Compression After Impact Load Prediction in Graphite/Epoxy Laminates Using Acoustic Emission and Artificial Neural Networks

Anthony Michael Gunasekera
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COMPRESSION AFTER IMPACT LOAD PREDICTION IN GRAPHITE/EPOXY LAMINATES USING ACOUSTIC EMISSION AND ARTIFICIAL NEURAL NETWORKS

by

Anthony Michael Gunasekera

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
Fall 2009
COMPRESSION AFTER IMPACT LOAD PREDICTION IN GRAPHITE/EPOXY LAMINATES USING ACOUSTIC EMISSION AND ARTIFICIAL NEURAL NETWORKS

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Anthony Michael Gunasekera

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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Title: Compression After Impact Load Prediction in Graphite/Epoxy Laminates Using Acoustic Emission and Artificial Neural Networks.
Institution: Embry-Riddle Aeronautical University
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The purpose of this research was to investigate the effectiveness of artificial neural networks (ANNs) in predicting the compression after impact (CAI) load of graphite/epoxy laminates from acoustic emission (AE) nondestructive testing (NDT) data. Thirty-four 24-ply bidirectional woven cloth laminate coupons were constructed and impacted at various energy levels ranging from 8 to 20 Joules, generating barely visible impact damage (BVID). Acoustic emission data were acquired as the coupons were compressed to failure. Not having been analyzed by previous experimenters, several noise tests were also performed to determine the impact of external noise on acoustic emission data during testing. Once the noise and other erroneous data were filtered out, several investigations were conducted using ANNs. First, a Kohonen self-organizing map (SOM) neural network was constructed and optimized in order to separate the AE data into noise plus the various failure mechanisms thought to be experienced by composite laminates undergoing compression. It was hoped that by quantifying the failure mechanisms, more accurate ultimate load predictions could be made. Secondly, a backpropagation neural network (BPNN) was constructed, which analyzed the AE amplitude distributions directly as inputs in order to arrive at accurate
CAI load predictions. The BPNN was trained using twenty-four of the samples, systematically optimized, and then tested on the remaining ten samples. The relatively large sample size allowed both the SOM and the BPNN to experience a wide variety of failure scenarios, thus leading to very good classification and prediction results. The worst case error from the prediction results was found to be -11.53%, which was within the desired prediction error range of ±15%. Microscopy and C-scans were also an important part of the project in order to analyze the extent of damage created by impact and compression after impact. It was hoped that these methods would allow a better understanding of the failure mechanisms in the material.
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CHAPTER 1
INTRODUCTION

1.1 Overview

As technology evolves, considerable resources are being utilized in the research and development of composites to replace metals in various structural applications. Composites have the advantages of better corrosion resistance, better fatigue properties, higher strength, as well as a higher stiffness to weight ratios than most metals. This is particularly advantageous in the aerospace industry where the main goal is to make aerospace vehicles lighter and faster without sacrificing structural integrity. Hence, a significant increase in the use of composites is being seen in the construction of military fighters. For example, the F-15 used approximately 2% composites by weight, the F-18 about 19%, and the F-22 around 24%, including radar absorbing composites for stealth capabilities. Among commercial airliners, the A380 employed approximately 21% composites by weight, while the 787 has the most extensive use of composites of any commercial aircraft, using about 50% by weight. The most common composites used in the aerospace industry are carbon/epoxy, graphite/epoxy, aramid/epoxy and glass/epoxy, all of which have light weight and high strength advantages. However, with increasing advantages there are also disadvantages.

The sudden failure of composites structures is one disadvantage that has been critically analyzed and has become an area of extensive research, as there are many factors that play major roles in composite performance. The most common failure mechanisms of composites are matrix crushing (matrix fragmentation) and cracking (longitudinal,
transverse, micro- and macro-matrix cracks), inter-laminar and intra-laminar delamination of plies, matrix fiber interface debonding (leading to longitudinal and transverse fiber-matrix splits), fiber breaks (micro- and macro-buckling and kinking of fibers), and fiber pullouts. Depending upon the type of force applied – tension, compression, shear or impact loadings – and upon the sequence of application of these forces which also may include environmental effects – different combinations of failure mechanisms are experienced.

