DAMAGE CLASSIFICATION OF ACOUSTIC EMISSION USING AEGIS PATTERN RECOGNITION SOFTWARE FROM TEN SMALL WIND TURBINE BLADE TESTS

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ABSTRACT: Current wind turbine blade certification requires static and fatigue tests on the blade, to assess whether the blade can sustain the applied loads. Within the scope of a current EC-funded research project, acoustic emission (AE) monitoring has been extensively applied during a series of 10 small blade tests. The AEGIS Pattern Recognition Software (PRS) was specially written and applied to the AE data to grade any "critical" class of AE data which might appear close to failure. This has enabled the formulation of specific criteria which can automatically assess criticality of damage both during static and fatigue testing.

1 INTRODUCTION

Acoustic Emission (AE) monitoring has been demonstrated during the testing to failure of ten small 4.5 m glass polyester wind turbine blades. Four of these ten blades had defects intentionally introduced. This paper provides an overview of the data generated in these tests and describes the development of test procedures which will next be applied to larger glass epoxy blades.

2 BLADE TESTING PROGRAMME

Acoustic Emission sensors were mounted to each of the ten blades and the blades were loaded statically or in fatigue until ultimate failure (Figure 1). Table I lists some of the relevant test parameters. The standard blade was designed according to IEC-61400-1 and comprised an outer load bearing skin with a pair of internal shear webs. A design with shorter shear webs was also used.

Figure 1: The view of the Trailing Edge of Blade 9 and the principal author immediately after blade failure

Blades 7 and 8 were of the Defect 1 design. This was the same as the standard design but with a delamination between layers 8 and 9 effected by means of a nylon rectangle (20 cm by 10 cm) inserted from 2 to 2.2 m on the compressive/suction side.

Blades 9 and 10 were of the Defect 2 design. This was also same as the standard design but with a web/skin disbond on the compressive/suction side from 2.0 to 2.2 m., and an additional trailing edge disbond from 0.9 to 1.1 m.

The standard certification test requires the blade to survive a static and fatigue test. The short duration static maximum test load (e.g. 10 seconds loading, 10 seconds load hold, 10 seconds unload) applied is typical of the maximum 50 year gust. The fatigue loading then applied is representative of accelerated in service loading.

The proposed static test load procedure [1,2] consists of applying:

- an initial AE examination load (AEL) representative of typical service loading, with a long load-hold period to allow time for the emission from any flaw to stabilise thus indicating its criticality,
- a repeat AEL, to ensure the AE activity is stable,
- a standard short duration maximum test loading (MTL) initially below the maximum design load,
- repeat of initial AEL to obtain information about damage criticality,
- progressively higher MTLs followed by AELs until blade failure, if required

To test the effectiveness of different levels of AEL, the tests reported here contain various AELs. Figure 7 shows this load pattern applied to blade 7.

#	Kg	Description (Design No.)	Load Point	Test Type	By	Days
1	60	Short Shear Webs (1)	3 m	Static	CRES	1
2	51	Short Shear Webs (2)	3 m	Static	DUT	1
3	51	Short Shear Webs (2)	3 m	Fatigue	DUT	171
4	51	Short Shear Webs (2)	2 m	Static	CRES	5
5	60	Standard (3)	3 m	Static	DUT	2
6	60	Standard (3)	3 m	Fatigue	DUT	127
7	60	Defect 1 (4)	3 m	Static	CRES	7
8	60	Defect 1 (4)	3 m	Fatigue	CRES	2
9	60	Defect 2 (5)	3 m	Static	DUT	4
10	60	Defect 2 (5)	3 m	Fatigue	DUT	72

Table I: The 4.5 m blade designs and test set up information

The fatigue test load procedure consists of applying:

- initial AEL (repeated),
- constant amplitude load cycles at high frequency,
- periodic slower cycles after every 5000 cycles,
- static test to AEL (maximum fatigue load + 10%) after every 500,000 cycles to assess blade condition.

