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Acoustic Emission Detection and Prediction of Fatigue Crack Propagation in Composite Patch Repairs using Neural Networks

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ACOUSTIC EMISSION DETECTION AND PREDICTION OF FATIGUE CRACK PROPAGATION IN COMPOSITE PATCH REPAIRS USING NEURAL NETWORKS

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ABSTRACT. An aircraft is subjected to severe structural and aerodynamic loads during its service life. These loads can cause damage or weakening of the structure especially for aging military and civilian aircraft, thereby affecting its load carrying capabilities. Hence composite patch repairs are increasingly used to repair damaged aircraft metallic structures to restore its structural efficiency. This paper presents the results of Acoustic Emission (AE) monitoring of crack propagation in 2024-T3 Clad aluminum panels repaired with adhesively bonded octagonal, single sided boron/epoxy composite patch under tension-tension fatigue loading. Crack propagation gages were used to monitor crack initiation. The identified AE sensor features were used to train neural networks for predicting crack length. The results show that AE events are correlated with crack propagation. AE system was able to detect crack propagation even at high noise condition of 10 Hz loading; that crack propagation signals can be differentiated from matrix cracking signals that take place due to fiber breakage in the composite patch. Three back-propagation cascade feed forward networks were trained to predict crack length based on the number of fatigue cycles, AE event number, and both the Fatigue Cycles and AE events, as inputs respectively. Network using both fatigue cycles and AE event number as inputs to predict crack length gave the best results, followed by Network with fatigue cycles as input, while network with just AE events as input had a greater error.

Keywords: Composite Patch Repair; Aging Aircraft; Acoustic Emission; Adhesively Bonded Composite Patches; Fatigue; Crack Growth; Artificial Neural Networks
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INTRODUCTION

The high acquisition costs associated with the purchase of modern aircrafts, military as well as commercial, coupled with the economic factors and budget cuts have resulted in the utilization of aircrafts beyond their design life (20-25 years). Many of these aging aircrafts have suffered structural damage from fatigue and stress corrosion, and hence maintenance or repair or reinforcement of the structure to restore its structural efficiency has become an important issue in recent years.

The technique of repairing cracked metallic aircraft structures using high strength advanced composite materials is commonly known as “Crack Patching,” and was pioneered by the Aeronautical and Maritime Research Laboratories (AMRL), for the Royal Australian Air Force (RAAF), in early 1970s [1]. The composite reinforcement, also

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known as a patch, can be attached to the damaged or weakened structure either by mechanical fastener or adhesive bonding.

Acoustic emission (AE) testing is amenable to real time monitoring of fatigue crack growth. Acoustic emission signals are high frequency transient stress waves produced by rapid release of energy from localized sources that travel through the material. During fatigue crack propagation a portion of the strain energy released by the growing crack is transmitted through the parent material as acoustic emission signal. These AE waves can be detected by broadband high fidelity AE sensors attached to the specimen, and can be digitized for analysis purposes. In service environment are generally very noisy, and AE signals are usually very weak. Thus, signal discrimination and noise reduction are extremely important for successful AE applications.

This paper presents the results of acoustic emission (AE) monitoring of crack propagation in 2024-T3 Clad aluminum panels repaired with adhesively bonded octagonal, single sided boron/epoxy composite patch under tension-tension fatigue loading. AE event signals were analyzed to develop correlation between crack propagation and AE events and fatigue cycles. Three back-propagation neural network models were developed to predict crack length from AE events and fatigue cycles as inputs to the network. Methodologies for noise reduction, accurate source location and crack prediction results are presented.

DESIGN AND FABRICATION OF PATCH

Patch Design

Composite patches used in this research were designed using CRAS® v0.3 [2] developed by the United States Air Force. CRAS stands for Composite Repair of Aircraft Structures. The patches were designed for single sided repair of a 1 inch crack on a 15 x 4x 0.063 inch sheet of 2024-T3 clad aluminum. Detailed design procedure for the composite patch is presented in a previous work of the authors [3].

Machining of Aluminum Panels

Dog-bone test specimen as shown in Figure 1, were machined from 2024-T3 Clad aluminum panels on Cincinnati Milacron SABRE-750 Vertical Machining Center. The aluminum was machined such that the grain direction was aligned with the loading axis. The dimensions of the panels were 4 x 0.063 inch in cross-section and length of 15 inch. A central through crack of 1 inch was machined by a wire EDM. A small hole of 0.02 inch at the center was drilled first for the EDM wire to go through.

