ABSTRACT

In the present paper, acoustic emission (AE) data obtained during a static test of a 12-m FRP wind turbine blade was analyzed and classified into classes using various unsupervised pattern recognition (UPR) techniques. Class criticality was revealed by means of correlation of each class’s activity with the applied load. Application of location techniques pinpointed the specific areas of activity of each class, on the blade. Using the UPR results, a supervised pattern recognition (SPR) method was trained, based on back propagation neural network, and applied to AE data obtained during a subsequent biaxial fatigue loading of the same blade. Similar classes appeared at the same regions of the blade, but were triggered at different phases of the loading cycle. The application of UPR on AE data proved to be a promising tool towards the characterization of damage evolution with monotonic or fatigue loading.

INTRODUCTION

Acoustic emission (AE) monitoring during full scale testing of FRP wind turbine (W/T) blades is a relatively new application. The difficulty in such tests arises mainly from the potentiality of different AE sources, such as delamination, matrix cracks, fiber breakage, etc., which, sometimes, occur concurrently and are expected due to the nature of FRP materials [1]. The separability of such material-failure mechanisms by means of UPR analysis of AE data has been demonstrated in the past [2,3]. However, the sophisticated structural design of modern W/T blades, containing reinforcement spars, internal cells and skin materials with different stacking sequences, introduces additional complexity in the understanding and characterization of the detected flaws. More specifically, particular sections of W/T blades (e.g. the internal spar ends) exhibit high AE activity, even at low load levels, due to local stress concentrations, but the corresponding mechanisms do not necessarily signify critical damage. Nevertheless, the same or another area of the blade might experience a different, more critical damage mechanism at higher loads, which has to be segregated and evaluated separately. Discrimination of the various damage mechanisms on FRP materials by means of conventional AE analysis imposes several restrictions and difficulties, as it is usually based on the location of the AE sources followed by tedious analysis of the characteristics of the located AE events. The analysis usually involves two-dimensional feature correlation (i.e. correlating two AE features at a time), as it is practically impossible to visualize the whole feature set. This approach does not always yield a reliable identification of the signatures of the various damage mechanisms. Even more so, it is not always possible to isolate a particular mechanism and monitor its activity in time, with increasing load, in order to assess its criticality.

The applicability of conventional AE analysis on full-scale testing of W/T blades was assessed by Sutherland et al. [4]. Further application of the AE technique proved to be successful in detecting and locating structural flaws on the blade, at very early stages and before they had become visible [5,6]. However, the necessity to discriminate and analyze the detected flaws by means of their AE features still exists and becomes even more apparent in the case of full-scale fatigue testing of a W/T blade [7]. The
purpose of this work is to separately investigate and compare the various classes of AE data, revealed by UPR techniques, which appear during static loading. Furthermore, application of neural networks for supervised classification of data obtained during fatigue loading of the same blade, offers a better insight into the nature of the existing flaws. Successful recognition of the different FRP damage mechanisms by means of their AE signatures could, ultimately, lead to the automation of the classification procedure for future W/T blade tests.

EXPERIMENTAL SET-UP

For the present work, two different AE tests are considered. The first was a static test performed while the blade was previously unloaded. Conventional AE analysis has already been performed and has successfully pinpointed “weak” areas of the blade [5,6]. The second AE test refers to the monitoring of 23 cycles of biaxial fatigue loading at 0.1 Hz, which took place after the blade had undertaken several millions of fatigue cycles in the laboratory, and a visible crack had developed on the trailing edge of the blade between sensors 6 and 10 (see Fig. 1). All tests took place at the Centre for Renewable Energy Sources (CRES) Wind Turbine Blades Testing Laboratory. The blade was loaded on a single point by means of a hydraulic actuator (two in the case of fatigue testing), and AE data were recorded by a Physical Acoustics Corporation (PAC), ten-channel “SPARTAN 2000” AE system and the associated, PC-based data acquisition software. Ten 60 kHz resonant frequency PAC R6I AE sensors, equipped with a 40dB internal preamplifier, were mounted on the compression (suction) side of the blade. The sensor positioning and the corresponding AE channel numbers are presented in Fig. 1. During acquisition, basic AE signal features were recorded and stored in file by the AE system software (PAC-“SP2-LOC”), including channel number, hit arrival time, rise time, counts, energy, duration, amplitude, average frequency, average signal level and counts-to-peak. During the fatigue test, loads in both flap and edge directions were measured by the load cells between the blade and the actuators.

