In-Flight Fatigue Crack Monitoring of an Aircraft Engine Cowling

Samuel Gordon Vaughn III

Embry-Riddle Aeronautical University - Daytona Beach

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In-Flight Fatigue Crack Monitoring of an Aircraft
Engine Cowling

by

Samuel Gordon Vaughn III

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, Florida
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In-Flight Fatigue Crack Monitoring of an Aircraft's

Engine Cowling

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Samuel G. Vaughn III

This thesis was prepared under the direction of the candidate's thesis committee chairman, Dr. Eric v. K. 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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ACKNOWLEDGEMENTS

Applying the skills and knowledge I have acquired at Embry-Riddle Aeronautical University to an actual research assignment such as the analysis of a Piper Cadet engine cowling has been a very enriching experience. It presented all the challenges I had expected and more. This thesis also yielded a great deal of reward and satisfaction as pieces of the research fell almost fortuitously into place.

First and foremost I would like to thank Dr. Hill for providing me the opportunity to pursue my Master’s degree here at Embry-Riddle. He has been a tremendous mentor to me for the past several years, encouraging and challenging me with my education, as well as being a kind and caring friend. Dr. Hill epitomizes what a teacher and educational advisor should be, always keeping things in a realistic perspective with just enough imagination to allow my goals and dreams to shine through. Also I would like to extend a large thank you to fellow graduate student Chris Rovik who sacrificed much time and effort in helping me with this research. Chris always was willing to lend an ear or a hand to whatever he could to help, and for that I am very grateful. Thanks especially to my wife Christine for all her encouragement and help. She has kept me pressing on even when times were frustrating, always keeping things in perspective for me. I would also like to extend thanks to Professor Bishop for his insight to my research into physics and for giving me a much better grasp and understanding of physics both through my teaching assistantship and in passing conversation.
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Finally, a thank you is extended to my thesis committee members, for their criticisms and help in getting my defense completed.
ABSTRACT

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Institution: Embry-Riddle Aeronautical University
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This research investigates the feasibility of implementing an in-flight fatigue crack monitoring system in an airplane to identify fatigue crack growth. An acoustic emission data acquisition system coupled with a Kohonen self organizing map neural network were used to perform the analysis.

Fatigue cracking was responsible for ripping the top of a fuselage off of an Aloha Airline’s Boeing 737-200 as it carried passengers over the Pacific Ocean, killing some aboard. This tragedy is perhaps a precursor of problems to come, as our nation’s aircraft age. These planes experience fatigue as they perform their daily routine of ferrying passengers from location to location. Fatigue can initiate cracking within the aircraft’s structure and at least damage a small expendable part of the plane, or at most damage a vital part of the airplane leading to disaster as happened to the Aloha Airline’s flight.

In an attempt to curb this sort of devastation, this research involves the development of an in-flight fatigue crack monitoring system. Such a system would have the ability to identify possible crack sources before the crack would have the chance to cause significant damage. Advantages of this type of system would be first, an obvious safety cushion, and second, lower maintenance costs because routine parts replacement and inspection could be minimized.
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1.0 INTRODUCTION

Aircraft continuously experience structural fatigue when in flight or while taxiing. This fatigue has initiated and or sustained fatigue crack growth within aircraft structures dating from when airplanes were constructed of wood all the way up to today when aircraft are made from high strength aluminum, titanium alloys, and composites. As with any structural damage, fatigue cracking could ultimately lead to structural failure which could possibly lead to loss of life and definitely loss of money. In an attempt to minimize the costly, mandatory inspections of aircraft structures and eliminate the element of not knowing the status of an aircraft’s structural integrity, a dynamic in-flight crack monitoring system was developed as a possible solution. The scope of this research was to determine whether or not a fatigue crack monitoring system could serve as an in-flight crack detection system. This research involved the use of acoustic emission equipment to monitor the cowling of a Piper Cadet aircraft in flight and a Kohonen self organizing map neural network to classify this acoustic emission data and ultimately determine if and when cracking was occurring.

Webster defines fatigue as “weariness from physical or mental exertion”. Relating to that physically, an athlete becomes fatigued while performing a vigorous workout, his body and mind fatigued from the added work load. Similarly physical structures are subject to a fatigue process due to the work done on them. An airplane for example is a complex structure which has work done on it by various aerodynamic, inertial and thermal loads. Those loads act in a cyclic fashion to fatigue the structure and initiate microscopic
damage on the crystalline level. Eventually this microscopic damage, leads to macroscopic damage of the structure. Acoustic emission sensing equipment gives the engineer an opportunity to "listen" to the structure as it is subjected to those loads during this fatigue process to determine if damage is being done to the structure and where it is occurring. A valuable element of this type of damage detection is that acoustic emission can detect the damage as it is occurring on a microscopic level. Detecting damage at that point will allow for repairs to be made before any structural degrading macroscopic damage takes place.

As mentioned earlier, the engine cowling of a Piper Cadet aircraft was used as the testing platform for gathering the acoustic emission data. Pictured in Figure 1.1 is the Piper Cadet aircraft with the cowling identified to give perspective of where on the aircraft the test data were acquired. It should be noted here that the fatigue cracking observed in this part was not critical to the airworthiness of this airplane.

Figure 1.1 Diagram of Piper Cadet aircraft with an enlarged front view.
This particular region of the aircraft was chosen for two reasons. First, the cowling undergoes a large amount of fatigue due to the turbulent aerodynamic loads applied to it by the air passing through the propeller. Secondly, it was noticed that the cowling on this particular aircraft already had some macroscopic cracking occurring. Therefore the chances of "hearing" crack growth signals on this part of the aircraft were very good. After the cowling was chosen to support the test, the number and placement of the acoustic emission transducers was determined. Four transducers were chosen, two on the right hand side (looking at the plane from the front) equidistant from an existing crack, and two on the left hand side of the cowling where there was no apparent cracking. The symmetric configuration and placement of the transducers on the underside of the cowling is shown in Figure 1.2. This photograph was taken during acoustic emission transducer installation.