Fabrication of Patches

Figure 2 shows the placement of the composite patches on the pre-cracked aluminum panels. The composite patch is made from boron/epoxy 5521 prepreg (Textron Specialty Materials Inc.) with a uni-directional lay-up of $[0]_n$ (where n is the number of plies), with fibers oriented in the direction of loading. Details of the curing conditions are given in [3].

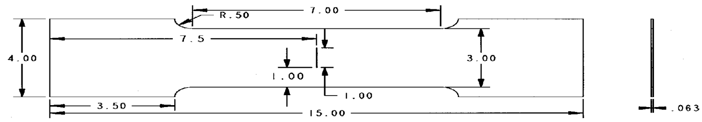


FIGURE 1. Specifications of an un-patched aluminum specimen.

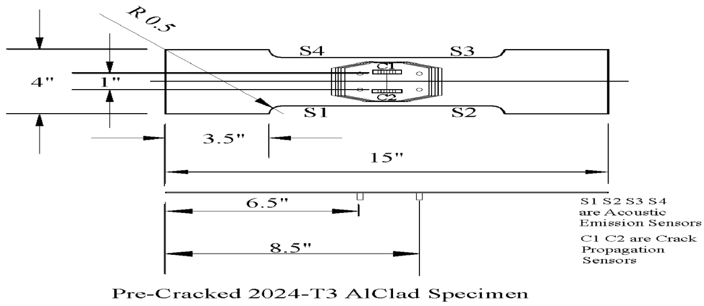


FIGURE 2. AE transducer location for fatigue testing.

EXPERIMENTAL SETUP AND PROCEDURE

Experimental Procedure

Two crack propagation gages model # TK-09-CPA01-005/DP (Vishay measurements group, Inc.) shown in Figure 3a, were adhesively bonded, one on each side of the crack and used to detect crack initiation and initial crack propagation. The bonding detail is given in [3]. The fatigue tests were conducted on MTS 880 Material Testing System with a maximum load capacity of 110,000 lbs as shown in Figure 3b with AE data acquisition set-up. The tests were conducted at 10 Hz and 17.4 ksi under tension-tension loading with a stress ratio (R) of 0.1. Four Digital Wave B-1025 broadband AE sensors with frequency response in the range 1 kHz – 1.5 MHz were used to detect AE waves. The sensors were placed at a distance of 1 inch on either side of the crack (Figure 2) and attached to the specimen with vacuum grease and electrical tape (Figure 3a).

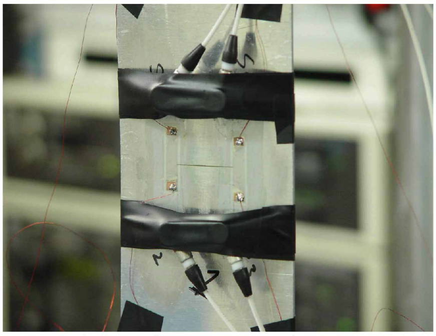
Digital Wave VLF-UT/AE data acquisition system (Digital Wave Corp.) was used to acquire AE waveforms at 25 MHz sampling rate using 4096 data points during the fatigue tests. The AE signals from the four sensors were pre-amplified at 24 dB then passed through the band pass filter set at 300 KHz and 5 MHz, respectively. The filtered signals were then passed through a signal conditioner unit where additional amplification of 24 dB was done. The trigger gain was set at 32 dB. The total system gain was set at 80dB. The threshold was set at 100mV to filter out noise signals that are far below the chosen threshold. A high-level signal output voltage from the MTS 880 was fed to the AE system parameter channel and also digitized, this enabled viewing of the MTS 880 loading cycle and elimination of events that occur in the lower part of the sine wave in loading that are not related to crack initiation and propagation. The acquired parameters and waveforms were stored in a computer for later processing. All specimens were fatigued up to failure. Crack lengths were measured visually by slowing down the frequency to 1 Hz.

Wave Propagation Theory

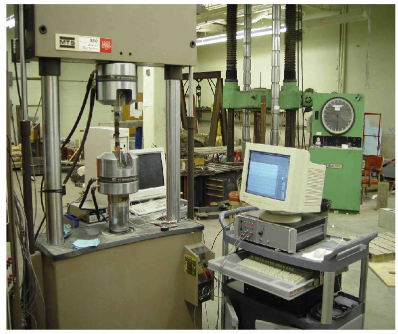
The dimensions and the material of the test specimen contribute to the type of wave propagation that will occur. Two important factors determining the type of wave emanating from a structure during fatigue are 1) Type of material, and 2) Velocity of propagation. The wavelength,λ, can be calculated by the following formula:

$$\lambda = \frac{c}{f} \tag{1}$$

where, c is the velocity of propagation and f is the frequency of the propagating disturbance.