In the case of the static test, one hydraulic actuator was mounted underneath the blade and was exerting force perpendicular to the blade’s surface plane, so that the blade’s pressure side was under tension, as in real conditions. The load was applied at a flapwise position, 7 m from the blade’s root and at 25% chord station (Fig. 1), resulting in a triangular distribution of the bending moment along the blade’s axis, aiming to simulate the maximum operational load.

In the fatigue test, two hydraulic actuators were used, at the same axial position as in the static test, one exerting force in the flapwise direction and the other in the edgewise direction. Both actuators were applying periodic force to the blade at the same frequency (0.1 Hz) and the resulting force had edgewise and flapwise components, with 90° phase shift, causing the blade to move elliptically.
PATTERN RECOGNITION ANALYSIS

Unsupervised pattern recognition (UPR) was applied on the data of the first static test using the commercially available “NOESIS” pattern recognition and neural networks software for AE applications. A “first-hit” analysis was followed; i.e., only the first hit of each AE event was used. The first step before application of UPR was to select a representative set of AE features based on which the data would be segregated into classes, exhibiting similar characteristics. For that purpose, feature correlation analysis [8,9] was performed for all the available AE features. The degree of correlation among features, presented in the dendrogram of Fig. 2, demonstrates very strong correlation for Counts and Duration. Subsequently, UPR was performed with a reduced set of AE features, comprising Rise Time, Counts to Peak, Energy, Duration, Amplitude and Average Frequency. Furthermore, all features were normalized individually to a range from 0 to 1, in order to avoid biasing the classification towards the feature exhibiting the highest physical dimensions.

Initially, UPR was performed using various clustering algorithms [8-10], to get indications for the data structure. Then, varying the number of the desired clusters, a parametric study was performed using the K-Means and LVQ-Neural Net algorithms, in order to assess the optimum number of classes by means of discrimination-efficiency heuristic criteria. Local minimization of the D&B $R_{ij}$ criterion [9-11] occurred at seven classes for both the K-Means and the LVQ clustering algorithms. Therefore, the respective results were used to separate the data into seven classes.

Following the clustering performed by UPR on the static test data, a back-propagation neural network (BPNN) supervised classifier [8,11] was trained to correspond AE hits, from any given data set, to one of the seven classes (output layer) based upon the values of their AE features (input layer). Various trials were performed changing the number of hidden layers that connect the input and output layers and showed that one “hidden” layer (Fig. 3) was adequate. Success of training was assessed by applying this classifier on a subset of the static test data. The supervised classification yielded only 1% of misclassified hits in comparison to the desired UPR classification.
FIRST STATIC LOADING

Figure 4 presents the cumulative AE energy vs. time for classes 4 and 6 with the loading envelope superimposed. It is observed that these classes exhibit similar activity trends. Comparing Fig. 4 with Fig. 5, which presents the cumulative AE energy vs. time for classes 1, 3, 5, it becomes evident that classes 4, 6 and are the only classes with continuous activity throughout the load holds. At the same time, although classes 3 and 5 exhibit high total AE energy, they totally cease at the end of the last load hold. Class 1 presents a burst of AE activity in the last load hold (also observed in class 3) and then ceases. Classes 0 and 2 are generally very low in AE energy and inactive during load holds.

Feature correlation can be visualized in Figs. 6 and 7, which are scatter plots of Amplitude vs. Counts (in log scale) for classes 4, 6 and 1, 3, respectively. In these two-dimensional correlation plots, the overlapping between classes is strong in the low and medium Counts-Amplitude region where classes 4, and 6 coexist (Fig. 6). In the high-medium region, classes 1, 3 are better separated (Fig. 7).
Aiming to correlate the different classes of data with particular areas of the blade, the linear location technique was applied separately for each class. For that purpose, the original data acquisition set of the test was used, which contained all-hits information. By means of specialized PAC software, this set was split into seven subsets, one for each class, each subset containing all-hits information only for its corresponding class. Two linear location groups were defined, one with sensors 1-5 and one with sensors 6-10 (see Fig. 1). Upon application of linear location, it was observed that: (a) Classes 4 and 6 were located mainly in the area between sensors 6 and 10 (see Fig. 8), (b) Classes 1 and 3 were located primarily very close to sensor 1 (see Fig. 9), (c) Class 5 was located right on sensor 5, which means that it might have been triggered anywhere from sensor 5 towards the load application point, and (d) Classes 0 and 2 gave very few locations.