![Figure 1.2 Underside of engine cowling during transducer installation.](image)
After the airplane was properly configured with the acoustic emission equipment it was flown through a series of three flights on three different days. On each flight the airplane went through a series of standard maneuvers during which the acoustic activity of the cowling was recorded and correspondingly tagged as to the particular maneuver. It was hoped that this information would shed light on whether cracking was indeed occurring, and also during which maneuvers cracking was more likely to occur. Following the acquisition of the in-flight data, a laboratory test under controlled conditions was performed.

This lab test involved an aluminum test specimen which was subject to fatigue loading while being monitored with acoustic emission equipment. The purpose of this lab test was to generate an acoustic emission signature for cracking of an aluminum alloy similar in composition to that of the Cadet's engine cowling. That acoustic emission signature would then be compared to the in-flight data to determine whether cracking was occurring during the in-flight test of the Piper Cadet. Details of this lab test and analysis of its results will follow.

After the data acquisition took place for both the tests, a Kohonen self organizing map neural network was trained with the data from the lab test to identify cracks and tested with the in-flight data to determine if there were cracks occurring during flight. A detailed overview of acoustic emission will provide an understanding of this type of technology and explain why it was chosen to be implemented for this application. Then the how and why of the neural networks will be covered, followed by an extensive analysis of the results recorded in the tests. Ultimately this will determine whether a fatigue crack monitoring system within an aircraft can in fact detect and properly monitor aircraft
structures in flight. Figure 1.3 below shows a flow chart of the entire process from the gathering of the acoustic emission data to the analysis of results utilizing a neural network.

Figure 1.3 Flow chart of the data analysis process.
2.0 ACOUSTIC EMISSION

Acoustic emission is a unique and powerful nondestructive testing tool. Nondestructive testing is a desirable means of testing because, as the name suggests, nothing destructive has to be done to the test article to carry out the actual tests. The test subject simply assumes its regular function and is monitored in service. Acoustic emission, being one of many nondestructive testing methods, further appeals in this sort of testing because of its ability to monitor globally. In the scenario of this cowling test two localized regions were monitored, but as this sort of technology is applied to aircraft abroad, it should be able to monitor a global region of an aircraft and locate a crack if one should occur. Another important advantage of acoustic emission is that it allows for testing to be performed remotely and in the case of monitoring the underside of the engine cowling this remote ability is necessary because of limited access to this part of the aircraft’s structure.

2.1 Acoustic Emission Terms

Acoustic emission is a transient elastic wave generated by the rapid release of energy within a material. These waves are emitted from a source, propagate through a medium, are sensed by an acoustic emission transducer, and are recorded by a computer with data acquisition capabilities. Shown in Figure 2.1 is a sample waveform that an acoustic emission software package would record.

That rapid release of energy can have many sources, and these various sources coupled with attenuation and specimen resonances, are what complicate acoustic emission.
analysis. For this analysis only three sources were considered: plastic deformation, cracking, and rubbing. Realistically speaking each one of these sources could be further broken down; however, for this research all that is of concern is if there is cracking occurring and when. A typical problem associated with acoustic emission testing is separating the desired crack data from plastic deformation, rubbing, and any extraneous noises. There are steps that can be taken to minimize some of these undesired sources. First, the data acquisition software maintains a threshold that will only record waveforms that exhibit usable amplitude characteristics of those desirable sources. This acts to eliminate unwanted low amplitude signals. Another “noise filter” can be the acoustic emission transducer itself. Some transducers are resonant transducers, registering frequencies predominantly within a limited dynamic range depending on the resonant range of the transducer. These tests employed wideband rather than resonant transducers which had frequency responses from 100 kHz to 1 MHz, since prior to this testing the exact characteristics of cracking were not known. Therefore a resonant frequency that should be chosen for the equipment was not known. On future tests, however, knowing the predominant frequency of a cracking signal in this type of material will allow for the use of resonant transducers. As mentioned above, this will give the testing system a better ability to key in on the particular cracking signals and filter out some of the unwanted noise.

Figure 1 is a representation of a sample acoustic emission waveform. Six important waveform characteristics used in the neural network analysis are energy, duration, counts, counts to peak, amplitude, and risetime. Noted on the waveform in
Figure 2.1 are these six acoustic emission quantification parameters. These and a few other acoustic emission terms are defined below.

Figure 2.1 A sample acoustic emission waveform (Nondestructive Testing Handbook).

- **Amplitude** - the largest voltage peak in the waveform signal.
- **Energy** - proportional to the integral of the voltage of the waveform squared.
- **Duration** - the time elapsed from when the waveform initially crosses the threshold until the crests of the waveform drop beneath the threshold.
- **Counts** - the number of times the waveform crosses the threshold when moving upward.
- **Cnts to Peak** - the number of counts to the highest amplitude.
**Risetime** - the time elapsed from when the waveform initially crosses the threshold unit it reaches it's peak amplitude.

**Threshold** - the minimal amplitude signal recorded (dB).

**Hit** - an acoustic emission waveform received by a transducer.

The acoustic emission parameters defined above were used to determine the source mechanism, whether it was a crack, plastic deformation, rubbing, or some kind of noise.