3a: Attachment of AE sensors and crack propagation gages



3b: MTS 880 fatigue testing system and AE data acquisition setup

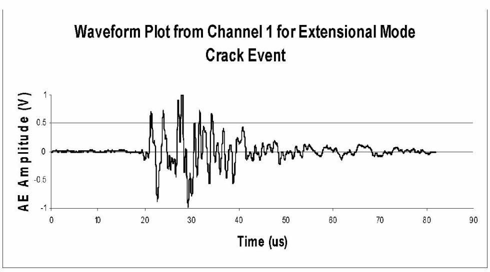
FIGURE 3. Experimental setup for fatigue testing and acoustic emission monitoring.

Acoustic Emission Waveforms

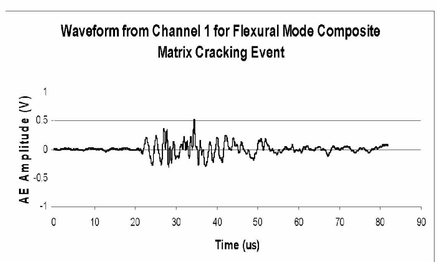
Figure 4a shows a typical AE event emanating from crack growth in 2024-T3 clad aluminum specimen which has very high frequency content and is almost completely extensional. Figure 4b shows an AE event emanating from matrix cracking of composite patch, as observed from the surface of the patch after failure, which is predominantly flexural in nature, and has high frequency content compared to noise.

Acoustic Emission Signal Processing and Noise Rejection

Analysis of the AE data was done on WaveExplorer® software. After acquiring all the data the signals were subjected to some filtering techniques in order to get rid of the noise and other events. Noise signals cause saturation of the A/D board. If the signal voltage is greater than the range of the A/D converter, the A/D converter saturates and the signal is clipped. The result is a signal that has been significantly altered and is difficult to analyze. A 10% saturation filter was applied to the waveforms in order to filter out the noise events. The threshold was also increased to 150 mV. After the application of the saturation filter the total number of events for the octagonal patch was reduced to 6,290. Figure 5 shows typical waveforms obtained from noise events due to A/D saturation.



4a: AE signal from an extensional mode crack event



4b: AE signal from a flexural mode matrix-cracking event

FIGURE 4. Typical waveform for crack events.

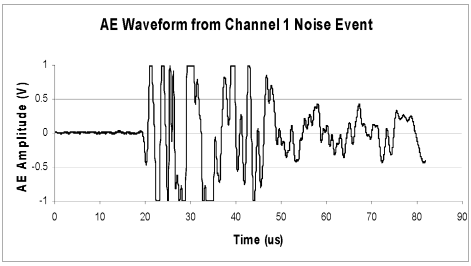


FIGURE 5. Typical waveform for noise events.

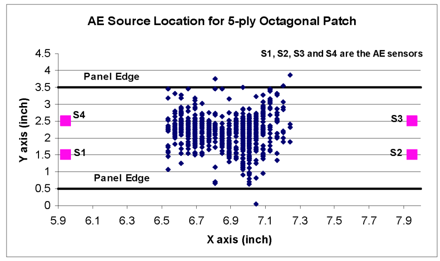


FIGURE 6. Results of AE source location.

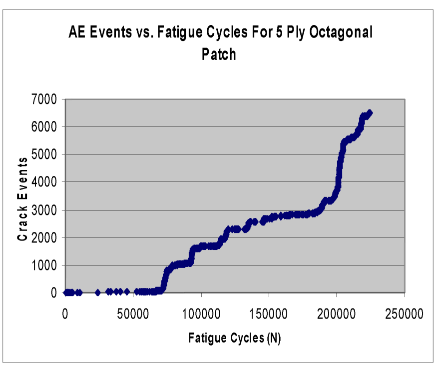
Event Source Location

One of the effective ways to filter out noise events is location filtering. All events that were outside the expected area of occurrence can be disregarded as noise. The waves generated by crack propagation are all within the specimen medium and hence are extensional waves. The front-end of the extensional waves is non-dispersive and hence a low threshold is needed to trigger the front end of the extensional wave on which the source location calculations are performed. The noise events were significantly reduced by applying 150 mV of threshold. The threshold was then dropped to 40 mV and the velocity of the waves set to 3018 m/s (825.13 inch/sec). The time of arrival were calculated using the Threshold crossing algorithm. After applying location filtering the No of events in the case of octagonal patch reduce to 1,460. The source location result is shown in Figure 6.