The AE was monitored all the time during the static tests but was confined to sampling during the slow cycles and the following 100 fast cycles during the fatigue tests to restrict the quantity of data.

Every set of AE data contains a number of AE hits arising from the AE activity of the blade during loading. Each hit is described by means of its AE features (e.g. Amplitude, Counts, Duration etc.), and some non-AE features (e.g. time of hit arrival, channel, parametrics (external signals e.g. load, deflection)).

3 DAMAGE LOCATION

Classical AE monitoring analysis was used to detect and locate damage in the blades before visible or audible indications were apparent to the test engineers.

Sometimes serious damage was simply detected by a pronounced change or 'knee' in the rate of events coming from an area of the blade e.g. blade 3. The simple plot in Figure 2 of events versus cycles shows a burst of activity giving an advanced warning of failure.

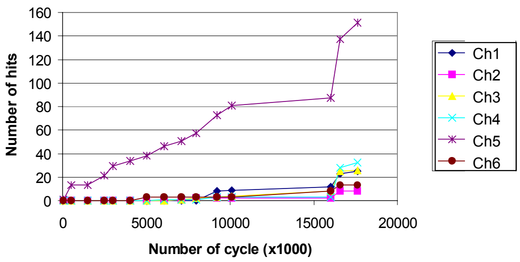


Figure 2: Cumulative first hits (i.e. events) of filtered blade 3 fatigue test data

Other serious damage was detected by a pronounced change in one or more of the AE features particularly Energy, Counts or Amplitude in a blade area. Figure 3 shows how the occurrence and spread of high amplitude signals predicts both imminent failure and its location. Note that the high amplitude signals seen at the root were observed in all blades but were not structurally critical.

These two examples clearly show that AE can give useful additional information on a blade's condition. However just looking for a change of this kind will not detect all damage occurring in all blades and thus cannot solely be relied on to assess the blade's condition. In addition there is also the problem of defining what constitutes a step change, which may appear obvious in hindsight but is very much harder to define in real time.

The AE signal is effected by many features. First there is the source itself since there are different modes of failure of the material i.e. fibre breakage, matrix cracking, disbonding, or a combination of the three. Second there is the transmission effect on the AE signal as it passes through the structure to the sensor. Third there are the variations in the route of the signal both in terms of the variation of profiles thickness, stacking sequences, discontinuities and joints in the structure but also in the short time frame of the local stress on the material and in the longer term accumulating damage. Fourth there are interfaces between different materials e.g. steel in the blade root, foam packing in the aerodynamic shaped areas towards the trailing edge. Fifth there are the variations in performance of the AE measurement system which will depend on the sensors used, the physical set up, the software settings and the hardware. An example of the variation of the physical set up is quality of the mounting of each the individual sensors. An example of the variation in the software setting is that of the threshold level that needs to be low enough to detect low amplitude emission but high enough to eliminate noise. The disc space available will impose a limit on the amount of AE recorded.

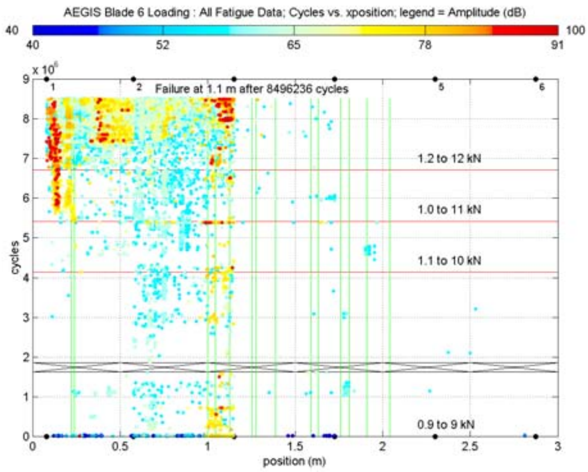


Figure 3: Linear location of raw data during the fatigue test of blade 6 coloured by Amplitude

The AEGIS Pattern Recognition Software suite has been designed to assess the extent and magnitude of acoustic emission activity and to grade zones of the blade according to any "critical" class of AE data which might appear close to failure. This has enabled the formulation of specific criteria which can be used for the automated assessment of a blade's integrity.