### 2.2 Acoustic Emission Hardware

The hardware necessary for acoustic emission analysis includes acoustic emission transducers and a computer with data acquisition capabilities. For the in-flight tests four Physical Acoustics Corporation (PAC) WDI wideband transducers were used. These particular transducers are labeled wideband because they have a frequency response from 100 kHz to 1 MHz. In most cases wideband transducers would not be used in an environment with so much noise; however, the main purpose of this research was to determine whether or not acoustic emission crack signals could be separated from other signals amidst a lot of noise. The transducers were connected to a data acquisition card in an IBM PC compatible computer loaded with the software package MISTRAS. For more specifications of the hardware or test settings see Appendix C. Throughout the tests MISTRAS was employed to record the data from these four transducers. After the data acquisition took place MISTRAS was further used to analyze the recorded data. The analysis was carried out by playing the data back on plots that were configured to view the various acoustic emission parameters and demonstrate how they interact with one another. In Figure 2.2 is pictured an example of how those plots that are generated by MISTRAS
are formatted. This particular graph is a duration versus amplitude plot of an in-flight data file. This particular plot will be cited later in the report to demonstrate how the ranges of signals compare between the lab and in-flight test data files.

Figure 2.2 An in-flight hits vs. amplitude acoustic emission plot.
This particular graph was used extensively in the classification of the lab test data. It was very valuable because the two parameters that were used, duration and amplitude can be physically defined to pre-identify what cracks, plastic deformation, and rubbing signals look like with respect to one another. Table 2.1 lists these three acoustic emission source mechanisms along with their corresponding duration and amplitude characteristics. Applying the information in this table to the data recorded from the lab test gives a means of identifying cracks, plastic deformation, and rubbing, and allows for the second step of the data analysis process, neural network analysis.

Table 2.1 Waveform characteristics of various acoustic emission sources.

<table>
<thead>
<tr>
<th>AE Source</th>
<th>Duration</th>
<th>Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crack</td>
<td>Short</td>
<td>High</td>
</tr>
<tr>
<td>Rubbing</td>
<td>Long</td>
<td>Low-High</td>
</tr>
<tr>
<td>Plastic Deformation</td>
<td>Short</td>
<td>Low-Medium</td>
</tr>
</tbody>
</table>
3.0 NEURAL NETWORKS

A neural network is a computer program that mimics the processing of the human brain, hence its name. Various neural network types are used to perform a variety of tasks. In this research an identification process was desired, therefore, a neural network that had the ability to classify data into separate groups was chosen. This particular classification network is called a Kohonen self-organizing map (SOM) neural network.

3.1 Kohonen Self Organizing Map (SOM)

The SOM, like other neural networks, is comprised of neurons which are linked together mathematically depending upon how the overall architecture of the map is designated. First, there is an input array in which the number of input neurons exactly match the number of parameters that are to be tested, in this case, the input parameters were the six acoustic emission parameters measured by MISTRAS. Following the input array, is the Kohonen processing layer or matrix. This matrix is described in planar dimensions as 2X2, 5X5, or maybe 1X3. The dimensions determine the overall resolution of the SOM as it processes the input data. A large dimensional map yielding high resolution may seem desirable because of the increased sharpness of the overall picture, but for this test and many others that deal with a low number of classification possibilities, too much resolution can lead to misclassification. Therefore, optimum dimensions for the SOM processing layer had to be determined to ensure proper classification. The size of the SOM was determined by training and testing the SOM with...
known data so that a percentage of correct classification could be determined. For this research a 1 X 3 Kohonen processing layer was used (Figure 3.1) such that there were only three classifications available for the data. This SOM structure was chosen such that

- the first neuron would classify the crack signals,
- the second neuron would classify the plastic deformation signals,
- and the third neuron would classify the rubbing and noise signals.

In a basic sense, the input layer and the Kohonen processing layer make up the SOM in its entirety. Although in the case of this test an additional output layer was used. The responsibility of the output layer was to assign an (x,y) coordinate to the information processed by the SOM so that it could be graphed using a spreadsheet after it was classified. All the classification, however, takes place solely between the input layer and the SOM layer.

In Figure 3.1 a one row by three column SOM similar to that used in this test is pictured showing all the connections or weights between the neurons, excluding the output layer. If there was an output layer in the figure, two neurons would be pictured above the Kohonen layer with connections between them and the SOM. The connections between the layers which are represented by lines in the figure are weights that the neural network adjusts as it is being updated by the training input. These weights are initially set randomly between zero and one, and then they are updated as the neural network goes through its training process.
3.2 Training and Testing the SOM

There are two stages involved in using a SOM neural network: the first is training of the SOM, and the second is testing the SOM. A comprehensive example of this training process can be found in Appendix B. Initially in the training process the weights of the neurons within the SOM are randomly set between zero and one. Then an input vector with one set of the chosen acoustic emission parameters is brought to the input layer. Planar geometry is used to calculate which neuron in the SOM layer has the smallest squared planar distance to the input vector. The neuron that has the smallest distance is declared the winner and is awarded that input vector. Before another input vector is considered, the winning neuron and its corresponding neighboring neurons, depending on the desired settings within the software program, update their weights to make them closer represent the winning input vector. This process continues over and
over until all the input vectors in the data set are considered and the SOM is configured as to which input is going to be classified by which neuron. A neural network that trains in this fashion is said to be unsupervised since the output is left entirely up to the neural network. In the case of some neural networks, a desired output is given with the input and the network’s responsibility then is to find the proper relation between the input and output. Training can be described as the stage where the baskets for apples are made to hold apples and the baskets for watermelons are made to hold watermelons.

After the network is trained, all the calculated weights remain constant and the network is ready to be tested. The testing stage of the neural network is a process of passing data through the trained network in order to classify it. The data that is sent through the network is in the same form as the data that was trained, the only difference between training and testing is, instead of updating the network as it is classified, the testing data is only classified according to how the network was trained. After all the data is tested, the output can then be analyzed in a spreadsheet or by graphical format to draw conclusions on what the acoustic emission test recorded and how the neural network classified it.
4.0 RESULTS

The analysis of the data took place in two stages with two separate technologies, acoustic emission and neural network. First, acoustic emission data taken from the lab test were analyzed and separated, into failure mechanisms, whereupon the lab test data were used to train a SOM neural network. Second, the in-flight data were processed through that trained neural network and classified. The following is a discussion of how those two stages were completed and what considerations went into completing them.