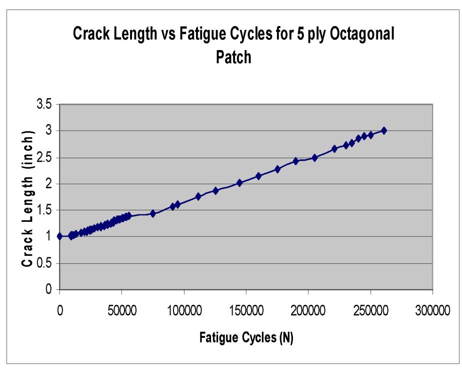
Results and Discussion

From the source location shown in Figure 6, almost all the events occur on or near the crack front, indicating that AE sensors were effective in detecting crack propagation.

Figure 7a, 7b, show the plot of AE events and crack length versus fatigue cycles for 5-ply octagonal patch bonded with FM-73. It can be seen that there are regions of rapid and moderate AE activity. It is observed that AE increases with crack propagation. It can be seen that near failure crack propagation becomes high. Correspondingly AE event increases considerably, showing a good correlation between crack propagation and AE event.



7a: AE event vs. fatigue cycles for
5-ply octagonal patch bonded with FM-73



7b: Crack length vs. fatigue cycles for
5-ply octagonal patch bonded with FM-73

FIGURE 7. AE events vs fatigue cycle and crack length vs. fatigue cycle for octagonal patches.

Another criterion for differentiating crack signals from other signals is by examining the frequency content of the signal. Figure 8 shows the frequency content of noise waveforms for channel 1. The frequency of a noise waveform rapidly decays in a short period of time whereas crack waveforms as shown in Figure 9 have more uniform or flatter frequency response.

PREDICTING CRACK LENGTH WITH NEURAL NETWORKS

Cascade feed forward back-propagation neural network [4] was used to predict crack length based on the number of fatigue cycles and number of AE events. Figure 10 shows the architecture of a feed forward neural network with one hidden layer and two inputs. A neuron with a scalar input vector, "p" and a scalar bias "b" is shown in the figure. The transfer function net input "n", again a scalar, is the sum of the input "wp" and the bias "b". This sum is the argument of the transfer function "f" given by:

$$n = \sum_{i=1}^{p} W_{i,p} P_i + b \qquad (2)$$

The weights, "w" and bias "b" are both adjustable scalar parameters of the neuron.

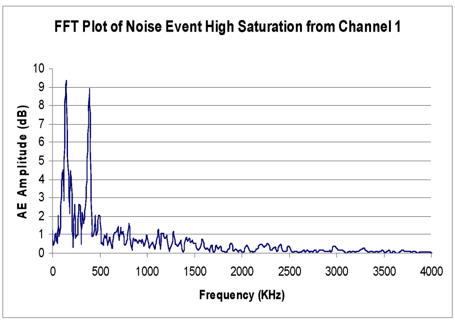


FIGURE 8. A FFT plots for noise events.

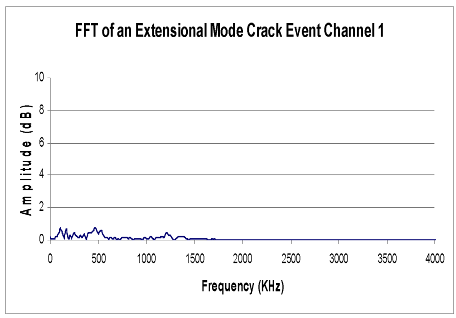


FIGURE 9. FFT plot for extensional mode crack event.

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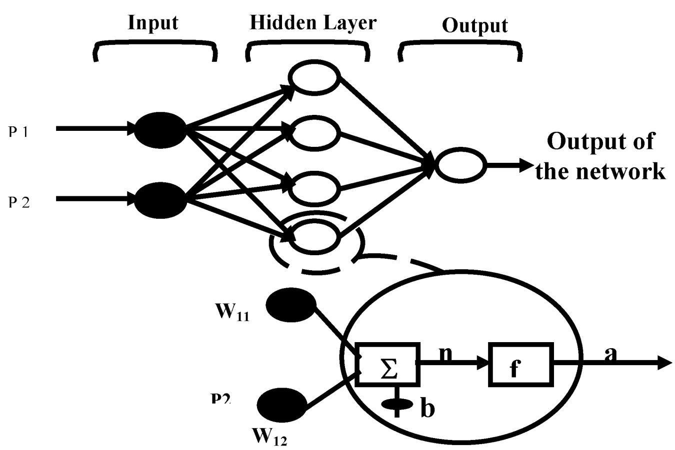

FIGURE 10. Architecture of a multi-layer feed forward network with two inputs.