**FATIGUE LOADING**

Supervised classification was performed on the fatigue loading first-hit data. To gain a thorough insight as to whether particular classes appear at specific parts of or throughout the loading cycle, Figs. 10 and 11 present two scatter plots of the flapwise load vs. edgewise load. The shape of these plots is a good representation of the ellipsoidal movement of the blade at the load application point. For the plot of Fig. 10, data classes 4 and 6 were used, while Fig. 11 uses only classes 1 and 3 to generate the plot. Strong dependence of class activity with load is apparent only for classes 1 and 3. On the contrary, classes 4 and 6 appear more or less throughout the loading cycle.
These observations can be summarized for all classes by artificially dividing the loading cycle into four sections, based on the elliptical shape of the flapwise and edgewise loads correlation. Following the convention of Fig. 10, the loading cycle was divided to the parts (0 to $\pi/2$), ($\pi/2$ to $\pi$), ($\pi$ to $3\pi/2$) and ($3\pi/2$ to 0), where 0 and $\pi$ coincide with the center values of the edge load and $\pi/2$ and $3\pi/2$ with the center values of the flap load. Table 1 summarizes the number of events per class, encountered on each section of the loading cycle.

<table>
<thead>
<tr>
<th>Section</th>
<th>Class 0</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 0 to $\pi/2$</td>
<td>169</td>
<td>25</td>
<td>166</td>
<td>122</td>
<td>512</td>
<td>132</td>
<td>1231</td>
<td>2357</td>
</tr>
<tr>
<td>2 $\pi/2$ to $\pi$</td>
<td>36</td>
<td>52</td>
<td>103</td>
<td>37</td>
<td>168</td>
<td>80</td>
<td>302</td>
<td>778</td>
</tr>
<tr>
<td>3 $\pi$ to $3\pi/2$</td>
<td>59</td>
<td>23</td>
<td>43</td>
<td>27</td>
<td>177</td>
<td>10</td>
<td>337</td>
<td>676</td>
</tr>
<tr>
<td>4 $3\pi/2$ to 0</td>
<td>131</td>
<td>-</td>
<td>92</td>
<td>19</td>
<td>377</td>
<td>86</td>
<td>976</td>
<td>1681</td>
</tr>
</tbody>
</table>

*Table 1: Number of events of each class, per loading cycle section.*

Very appealing on Table 1 are the strong variations of each class’s total events among the sections of the loading cycle. In total, the vast majority of AE is produced at the lower part of the cycle (sections 1 and 4). This trend is followed by all classes except for Classes 1 and 3, which seem to be very concentrated only on sections 2 and 1, respectively.

**CONCLUSIONS**

Unsupervised pattern recognition on AE data obtained during the first static loading of a W/T blade yielded seven classes of data. Class criticality was assessed and it was demonstrated that classes 4 and 6 were the only active classes during the load hold periods. Although classes 1, 3 and 5 were more “intense” in terms of their AE features, their AE activity was rather occasional during static loading with sudden bursts of emission and emission during load increases. Further application of linear location indicated that different classes mainly originated from different areas of the blade. More specifically, classes 1 and 3 were located very close to sensor 1 where the internal spar ends. Classes 4 and 6 were located between sensors 6 and 10. In this area, although there were not any visual indications after the first static test, a crack was developed upon further application of several millions of fatigue cycles on the blade. Finally, class 5 was located on sensor 5 and it is believed to be associated with the skin damage that was observed at the load application point.

Based on the results of the UPR on the static test, supervised classification was performed on AE data obtained during fatigue testing of the same blade. Most classes exhibited strong periodicity and were active at particular sections of the loading cycle.

It is worth noting that segregation of the different classes, which was successfully performed with UPR, would be almost impossible with traditional AE analysis, because of the strong overlapping of the classes in any two-dimensional space defined by any two of the AE features. On the other hand, extracting first-hit information from the located AE sources still would not suffice, as one location of the blade might be associated with more than one damage mechanisms. Even more apparent is the need for pattern recognition in cases of fatigue loading since the complexity of the AE analysis increases.
REFERENCES


