Acoustic Emission Fatigue Crack Monitoring of a Simulated Aircraft Fuselage Structure

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ACOUSTIC EMISSION FATIGUE CRACK MONITORING OF A SIMULATED AIRCRAFT FUSELAGE STRUCTURE

by

Jeremy James Lucas

A Thesis Submitted to the Graduate Studies Office in Partial Fulfillment of the Requirements for the Degree of Master of Science in Aerospace Engineering

Embry-Riddle Aeronautical University
Daytona Beach, FL
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This thesis was prepared under the direction of the candidate’s thesis committee chairman, Dr. Eric Hill, Department of Aerospace Engineering, and has been approved by the members of his thesis committee. It was submitted to the School of Graduate Studies and Research and was accepted in partial fulfillment of the requirements for the degree of Master of Science in Aerospace Engineering.

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ABSTRACT

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The purpose of this research was to replicate the fatigue cracking that occurs in aircraft placed under loads from cyclical compression and decompression. As a fatigue crack grows, it releases energy in the form of acoustic emissions. These emissions are transmitted through the structure in waves, which can be recorded using acoustic emission (AE) transducers. This research employed a pressure vessel constructed out of aluminum and placed under cyclical loads at 1 Hz in order to simulate the loads placed on an aircraft fuselage in flight. The AE signals were recorded by four resonant AE transducers. These were placed on the pressure vessel such that it was possible to determine the location of each AE signal. These signals were then classified using a Kohonen self organizing map (SOM) neural network. By using proper data filtering before the SOM was run and using the correct classification parameters, it was shown that this is a highly accurate method of classifying AE waveforms from fatigue crack growth. This initial classification was done using AE waveform quantification parameters. The method was then validated by using both source location and then examining the waveforms in order to ensure that the waveforms classified into each category were the expected waveform types associated with each of the AE sources. Thus, acoustic emission nondestructive testing (NDT), in combination with a SOM neural network, proved to be an excellent means of fatigue crack growth monitoring in a simulated aluminum aircraft structure.
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1. INTRODUCTION

1.1 General Overview

Fatigue cracking has been a problem for centuries. Every structure that is built and undergoes cyclic loading is potentially at risk for fatigue crack growth, and steps must be taken in the design, construction, and upkeep of such structures to deal with this issue accordingly. With the dawn of the aviation age, this problem took on an entirely new importance. As an increasing number of lives were at risk on aircraft, the margin of error allowed when it came to fatigue crack growth shrank dramatically. Since the beginning of the jet age, where aircraft were expected to fly higher and faster with longer service lives, this problem has come to the forefront.

The importance of understanding fatigue crack growth was catastrophically shown with the first commercial jet aircraft, the de Havilland Comet [1]. It was only after two of these aircraft broke up in flight that it was realized that the cause was metal fatigue. The constant pressurization and depressurization combined with stress concentrations around the square corners of the windows led to both mid-air tragedies. This resulted in a redesign of this aircraft and ensured that all future designs would use the now-familiar commercial aircraft windows with rounded corners. In 1988, Aloha Airlines flight 243 sustained massive damage in one of the best known cases of combined metal fatigue and corrosion [2]. The 737-200 involved in this accident was used on many short flights between the Hawaiian Islands, and as such it was subject to a large number of pressurizations and depressurizations. This would eventually lead to a catastrophic failure where a large section of the upper fuselage ripped off the top of the aircraft. It is clear that fatigue cracking is going to continue to be problematic, especially as aircraft are
pushed into service years past their original design lives in an attempt to keep the cost of air travel to a minimum. Such attempts at cost cutting have their potential dangers as well. Without an appropriate system in place to monitor fatigue crack growth in flight, more disasters like the Comet and the Aloha Airlines 737 can, and most likely will, continue to occur.

Airlines have dealt with the problem of fatigue crack growth in the past by scheduling regular inspections and replacement of critical parts that are at risk from fatigue crack growth. These fixes, however, are only temporary. Every time such an inspection takes place, the aircraft must be taken out of service, costing the airline valuable flight time. Another method, one that can be implemented in real time, would be clearly beneficial over the current system that is in place. An in-flight system that can detect fatigue crack growth, and not just make a conservative guess as to when it might occur, would allow down time to be scheduled only when it is actually needed. Additionally, such a system could warn of anomalies that are occurring on an aircraft that under the current inspection system is deemed safe to fly, problems such as cracks due to overstressing the aircraft beyond its design limits. One potential method of real time in-flight fatigue crack monitoring is based on acoustic emission (AE) nondestructive testing (NDT). Combined with a properly trained neural network, this would allow both the engineers and the ground crews to have advanced knowledge of when and where fatigue cracks are growing, allowing them to fix the problem both efficiently and safely.

1.2 Past Research

The idea of using acoustic emissions to detect fatigue crack growth in aircraft in real time has been around for decades. Bailey [3] and Bailey and Pless [4] did research on in-flight monitoring using AE systems on the C-5 transport aircraft in the mid-1970s. Another in-flight application was attempted on the C/KC-135 fleet in by Mizell and Lundy [5] and Parrish [6,7] in
the late-1970s. The success of this 625 aircraft deployment demonstrated that in-flight fatigue crack monitoring was feasible, but not without some difficulty. These tests focused only on sensing critical fatigue cracks in the 7178-T6 aluminum lower wing skin panels with a thickness of over 0.070 inches. Unfortunately, two “squawking” systems led to scrapping the project for the entire C/KC-135 refueling tanker aircraft fleet. Other work on this same subject was done using the F-105 by Rodgers [8] in 1979 and on the Australian MACCHI aircraft by Scott [9] and Hutton, et al [10] in the 1980s. In-flight fatigue crack monitoring of the Canadian C-130 Hercules was accomplished in 1984, showing that in-flight monitoring was possible despite the large amount of noise present [11].