Three separate networks were used to predict crack length; network #1 was used to predict crack length (output) from the number of fatigue cycles (input) with 1-node, 4-nodes, and 1-node in the input layer, hidden layer, and output layers respectively (1x4x1 architecture); while network #2 was trained to predict crack length from the number of AE events (1x4x1 architecture); and network #3 was used to predict crack length from both fatigue cycles and AE events as inputs (2x4x1 architecture). All the networks were cascade feed forward networks with three fully connected layers. All networks had a Tan sigmoid function in the input layer, a Log sigmoid function in the hidden layer and a linear function Back-propagation was created by generalizing the Widrow-Hoff learning rule to multiple layer network and non-linear differentiable transfer functions [4, 5]. All networks were trained to 500 epochs with the Levenberg-Marquardt training algorithm.

Network #1 was trained with 38 inputs, after training the network these training sets were presented to the network as inputs. The maximum percentage error was about ±1.5%. Nineteen unknown inputs were also presented to the network, these were totally new inputs and the network had not been trained on these inputs before. The maximum percentage error was +9%.

Network 2 was used to predict the crack length based on the number of AE events. This network was trained on 62 data sets and was later presented with 18 unknown inputs. It was found that the convergence of network 2 was much slower than Network 1 since the relationship between the AE events and crack length is highly non-linear. However the network was still able to predict the crack length based on the AE events with acceptable accuracy.

Figure 11a and 11b show the comparison of measured and predicted crack length by neural network 3. Network 3 predicted the crack length based on both the fatigue cycles and AE events as inputs. This network was trained on 57 data sets and was presented with 23 unknown inputs. This network was found to work really well in predicting the crack length and gave the most consistent results. The maximum percentage error was 1.2 % and -3.2 % respectively.

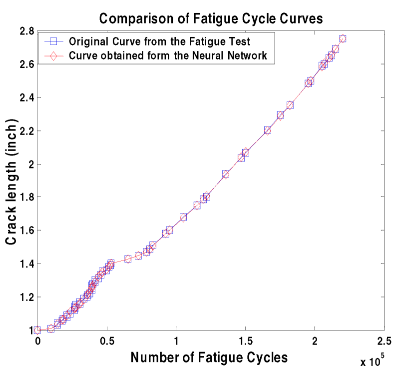

FIGURE 11A. Measured and predicted crack length vs fatigue cycles for neural network 3

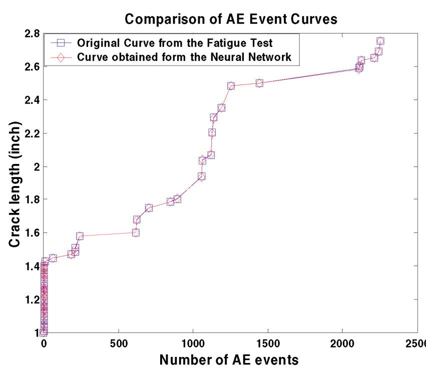

FIGURE 11B. Measured and predicted crack length vs AE Events for neural network 3

CONCLUSIONS

A method has been developed and demonstrated for real-time monitoring and detection of crack propagation in 2024-T6 aluminum repaired with adhesively bonded octagonal single sided boron/epoxy composite patch. A method for predicting crack propagation in the patched panels using neural networks has also been developed and demonstrated. From the results of the research the following conclusions can be made:

1. Crack propagation and AE event increases with fatigue cycle and there is a strong correlation between crack propagation and AE event.
2. Use of 4 AE sensors is necessary for accurate source location and screening of non-crack related events like fretting, gripper noise and structural vibration.
3. Acoustic emission is capable of detecting crack propagation even at the high noise condition of 10 Hz loading.
4. Noise signals can be differentiated from crack propagation signals by application of filtering techniques such as saturation, threshold and source location.
5. Crack propagation events in aluminum panels produce extensional waves which can be differentiated from matrix cracking events that produce flexural waves.
6. Noise signals have a lower frequency content, which sharply decays with time, while crack propagation signals have higher frequency content and a flatter frequency response.
7. It has been demonstrated that artificial neural networks can be used to accurately predict crack length from fatigue cycles and AE crack events. Three different neural network models have been successfully used to predict crack length with acceptable errors.

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