4.1 Lab Test Analysis

The lab test consisted of over twenty individual acoustic emission files. These files were all from one continuous fatigue test that was performed on a 7075-T6 aluminum test specimen. For the majority of the test, the aluminum specimen did not undergo cracking. Toward the end of the test, during the twentieth file, the specimen did start to crack. The cracking was monitored visually and audibly as it grew over a period of about a minute and thirty seconds. Figure 4.1 shows the fatigue test specimen mounted in the shaker table prior to the test. This picture also shows the stress concentration notch at the center, and the two acoustic emission transducers mounted on either side of the notch. The left side of the test specimen, as pictured in Figure 4.1, was secured to a fixed metal standard, while the right side was fastened to the shaker table. The shaker table was cycled between 1 to 3 Hz throughout the lab test to simulate a fatigue loading.
After the testing was completed, file twenty was selected as a file that would be of interest because the acoustic emission analysis should include cracking activity that was physically observed during that segment of the test.

File twenty recorded over seventy-eight thousand acoustic emission hits over three and a half minutes. Thus, the quantity of the hits was not lacking, and the quality turned out to be equally as good. The file offered excellent separation of rubbing, cracking, and plastic deformation hits. As the test was observed in real time through MISTRAS, a duration vs. amplitude plot demonstrated this distinct separation. As the file was replayed, from the beginning there were growing regions of plastic deformation and rubbing evident
but no cracking. Then at about two minutes and five seconds into the file a third region of acoustic activity became visible on the duration vs. amplitude plot, and as expected, this high amplitude, low duration data proved to be the cracking region. The initiation of cracking at this time during the replay of the file was consistent with the time that cracking was physically observed as the test was actively being monitored.

Figure 4.2 Duration vs. amplitude plot of file twenty.
In Figure 4.2, the duration vs. amplitude plot from file twenty is shown in its entirety. Highlighted on the plot are the three acoustic emission regions of interest.

An accompanying MISTRAS utility program, ATPOST, which allows acoustic emission files to be filtered based upon their recorded parameters, was then used to separate the three regions of interest so that cracking could be individually examined. Table 4.1 lists the filtering limits set to filter the three regions. These limits correspond to the guidelines assumed in Table 2.1 as to which characteristics crack, rub, and plastic deformation signals would possess.

Table 4.1 Filtering limits used in ATPOST for the three mechanisms.

<table>
<thead>
<tr>
<th>Mechanism</th>
<th>Duration (μs)</th>
<th>Amplitude (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crack</td>
<td>0-6,000</td>
<td>65-100</td>
</tr>
<tr>
<td>Rub</td>
<td>6,000-32,000</td>
<td>30-70</td>
</tr>
<tr>
<td>Plst. Def.</td>
<td>0-6,000</td>
<td>30-65</td>
</tr>
</tbody>
</table>

After the three acoustic emission sources were separated, the data was ready to train the neural network. Before the training took place, however, the cracking region of file twenty was examined more closely to get a better understanding as to the type of cracking that was occurring. This process involved generating some new plots that would monitor other characteristics of the cracking process. The plots that were generated to perform this task were duration vs. amplitude, duration vs. counts, and counts vs. energy as shown in Figure 4.3. These post-processed “crack only hits” were further separated in Figure 4.3 by channel. Channel 1, or the channel closest to the shaker table and closer to the crack, is given by the three plots on the left. Correspondingly, Channel 2, or the transducer closer to the fixed end of the test specimen and further from the crack, is
pictured in the right three plots. The counts vs. energy graphs at the bottom gave a very interesting and unexpected picture of the crack region as it grew through file twenty.

Figure 4.3 File twenty filtered to contain only crack data.
First as the crack was initiated and began to grow in the aluminum test specimen (Figure 4.4), it propagated vertically downward for about one minute and five seconds. Then the crack stopped its vertical propagation and changed to a forty-degree orientation and continued propagating in this new direction for the last twenty-five seconds of the test.

Figure 4.4 Planform of the aluminum test specimen highlighting the crack.

The counts vs. energy plot for Channel 2 (Figure 4.3) gives an interesting picture of the crack growth as a second region developed separately. This region corresponds to the cracking that was occurring for the last twenty-five seconds of the test. Upon
initiation of the crack at two minutes into the file, acoustic emission energy in the form of extensional Lamb waves emanated from the source. Then at three minutes and five seconds into the file, the crack source changed from an extensional mode to a flexural mode. The individual characteristics of these two wave types coupled with the fact that Transducer 2 was further from the source than Transducer 1 explains why there is a separate region on the Channel 2 counts vs. energy plot.

Lamb waves are acoustic emission waves that propagate through thin plates. One distinct characteristic common to both Lamb wave modes, extensional and flexural, is that their speed of propagation is dependent upon frequency. The wave speed of the extensional waves in this test was calculated to be 5500 m/s, and the wave speed of the flexural waves was 2500 m/s (Appendix D). Unlike other acoustic emission energy whose velocities are not frequency dependent, Lamb waves exhibit a large amount of dispersion as the energy propagates through a medium. This dispersion acts to separate the different wave groups, as their frequency variations cause them to propagate at different velocities with respect to one another. It turns out that this physical phenomenon of dispersion was, in part, responsible for the development of the second region on the counts vs. energy plot (Figure 4.3).

The additional factor that was responsible for the second region on the counts vs. energy plot was the asymmetric spacing of the acoustic emission transducers which made a longer path of travel for the acoustic emission energy as it propagated to Channel 2. The distance from the source to channel two was 89 mm as compared to 36 mm to Channel 1. Although this does not seem like a very large interval on the macroscopic scale, to an acoustic emission signal traveling between two and six thousand meters per
second, the larger interval can allow for some separation and dispersion as different waves propagate at different velocities. In the case of this fatigue test, that is exactly what had happened.