In the mid-1990s, two students at Embry-Riddle Aeronautical University (ERAU), Thornton [12] and Marsden [13], worked on this problem by applying neural networks to analyze AE data from a simulated fuselage structure. Thornton attempted to classify the signals given off by acoustic emissions using the frequency-domain power spectrums of the waveforms, whereas Marsden used the five standard time-domain acoustic emission waveform quantification parameters to classify his data. Both of these research attempts were relatively successful, but it was clear that more work needed to be done on classification accuracy before it could be used for in-flight monitoring.

In the late 1990s, another pair of ERAU students, Vaughn [14] and Rovik [15], successfully performed in-flight fatigue crack monitoring on two civil aviation aircraft. Vaughn monitored fatigue cracking that occurred predominantly during takeoff on the engine cowling of a Piper PA-28 cadet aircraft, while Rovik, on the other hand, was able to detect fatigue cracking in a redundant structure placed in the vertical tail of a Cessna T-303 Crusader twin-engine aircraft during maneuver activity. The AE activity in this T-tailed aircraft was especially
pronounced during roll and Dutch roll maneuvers. Ironically, the later project was terminated early when the T-303 aircraft was sold due to fatigue cracks found in the wing ribs.

1.3 Current Research

The current research again focuses on detecting fatigue crack growth in a simulated fuselage structure as it was undergoing cyclic stresses from pressurization/depressurization. Given the advances in computer technology since Thornton and Marsden [12,13], the objective here was to improve the classification accuracy of the various failure mechanisms detected by the AE transducers. This research incorporated two different types of aircraft aluminum, 2024-T3 and 7075-T6. Cylinders were made from both types of aluminum and placed under cyclic loads while being monitored by resonant AE transducers that recorded any acoustic emission activity. The cylinders were loaded from approximately 40 to 70 psi at a cyclic rate of 1 Hz. This loading was used as an accelerated fatigue life test of an aircraft simulating use for many years.

The primary classification method for the acoustic emission data focused on using the AE waveform quantification parameters instead of frequency spectra, as the former proved to be both less difficult and more accurate. However, the actual AE waveforms were also recorded during testing, and these were later examined to validate the neural network classification of the AE data. A third check was provided by using multiple sensors to locate the source of each AE signal, allowing for verification that the signals being collected by the testing were indeed originating from the area of expected fatigue crack growth.

Unlike the research done by Thornton, this research uses the standard time-domain acoustic emission waveform quantification parameters to classify the data, and only used the frequency-domain power spectrums of the waveforms as a validation for the results. Marsdens
research was similar to what is presented in this thesis due to the use of the acoustic emission parameters. However, the amount of data that was able to be collected in this research was far greater than what Marsden was able to collect, due to improved computer technology. Additionally, improvements in neural network software and has allowed for a much cleaner classification in this research than what was possible at the time that that Marsden’s research was done. Finally, this research gives verification based on source location and the power spectrums of the waveforms to validate the results. This same verification was used by Vaughn and Rovik, but on a much different structure than what was used in this research. Additionally, the structure of the neural networks used in this research, including the number of layers and the number of neurons in these layers, as well as the parameters used, differ significantly from any other the previous research describe herein.
2. ACOUSTIC EMISSION NONDESTRUCTIVE TESTING

2.1 Basic Overview

Nondestructive testing (NDT) is a term that incorporates all methods of analyzing structures or materials in such a way that there is no impairment of the ability of the part to perform its intended function. NDT methods are broken down into two general categories: surface and volumetric. Surface techniques include methods such as liquid penetrant testing and optical microscopy. As the name implies, these NDT methods can only detect a flaw if it is present on the surface of the part to be examined. Volumetric methods, on the other hand, can detect a flaw anywhere on or within the structure. These methods include radiography, ultrasonics, and acoustic emission (AE).

Acoustic emissions are the elastic waves that are propagated throughout a loaded part by the rapid release of energy from localized areas of stress concentration. These elastic waves can be from a variety of sources. Some of the sources that indicate failures in a metal structures are fatigue crack growth, grain boundary sliding, moving dislocations, and fracture of inclusions. Each of these sources transmits energy throughout the structure, and this sound can be detected using piezoelectric transducers. These transducers convert the elastic wave in the structure into a voltage versus time representation of the wave. Multiple transducers are often placed on the structure in various locations during testing, allowing for improved data collection.

By recording the acoustic emission signals given off during fatigue cracking in a controlled environment, it is possible to use the data obtained to detect fatigue crack growth during in-flight tests. Acoustic emission transducers must be extremely sensitive to pick up the signals given off by fatigue crack growth. This sensitivity is simultaneously one of the greatest strengths and greatest weaknesses of AE nondestructive testing. Though this allows the data
acquisition system to record information on fatigue crack growth, it also records signals from many other sources as well. Some of the main sources that are found both in the laboratory tests and in-flight tests are metal rubbing and rivet fretting. Another source of extraneous noise that will be recorded by the system is electromagnetic interference (EMI) caused by electronic devices in the lab or on the aircraft. Since the piezoelectric transducers used in this experiment convert the elastic waves into a digital wave that is transmitted as an electrical signal to the data collection computer, EMI can cause the data acquisition system to pick up waveforms that are not, in fact, present in the material. Because of these sources of noise, it is necessary to be able to classify which signals come from fatigue crack growth and which signals come from noise.