4 AEGIS PATTERN RECOGNITION SOFTWARE

4.1 Description

The AEGIS Pattern Recognition Software was specially written by Envirocoustics [1] for AE applications of wind turbine blade testing. It is capable of performing both Unsupervised and Supervised Pattern Recognition as well as classical AE data analysis. Its main function is to mathematically segregate Acoustic Emission (AE) data, based on their AE features. The AEGIS software can then grade the structural integrity of wind turbine blade sections (zones), by means of user-selectable criteria, based on the AE activity during loading and/or the activity of a particular class of AE data.

4.2 Unsupervised Pattern Recognition (UPR)

The AEGIS software uses mathematical algorithms (clustering algorithms) to divide the AE hits into classes (or clusters) based on the similarity of their features (i.e. the closeness of their corresponding vectors). This classification process is known as Unsupervised Pattern Recognition (UPR). The user selects such features in the analysis and in the clustering algorithms, so as to come up with a classification that has a physical importance. The AEGIS software offers lots of options including the 5 different classification methods that can modify the classification results (e.g. selection of the AE features that will form the vector, vector normalisation, definition of number of classes etc.). By experimentation, the user can select (and store) the options and features that have led to the optimum classification of the AE data.

The hypothesis is that each AE class corresponds loosely to a blade failure mechanism. The user can grade a given zone around the sensor according to the level of hits from a given class. Figure 4 shows the 5 gradings available whereby green ‘A’ indicates the small presence of a class of data and red ‘E’ indicates a much higher presence. When tied into the formation of some damage the green can be interpreted as the presence of damage and the red the presence of critical damage. If a zone is not graded this indicates the absence of any emission in a particular class.

4.3 Applying Unsupervised Pattern Recognition (UPR)
Blade 1 failed by local buckling just inboard of sensor 8, 2.3 m from the root. Figure 5 shows the results of UPR applied to the last but one static loading on blade 1 before the failure loading. This penultimate loading was chosen to get the AE that was a warning of failure but not failure itself. The software identified 3 classes within the data. Class 2 was found to be present only in the final two load steps and it was possible to use it and method 5 to grade the blade to show that critical damage is occurring. Figure 5 shows this red ‘E’ grading. Hence class 2 and method 5 was used for future Supervised Pattern Recognition.

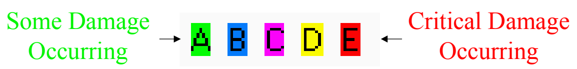


Figure 4: Blade Gradings

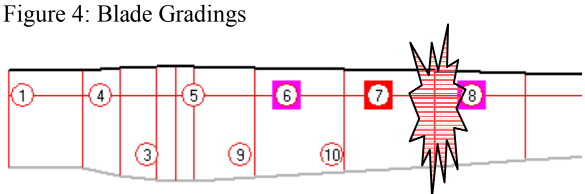


Figure 5: UPR gradings applied to Blade 1 AE data using Method 5 Class 2 during the penultimate static loading (6.5 kN) with the ultimate point of failure shown.

UPR has also been applied to the fatigue data files for blade 3 which failed by buckling 2.25 m from the root. The fatigue data files are much larger than those for the static loads (AELs and MTLs). Initial processing gave the grading as shown in Figure 6.

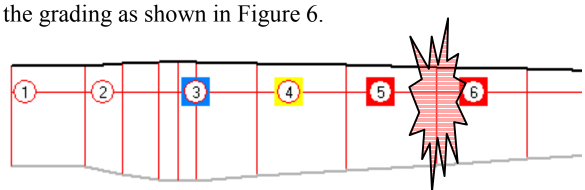


Figure 6: UPR gradings applied to Blade 3 AE data during the penultimate fatigue loading compared with the ultimate point of failure.