Upon initiation, vertical propagation of the fatigue crack was occurring, and its associated acoustic emission was in the form of extensional Lamb waves. This type of emission continued until the crack changed into a tearing or shearing crack which propagated at a 45 degree angle to the primary crack. With the change in direction, a change in cracking mode also took place, instead of extensional waves being emitted from the source, flexural waves with a lower speed of propagation were emitted. Table 4.2 lists some characteristics of the acoustic emission as it propagated through the medium.

Table 4.2 Acoustic emission parameters associated with the two crack modes.

<table>
<thead>
<tr>
<th>Channel #</th>
<th>Time (m:ss)</th>
<th>Total Hits</th>
<th>Avg. Counts</th>
<th>Avg. Energy</th>
<th>Avg. Duration</th>
<th>Avg. Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel 1</td>
<td>1:55&gt;3:05</td>
<td>264</td>
<td>372</td>
<td>365</td>
<td>3508</td>
<td>84</td>
</tr>
<tr>
<td>Channel 2</td>
<td>1:55&gt;3:05</td>
<td>259</td>
<td>433</td>
<td>393</td>
<td>3535</td>
<td>82</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Channel #</th>
<th>Time (m:ss)</th>
<th>Total Hits</th>
<th>Avg. Counts</th>
<th>Avg. Energy</th>
<th>Avg. Duration</th>
<th>Avg. Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel 1</td>
<td>3:05&gt;3:30</td>
<td>63</td>
<td>327</td>
<td>183</td>
<td>2499</td>
<td>82</td>
</tr>
<tr>
<td>Channel 2</td>
<td>3:05&gt;3:30</td>
<td>72</td>
<td>437</td>
<td>181</td>
<td>2988</td>
<td>79</td>
</tr>
</tbody>
</table>

Table 4.2 shows an average increase in counts on Channel 2 when the flexural waves are being recorded. This increase in counts at a lower energy is responsible for the development of the second region on the counts vs. energy plot on Channel 2. This interesting phenomenon was noted because as this sort of testing progresses, identifying the type of crack waves could be vital in determining where and what the source is.
One final point before the in-flight test analysis can take place is whether or not the acoustic emission from the lab test is directly comparable to the in-flight test because of their material differences. The cowling was constructed of 2024-T3 aluminum, whereas the aluminum used in the lab test was a more brittle 7075-T6. For the neural network to be able to test the in-flight data properly, the lab test data used to train the network must be within the same range. Figure 2.2 is a duration vs. amplitude plot for an in-flight test that included cracking, rubbing, and plastic deformation. This plot shows the cracking and plastic deformation regions share similarities in both duration and amplitude to the lab test. Rubbing also is comparable to the lab test; however, some of the durations recorded in the in-flight test as seen on Figure 2.2 have a higher amplitude than those recorded during the lab test. This should not present a problem though, since duration can be used unambiguously to separate rubbing from cracking and plastic deformation. The acoustic emission settings for both the lab test and in-flight tests can be found in Appendix C. With the acoustic emission data from the lab test identified and tagged, it was ready to be used to train the neural network.

4.2 In-Flight Data Analysis

The last step of acoustic emission analysis was the first step in the neural network analysis. This was the process of generating a training file for the SOM neural network. The training file was comprised of one hundred random cracking, rubbing, and plastic deformation hits for a total of three hundred acoustic emission hits from the lab test. As indicated, these hits were random hits, so the training file included activity from all over the regions of the three acoustic emission sources. The dimensions of the Kohonen
processing layer were selected to be one row by three columns (1X3). This particular network proved to have a ninety-nine percent correct classification rate when it was tested on the remaining seventy thousands hits from the lab test file twenty. Other networks of larger dimensions (3X3, 4X4, 5X5) proved to misclassify due to their increased resolution.

With the 1X3 network trained, selected files of the in-flight data were tested. The files selected were chosen by maneuver, channel, and date. First, the aircraft maneuvers that were tested were taxi, takeoff, climb out, steady level flight, and final approach. These maneuvers were chosen because they are typical maneuvers that an airplane executes on every flight. Also the files were chosen by channel so that the non-crack side (Channels 3 and 4) could be unambiguously compared to the crack side of the cowling (Channels 1 and 2). Finally the date was the last parameter in choosing which files to analyze. By taking files from each of the three days both sides of the cowling were tested twice with the SOM neural network. Tables 4.3, 4.4, 4.5, and 4.6 list the results of the neural network data processing.

Table 4.3 Neural network data from the crack side of the engine cowling (Day 1).