2.2 Waveform Analysis

One of the most basic ways to classify the data collected from acoustic emission research is to compare the waveforms of the various hits to one another. This requires that the entire waveform be captured, and then a method such as a Fast Fourier Transform is used in order to compare the signals. Although this method has been shown to be reasonably accurate [12], it also requires a large amount of work to transform the signals into a usable form and subsequently classify the signals properly. Hence, this method was not used to classify the data collected herein. Instead, the waveforms collected were viewed after the data had been classified, which allowed for both verification of the classifications found, and a better understanding of the physical origins each of these classifications.
2.3 Acoustic Emission Parameters

One of the most widely used methods of analyzing data from acoustic emission testing is to utilize what are known as the acoustic emission parameters. There are five primary quantification parameters that are used, and are each related to various aspects of the waveform (Figures 1). The first parameter is the amplitude, which measures the maximum amplitude that a signal attains measured in decibels [dB]. The second parameter is the duration, which is the length of the signal measured in microseconds [μs]. To avoid excessive amounts of noise, an amplitude threshold is set that rejects any waveform that fails to meet the minimum threshold. The number of times that a signal crosses this threshold is known as the counts, which is another

![Acoustic Emission Parameters](image)

**Figure 1. Acoustic Emission Parameters**
of the primary acoustic emission parameters. The energy of the waveform is recorded as the mean area under the rectified signal envelope, or MARSE, measured in energy counts. The fifth of the primary parameters is the rise time. This is a measure of the time in microseconds [μs] that it takes for a signal to reach its peak amplitude. There are other acoustic emission parameters that are also used, but these are secondary parameters and are derived from these five primary parameters. For instance, the average frequency of a signal is used herein; it is the duration of the signal divided by the counts. Using the time domain acoustic emission parameters allows for quicker and easier data analysis than using the frequency domain parameters such as the frequency spectrum. It is for this reason that is has become one of the most popular ways to analyze acoustic emission data.

These AE digital waveform quantification parameters can be plotted versus each other in various graphs that each give a better understanding of the data. Two of the primary graphs that are oftentimes used are the hits vs. amplitude histogram and the duration vs. counts plot. The first one, the amplitude histogram, shows how many AE hits have occurred at each amplitude. All acoustic emission sources vary in the amplitude of signal given off, and this variation tends to follow a normal distribution for each failure mechanism. An example of an unclassified set of data is shown in Figure 2. Once classified, distinct humps should appear in the data, indicating the various failure mechanism classifications. The classified data, with the humps drawn, are shown in Figure 3.
Figure 2. Unclassified Amplitude Histogram

Figure 3. Classified Amplitude Histogram
The duration vs. counts plot is valuable in that it can show the difference between the various acoustic emission sources based on average frequency. Each source of AE tends to release energy in a distinct frequency band. Since the average frequency of a wave is the number of counts divided by the duration, the duration vs. counts graph will show each source of data as a band of points that radiates from the origin. A set of data, classified into two distinct average frequency bands, is shown in Figure 4.

Figure 4. Classified Duration vs. Counts Graph
2.4 Source Location

Source location can be an important step in acoustic emission research. Determining the location of an AE event will lead to the ability to better understand what is causing the event, and if used in actual in-flight testing, will allow ground crews to determine where a fatigue crack is located. In order to use source location, multiple transducers are required, and each must pick up the acoustic emission hit [16]. By understanding the speed at which a wave travels through the structure, and measuring the time difference it takes for the wave to reach the various transducers, it is possible to calculate where the wave originated. In order to calculate the location of the source of an event in one dimension, at least two transducers must be used; for two dimensional source location, at least three transducers must be used. However, it is important to note that more transducers than the minimum required can be extremely helpful. A waveform changes in shape and dissipates as it moves through a structure, so using multiple transducers placed at regular intervals allows for better location of all signals produced in the structure.
3. NEURAL NETWORKS

3.1 Neural Network Overview

A neural network is a computer program that is made to artificially replicate the working of the mammalian brain. The purpose of these programs is to use a mathematical algorithm to be trained, or “learn”, much the same as how the human brain learns, allowing it to recognize complex patterns. Once properly trained, a neural network can recognize patterns in data similar to that on which it was initially trained. The program accomplishes this task using artificial neurons, or processing elements (PEs), to simulate the way real neurons work in the brain. Most computer programs that are written are linear and deterministic, which means that any set of data input to the program will always generate exactly the same output. Neural networks, however, are typically non-linear and non-deterministic. Therefore, the output that is generated for a given input will vary somewhat each time the program runs. In a neural network the PEs are interconnected, with the PEs arranged in a number of layers. There is always an input layer, with each PE in this layer corresponding to an input variable that is to be used to classify the data. Each network also has an output layer, with each PE in this layer corresponding to one of the desired output classes. Neural networks can also have one or more hidden layers, which act to process that data in some way as specified by the program. As data is initially inputted into the network, the network responds by varying how it classifies each input into an output classification. This process is the training phase for the neural network. The result of this process is a neural network that will recognize new inputs that are similar to a group of inputs it has already seen, allowing it to classify data accurately after it has been properly trained. This is very similar to the way a human will learn. After seeing an object such as a pencil a number of times, the person will understand what a pencil is when they see another one, even if some of the
properties of the new pencil such as length or color vary slightly from the others the person has seen.

There are two types of learning that a neural network can use. These are supervised and unsupervised. In supervised learning, the neural network is given some information as to what the output classifications of the data are expected to be like, and the program attempts to match this information as closely as possible. In unsupervised learning, the program is not given any information as to the expected output of the data, and instead is only given the number of classifications that it must use. For this research, an unsupervised network known as a Kohonen self-organizing map was used.