When laminates are used for the skin of aircraft, these composites will be subjected to environmental conditions and other damaging occurrences during operation, which can alter their properties significantly. Low energy impact damage (8-20 Joules), such as small bird-strikes, hail, dropping of tools on a wing section, or runway stones and debris, can cause different modes of failure such as matrix cracking, delaminations and fiber breaks within the composite. Although this damage may be barely visible from the exterior of the structure, it can result in an extensive reduction in the compressive performance or residual strength of the part. Hence, this type of impact damage is referred to as barely visible impact damage (BVID), further weakening these materials which are characteristically much weaker in compression than in tension. Under compression, the matrix coupled with the fibers bear most of the load, but the matrix being considerably weaker than the fibers, is prone to matrix crushing or fragmentation followed by buckling of the fibers. Composites in general are brittle and therefore provide little to no warning before failure. BVID causes composites to fail or buckle under much lower compressive loadings than usual. Therefore, implementation of a
reliable method to predict the residual strength of a composite under compression would greatly reduce the risk of sudden failure in a composite structure while in service. \(^8\text{--}^{13}\)

Identification and monitoring of these changes in aircraft structures is therefore crucial, as it will allow success in predicting certain failures and failure mechanisms. Acoustic emission (AE) nondestructive testing (NDT) has been shown on a broad scale to have a potential for distinguishing and classifying failure mechanisms based on the acoustic signatures of virtually all fiber-matrix composites.\(^7\text{,}^9\text{--}^{13}\) Although it is challenging to accurately distinguish between coupled failure modes, failure mechanisms may be able to be distinguished by the acoustic signature emitted during failure of the composite.\(^2\text{--}^4\text{,}^7\text{,}^9\text{--}^{13}\)

While manufacturing defects, flaws, and stress concentrations all produce a fair degree of variability in composite performance, failure mechanisms tend to emit sounds in a unique and consistent manner. Even though the ultimate failure loads between two different cases may differ considerably, the acoustic characteristics maintain similar failure mechanism trends. These trends can be exploited by artificial neural networks (ANNs), computer algorithms which can easily handle complex multivariate data sets, which have been shown to both accurately classify failure mechanisms based on data trends and to make predictions for composite compression after impact residual (CAI) strength.\(^9\text{--}^{13}\)

For this research graphite/epoxy coupons were fabricated and then impacted at various energy levels, simulating low velocity impact damage. The coupons were then placed in a Boeing compression fixture and compressed to failure using a Tinius-Olsen (Willow Grove, PA) model 290 Lo Cap testing machine to determine their compression
properties. Acoustic emission transducers were used to listen and collect flaw growth activity data from the coupons under compression. Additionally, ambient noise from the testing environment was also recorded in order to appropriately filter it out of the data set. Then, two investigations regarding artificial neural networks were conducted.

Using a few important AE parameters, a Kohonen self organizing map (SOM) neural network was constructed and optimized in order to separate the AE data into the various failure mechanisms experienced by composite laminates undergoing compression. It was hoped that by quantifying the failure mechanisms, more accurate ultimate strength predictions could be made. Secondly, two backpropagation neural networks (BPNNs) were constructed and optimized to weigh AE amplitude distribution data in order to arrive at accurate CAI load predictions. The first BPNN analyzed AE amplitude data that had not been filtered for noise and had not been classified into failure mechanisms using a SOM. The second BPNN analyzed data that the SOM had classified into distinct failure mechanisms so as to eliminate noise. This way, comparisons could be made as to the effectiveness of SOMs in data classification for prediction purposes.

In previous research conducted by Hill and Hess, the rubbing noises between the impact damaged specimens and the Boeing compression fixture made the neural network ineffective in predicting CAI loads from the AE data.\textsuperscript{9,13} In that work the amplitude range was taken to be 60 to 100 dB which excluded low amplitude noise. For the present research, it was thought to be beneficial to test between 30 and a 100 dB to gain an understanding of how low amplitude noise interacts with acoustic emission emitted from
the specimen itself. The 30 dB starting amplitude was thought to be the point at which
the onset of matrix cracking in the composite material would occur; however, it would
probably introduce additional low amplitude noise into the data set. Therefore, noise had
become an important parameter and noise tests were performed in order to clearly
distinguish AE data from noise and that of the composite specimen. It was hoped that
this testing would clarify the exact amplitude range for this low amplitude quiescent
noise. A SOM was also employed to sort these data into separate clusters of noise and
composite failure mechanisms.

