Abstract

This research involved the in-flight monitoring of fatigue crack growth in the vertical tail of a Cessna T-303 Crusader twin-engine aircraft. A notched 7075-T6 aluminum aircraft channel beam support structure was cyclically tested in the laboratory. Acoustic emission (AE) data were taken during these fatigue tests, which were subsequently sorted into three failure mechanisms: fatigue cracking, plastic deformation, and rubbing noise. These data were then used to train a Kohonen self-organizing map (SOM) neural network. At this point, a similar channel beam support structure was installed as a redundant structural member between the ribs in the vertical tail of the T-303 aircraft. AE data were subsequently gathered from initial taxiing and takeoff to the final approach and landing. The AE data recorded during the in-flight tests were then classified using the laboratory trained SOM neural network into the three above mentioned mechanisms. From this it was determined that plastic deformation occurred throughout all regions of flight but was most prevalent during taxi operations, fatigue crack growth activity occurred mostly during flight operations -- particularly during roll and Dutch roll maneuvers -- while the mechanical rubbing noise occurred mainly during flight with very little occurring during taxi. The success of the SOM classification of failure mechanisms indicated that the prototype in-flight structural health monitoring system for aging aircraft was highly successful at capturing fatigue crack growth data. It is envisioned that the application of such structural health monitoring systems in aging aircraft could warn of impending failure and allow for replacement of parts when needed rather than at conservatively calculated intervals. As such, continuation of this research should eventually help to minimize maintenance costs and extend the service lives of aging aircraft.

Keywords: Aging aircraft, in-flight fatigue crack monitoring, Kohonen self-organizing map, neural network, structural health monitoring

Introduction

Fatigue Cracking in Aircraft

Aircraft today typically are expected to last longer than automobiles. This is due to many factors, including the cost of the aircraft, government regulations, and the dramatic consequences of failure. There are many problems that arise from the fact that aircraft are expected to last so long. Perhaps the major source of problems, which is the subject of this research, is the presence and growth of fatigue cracks. The ability to repair damage from fatigue cracks has not been a problem, but the detection and monitoring of fatigue crack growth has proven to be a real challenge.

Fatigue cracking is the brittle fracture that results from cyclic loading below the yield strength of a normally ductile metal. The highly concentrated stresses at the crack tip result in the formation of a heart-shaped plastically deformed zone ahead of the crack. This plastic zone strain hardens with cyclic loading and fractures when the ductility of the metal has been exhaust-
ed, thereby extending the crack. This fatigue crack growth process repeats itself over and over again until final failure of the part.

Aircraft experience different types of fatigue loadings. Takeoffs and landings are very fundamental types of cyclic loadings on aircraft. Cabin pressurization is also a type of cyclic loading, since the fuselage of an aircraft is a large pressure vessel that undergoes a breathing process as the plane pressurizes and depressurizes to accommodate passengers at varying altitudes. Vibration due to atmospheric turbulence and engines is also a major cause of fatigue cracking in aircraft. Thus, all aircraft develop fatigue cracks over time.

Detecting fatigue cracks in aircraft structures is important because, if left unchecked, the cracks will eventually reach critical length, at which point they progress to catastrophic failure within a relatively short period of time. As a structure with a crack is cycled, the crack will grow until it is stopped -- for instance by grain boundaries -- but it will then typically change directions within a few cycles and continue to progress to failure. The affected parts must be replaced before this happens. Currently this is accomplished at conservatively calculated intervals based on linear elastic fracture mechanics. However, it would be beneficial to develop a system to monitor the growth of fatigue cracks so that replacements are installed only when needed, rather than at calculated intervals that are of necessity, highly conservative.

Detecting Fatigue Cracks

There are several nondestructive testing methods commonly used to detect fatigue cracks in aircraft. Two of the most common are eddy current testing and radiographic testing. The main disadvantages to eddy current and radiographic testing are that they are both time consuming and therefore very expensive. But more than that, these two techniques oftentimes require disassembly of the structure in question to obtain access for the inspection, and as such, crack growth monitoring is at best intermittent rather than continuous. The ability to detect a growing fatigue crack and identify its location is fundamental to reducing the maintenance costs associated with aircraft ownership and at the same time improving aircraft safety.