3.2 Kohonen Self Organizing Maps

A Kohonen self-organizing map (SOM) is an artificial neural network that is often used to classify data into distinct categories. The SOM, like all artificial neural networks, is organized into multiple layers. However, the SOM employed herein had only two layers. The first layer is the input layer. This layer has a single PE that corresponds with each of the input parameters used to classify the data. For instance, in a simple SOM that is classifying AE data based on amplitude (A), counts (C), and duration (D), there would be an input PE that represented each of these parameters, for a total of three PEs in the input layer. The second layer is known as the Kohonen or output layer. This layer has one PE that corresponds to each of the desired output categories. For instance, if it was desired to place the data into three categories or three failure mechanisms, then it would be necessary to use three PEs in the output layer as well. A three input, three output neural network is shown in Figure 5.
One of the key features in any neural network is scaling of the data to a set range, typically either from 0 to 1 or from -1 to 1, depending on the chosen activation function. The data from each of the inputs is scaled from its original range to this new range. This ensures that no one set of parameters outweighs another in the processing of the data. For instance, if the range of the amplitudes in the previous example ranged from 30 to 60 dB, and the counts ranged from 5 to 10, without scaling the data to the same interval the amplitude would outweigh the counts, and the classification would be based predominantly on the amplitude.

Before any data is fed into the SOM, the output PEs are given random values, or weights, from 0 to 1. The SOM is based on competitive learning, in which each PE wants to classify each data point into its category. As each of the input data points are fed through the SOM during
training, the scaled parameters of the AE input data are compared to the weights of the output PEs, and whichever output PE has the weights the closest to the values of the input parameters is said to win. This means that the input data point is classified into the category represented by this output PE. Additionally, the weights of the output PE are updated to be closer to that of the just classified AE input data point. This is done to ensure that other input data points that are similar to this are classified into the same category.

Another feature of the SOM is that it also recognizes the topography of the output data, and uses this in training as well. This means that the output PEs are arranged in a user-defined pattern on a two-dimensional plane, and the program recognizes the distance between each of the PEs. In most programs, the user can define a “neighborhood” that will be updated during the training phase. The distance between PEs is determined by the minimum Euclidian distance between the two PEs. If a neighborhood is set at three, each time a PE “wins”, every PE within a distance of three of the winning PE will also have their weights updated to be closer to the input data point as well. The neighborhood size in some programs can be varied during the training phase, allowing it to become gradually smaller as the training progresses. This allows the changes made to the network as a whole to gradually become less drastic as the weights of the output PEs get closer to their final values. This is known as “soft” training, as opposed to “hard” training, where only the winning PE is updated. Once a network is fully trained, more sets of data that are similar to the original set can be classified by the neural network. Since the data set that is used for training is run through the neural network many times in order for the network to be trained to the input data, and the data set that is classified after training is run through the network just once, the actual classification of the data is much faster than the training.
One thing that must be kept in mind about SOM neural networks is that they will classify data based on the parameters that the program sees, and it is up to the person running the program to make sense of what each classification physically means. Even though these programs can greatly increase the speed at which signals are examined and classified, without a good understanding of the physical phenomena of each of the sources of acoustic emission signals, it is very easy for the programs operator to assign each of the classifications the SOM uses to the wrong source of AE signals.
4. EXPERIMENTAL SETUP

4.1 Pressure Vessel Construction

This experiment was performed using multiple pressure vessels loaded cyclically until fatigue crack growth occurred. One of the goals of this research was to compare the results of two different types of aircraft aluminum, 2024-T3 and 7075-T6. To accomplish this, three cylinders were made from each of these types of aluminum. The first three pressure vessels that were constructed were made out of the 2024-T3 aluminum, and tests were conducted on these prior to the construction of the 7075-T6 cylinders. Each cylinder measured 12 inches long and 12 inches in diameter, with open ends. The original construction of the 2024-T3 cylinders featured a single lap joint on one side, fastened together with a row of rivets. The lap joint was constructed so that the inside of the cylinder was smooth, and to do so, a small bend had to be made in the cylinders’ skin. Due to the unexpected failure at this bend during the initial test, a fourth cylinder 2024-T3 was aluminum fabricated which did not have this bend. Additionally, all of the cylinders constructed out of 7075-T6 aluminum did not have this bend either. A hole one-inch in diameter was drilled directly opposite the lap joint at the center of the cylinder, and a small notch was cut out of the top of this hole. This was designed to provide a stress concentration where fatigue crack growth would initiate. A piece of aluminum was riveted behind this notched hole to simulate a patch that might be used on an aircraft with such damage. This intentional (fatigue crack starter) defect is shown in Figure 6.
Figure 6. Intentional (Fatigue Crack Starter) Defect

Figure 7. Testing Apparatus
4.2 Testing Apparatus Construction

A bladder made out of a sheet of PVC rubber was placed inside each cylinder to provide a leak proof barrier. The bladder itself was cylindrical in shape with a 12 inch diameter but was several inches longer than the aluminum cylinders, as shown in Figure 7. This allowed the ends of the bladder to fold back over the ends of the cylinder. Two steel endplates were constructed with the inside covered by aircraft baffling rubber. The two end plates had holes drilled around their perimeters where long threaded rods could be inserted to apply clamping pressure. Nuts were placed on either end of the rods and were used to tighten the end plates down onto the open ends of the cylinders. By compressing the side of the end plate covered with baffling rubber against the PVC rubber covering the end of the aluminum cylinder, a watertight seal was formed. Ports were placed in the end plates using compression fittings to prevent leakage. On one of the end plates, two ports were installed. The first of these was used to fill the cylinder with water, and the other was fitted with a pressure gage. The other end plate had only one port, which was used to pressurize and depressurize the cylinder. A hose was attached from this later port to a hydraulic cylinder /piston that was driven by a MTS tension/compression test machine. The hydraulic cylinder, attached to the MTS machine, is shown in Figure 8. By moving the piston up and down at 1 Hz, it was possible to create a cyclic pressure of approximately 40 to 70 psi to simulate pressurization/depressurization of the cylindrical aircraft fuselage structure.
4.3 Acoustic Emission Transducers

Acoustic emission data were collected in this research through the use of a number of piezoelectric transducers. These resonant AE transducers were placed at various points around the cylinder where acoustic emission signals were expected to be found. During the initial testing, only two transducers were used. For the first hour of each of these tests, both of the transducers were placed near the lap joint in order to pick up signals coming from metal rubbing and rivet fretting. After the initial hour of testing, the transducer placement was changed. One of the transducers was placed directly above the intentional defect, with the other off to the left of the defect, in order to collect AE signals from fatigue cracking. This method was used until a data acquisition system was obtained that was able to accommodate up to four sensors (Figures 9
and 10). The four AE sensors were then placed on a line two inches above the defect, and were positioned around the cylinder in order to determine the location of any acoustic emission signal.

