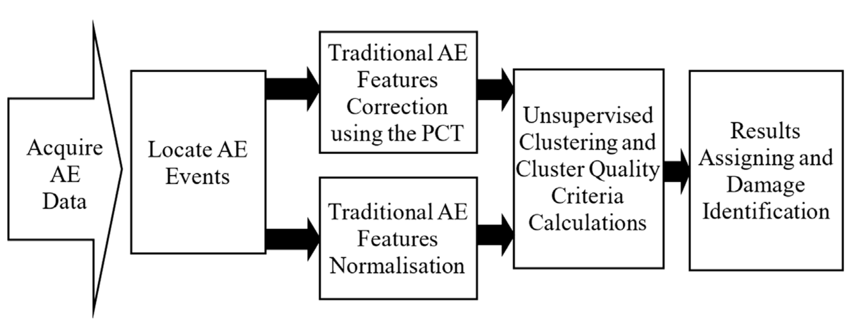

Fig. 1. Flow chart representation of the methodology proposed in the analysis.