A worst care error of ±15% between the predicted load and the actual test coupon failure
load was desired for this analysis. since composites have a high degree of variabity.
Previous researchers performing similar experiments had acquired errors greater than
±30% with some reaching as high as a 100% for prediction. ⁹⁻¹³ If these neural networks
could be successfully trained using AE test data with prediction errors less than ±15%, it
would then be possible to apply this technique to real world aircraft. AE transducers
could be mounted on the skin panels or other structures and used to listen to and collect
flaw growth AE data. These data could then be fed into previously trained neural
networks to accurately predict the failure modes and the residual CAI load of the
structure. This procedure could be done both continuously in-flight and on the ground
and would save money as it would reduce maintenance inspections and unnecessary
changes in parts before the actual failure life was reached.
2.1 Acoustic Emission Nondestructive Testing

Acoustic emission (AE) is a passive (energy is not introduced) form of NDT with many applications. It refers to the rapid release of elastic energy, in the form of stress waves, from a material undergoing deformation. When subjected to an external load, any type of flaw growth mechanism will release stress waves. These stress waves propagate throughout the structure. AE testing senses these stress waves as they propagate to the surface of the structure. At the surface, a piezoelectric transducer detects the waves and converts them into an electrical voltage versus time signal. The signal is then amplified and sent to an AE computer for analysis. The AE analyzer converts each signal waveform into the AE quantitative parameters: counts, duration, amplitude, rise time, energy, and average frequency. Finally, the AE parameter data for each signal or hit are imported into software programs for playback, filtering, and graphical analysis. This process is depicted in Figure 1.

![Figure 1. Acoustic emission testing process.](image-url)
The six different AE quantification parameters compose the input vectors for the neural networks generate herein, so it is important to understand each parameter. As shown in Figure 2 below, counts is the number of times the signal crosses a specified voltage level known as the threshold. Duration is the length of the signal from when it first crosses the threshold to when it finally passes under it for the last time. Amplitude is the highest peak voltage of the signal. The mean area under the rectified signal envelope (MARSE), also known as energy, is a measure of the overall signal envelope. Rise time is the time from the first threshold crossing to the peak voltage. Another useful parameter is average frequency, which is equal to the number of counts \( C \) in an AE signal divided by the duration \( D \) in \( \mu \text{sec} \) of the signal, shown in Equation 1.

\[
f_{\text{avg}} = 1000 \frac{C}{D} \quad [kHz]
\]  

These six parameters give a quantitative picture of each AE signal, or hit.

![Figure 2. Acoustic emission signal parameters.](image)
This voltage representation of an AE hit can also be represented in an amplitude form, which is on a logarithmic scale for voltage. Equation 2 corresponds to this conversion from volts to decibels [dB], where $V_{\text{sig}}$ is the maximum voltage is recorded from an AE hit, and $V_{\text{ref}}$ is a reference voltage of 1 microvolt [$\mu$V].

$$A = 20 \log \frac{V_{\text{sig}}}{V_{\text{ref}}} \ [\text{dB}]$$

Figure 3 depicts this amplitude representation in decibels. The noted difference between Figure 2 and Figure 3 is the maximum voltage or amplitude, is called the peak amplitude, which is the main variable used throughout the project. Hereinafter, any amplitude distribution or amplitude representations in any figures or text have reference to the peak amplitude.

![Figure 3. Amplitude representation of an AE hit.](image)

The four primary failure mechanisms thought to be experienced in composites under compression are matrix cracking, delaminations, fiber breaks, and fiber-matrix
debonding. These will be discussed in more detail later. Other mechanisms may be experienced during failure, and each mechanism's acoustic signature is typically different. Matrix cracking for instance is thought to include hits at relatively low amplitudes (approximately 20-60 dB). Also, different mechanisms may occur in different portions of the loading sequence, so it is important to record load and time of occurrence as parameters during any testing.

One of the most common ways of analyzing acoustic emission data is graphically. The primary graphs employed herein include amplitude vs. hits, duration vs. amplitude, and duration vs. counts, but there are several other useful graphs which can be employed as well. Graphs plotting amplitude vs. hits, or the amplitude histogram, may reflect different failure mechanisms as overlapping humps. Graphs plotting duration vs. amplitude may reflect different failure mechanisms as clusters of points. Lastly, graphs plotting duration vs. counts may show different mechanisms as linear bands of points, as they occur in a consistent average frequency range.