Acoustic emission (AE) nondestructive testing has been employed previously for continuous in-flight monitoring of aircraft fatigue crack signals [1-5]. In order to detect fatigue crack growth in an in-flight environment, it is necessary to determine the characteristics of the cracking signal. The problem arises from the fact that amongst the crack signals, there also exist signals due to plastic deformation and mechanical noise. Neural networks have been employed herein to separate these signals and classify them as to the appropriate mechanism.

The test bed used for the in-flight fatigue crack growth monitoring was the vertical tail of a Cessna T-303 Crusader aircraft shown in Fig. 1. It is interesting to note here that the crack growth data acquisition for this aircraft was prematurely terminated because of the unexpected discovery of fatigue cracks in its wing ribs. This resulted in the decision to sell the aircraft rather than repair it; consequently, the planned data acquisition from the controlled fatigue cracking in the vertical tail was cut short. Ironically, such an acoustic crack detection system as utilized in this research, when fully developed, could have monitored those wing rib fatigue cracks in flight to ensure safety while the airplane was being returned for repairs.
The experimental research associated with this study consisted of two segments. The first segment dealt with the testing of a fatigue crack growth specimen in a controlled laboratory environment. The second segment of the research involved the testing of a similar specimen installed in the vertical tail of the Cessna T-303 Crusader test bed aircraft. The in-flight specimen was a redundant structure, as it was not installed to replace any structure of the aircraft but simply to provide a structure that could undergo fatigue cracking without compromising the structural integrity of the aircraft. Data were taken during various flight regimes, including taxi, takeoff, steady level flight, rolls, and Dutch rolls. The purpose of the two roll maneuvers was to impose significant bending loads on the vertical tail which would hopefully induce fatigue crack growth in the notched portion of the redundant specimen.

**Acoustic Emission**

Acoustic emission nondestructive testing was the tool used in this research to monitor fatigue cracking. Acoustic emissions are typically referred to as sound waves, but more appropriately, they are the stress waves that propagate throughout a medium as a result of a sudden release of energy [6]. The purpose of this study was to identify and monitor the growth of fatigue cracks; therefore, the waveforms associated with a fatigue cracking were of particular interest here.

The research presented herein was based on identifying and monitoring fatigue crack growth in the redundant internal structure mounted between the ribs in the vertical tail. A concurrent research project involved AE monitoring of fatigue cracking in the engine cowling of a Piper PA-28 Cadet general aviation aircraft [7]. The results of these two research projects will provide the basis for the development of an operational, in-flight acoustic emission fatigue crack growth monitoring system for aging aircraft.

**Experimental Procedure**

*Data Acquisition and Digital Signal Processing*

Digital signal processing is the process by which an analog waveform is converted into a discrete approximation of the analog signal. An understanding of the data acquisition system is necessary in order to understand the process of converting an analog signal into a digital representation.
As shown in the block diagram of Fig. 2, included in the AE data acquisition system is a filter for each transducer used. It is a critical first step to determine all possible sources of background noise so that these sources, where possible, can be filtered out \textit{a priori} from the rest of the signals. Many sources of background noise were identified for both the laboratory and the in-flight environment and are summarized in Table 1.

The laboratory test involved testing a fatigue specimen attached to a cyclic MTS tensile test machine as well as a VTS shaker table. The many possible sources of background noise in the lab were identified and filtered out. For example, high frequency electromagnetic interference (EMI) signals can be filtered out using a low pass filter.

The presence of mechanical noise was very obvious in the laboratory during the tests associated with the MTS machine. The MTS machine operates using a hydraulic system to deliver a force to the collar to which the specimen was attached. Some of these concerns were alleviated by the fact that the hydraulic servo was mechanically isolated from the actual test platform by the use of hoses rather than mechanical connections. Nevertheless, there was still a significant amount of hydraulic noise that had to be filtered out. Also the fluorescent lighting in the lab emitted a 60 Hz wave, which can impact the data acquisition system through radiation and simple electrical induction. Both of these noise sources were eliminated through the use of high-pass filters.