4.4 Supervised Pattern Recognition (SPR)
Once the user has achieved a satisfactory UPR-classification for a specific data set (e.g. data set “A”), the AEGIS software can be trained to classify any new data set (e.g. data set “B”) based on the classification results of data set “A”. This procedure is known as Supervised Pattern Recognition (SPR) and is performed by Supervised Classification Algorithms (Supervised Classifiers). In SPR, the vectors (AE hits) of the new data set “B” are individually classified one by one, based on their AE features, to one of the predetermined classes yielded by the Unsupervised classification of data set “A”. In other words, each hit of data set “B” will be classified in accordance with the similarity of its features with the features of one of the classes of data set “A”. The first step, however, towards SPR is the training and testing of the Supervised Classifier. This training “teaches” the classifier a mathematical logic for classifying new vectors into one of the classes yielded by the UPR of the data set “A”. To do so, the software divides the data set “A” into two subsets; subset “A1” and subset “A2” (both with known classification). Subset “A1” is used to actually train the classifier. Once the classifier is trained, it is automatically applied to re-classify subset “A2” and the results of this supervised classification are compared with the results of the initial, unsupervised classification of “A2”. If the results match within an appropriate error margin, then the supervised classifier is considered trained, and can be applied to any new data set “B”. As is the case for the UPR procedure, in AEGIS software there are plenty of features and options for the SPR procedure, and it is up to the user to achieve optimum results by selection of appropriate values for these features.

5 APPLYING SUPERVISED PATTERN RECOGNITION (SPR)

5.1 SPR applied to blade 7 static test data
Blade 7 had a deliberate delamination in the main spar (2.0-2.2 m). The static loading of blade 7 (Figure 7) consisted of maximum test loads (MTLs) typical of the conventional blade test followed by AE examination loads (AELs) at 4 levels 50, 60, 70 and 80% of the preceding MTL. The blade ultimately failed by a crack propagating at 2.2 m from the root. The damage at failure is shown in the sketch at the bottom of Figure 8.

Classical AE analysis for all AELs (as in Figure 8: Amplitude, Events, Energy vs. x-position) shows that the linearly located AE clearly identifies the damaged areas.

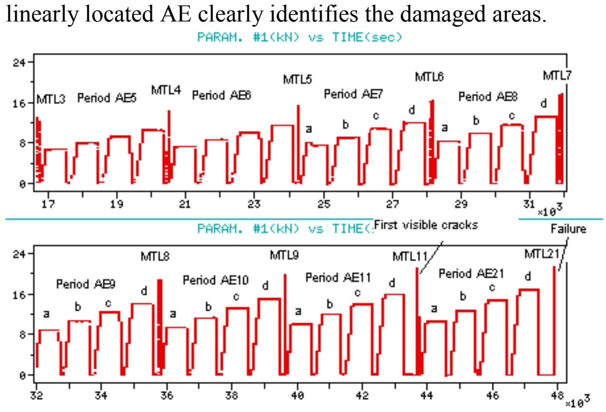


Figure 7: Loading Envelope of Blade 7 (after MTL3)

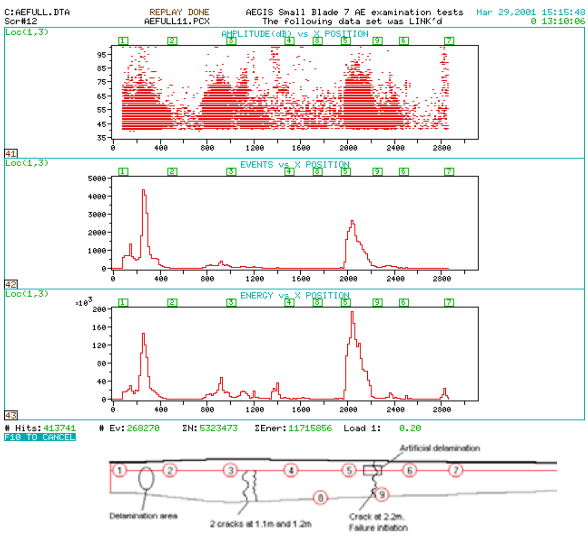
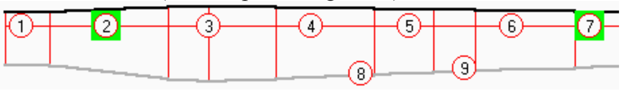