2.2 Ultrasonic C-Scan Testing

After some of the laminates were impacted, they were ultrasonically scanned in order to analyze the damaged area. Ultrasound is a volumetric nondestructive testing method that uses ultrasonic pulses to probe a part without damaging it. These pulses are high frequency sound waves that are above the range of human hearing. Ultrasonic testing (UT) uses a transducer that converts sound waves to electric signals or electric signals to sound waves. In order for an ultrasonic scanner to work, a transducer must create
ultrasonic waves. The transducer contains a thin disk made of a crystalline material with piezoelectric properties, such as quartz\textsuperscript{15}. This piezoelectric material vibrates when electricity is applied and this vibration is what creates the sound waves. Vice versa, the piezoelectric material also creates electric signals when it is vibrated by an external stimulus. An ultrasonic scan works by using the transducer to send a sound pulse into the part and then it switches to listening mode to analyze the reflected pulse waves it receives back. When a change in density is detected in a part, a pulse echo will be returned to the transducer; this includes defects or impurities under the surface as well as determining the thickness of the part. Figure 4 shows an example of how an ultrasonic scan works. The different peaks in the amplitude represent some kind of change in density that is returning an echo. By noting the location of the pulse it is possible to determine the size of the flaw as well as the depth at which it is located.

![Ultrasonic Probe With Graphical LCD](image)

The Posilector 100 measures the individual layers in a multilayer system. In this example, Layer 1 is 1.2 mils thick, Layer 2 is 4.4 mils thick, Layer 3 is 2.5 mils thick. Total thickness is 8.1 mils. The graphical LCD displays three "peaks" representing three material interfaces.

Figure 4. Ultrasonic reading\textsuperscript{15}
The specific application of ultrasonic testing being used in this project is called the C-scan. It operates by establishing a data collection gate, or flaw gate, and then it records the amplitude and time-of-flight of the pulses at regular intervals as the transducer is scanned over the part. These returning signals are then displayed for each recorded position using a color or gray scale. The system used for this project was the Physical Acoustics Corporation (Princeton Junction, New Jersey) UltraPAC II immersion scanning system. This means that the part and the transducer are both submerged in a tank of water. The water is the couplant that carries the sound waves from the transducer to the part and back again. Figure 5 shows the set up of the immersion tank and the computer.

![Figure 5. C-scan setup.](image)

### 2.3 Radiography

Radiography is capturing an image from an object to view its internal structure or density variations through the use of X-rays. An X-ray generator is a device that is used to produce X-rays. It generally includes an X-ray tube, which is usually made of glass but
can also be made from a ceramic or metal.\textsuperscript{18} It contains a filament that is heated and used to excite and emit electrons which are then focused onto certain materials like tungsten, molybdenum or copper. Electrons within these materials are further excited and release radiation called X-rays.\textsuperscript{19} Figure 6 shows a basic X-ray imaging set up.

\begin{figure}
\centering
\includegraphics[width=0.5\textwidth]{x-ray-machine.png}
\caption{X-ray machine\textsuperscript{19}}
\end{figure}

A radiograph is produced by passing this radiation through an object onto a film in order to create a photographic image. The quality of the radiograph depends on the amount of radiation absorbed by the film. These radiographic images can also be analyzed through a computer and a digitally enhanced image can be acquired. For the purposes of this project, radiography was used to physically visualize the internal damage associated with a BVID on a composite coupon using the Faxitron (Lincolnshire, IL) cabinet X-ray system model 43855C. This is a real time radiography system with digital, not film, outputs.
2.4 Microscopy

Microscopy is a technique used in various disciplines of biology and materials engineering where a microscope is used to analyze particles on a microscopic level. Optical microscopy was used in this project to visualize certain failure mechanisms and other manufacturing flaws that led to the failure of a composite on a microscopic scale. The optical metallurgical microscope (Meiji, Japan) model ML7100 uses visible light, reflected through a series of lenses, to achieve a magnified view of the sample. Images can also be digitally captured through a digital microscope camera (Ottawa, Ontario, Canada) which is attached to the microscope. The sample being analyzed (in the case of this project, cured graphite coupons) was cut at failure locations to view the internal damage associated with BVID using a diamond tip wet saw. The surface was sanded and polished to enhance visualization under the microscope.