The position of the stress concentration notch for this experiment was considered to be position zero. Here the transducers were placed at +2 inches, -4 inches, -6 inches, and -18 inches from this point as seen in Figure 7. This allowed for determination of the location of a source of acoustic emissions anywhere on the cylinder, and ensured that any AE source signal originating from the lap joint directly opposite the stress concentration notch would not be misinterpreted as having originated from the notch. All of the sensors used were 150 kHz resonant transducers with integral parameters and were attached to the metal cylinder using hot melt glue. The hot melt glue acted to not only hold the transducers to the cylinder, but also to effectively couple the AE signals from the metal to the transducer. In the initial testing the data collected from the two transducers were recorded by the Pocket AE data acquisition system. For the subsequent four channel tests, the data were collected by the multi-channel AE analyzer that was connected to a laptop which recorded the AE parameter data.
Figure 9. Multi-Channel Acoustic Emission Analyzer

Figure 10. Multi-Channel Acoustic Emission Analyzer Ports
5. NOISE SOURCES

5.1 Sources Of Noise Unique to this Experiment

One of the main objectives of this research was to be able to filter out the sources of noise from the desired acoustic emission signals emanating from fatigue crack growth. There were many sources of noise to consider, and a noise test was initially performed to determine the type of data that represented noise. For this test, the cylinder was filled with water, and the MTS tension/compression machine was turned on and left at idle. Acoustic emission data was collected during this time and subsequently compared to operational AE data. This setup represented the closest the cylinder could be to actually being tested without the possibility of fatigue crack growth. However, the noise test missed several sources of noise that were present in the actual testing. This was due to the fact that some of the extraneous noise was caused only during the testing itself, and would not have been present in this initial noise test.

One of the types of noise that could have been present in the actual testing but not in the initial noise test was the turbulent eddies from water moving into and out of the cylinder. This happened every time the cylinder was pressurized or depressurized. However, it is also possible that this noise was dampened by the internal PVC bladder, and this noise may not have had much of an effect on the overall data. Another potential cause for noise would have been the rubbing of the PVC bladder against the aluminum cylinder. Although every effort was made to make the cylinder and the bladder fit together as tightly as possible, there were some small wrinkles in the PVC bladder on the inside of the cylinder that did not allow it to rest evenly against the cylinder at all times. Also, as the rivets protruded into the cylinder, these caused a gap between the inner cylinder wall and the PVC bladder. Due to the constant changes of pressure inside the cylinder, it is likely that the PVC bladder was forced to rub against the cylinder at times, which may have
also caused noise to appear in the data. However, it was assumed that this noise data would have been a longer duration that the acoustic emission sources of interest, and therefore it was removed through the initial duration setting and subsequent filtering of the data during post test analysis.

A final source of noise that was unique to this type of testing was leak noise. Since the cylinder is filled with water, it is imperative to make sure that it is watertight. Any water that leaks from the cylinder would show up as continuous noise in the data, and thus could provide difficulties in sorting out the fatigue crack growth data. This was a common problem in past research attempts with this type of setup and therefore was one of the first problems addressed in this experiment. By experimenting with various materials and sealants, a method was found to ensure that the cylinder was leak free for the majority of the testing. Although leaks did occur at times, most of the testing was accomplished without this problem, and the data analyzed were taken only from the leak free testing.

5.2 Other Sources of Noise

There were other sources of noise that were also considered that were not unique to this experiment. These sources of noise have been known for years to be a problem in acoustic emission NDT and therefore were filtered out using proven techniques. Suleman, et al. [17] showed that much of the noise data can be filtered out using frequency filters. Although their research found that a low frequency filter of 25 kHz worked well for testing of notched aluminum specimens, the results from this experiment seemed to indicate that a low average frequency filter would remove some of the valid data as well. Therefore, a low average frequency filter was not used in this data analysis, and later filtering by the SOM was relied on instead to filter out unwanted low average frequency noise. This low average frequency filter
was intended to remove data points that were due to a wave not being completely captured. In this case only the back half of a waveform would be captured, which would lead to a waveform with a very low rise time. A sample of low average frequency noise is shown in Table 1.

**Table 1. Typical Low Average Frequency Noise**

<table>
<thead>
<tr>
<th>Rise Time (μs)</th>
<th>Counts</th>
<th>Duration (μs)</th>
<th>Amplitude (dB)</th>
<th>Average Frequency (kHz)</th>
<th>Energy (aJ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>30</td>
<td>0</td>
<td>1.51E-02</td>
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<tr>
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<td>1</td>
<td>784</td>
<td>31</td>
<td>1</td>
<td>1.64E+00</td>
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<tr>
<td>1</td>
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<td>31</td>
<td>2</td>
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<tr>
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<td>31</td>
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<tr>
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<td>565</td>
<td>30</td>
<td>2</td>
<td>2.56E+00</td>
</tr>
<tr>
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<td>1</td>
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<td>30</td>
<td>3</td>
<td>8.36E+00</td>
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<tr>
<td>1</td>
<td>2</td>
<td>491</td>
<td>31</td>
<td>4</td>
<td>2.03E+00</td>
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<tr>
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<td>3</td>
<td>421</td>
<td>36</td>
<td>7</td>
<td>3.53E+00</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>107</td>
<td>31</td>
<td>9</td>
<td>1.02E+00</td>
</tr>
</tbody>
</table>

Another problem was high average frequency noise. In these cases, a single large spike was seen that could reach well past the amplitude threshold of 30 dB, but there was no wave associated with the single spike. After the spike was over, the noise level returned to an ambient level well below the threshold, and therefore a count of one was recorded. This did not represent any actual relevant data, and therefore was filtered out using a high average frequency filter of 1000 kHz. Typical high average frequency noise is shown in Table 2.