There was also a significant amount of mechanical noise emanating from the structure itself. These sources of noise were mechanisms such as rivet fretting and bearing failure in the bolt holes. The goal of our test was \textit{not} to eliminate these signals, as their presence in the airplane is unavoidable; hence, they were not filtered out. However, there were other sources of mechanical noise present, which were not necessarily directly associated with the test structure. Due to the fact that the MTS tensile test machine secures a specimen by using a hydraulically operated grip, there was noise associated with the plastic deformation between the specimen and the grip. A high-pass filter was used to eliminate as much of this mechanical noise as possible, while not removing noise associated with rivet fretting and bearing failure [8]. Similar mechanical noises were present in the VTS shaker table tests.

Moreover, there was also a substantial amount of noise present during the in-flight test. There was EMI noise from the strobe light tail beacon. There was also mechanical noise from the control cables that run through the empennage to operate the control surfaces. In addition, the noise associated with turbulent airflow over the empennage was a source of continuous noise that was very difficult to eliminate.

Fig. 2. AE data acquisition system.
Table 1. Sources of background noise.

<table>
<thead>
<tr>
<th>Noise Source</th>
<th>Noise Type</th>
<th>Noise Source</th>
<th>Noise Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fluorescent Lights</td>
<td>EMI</td>
<td>Tail Beacon</td>
<td>EMI</td>
</tr>
<tr>
<td>MTS Hydraulics</td>
<td>Hydraulic Noise</td>
<td>Control Surfaces</td>
<td>Mechanical Noise</td>
</tr>
<tr>
<td>Grip Rubbing</td>
<td>Mechanical Noise</td>
<td>Interface Rubbing</td>
<td>Mechanical Noise</td>
</tr>
<tr>
<td>Rivet Fretting</td>
<td>Mechanical Noise</td>
<td>Rivet Fretting</td>
<td>Mechanical Noise</td>
</tr>
<tr>
<td>Bearing Failure</td>
<td>Mechanical Noise</td>
<td>Bearing Failure</td>
<td>Mechanical Noise</td>
</tr>
</tbody>
</table>

A graphical representation of AE activity is quite useful in qualitatively examining the data gathered during the tests. There are several combinations of the six parameters recorded, in addition to the variants derived from these parameters, which are commonly used to determine the presence of various mechanisms in a data set (Fig. 3). Analysis of these plots provided evidence that there were at least three distinctly discernable mechanisms.

The data acquisition software provided real-time analysis of the AE data. Thus, it was possible to study the incoming signals as they occurred. This is quite beneficial for monitoring structures. For example, in the AE analysis of the structural integrity of pressure vessels it is possible to determine from the real-time analysis of data that a leak is occurring and that failure is imminent [6]. Such information is invaluable because it allows the operator to relieve pressure before irreparable damage occurs. The same technology was beneficial for this research, as the goal was to identify and monitor in-flight fatigue crack growth in real time. The detection of a critical defect at the earliest possible time is the key to saving lives and property and minimizing maintenance costs.

Fig. 3. Graphical representation of AE data.
The four scatter plots that were used here to qualitatively discern the presence of different AE mechanisms are shown in Fig. 3. These include duration vs. amplitude (Fig. 3a), counts vs. energy (Fig. 3b), duration vs. counts (Fig. 3c), and hits vs. amplitude (Fig. 3d). The first three plots show what appear to be three clearly discernable mechanisms. Analysis of the fourth graph, hits vs. amplitude, would require classification and separation of the various source mechanism groupings, which typically overlap in the amplitude domain.