2.5 Introduction to Artificial Neural Networks

The structure of the brain, known as a neural network, is composed of a massively parallel system of billions of neurons. Artificial neural networks (ANNs) follow a similar structure, but rely less on the sheer number of neurons, or processing elements (PEs), and more on the rapid iterative power of a computer's central processing unit. Like the human brain, ANNs are an excellent tool to model complex relationships between inputs and outputs, or to recognize patterns in vast quantities of data. They operate by first randomly assigning weights between the various PEs in the network, arranged in different groups known as layers. The random weights then adapt based on external or internal information that flows from the network. As shown in Figure 7, weighted inputs are typically summed, then input into a mathematical activation or
transfer function in order to arrive at an output. Outputs can be a single value, such as in a prediction, or a series of values, as in data classification.

The specific configuration and learning style of ANNs take many forms. Network configurations may be single layer or multi-layer, feed-forward or feedback, depending upon the problem being modeled. Additionally, networks may have supervised or unsupervised learning schemes. Supervised learning means that the weights are adjusted to train the network to reach a known output, preparing the network for predictions on new sets of data. Unsupervised learning means that the network has no knowledge of a desired output, and relies solely on the mathematical relationship between weighted inputs in order to operate. Unsupervised learning is useful in classifying highly complex nonlinear sets of data. Lastly, the mathematical activation or transfer function may be linear, non-linear, or decaying, depending on the characteristics of the data being modeled. It should be noted that non-linear problems require the use of a non-linear transfer function; hence, these are most commonly employed.
The applications of ANNs are as numerous as the configurations. Artificial neural networks play an ever increasing role in the development of modern technology used in a variety of fields. Table 1 lists several of these modern applications.

Table 1. Artificial neural network applications.

<table>
<thead>
<tr>
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<th>Medical Diagnosis</th>
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<tbody>
<tr>
<td>Video-game Artificial Intelligence</td>
<td>Financial Modeling</td>
</tr>
<tr>
<td>Radar Systems</td>
<td>Email Spam Filtering</td>
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<tr>
<td>Facial and Fingerprint Recognition</td>
<td>Mechanical Failure Prediction</td>
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<tr>
<td>Speech Recognition</td>
<td>Data Mining</td>
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</table>

2.6 Kohonen Self-Organizing Maps

Kohonen self-organizing maps (SOM) are unsupervised, competitive, two-layered ANNs which are incredibly useful for data classification applications. This mapping system is based on the human brain, which uses special organization to classify certain objects or organisms into separate groups. Where the human mind can easily distinguish between faces, voices, colors, and patterns, teaching a machine to do so is a complex problem. Self-organizing maps are an excellent resource for this, and can even classify noisy or seemingly inseparable non-linear data, making them a valuable tool for use in the engineering world.

Kohonen SOMs typically consist of two layers, the input layer, and the Kohonen processing layer. Input data are linked to an input layer containing input neuron or PEs which also contain an input vector of a given dimension. From the input layer, these
neurons are also connected to each PE in the Kohonen layer via a randomly assigned weight vector of the same dimension. All of the PEs in the Kohonen layer are also interconnected to each other for use in an iterative learning process where data may be formed into groups or clusters. So neurons in the Kohonen layer which show similar characteristics in the input layer (input data) will be grouped together as a neighborhood cluster. Most SOMs do not produce an output; rather, final values of the weight vectors themselves are the product of interest. The weight vectors adapt to the data through the iterative process, and can eventually reveal to the user commonality between the input vectors or input data. Further, some SOMs are configured to produce an X-Y output for each input vector, thereby taking a complex multidimensional data set and mapping it onto a two dimensional plane. The useful data are not the X-Y coordinates, but the clusters of X-Y outputs and how they relate to the input data. As stated before, classification is the primary purpose of SOMs. A simple SOM with three inputs, five Kohonen PEs (or classification choices), and a forced X-Y output is shown in Figure 8.

Figure 8. Simple SOM with an X-Y output.
So how does the SOM adapt to the data? The multidimensional Euclidean distance (a logical extension of the planar Pythagorean Theorem) between the input vectors and the randomly assigned weight vectors is computed for each connection, and the Kohonen PE containing the shortest distance is chosen as the winning PE. Then, a certain number of PEs in the immediate vicinity of the winning PE in the Kohonen layer, as determined by the neighborhood factor (which states how big each cluster should be depending on how many groups or clusters have been specified), will undergo the learning process, having their weight vectors updated. Once the neighborhood weight vectors are updated, the entire cycle is repeated, with a new winning PE being determined and weight vectors in neighbourhoods further adjusted.