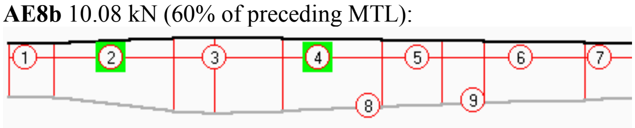
Figure 8: Classical AE analysis of all the last MTLs with a sketch of visible damage.

The classifier derived from applying the Unsupervised Pattern Recognition to the penultimate loading prior to failure of Blade 1 was used.
Figure 9 shows the resulting gradings of all the AELs after MTL6. The reference name for each AEL is shown in Figure 7.

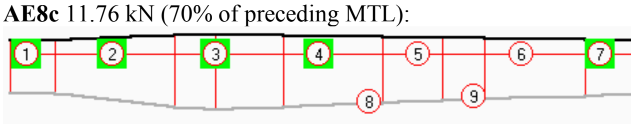
MTL6 16.8 kN
AE8a 8.04 kN (50% of preceding MTL):



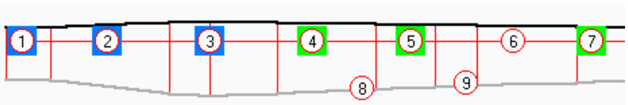
AE8b 10.08 kN (60% of preceding MTL):



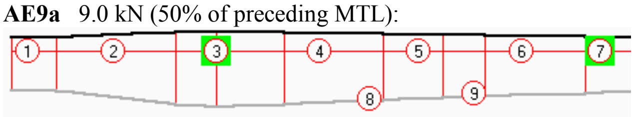
AE8c 11.76 kN (70% of preceding MTL):



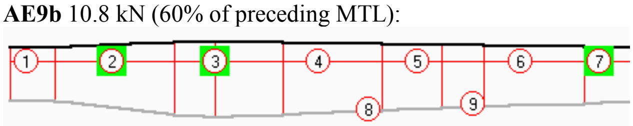
AE8d 13.44 kN (80% of preceding MTL):



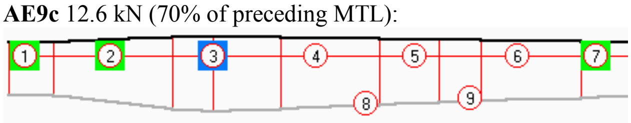
MTL7 18.0 kN
AE9a 9.0 kN (50% of preceding MTL):



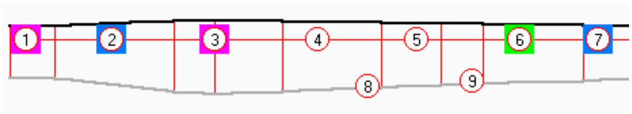
AE9b 10.8 kN (60% of preceding MTL):



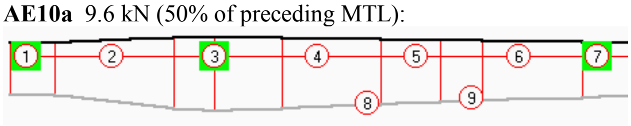
AE9c 12.6 kN (70% of preceding MTL):



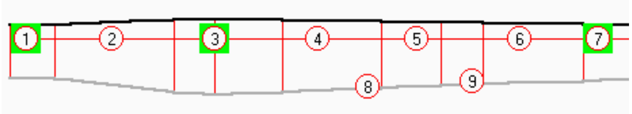
AE9d 14.4 kN (80% of preceding MTL):



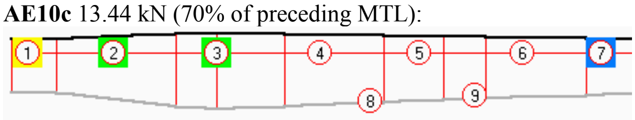
MTL8 19.2 kN
AE10a 9.6 kN (50% of preceding MTL):