**Neural Networks**

Neural networks get their name from the fact that they closely mimic the operation of the human brain, the most powerful computing device known to man. The key component of the human brain that facilitates the processing of data is the neuron. This biological neuron is a formidable processor, composed of dendrites, soma, and axon [9]. Dendrites are the data collection components of the neuron, as they gather data from other neurons. The main purpose of the soma is to sum the incoming data; hence, the name soma, for sum. The axon is the transmitter of the neuron. Its purpose is to send a signal to other neurons. There are quite a few similarities between biological neurons and artificial neurons, which are at the heart of neural networks. Because of the fact that a method for classification of signals was required, it was necessary to choose an artificial neural network that was well suited to the task. The Kohonen self-organizing map (SOM) was chosen because of its excellent classification ability even when several variables (n-dimensional data) are involved.

**The Kohonen Self-Organizing Map (SOM)**

In order to understand how classification is accomplished, it is necessary to understand how a neural network operates. The most basic aspect of a neural network is that it accepts input data through input neurons. In the case of the Kohonen self-organizing map used for the fatigue crack analysis, the AE parameters recorded through digital signal processing were applied to the input neurons. The six input neurons are the AE quantification parameters: amplitude, duration, counts, energy, rise time, and counts-to-peak.

The function of a SOM is to operate as a topological map, where the output of the map is a graphical representation of the input data. For the purpose of the classification performed in this analysis, the main concern was to distinguish fatigue cracking signals from plastic deformation and mechanical noise, the two other mechanisms present. Since the concern of this analysis was dealing with a small set of mechanisms, care was taken not to overcomplicate the classification layer of the SOM, because misclassification can result if too many choices are provided. Therefore, a small neural network consisting of a 1 × 3 Kohonen layer was used (Fig. 4), giving the network only three choices for classification.

The output of the SOM provides a graphical representation of data in the form of an x-y scatter plot showing visual clustering of data. The ability to visualize the output data allows the component mechanisms to be readily identified. The only function served by the output layer is to generate the visual data; no computation is performed within this layer.

The SOM depicted in Fig. 4 shows the three Kohonen or classification neurons. Neuron 1 is used to classify a signal as the desired fatigue crack Mechanism 1. All signals classified as Mechanism 2 are defined as plastic deformation signals, while the signals classified as Mechanism 3 represent mechanical noise, which includes rivet fretting and bearing failure.
Training a Kohonen SOM

In order for a neural network to be used for classification, it must first be trained. The connections between the input layer and the Kohonen layer represent weights that are used for training [9]. Initially, the weights are set as a collection of random numbers ranging from 0 to 1. The weights are updated as the network learns. The updating of the weights is a mathematical function relating to the minimum Euclidean distance between the input variables and a particular neuron. The weights are updated according to the composition of the vector stored within the Kohonen neuron, after which the next set of input variables is processed. This process is continued until all of the training vectors have clustered into three clearly definable regions on the x-y plane, at which point network training is complete.

Testing Data with a SOM

Data from the laboratory tests were used to train the network. An analysis of the data provided a reference set of what the AE parameter data from each mechanism “looked” like. The test data were then classified using the trained network. The data obtained from the AE software are time-ordered; therefore, the network classified signals in the order they were recorded. During testing with the neural network, the weights are no longer updated; rather, they remain constant, and the AE signals are simply classified by the network from the six AE parameter input variables for each hit.

Laboratory Setup

The first segment of this research involved growing a fatigue crack in a controlled laboratory environment using a notched sample, which was monitored with two wideband AE transducers. The AE sensors used for this research were Physical Acoustics Corporation (PAC) WDIs, which contain built-in 60 dB preamplifiers. The specimen tested was constructed of 7075-T6 aluminum [10] and bent into a channel configuration. The AE transducers were mounted with hot melt glue in a 1/3 to 2/3 distance relationship on the structure. The purpose of this configuration was
to obviate the time difference that occurs due to the fact that it takes an AE signal from the stress concentration notch longer to reach Channel 2 than Channel 1. If the transducers were mounted at an equal distance from the stress concentration notch, the AE signals would tend to reach both transducers at the same time, thereby confusing the location analysis.