**Table 2. Typical High Average Frequency Noise**

<table>
<thead>
<tr>
<th>Rise Time (μs)</th>
<th>Counts</th>
<th>Duration (μs)</th>
<th>Amplitude (dB)</th>
<th>Average Frequency (kHz)</th>
<th>Energy (aJ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>31</td>
<td>1000</td>
<td>7.69E-02</td>
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<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>31</td>
<td>1000</td>
<td>8.70E-02</td>
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<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>30</td>
<td>1000</td>
<td>5.23E-02</td>
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<td>1</td>
<td>1</td>
<td>30</td>
<td>1000</td>
<td>8.09E-02</td>
</tr>
</tbody>
</table>
A final problem encountered was multiple hit data. Here, a second signal was picked up before the initial wave died out completely, and the data acquisition system captured both as if they were one signal (Figure 11). These data, due to the extended duration and relatively low counts, had low average frequencies (counts/duration) and were therefore filtered out using the classifications from the SOMs described in Section 6.2.

Figure 11. Typical Multiple Hit Waveform
6. RESULTS

6.1 Initial Results

A large amount of AE data were collected from the experiment. Data were collected from the time that initial loads were placed on the cylinder until visual fatigue crack growth was seen. This ensured that data from the fatigue crack growth were collected. For one of the 7075-T6 aluminum cylinders, data were collected all the way through to final failure of the cylinder. This failure is described in detail later on. The first step taken in the analysis was to classify the AE data. After this was completed, the acoustic emission waveforms and the source location data were both examined to confirm the validity of the data classifications. The initial raw data are shown in Figures 12 though 15, the amplitude histogram, duration vs. counts, amplitude vs. average frequency, and amplitude vs. duration plots of the initial, unfiltered and unclassified data.
Figure 12. Amplitude Histogram of Unfiltered Data

Figure 13. Duration vs. Counts Graph of Unfiltered Data
Figure 14. Amplitude vs. Average Frequency Graph of Unfiltered Data

Figure 15. Duration vs. Amplitude Graph of Unfiltered Data
6.2 Classified Data

Many attempts at classifying data were made. These attempts were based past research, knowledge of the physics of failure, and knowledge gained through trial and error during initial classification attempts. At first it was attempted to classify the data without pre-filtering, in an attempt to reduce the number of steps that were required to analyze the data. However, it was quickly found that the data that was known to be noise due to the high average frequency was confusing the neural network, and making it impossible to get a clean classification. The number of classifications and the parameters used for classification were both varied to try and compensate for this, but it was eventually found that pre-filtering was necessary. The pre-filtering process that was used was based on work done Suleman, et al. [17]. Here initial high and low frequency filters were used to remove what was known to be noise. Although Suleman found that both high and low frequency filters were useful in the filtering of the data, using a low frequency filter removed desired data in this research, and therefore only a 1000 kHz filter was used. Eventually it was found that the optimal solution after filtering consisted of running a neural network to classify the data into three categories, then sorting these classifications again using neural networks into further classifications. This was used as filtering the data into the final classifications in one step seemed to confuse the neural network, and would not give as accurate classifications as using the two-step approach. The parameters that were used in the first of these neural networks were duration, amplitude and average frequency. Energy was used at times in the initial neural networks, but was found to give no better results than using amplitude. Additionally, attempts at using counts were also done, but this seemed to only confuse the neural networks. It should also be noted that using amplitude and average frequency gave results that were very similar to the classification that also included duration, but gave a
very distinct cutoff on amplitude, which resulted in some misclassifications. Using duration resulted in a more refined classification for the initial neural network. The second neural network, however, seemed to be optimal using only amplitude and average frequency. The software used to classify this data was NeuralWorks Professional II/Plus by Neuralware. The settings of the SOM neural network are listed in Table 3.

The initial results of this SOM gave an output that had three clearly defined categories. These categories were initially dubbed Mechanisms 1, 2 and 3, and then the properties of each were examined. The same four graphs used previously for the unfiltered data were created for the filtered data after classification. These plots are shown in Figures 16 through 19. All results in this section are given for 7075-T6 aluminum. A comparison to 2024-T3 aluminum is given in the next section.

<table>
<thead>
<tr>
<th>Setting Name</th>
<th>Setting Used</th>
<th>Setting Name</th>
<th>Setting Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inputs</td>
<td>2</td>
<td>Output Network</td>
<td>Off</td>
</tr>
<tr>
<td># Rows</td>
<td>3</td>
<td>MinMax Table</td>
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</tr>
<tr>
<td>3 Columns</td>
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<td>Neighborhood</td>
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<tr>
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</tr>
<tr>
<td>LCoef</td>
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<td>End Width</td>
<td>0</td>
</tr>
<tr>
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<td>Set From File</td>
<td>Wrap Around</td>
<td>Both Off</td>
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<tr>
<td>Beta</td>
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<td>Connect Prior</td>
<td>On</td>
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<tr>
<td>Gamma</td>
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<td>Connect Bias</td>
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<td>LCoef Ratio</td>
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<td>Epoch</td>
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<td>10000</td>
<td>Learn Rule</td>
<td>Norm-Cum-Delta</td>
</tr>
<tr>
<td>Coord. Layer</td>
<td>Off</td>
<td>Transfer Function</td>
<td>TanH</td>
</tr>
</tbody>
</table>
Figure 16. Amplitude Histogram of Filtered Data