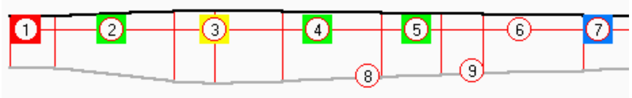
AE10b 11.52 kN (60% of preceding MTL):



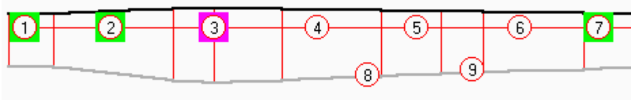
AE10c 13.44 kN (70% of preceding MTL):



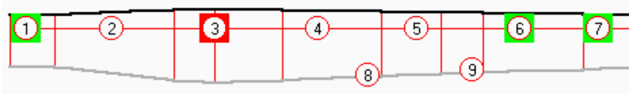
AE10d 15.36 kN (80% of preceding MTL):



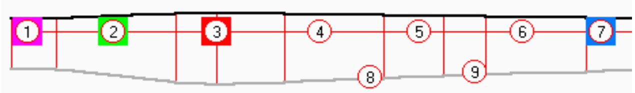
MTL9 20.4 kN
AE11a 10.2 kN (50% of preceding MTL):



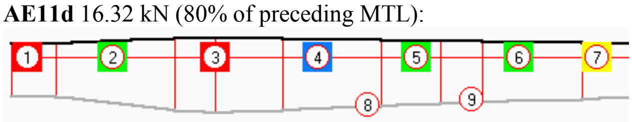
AE11b 12.24 kN (60% of preceding MTL):



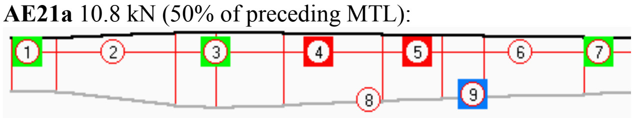
AE11c 14.28 kN (70% of preceding MTL):



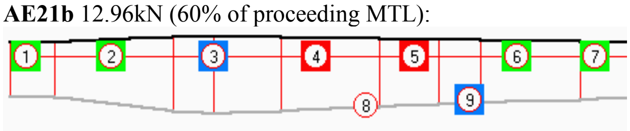
AE11d 16.32 kN (80% of preceding MTL):



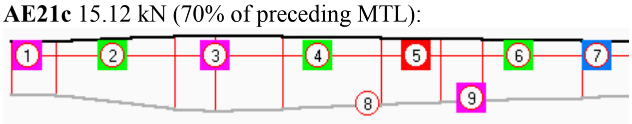
MTL11 21.6 kN
AE21a 10.8 kN (50% of preceding MTL):



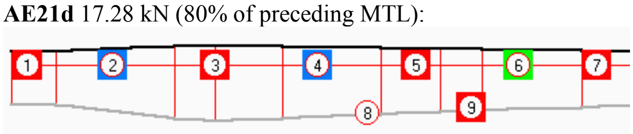
AE21b 12.96kN (60% of proceeding MTL):



AE21c 15.12 kN (70% of preceding MTL):



AE21d 17.28 kN (80% of preceding MTL):



MTL21 22.8 kN = blade failure

Figure 9: SPR gradings of the MTL's applied blade 7 from UPR on blade 1 penultimate loading

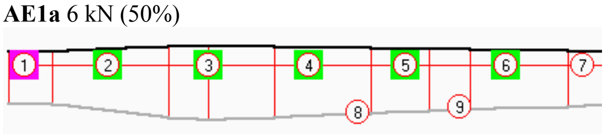
Note that the failure area is between sensors 5 and 9, and their zones are either ungraded or on the lowest grading green 'A' until MTL11. SPR applied to the next AEL (AEL21a), at only 50% of the MTL11, grades sensor 5 red 'E' critical, and at 80% of MTL11 (AE21d) both sensors are critical (red 'E'). This is a clear indication of damage occurring and being detected in the blade.