<table>
<thead>
<tr>
<th>Maneuver</th>
<th>File</th>
<th>Time (mm:ss)</th>
<th>Total hits</th>
<th>Crk hits</th>
<th>%</th>
<th>Rub hits</th>
<th>%</th>
<th>Pist. Hits</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi</td>
<td>ft925016</td>
<td>00:25.0</td>
<td>16373</td>
<td>771</td>
<td>4.7</td>
<td>502</td>
<td>3.1</td>
<td>15099</td>
<td>92.2</td>
</tr>
<tr>
<td>Take-Off</td>
<td>ft925004</td>
<td>00:57.0</td>
<td>16734</td>
<td>496</td>
<td>3.0</td>
<td>648</td>
<td>3.9</td>
<td>15229</td>
<td>91.0</td>
</tr>
<tr>
<td>Climb Out</td>
<td>ft925006</td>
<td>00:57.0</td>
<td>234</td>
<td>0</td>
<td>0.0</td>
<td>233</td>
<td>99.6</td>
<td>1</td>
<td>0.4</td>
</tr>
<tr>
<td>Steady Level Flight</td>
<td>ft925008</td>
<td>00:32.0</td>
<td>132</td>
<td>0</td>
<td>0.0</td>
<td>132</td>
<td>100.0</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>Final/Touch and Go</td>
<td>ft925014</td>
<td>01:08.0</td>
<td>287</td>
<td>1</td>
<td>0.3</td>
<td>285</td>
<td>99.3</td>
<td>1</td>
<td>0.3</td>
</tr>
</tbody>
</table>
The data in the tables displays the number of crack hits, rub hits, and plastic deformation hits, as well as what percentage of the total hits each source was for that particular file. As expected, Channels 1 and 2 show cracking occurring throughout the flight, predominantly during taxi, takeoff, and final approach. The data indicate that cracking and plastic deformation occur predominantly on the ground when the airplane is preparing for take-off or landing. It is during this time that the airplane experiences a
large amount of vibrations because of the hard contact with the ground. When the airplane is in flight, vibrations from the engine or aerodynamic loads can be readily transmitted to the air with out much reflection. On the ground the same vibrations are transmitted through the landing gear and reflected back into the structure of the aircraft. Prior testing on F-16’s and F-111 military aircraft demonstrated similar fatigue problems with considerable fatigue damage occurring while the planes were on the ground.

The vibrational loads applied to the cowling during this time could also be aggravated by another type of loading, thermal loading. Though thermal loading would not be expected to cause the fatigue cracking, it may help the vibration in sustaining the process. When the plane is on the ground, it is moving about slowly, and the propeller is rotating at a relatively low RPM; consequently, the air intakes are not passing as much air over the engine as when it is in flight. The air that is passed over the engine through the intakes acts as a shield to the cowling while the airplane is in flight. However, when the plane is on the ground, that cushion of cool air between the engine and cowling is not there, and as a result the cowling heats up. This heating and consequent expansion of the metal comprising the cowling could accelerate the fatigue process and help the vibrations initiate and sustain cracking.

Somewhat unexpected was the cracking output of Channels 3 and 4. At first it was thought that something was wrong with the training of the neural network and its classification. However, with the knowledge that cracking appeared to be happening in the vicinity of Channels 3 and 4, and assuming that the neural network was trained properly, further investigation of the aircraft was conducted. Upon inspection of the aircraft, it was found that not only was cracking physically occurring between Channels 3
and 4, but it was in the analogous location as the cracking between Channels 1 and 2.

When the cowling test was originally performed, the crack that was now visible between Channels 3 and 4 was probably beneath the rivet head and therefore would not have been visible on the surface of the cowling. Even though this crack was not visually noticeable, it was detected by the crack monitoring system. This proves the ability of such a system to detect in-flight crack growth in real time.

The cowling is pictured close-up in Figures 4.5 and 4.6 showing cracks on both the right and left hand side of the Piper Cadet’s cowling. The cracks appeared to have originated from symmetric rivets positioned on each side of the cowling that fasten the cowling to a stringer. Note in Figure 4.5 that holes have been drilled at the crack tips to alleviate stressed and thereby stop crack growth.

Figure 4.5 Crack between Channels 1 and 2, expected crack side.
The similar positions of the cracks on the right hand side and left hand side of the cowling indicated that the areas around the two rivet heads were more susceptible to cracking than other areas. Reasons for this high susceptibility around the rivets are because the metal in these regions had been strain hardened when the rivets were punched into the structure. This “stronger,” more brittle region would be more likely to sustain crack initiation and growth than the rest of the metal that was not strain hardened. Also this circular region around the rivet heads is a stress concentration region, yielding locally higher loads.

Figure 4.6 Crack between Channels 3 and 4, unexpected crack side.
Prior to passing the acoustic emission data through the neural network, there was a problem cited with some of the recorded hits in the in-flight MISTRAS files. This problem was associated with two of the recorded acoustic emission parameters, duration, and energy. The problem was that the duration was pegged, meaning that acoustic emission signals longer than the MISTRAS software can record were being partially captured. These very long duration signals also had correspondingly high energies. These signals were probably due to aerodynamic fluttering of the two side doors that are attached to the top of the cowling by the hingeline parallel to the transducers' position. In this case, the signals did not overwhelm the system, and as shown in the results of Tables 4.2 and 4.3, cracking and plastic deformation were successfully monitored. These pegged signals were a good test of the in-flight monitoring system's ability to work in noisy conditions. Thus, despite the extra noise picked up by the acoustic emission transducers, cracking was successfully recorded and separated from the noise.
5.0 CONCLUSIONS

The scope of this research was to prove the ability of an in-flight crack monitoring system to perform, with the difficult part of this task being the system’s ability to extract very small crack acoustic emission signals from a great deal of noise that accompanies an airplane in flight. As the results were reviewed, the prospects of such a system are shown not only to be a possibility, but rather a reality.

In conclusion, the major portions of this research are summarized as follows.

- Distinct separation of cracking, plastic deformation, and rubbing in the lab test gave the neural network a very clean data set on which to train.

- The neural network indicated that cracking was occurring between Channels 1 and 2, and also between Channels 3 and 4 on both sides of the cowling near the hingeline.

- Further inspection of the engine cowling verified that cracking was unexpectedly occurring between Channels 3 and 4, verifying the neural network results.

- Cracking occurred predominantly when the aircraft was on the ground, prior to takeoff and after landing.