Figure 17. Duration vs. Counts Graph of Filtered Data
Figure 18. Amplitude vs. Average Frequency Graph of Filtered Data

Figure 19. Amplitude vs. Duration Graph of Filtered Data
What was classified as Mechanism 3 in these data, upon closer inspection, appeared to be noise that was not filtered out during the initial frequency filtering. These noise data were removed from the rest of the data. Upon inspection of Mechanism 1 and Mechanism 2 it was determined that each of these were composed of two distinct classifications, making a total of four failure mechanisms. Hence, Mechanisms 1 and 2 were both classified again separately. These were both classified into two categories using amplitude and average frequency, but not duration. What was known physically about Mechanism 1 was that it would probably be a combination of fatigue cracking and rivet fretting. The classification of Mechanism 1 is shown in Figures 20 through 23.

![Amplitude Histogram – Rivet Fretting and Fatigue Cracking](image)

**Figure 20. Amplitude Histogram – Rivet Fretting and Fatigue Cracking**
Figure 21. Duration vs. Counts – Rivet Fretting and Fatigue Cracking

Figure 22. Amplitude vs. Average Frequency – Rivet Fretting and Fatigue Cracking
Figure 23. Amplitude vs. Duration – Rivet Fretting and Fatigue Cracking

The data that are shown as Mechanism 2 in Figures 14 through 17 were then determined to be a combination of plastic deformation and metal rubbing. This data was therefore classified on its own again into two categories, which are shown in Figures 24 through 27.
Figure 24. Amplitude Histogram – Metal Rubbing and Plastic Deformation

Figure 25. Duration vs. Counts – Metal Rubbing and Plastic Deformation
Figure 26. Amplitude vs. Average Frequency – Metal Rubbing and Plastic Deformation

Figure 27. Duration vs. Amplitude – Metal Rubbing and Plastic Deformation
6.3 Comparison of 2024-T3 and 7075-T6 Aluminum

The results shown in the previous section were specific to 7075-T6 aluminum. 2024-T3 aluminum was also tested in this research, and the results are shown in this section. The differences in the physical properties between these two types of aluminum result in the 2024-T3 aluminum being much quieter. This is to say that the amplitudes and number of fatigue cracking hits in the 2024-T3 will be much lower than in the 7075-T6 aluminum. These differences were seen clearly in the resultant plots that were made after classifying both types of aluminum. Because of these differences, it is not recommended to train a neural network on one of these types of aluminum and then test on the other. Instead, separate neural networks should be used for failure mechanism classification in each type of aluminum. The same four plots that were used for the 7075-T6 aluminum are shown again for the rivet fretting and fatigue cracking data for the 2024-T3 aluminum (Figures 28 though 31).
Figure 28. Amplitude Histogram - 2024-T3 Aluminum

Figure 29. Duration vs. Counts - 2024-T3 Aluminum
Figure 30. Amplitude vs. Average Frequency - 2024-T3 Aluminum

Figure 31. Duration vs. Amplitude - 2024-T3 Aluminum
6.4 Acoustic Emission Waveforms

Once the data were sorted into the four final categories, the waveforms were examined in order to see the typical waveform that was created by each of these acoustic emission sources. Using the above classification, the following waveform, shown in Figure 32, was found to be a good representation of a fatigue crack growth signal. Figure 33 shows a typical plastic deformation waveform. The waveforms for the other two mechanisms examined, rivet fretting and metal rubbing, are similar to the two shown. The main difference is that these have longer duration than the two waveforms shown, as these mechanisms are usually much longer in length than either plastic deformation or fatigue crack growth.

![Figure 32. Typical Fatigue Crack Waveform](image)
6.5 Source Location

There are two types of Lamb waves that are produced during the testing of the cylinder, symmetric \((s_0)\) plane strain (Mode I tensile fracture) extensional waves and anti-symmetric \((a_0)\) plane stress (Mode III tearing fracture flexural) waves. In the first part of testing, when the fatigue crack is small, the waves that will be seen are Mode I extensional waves. The other waves generated by fatigue crack growth late in life are the Mode III flexural waves associated with ductile tearing just prior to final failure. Both Lamb wave types are shown in Figure 34. Each of these waves travels at its own group velocity, which can be determined from the dispersion curves for aluminum of Figure 35.
Figure 34. Lamb Waves [18]
The transducers used in this experiment were 150 kHz resonant AE transducers, and the thickness of the aluminum used was 0.0040 inches, or 0.1015 mm. Using these values in the equation

\[ x = tf \]

the frequency dispersion value for the test cylinder can be determined as follows:

\[ x = (0.1015)(0.150) = 0.0152 \text{ mm-MHz} \]

Using this value in Figure 35, the first anti-symmetric \((a_0)\) wave speed is determined to be 2.8 km/s or 110, 240 in/s, and the first symmetric \((s_0)\) wave speed is 5.4 km/s or 212, 600 in/s.
For source location, the first symmetric wave, $s_0$, will be the one captured by the data acquisition system, as it is the first to reach the sensors. This wavespeed was used in conjunction with the source location algorithm built into the multi-channel AE analyzer system to find a location for each acoustic emission signal or hit captured during testing. The graph of the source location data indicated a grouping of hits around the expected source of fatigue crack growth, the stress concentration notch. There were also other groupings on this graph, each of which indicated another source of noise. By comparing the output of groupings given by this source location chart to the groupings given by the neural networks, it was possible to validate that the source of the expected crack growth was indeed the region of the stress concentration notch.