**MTS Test Machine**

An MTS test machine was used for the first laboratory fatigue test. One end of the specimen was attached to a rigid support structure. The other end of the specimen was secured to the lower grip of the MTS machine (Fig. 5). The machine was programmed to displace a peak-to-peak distance of 12.7 mm at a frequency of 2 Hz. An amplitude threshold of 30 dB was set, and a series of AE data files were recorded.

![Fig. 5. MTS equipment setup.](image)

**VTS Shaker Table**

For the second laboratory fatigue test, a VTS shaker table was used to cycle the specimen. One end of the specimen was firmly attached to a rigid support structure. The other end of the specimen was bolted to a vertical post attached to the table. The VTS machine, like the MTS machine, was programmed to displace a peak-to-peak distance of 12.7 mm at a frequency of 2 Hz, and the AE data acquisition and equipment setup was as described previously. A third laboratory test was performed using the VTS shaker table with the equipment threshold set at both 10 dB and 30 dB in order to correlate the AE data taken at different threshold values. These correlations (discussed in reference [11]) allowed the data to be analyzed in order to sort out fatigue crack growth signals from plastic deformation and mechanical noise signals from both the laboratory and the in-flight data.

**In-Flight Setup**

The second part of this analysis involved monitoring a fatigue specimen, similar to the laboratory specimen, during flight. Like the laboratory specimen, the in-flight fatigue specimen was constructed of 7075-T6 aluminum bent into a channel configuration. Figure 8 shows the specimen with two wideband AE transducers and installed in the vertical tail of the Cessna T-303 Crusader aircraft [11]. These transducers were wired into a portable computer running the real-time data acquisition software. The industrial grade portable computer received power from two portable battery packs and not from the airplane electrical system.
Acoustic emission data were recorded during a variety of in-flight maneuvers including taxi, takeoff, steady level flight, rolls, and Dutch rolls. However, the collection of data during in-flight tests was limited to a single flight. This limited data collection was due to the fact that fatigue cracks discovered in the wing ribs after the first test flight led to the sale of the aircraft. Another limitation in the ability to collect data arose from FAA regulations. Due to the fact that the installation of the fatigue specimen was deemed by the FAA to be an experimental modification, student pilots were prohibited from operating the aircraft. Moreover, because the installation of the fatigue specimen was considered an experimental modification, extensive pre-installation tests were required. The FAA also required that a Designated Engineering Representative (DER) sign off on the proposed installation. Consequently, there was insufficient time to conduct the structural tests required for the installation of a fatigue specimen on an alternate aircraft.

One other disappointment surfaced during the in-flight test phase. The amplitude threshold was set to 10 dB for the first test. It was expected that additional flights would be possible and would be conducted, like most of the laboratory data, at the higher 30 dB threshold. Since these flights were not conducted, the data collected were limited to the 10 dB set. This necessitated the previously mentioned third laboratory test in order to correlate the data taken at the 10 dB and 30 dB thresholds [11]. Once this was accomplished, it was found that the data collected during the in-flight test did indeed contain fatigue cracking signals.

Results

The results obtained during the laboratory and in-flight tests were analyzed using both AE parameters and neural networks. The results from the laboratory test were used to train the neural network. The data from the in-flight test were then tested in the trained neural network in
order to classify the signals as cracks, plastic deformation, or mechanical noise. The first step in the analysis of the results recorded during the laboratory tests was a study of the AE data.

Source location is a very beneficial asset of AE testing. Depending upon the material and structure through which the wave propagates, there is a characteristic velocity at which the wave travels. The material used throughout the tests, 7075-T6 aluminum, is a relatively popular alloy in the aerospace industry. Since the material used throughout the tests was 0.040 inch thick sheet, the main concern was with Lamb waves, which are the stress waves that propagate in thin plates or sheets.

One problem encountered in AE study is the attenuation of waves that propagate through a structure. The major concern involved with thin plates is dispersion. Dispersion causes not only the amplitude to diminish but also the shape of the waveform to change as different frequency components travel at different speeds.