Other critical gradings occur in the root zone (sensor 1) and in the maximum chord zone (sensor 3). Considerable AE activity (and associated delamination) was seen in the root area for all blades but was not structurally critical. The high grading at the maximum chord zone (sensor 3) appears in AEL11b, c and d. This is before any damage can be seen. However during the following MTL11 two cracks appear outboard of sensor 3 at 1.1. and 1.2 m. This is a clear detection of the onset of damage before it became visible.

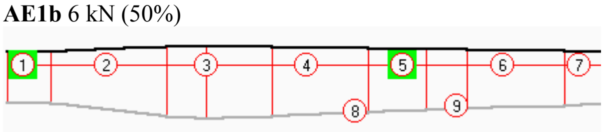
5.2 SPR applied to Blade 8 Fatigue Data
Blade 8 failed by cracking at 1.9 m (between sensors 8 and 5) after only 70k cycles. Prior to fatigue loading, two pairs of AEL test loads were applied at 6 kN and 13.2 kN. The second AEL at a particular load level gives very important information on the blade condition since it identifies areas of propagating damage. Again applying the classifier learnt from blade 1 clearly shows the blade was healthy after the second AEL at 6 kN (AE1b) since the zones, at worst, show emission of the lowest grade (Figure 10).

The first loading to 13.2 kN shows lots of emission belonging to the class previously seen prior to failure. The second AEL to 13.2 kN clearly shows that critical damage had occurred such that one sensor is graded the red 'E', another is graded the purple 'C' and two the blue 'B'. Knowing this was the blade's condition prior to the actual start of the fatigue loading, failure when the fatigue loading started was thus entirely expected.

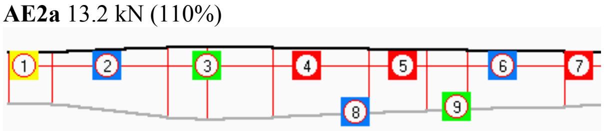
AE1a 6 kN (50%)



AE1b 6 kN (50%)



AE2a 13.2 kN (110%)



AE2b 13.2 kN (110%)

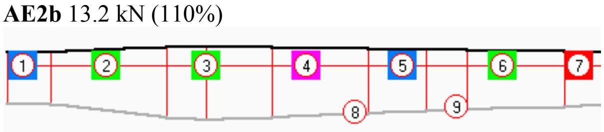


Figure 10: Blade 8 initial AELs with the second 13.2 kN loading showing the blade to be severely damaged.

5.3 SPR applied to Blade 10 Fatigue Data
Blade 10 failed by cracking at a shear web debond at 2.05 m (between sensors 4 and 5) after 4 million cycles. Applying the classifier learned from blade 3 penultimate fatigue loading to blade 10's penultimate fatigue loading AE data successfully identified the critical area by grading its nearest zones red 'E' (Figure 11).

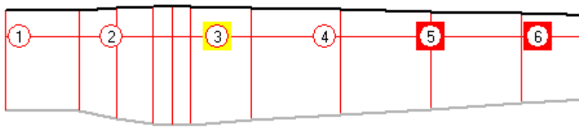


Figure 11: Grading of Blade 10's penultimate fatigue loading showing criticality

6 FORTH COMING WORK

Two large (16.25 m) blade tests (one fatigue and the other static) are being conducted to test the application of the AE test procedures developed in this project.

AE monitoring of an operating wind turbine will also be conducted to evaluate the role that AE monitoring can play in condition monitoring.

7 CONCLUSIONS

Procedures have been developed for the application of AE monitoring to both static and fatigue certification tests. The results from testing 10 small blade tests have revealed characteristic changes in AE behaviour as damage develops. The procedures will now be applied during two large-scale (16.25 m) blade tests.

Most significantly, the AEGIS Pattern Recognition Software (PRS) has been developed to identify damage criticality from the AE data and has been successfully applied during static load tests. The AEGIS PRS also shows considerable promise for monitoring during fatigue testing.

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