This unequivocally demonstrates the ability of such a system to identify crack sources, along with the possibility of locating them as well, in an in-flight environment.
6.0 RECOMMENDATIONS

Further testing of this particular system should include a thermal analysis of the engine cowling since the activity noted in these tests point to the possibility that thermal loading may play a significant role in the fatigue process of an engine cowling. Also the MISTRAS system needs to be set up such that high duration files do not overwhelm the system as happened during portions of the in-flight tests. This could be done by adjusting the threshold setting higher in MISTRAS prior to data acquisition. A threshold such as 50 dB or possibly a little higher could be used to eliminate this problem. A direct waveform analysis of the crack data would be a good step also in crack identification. This sort of neural network analysis could be a precursor to such work. Now that it is apparent that an in-flight crack monitoring system is feasible, the next step should be in locating the identified sources. This could be accomplished by strategic placement of the acoustic emission transducers along with analysis of the corresponding plots.
7.0 REFERENCES


7 Vahaviolos, Dr Sotiros J, *AE & Other NDT Techniques*, Metal Progress, 1980


APPENDICIES
Appendix A: Neural Network Example

An example of how a Kohonen self organizing map is mathematically trained when an input vector is introduced. The SOM in this example is a three column by one row map with two inputs. The inputs used are the acoustic emission parameters duration and amplitude. These steps will give a picture of the process the computer program NeuralWorks goes through when training a SOM neural network on a given data set.

Classification:  
1 -----> Crack  
2 -----> Plastic Deformation  
3 -----> Rub

Inputs:  
X₁ -----> Duration  
X₂ -----> Amplitude

Sample Input Vectors:  
Crack (0 1,0 9)  
Rub (0 9,0 5)  
Plastic Deformation (0 1,0 5)

Learning Rate (α): 0.6

SOM Weights (Wᵢⱼ):  
W₁₁ - weight from duration to processing element 1  
W₁₂ - weight from duration to processing element 2  
W₁₃ - weight from duration to processing element 3  
W₂₁ - weight from amplitude to processing element 1  
W₂₂ - weight from amplitude to processing element 2  
W₂₃ - weight from amplitude to processing element 3
The above figure is a representation of the SOM in this example.

Training steps of the SOM

**Step 1.** Randomly set the SOM weights between 0 and 1

\[
\begin{bmatrix}
W_{11} & W_{12} & W_{13} \\
W_{21} & W_{22} & W_{23}
\end{bmatrix} = \begin{bmatrix}
0.3 & 0.4 & 0.6 \\
0.5 & 0.7 & 0.8
\end{bmatrix}
\]

**Step 2.** Bring the first input vector into the program for mathematical reduction

The crack input vector was given as \((0, 1, 0, 9)\)

**Step 3.** Calculate the square of the planar distance between the input node and the processing element within the SOM

\[
D(j) = \sum_i (W_{ij} - X_i)^2
\]

\[
D(1) = (W_{11} - X_1)^2 + (W_{21} - X_2)^2
\]

D(1) = (0.3 - 0.1)^2 + (0.5 - 0.9)^2 = 0.20

D(2) = (0.4 - 0.1)^2 + (0.7 - 0.9)^2 = 0.13

D(3) = (0.6 - 0.1)^2 + (0.8 - 0.9)^2 = 0.26

**Step 4.** The output that represents the smallest planar distance determines which processing element receives the input

Node 2 is the winning processing element
Step 5. Updating the weights on the winning processing element.

\[
W_n(new) = W_n(old) + \alpha [X_n-W_n(old)] \\
W_{11}(new) = W_{11}(old) + \alpha [X_{11}-W_{11}(old)] \\
W_{11}(new) = 0.4 + 0.6 [0.1 - 0.4] = 0.22 \\
W_{21}(new) = 0.7 + 0.6 [0.5 - 0.7] = 0.58
\]

New updated weight matrix

\[
\begin{bmatrix}
0.22 & 0.4 & 0.6 \\
0.58 & 0.7 & 0.8
\end{bmatrix}
\]

At this point, a new updated weight matrix has been generated, and another input vector can be considered. In this case there are only three input vectors, so updating the learning rate would not be necessary. However, in reality, many input vectors are used to train the neural network, and the learning rate can be automatically be updated if selected to do so. This can be accomplished by setting an epoch size which is less than or equal to the number of input vectors, and what will happen is, when the number of input vectors considered equals the epoch size, the learning rate is updated by the following equation:

\[
\alpha(t+1) = 0.5 \alpha(t)
\]

After this process is completed and all the input vectors have been used to train the neural network, testing with the trained network can be accomplished.
Appendix B: Additional Neural Network Data

Tables B 1 and B 2 below show the results of the neural network as it processed similar acoustic emission data to that processed within the thesis. In this case, though the AE parameter duration was left out to see what effect this would have on classification. The reason for trying this technique was because some of the in-flight data had pegged durations. The other acoustic emission parameters appeared to be good. The tables below show two of the flights analyzed before, one flight from October 10, 1997, and another from October 7, 1997. The data from the 10th was from the side of the cowling with Channels 1 and 2, and the data from the 7th was from the side of the cowling with Channels 3 and 4.

Table B 1 Neural Network Data from Channels 1 & 2 W/O Durations

<table>
<thead>
<tr>
<th>Maneuver</th>
<th>File</th>
<th>Time (mm:ss)</th>
<th>Total hits</th>
<th>Crk hits</th>
<th>%</th>
<th>Rub hits</th>
<th>%</th>
<th>Plist. hits</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi</td>
<td>ft101009</td>
<td>00 46 0</td>
<td>16376</td>
<td>70</td>
<td>0.4%</td>
<td>595</td>
<td>3.6%</td>
<td>15711</td>
<td>95.9%</td>
</tr>
<tr>
<td>Take-Off</td>
<td>ft101011</td>
<td>01 02 0</td>
<td>16374</td>
<td>276</td>
<td>1.7%</td>
<td>1587</td>
<td>9.7%</td>
<td>14511</td>
<td>88.6%</td>
</tr>
<tr>
<td>Climb Out</td>
<td>ft101012</td>
<td>04 26 0</td>
<td>1123</td>
<td>1067</td>
<td>95.0%</td>
<td>55</td>
<td>4.9%</td>
<td>1</td>
<td>0.1%</td>
</tr>
<tr>
<td>Steady Level Flight</td>
<td>ft101013</td>
<td>04 22 0</td>
<td>2174</td>
<td>990</td>
<td>45.5%</td>
<td>964</td>
<td>44.3%</td>
<td>220</td>
<td>10.1%</td>
</tr>
<tr>
<td>Final/Landing</td>
<td>ft101015</td>
<td>00 32 0</td>
<td>16378</td>
<td>201</td>
<td>1.2%</td>
<td>2470</td>
<td>15.1%</td>
<td>13707</td>
<td>83.7%</td>
</tr>
</tbody>
</table>