The velocity at which waves travel through a medium is the key to source location. The fundamental velocity at which waves travel in thin plates is the plate wave velocity \([12]\). In order to calculate the plate wave velocity, the transverse or shear wave velocity, \(c_2\), was determined for 7075-T6 aluminum to be 3.10 mm/µs. The velocity of the symmetrical (extensional) Lamb wave is a function of transverse velocity and is calculated as 5.36 mm/µs for 1.02 mm plate. This value was verified to be reasonably accurate, in that when it was employed in the location analysis, it correctly indicated activity emanating from the approximate location of the stress concentration notch.

A major consideration involved in the testing process is the determination of what a crack signal looks like. The purpose of conducting the laboratory tests was to determine the AE parameters associated with fatigue cracking, plastic deformation, and mechanical noise. A method for determining these parameters had to be developed. Due to the design of the specimen, it was safe to assume that all of the crack signals would originate at the stress concentration notch in the center of the specimen. It was also assumed that there would be a great deal of plastic deformation originating from an area in close proximity to the stress concentration notch or the tip of the fatigue crack. By using source location, it was possible to look at signals originating from the center section only (Fig. 7). It was also reasonable to assume that all signals found in this location were either cracking signals or plastic deformation signals and not mechanical noise.

![Source Location Zone](image)

Fig. 7. Source location zone.
The first step in the analysis was to use acoustic emission processing to determine what a typical waveform representing each type of mechanism looked like. Linear location analysis was used to filter out mechanical noise by keeping only signals occurring in the center section of the specimen. It was possible to develop a location plot representing events vs. distance (Fig. 8). Notice that the plot displays AE events and not individual hits. There was clear evidence of a higher number of events around the 3 inch mark. These events represent fatigue cracking and plastic deformation only. Any mechanical noise signals would show up at the far extremes of the plot.

Source location proved to be an excellent tool for differentiating mechanisms that were present in a particular data set. Figure 9 shows a typical duration vs. amplitude plot containing all three mechanisms. Figure 10 is a plot of the exact same data, except that it was filtered using source location to contain only fatigue crack and plastic deformation signals from the center of the specimen. Therefore, it was possible to sort all the AE signals into three categories. In Fig. 10, the high amplitude signals are fatigue crack signals, and the lower amplitude signals are plastic deformation signals. The rest of the signals (Fig. 9), those having longer durations, are mechanical noise.

A brief understanding of AE parameters leads to the realization that plastic deformation signals do not have the same AE parameters as cracking signals. Looking at only the signals concentrated around the notch yields a better representation of the data of interest (Fig. 10). From this second plot it is evident that location analysis provides an effective means by which to isolate these two mechanisms from mechanical noise. Here it appeared that 67 dB was the dividing line between fatigue cracking and plastic deformation. Thus, signals with an amplitude of 67 dB or lower were classified as plastic deformation, while those with an amplitude of 68 dB or greater were classified as fatigue cracks.
Fig. 9. Duration vs. amplitude plot for all mechanisms.

Fig. 10. Duration vs. amplitude for fatigue cracking and plastic deformation.

Photographs of the fatigue specimen used in the first shaker table test were taken in order to document the size and location of the fatigue crack (Fig. 11). The photographs indicate that a fatigue crack did indeed grow where anticipated. In addition, a finite element analysis was performed [11] in which the color bands closely resembled the plastic deformation zone ahead of
the crack tip. The plastic deformation zone is somewhat difficult to discern from the photograph of Fig. 11; however, its presence along with the presence of the crack reinforces the validity of the classification process.

The above techniques were used to classify the signals received by the AE transducers in the laboratory tests. Reference [11] gives all of the details for each of the laboratory tests, plus explaining the steps required to sort, train, test, and classify AE signals as fatigue cracking, plastic deformation, or mechanical noise. (This includes the correlation of data taken at the two different threshold values, 10 dB and 30 dB.) The correctly classified signals were subsequently used to train a neural network.