6.6 Cylinder Failure

As mentioned previously, one of the 7075-T6 cylinders was tested all the way to failure. When a part nears failure, the waveforms and acoustic emission parameters change as the crack begins to emit much more energy during this time of rapid fatigue crack growth. Since the goals of this research were to be able to detect and monitor fatigue crack growth in its early stages, the data from the time close to failure were not used in any classification of the data. However, this failure and the data collected from it were examined in order to see what differences appear as the test vessel neared failure. A photograph of the failed cylinder is shown in Figure 36.
6.6.1 Failure Mechanisms

There are three main modes of crack growth in metal. These modes, known as Mode I, II, and III, are displayed in Figure 37. The two modes of fatigue crack growth that were seen in this research were Modes I and III.
Mode I Cracks

Mode I cracks are plane strain tensile cracks. In this scenario, the force in the crack opening direction is much larger than the force in the other two directions. For these types of cracks, it is assumed that the strain in one direction is large enough that the other (much smaller) strains can be assumed to be zero in comparison. Therefore, this type of failure results in the metal fracturing in only one direction and in a single plane. A typical diagram of plane strain is shown in Figure 38.
Mode III Cracks

Mode III cracks are plane stress or tearing shear cracks. In these cracks, the force is assumed to act primarily perpendicular to the thin dimension of the plate. This results in the tearing apart of the plate rather than the pulling apart seen in Mode I cracking.

6.6.2 Failure Description

As the cylinder was tested, a crack began to grow vertically from the point of stress concentration on the cylinder. This crack grew slowly, taking approximately twelve hours to become visible. It continued to grow for approximately eight more hours, increasing in the rate at which it was growing, until it was approximately two inches in length. During this time, the crack was composed almost entirely of Mode I cracking. At this point, the main cylinder was being pushed away from the patch during each pressure cycle. This placed an increasing load on
the rivets holding the patch plate to the cylinder. At the end of the testing, the top left rivet failed, with the rivet head breaking off and therefore no longer supporting any load. At this point the crack rapidly extended to the top of the cylinder, and the only thing holding the cylinder together was the portion below the hole. From later analysis of the cylinder, it was theorized that two fatigue cracks started growing almost simultaneously: one from the bottom of the hole and the other from the bottom of the cylinder. The crack at the bottom of the hole began to grow downward, and the crack at the bottom of the cylinder began to grow upward. These two started out on paths that would not intersect, but after growing for a few inches, each changed direction and grew toward each other until they met, resulting in total failure of the cylinder. The time from the rivet failing to the failure of the cylinder was less than one second. This critical fatigue crack growth at the end of life of the cylinder was all Mode III cracking.

6.6.3 Failure Data

The following data were collected from the acoustic emission testing during the time just prior to failure. Figures 39 through 42 show the same graphical representations used previously. The main change between this data is the addition of high amplitude data to what was already present in the previous tests. This data, which ranges up to about 66 dB, is the higher energy waves that are produced by the unstable crack growth at the end of the cylinder’s life.
Figure 39. Amplitude Histogram of Failure Data

Figure 40. Duration vs. Counts Graph of Failure Data
Figure 41. Amplitude vs. Average Frequency Graph of Failure Data

Figure 42. Amplitude vs. Duration Graph of Failure Data
7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

From this research it is clear that acoustic emission NDT is a viable method for monitoring an aircraft for fatigue cracking while in flight. Just as AE has been used successfully in many other applications for real time crack growth monitoring, it can be used in this application for in-flight monitoring. However, it is important to first understand the potential problems associated with this method. It is crucial to identify, based on what is known about the physical properties of the material and the failure mechanisms, what data recorded is useful data and what is noise. Appropriate filters must be applied to the data in order to remove unwanted noise data. The type and level of these filters will vary for different applications.

The Kohonen self organizing map (SOM) neural network was a critical tool in this process. The evolution of computer technology since the first attempts at collecting and classifying acoustic emission data have made it now much easier to collect and analyze the large amounts of data generated. The unsupervised soft learning that is possible with the SOM software now available allows for accurate classification of data, assuming that it is first filtered properly to remove any noise. However, it must also be stressed that only through a proper understanding of the physics of failure of the material being tested can the classification of the SOM outputs be fully understood.

Waveform frequency analysis is much more labor intensive that simply analyzing AE parameter data from the time-domain waveforms. However, it is possible to use frequency-domain analysis as a validation for the classifications obtained based on the AE quantification parameters. Since the difference between a clearly defined acoustic emission hit emanating from a source such as fatigue crack growth and a waveform caused by noise is very easily seen, this
provides another good validation technique. Additionally, this allows for a better understanding of the physics behind each acoustic emission wave collected.

Finally, source location is also a valuable tool for use in conjunction with the AE parameters. This can further validate that the data collected is being emitted from the expected source of acoustic emission. Additionally, during in-flight monitoring, this could be used to determine the location of a fatigue crack that is growing due to loads placed on the aircraft in flight.

It was also seen that these classifications were an improvement over the earlier fatigue crack classification efforts accomplished at ERAU [12-15]. This was due to advances in computer technology since this previous research, as well as advances in neural networks and improved initial filtering of noise data. Additionally, the present research was able to combine the research efforts done previously by using the AE parameters as the primary classification, and then source location and waveform verification to validate the results.

7.2 Recommendations

There are multiple extensions that can be done to carry on this project in the future. One potential next step would be to combine information about the pressure of the cylinder with the acoustic emission parameter data – counts, amplitude, duration, rise time, and energy. Since fatigue crack growth should occur only when the cylinder is at maximum load/pressure and plastic deformation occurs on crack closure or at minimum load/pressure [20], this could lead to an even better understanding and classification of each of the AE signals collected during testing. The eventual goal of this research would be to place acoustic emission sensors on an aircraft to detect and monitor fatigue crack growth during flight.
8. REFERENCES