Table B 2 Neural Network Data from Channels 3 & 4 W/O Durations

<table>
<thead>
<tr>
<th>Maneuver</th>
<th>File</th>
<th>Time (mm:ss)</th>
<th>Total hits</th>
<th>Crk hits</th>
<th>%</th>
<th>Rub hits</th>
<th>%</th>
<th>Plist. hits</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi</td>
<td>ft107004</td>
<td>01 31 0</td>
<td>16373</td>
<td>1130</td>
<td>6.9%</td>
<td>100</td>
<td>0.6%</td>
<td>15143</td>
<td>92.5%</td>
</tr>
<tr>
<td>Take-Off</td>
<td>ft107006</td>
<td>01 50 0</td>
<td>985</td>
<td>516</td>
<td>52.4%</td>
<td>356</td>
<td>36.1%</td>
<td>113</td>
<td>11.5%</td>
</tr>
<tr>
<td>Climb Out</td>
<td>ft107007</td>
<td>05 41 0</td>
<td>1366</td>
<td>1134</td>
<td>83.0%</td>
<td>232</td>
<td>17.0%</td>
<td>0</td>
<td>0.0%</td>
</tr>
<tr>
<td>Steady Level Flight</td>
<td>NA</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>Final/Landing</td>
<td>ft107011</td>
<td>01 09 0</td>
<td>16377</td>
<td>527</td>
<td>3.2%</td>
<td>1736</td>
<td>10.6%</td>
<td>14115</td>
<td>86.2%</td>
</tr>
</tbody>
</table>

These results when compared to the results with the neural network used earlier in the report show that the classification of plastic deformation does not seem to be affected by leaving out duration. However, cracking and rubbing classifications are significantly different from what was generated by the neural network used earlier. This leads to the conclusion that the AE duration parameter is essential to the valid classification of cracking and rubbing signals.
Appendix C: Data Acquisition Settings

Throughout the testing, different settings were used in the data acquisition process. Listed below are various software and hardware settings that were noted at the times the tests were conducted.

<table>
<thead>
<tr>
<th>Lab Test</th>
<th>Threshold</th>
<th>Gain</th>
<th>Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flight Test 25-Sept-97</td>
<td>30 dB</td>
<td>40 dB</td>
<td>None</td>
</tr>
<tr>
<td>Flight Test 07-Oct-97</td>
<td>30 dB</td>
<td>40 dB</td>
<td>10 kHz high pass</td>
</tr>
<tr>
<td>Flight Test 07-Oct-97</td>
<td>30 dB</td>
<td>40 dB</td>
<td>100 kHz high pass (set to reduce noise from propeller)</td>
</tr>
</tbody>
</table>

Transducer specifications

<table>
<thead>
<tr>
<th>Dimensions (dia x ht) [in]</th>
<th>1 13 x 1 16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight [gm]</td>
<td>70</td>
</tr>
<tr>
<td>Operating Temperature [°C]</td>
<td>-45 to 85</td>
</tr>
<tr>
<td>Face Material</td>
<td>Ceramic</td>
</tr>
</tbody>
</table>
Appendix D: Wave Speed Determination

In both the lab test and the in-flight test, the metal structure that was being tested was considered a thin plate. This thin plate assumption is true because the dimension of thickness was orders of magnitude smaller than the dimensions of length and width. The speed at which the acoustic emission energy propagates through a material depends in part on what kind of wave is propagating through the material. In the case of an infinite medium the two dominant wave types are longitudinal and shear waves. If this infinite medium were to have a surface and the AE energy propagated to the surface, the energy would take the form of Rayleigh waves and propagate along the surface.

A finite medium such as a thin plate restricts the AE energy to propagate in the form of Lamb waves which further can be grouped as extensional (symmetric) and flexural (antisymmetric) waves. The extensional wave is a wave in which opposite sides of the plate move in opposite directions about a central plane. The Flexural wave causes the plate to move in similar directions about a central plane. Unlike longitudinal, shear, and Rayleigh waves the velocity of a Lamb wave is function of frequency and thickness of the plate rather than being a function of the material properties of the medium. So rather than a simple calculation to determine the wave speed of the AE within the tested medium, a graph was used to empirically estimate the value. On the next page Figure D.1 shows a plot by Krautkramer on which acoustic emission wave speed can be estimated by knowing the thickness of the plate and the approximate frequency of the acoustic emission energy. On Figure D.1 a dotted line represents the wave speed of the AE in the lab and in-flight tests. The 0.19 mm-MHz on the horizontal axis is the product of the thickness of frequency for these particular tests.

Thickness: 0.635 mm
Frequency: 300 kHz
Thickness\times Frequency = 0.635 \text{ mm}\times300\text{kHz}
= 0.19 \text{ mm-MHz}

The estimated velocities as taken from the plot in Figure D.1:

\begin{align*}
\text{Velocity}(T\times F) \quad S_v &= 5500 \text{ m/s} \\
A_v &= 2600 \text{ m/s}
\end{align*}
Figure D.1 Velocity curves for the first four Lamb wave modes.