The neural network was trained using the data recorded during the laboratory tests. The training file was made up of 300 signals. Of these 300 signals, there were equal numbers of cracking, plastic deformation, and mechanical noise -- 100 of each. These signals were gathered randomly with respect to time.

Once the neural network had been trained, it was possible to test the in-flight data by passing it through the trained network. All 15 in-flight data files were tested one at a time. The output of the neural network using the test data was graphed to provide a visual representation of the classified mechanisms (Fig. 12). The output file contains three distinct regions, representing the three failure mechanisms. The first mechanism, fatigue cracking, is seen at the location \( x = 1 \) and \( y \geq +0.212 \). The second mechanism, plastic deformation (PD), can be seen at \( x = 3 \) and \( -0.212 < y < +0.212 \). Finally, the third mechanism, mechanical noise (MN), is at \( x = 2 \) and \( y \leq -0.212 \). The values on the x-y plane are the output values of the neural network and can perhaps be represented most simply by the y ranges given in Table 2.

**Table 2. Neural network x-y output.**

<table>
<thead>
<tr>
<th>Mechanism</th>
<th>Neural Network Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatigue Cracking</td>
<td>( y \geq +0.212 )</td>
</tr>
<tr>
<td>Plastic Deformation</td>
<td>(-0.212 &lt; y &lt; +0.212)</td>
</tr>
<tr>
<td>Mechanical Noise</td>
<td>( y \leq -0.212 )</td>
</tr>
</tbody>
</table>

Fig. 11. Fatigue crack, before (a) and after (b) formation.
It is evident from the summary of the in-flight test results (Table 3) that a fatigue crack did indeed grow in the specimen installed in the vertical tail of the Cessna T-303 Crusader. It is interesting to note that no fatigue cracking signals were recorded during taxi, either before or after flight; this is most certainly due to the fact that there is little to no load applied to the tail section during taxi.

Most of the ground loads experienced by this aircraft were experienced in the engine compartment and landing gear and were due to vibration of the engine. The ratio of mechanisms classified during the taxi maneuvers was very similar, which came as a bit of a surprise since the maneuvers occurred so far apart. The vast majority of the signals recorded were plastic deformation signals. A small percentage of the signals were attributed to mechanical noise. The probable explanation for this phenomenon arises from the fact that the loads are so small that there are no large deflections, so the mechanical noise is subdued.

The fatigue crack growth activity begins to rise during takeoff. This seems quite reasonable, as there are higher loads present in the vertical tail during takeoff, probably as a result of crosswinds. The percentage of signals resulting from mechanical noise also increases and may also be attributed to the higher aerodynamic loads. There was a relatively similar breakdown of mechanisms during landing.

The crack signals increased during steady level flight. However, the signals subsided during the initiation of the rolling maneuvers. This was not expected, but could be attributed to the crack growth being stopped by a grain boundary. The mechanical noise signals continue to increase during the early rolls, indicating there is rivet fretting, bearing failure, and interface rubbing present under increased loading conditions.
Table 3. Summary of In-Flight Results.

<table>
<thead>
<tr>
<th>Maneuver</th>
<th>Crack Events</th>
<th>Crack %</th>
<th>PD Events</th>
<th>PD %</th>
<th>MN Events</th>
<th>MN %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi</td>
<td>0</td>
<td>0.0%</td>
<td>963</td>
<td>93.0%</td>
<td>73</td>
<td>7.0%</td>
</tr>
<tr>
<td>Takeoff</td>
<td>69</td>
<td>14.4%</td>
<td>250</td>
<td>52.3%</td>
<td>159</td>
<td>33.3%</td>
</tr>
<tr>
<td>Flight</td>
<td>277</td>
<td>23.3%</td>
<td>515</td>
<td>43.3%</td>
<td>398</td>
<td>33.4%</td>
</tr>
<tr>
<td>Flight</td>
<td>1</td>
<td>0.1%</td>
<td>782</td>
<td>66.1%</td>
<td>400</td>
<td>33.8%</td>
</tr>
<tr>
<td>Flight</td>
<td>7</td>
<td>3.5%</td>
<td>104</td>
<td>52.5%</td>
<td>87</td>
<td>43.9%</td>
</tr>
<tr>
<td>Dutch Roll</td>
<td>10</td>
<td>3.9%</td>
<td>113</td>
<td>44.5%</td>
<td>131</td>
<td>51.6%</td>
</tr>
<tr>
<td>Roll</td>
<td>40</td>
<td>5.1%</td>
<td>383</td>
<td>48.7%</td>
<td>364</td>
<td>46.3%</td>
</tr>
<tr>
<td>Roll</td>
<td>212</td>
<td>71.9%</td>
<td>52</td>
<td>17.6%</td>
<td>31</td>
<td>10.5%</td>
</tr>
<tr>
<td>Dutch Roll</td>
<td>204</td>
<td>73.9%</td>
<td>42</td>
<td>15.2%</td>
<td>30</td>
<td>10.9%</td>
</tr>
<tr>
<td>Flight</td>
<td>472</td>
<td>64.1%</td>
<td>160</td>
<td>21.7%</td>
<td>104</td>
<td>14.1%</td>
</tr>
<tr>
<td>Landing</td>
<td>11</td>
<td>2.3%</td>
<td>331</td>
<td>69.0%</td>
<td>138</td>
<td>28.8%</td>
</tr>
<tr>
<td>Taxi</td>
<td>0</td>
<td>0.0%</td>
<td>895</td>
<td>93.7%</td>
<td>60</td>
<td>6.3%</td>
</tr>
</tbody>
</table>

During the second roll, the fatigue crack activity began to increase at a rapid rate, peaking during the final Dutch roll. The Dutch roll is a wig-wag maneuver that imposes tremendous aerodynamic loads on the aircraft, especially the vertical tail. These increased loads were the main reason that the crack activity increased at such a high rate. This higher rate of crack activity was accompanied by a reduction in the presence of mechanical noise as well as plastic deformation. Returning to steady, level flight led to a reduction in the crack signals, followed by landing, where the fall-off continued.

Conclusions

The goal of this research was to develop an aircraft structural health monitoring system for keeping track of fatigue crack growth while in flight. It has been shown that it is indeed possible to monitor fatigue crack signals in a noisy in-flight environment using AE nondestructive testing techniques in combination with neural networks. In conclusion, this research successfully demonstrated a prototype in-flight AE fatigue crack monitoring system for aircraft structures. It is envisioned that the application of such structural health monitoring systems in aging aircraft could warn of impending failure and allow for replacement of parts when needed rather than at conservatively calculated intervals.

Recommendations

The next step in the development would be to incorporate the current research being done in back-propagation neural network (BPNN) fatigue life prediction such that it can be applied to the data gathered by in-flight aircraft structural health monitoring systems. Reasonably accurate BPNN fatigue life predictions have been obtained in aerospace bellows [14], notched tensile fatigue specimens [15-16], and bridge steel I-beams [17]. In each case, the entire acoustic AE amplitude distribution for various ranges in the fatigue cyclic life (0-25%, 25-50%, and 50-75%) was input to a BPNN, and the associated fatigue life predictions were made with worst case errors of between 5-20% for the three different structures.
Analogous work has been done for low proof load (≤25% \(P_{\text{burst}}\)) burst pressure predictions in composite pressure vessels in which ±5% worst case errors have been obtained by using the matrix cracking only (since matrix cracking is a precursor to delamination and fiber breaks) portion of the AE amplitude distribution as input to the BPNN [18]. Hence, for the fatigue life prediction problem, it is recommended that the plastic deformation only data portion of the AE amplitude distribution be used as input to a BPNN (since plastic deformation is a precursor to both plane strain and plane stress fatigue crack growth), which should reduce the worst case error predictions to a similar ±5% range. Such prediction accuracies would lead to minimized maintenance costs and extended service lives of aging aircraft, which is the ultimate goal of this research effort.

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