Equation 3 gives the Euclidean distance, \( E_D \), between a weight vector \( W = (w_1, w_2, ..., w_n) \), and an input vector \( X = (x_1, x_2, ..., x_n) \).

\[
E_D = \sqrt{(w_1 - x_1)^2 + (w_2 - x_2)^2 + \ldots + (w_n - x_n)^2} = \sqrt{\sum_{i=1}^{n} (w_i - x_i)^2}
\]  

(3)

Equation 4 shows how new weight vectors are calculated for the PEs that will undergo learning. Note that \( W \) is the weight vector, \( X \) is the input vector, and \( \alpha \) is the learning coefficient, a quantity that determines how fast the learning process occurs. If the learning coefficient is too small, the network will take a very long time to learn the data, but if it is too large, there will be a significant amount of overshoot in the weight vector calculations causing the network to not home in on a solution.
Each time the cycle repeats is known as an epoch (this can also be specified by the user). Typically, the number of epochs is directly related to the number of inputs into the network (number of input data points). The larger the network, the longer it will take to fine tune the weights. Eventually, as the process runs through enough epochs, the weight vectors will adapt to fit the training data. More specifically, the weight vectors will begin to cluster into noticeable groupings that reflect trends in the data. The more PEs there are in the Kohonen layer, the more possible groupings the SOM may discover. A short explanation and numerical example of this iterative process has been presented in Appendix C.

For this project, SOMs will be used to classify failure mechanisms evident in the acoustic emission data. Different input vectors, namely amplitude, energy, duration, and average frequency, will be experimented with, as well as different Kohonen layer dimensions. Further, quantified data from the SOM classification will be used for inputs into a backpropagation neural network. It is thought that classifying the data before inputting it for BPNN prediction will yield more accurate results. This hypothesis will be tested.
2.7 Backpropagation Neural Networks

A backpropagation neural network (BPNN) is a feed-forward, multilayered, supervised network. The basic structure of a backpropagation ANN consists of an input layer, one or more hidden layers consisting of several PEs each and an output layer. The whole process for the BPNN has two phases, a training phase and a testing phase. In the first phase the network needs to be trained on a known solution (it is given the answer) before it can be applied or tested on an unknown case in the second phase. In this training phase, the input layer presents the input data to the network. The connections are assigned random weights or coefficients before passing the data along to the hidden layer or processing PEs. Typically, two PEs are needed for each significant attribute of the input data in the hidden layer. In this project four failure mechanisms are being analyzed,
so the number of PEs in the hidden layer will be nine, two for each failure mechanism plus an additional PE. This structure may not always be the case though, and different combinations of hidden layer PEs will be tested. The PEs process the data using sigmoidal transfer (squashing) functions after which they pass the results on to the output layer. The network analyzes all the input data coefficients and has to learn as to how closely or tightly the user wants the network to stay close to these coefficients (RMS error), and how it is linked to a value of output data which the user gave the network at the beginning. This final data trend of weighted coefficients is then compared to the known result. The network also looks at all other input files with similar data and similar known results and readjusts all the weighted coefficients between each of the files.

The process is repeated until the weights have been adjusted to the point where the error is within a preselected RMS value. This can take several thousand iterations, which can be accomplished fairly quickly with modern day computing power. In order to obtain the best prediction results, an optimization process is required to determine the optimum number of neurons in the hidden layer, as well as other network parameters such as the learning coefficients for the various layers. Once the network is trained, the testing phase can be started, where data with an unknown solution can be introduced to the network, and an output value can be predicted. Based on its training, the network will apply the weighted coefficients determined during the training phase to the new data to predict the compressive failure load.
Two BPNNs will be constructed and optimized to weigh or analyze the AE amplitude distributions in order to arrive at accurate CAI load predictions. The first BPNN will analyze data that has not been filtered for noise and has not been classified into failure mechanisms using a SOM. The second BPNN will analyze data that the SOM has classified into distinct failure mechanisms and has been used to eliminate noise. In this way, comparisons can be made as to the effectiveness of SOMs in data classification for prediction purposes.
CHAPTER 3

EXPERIMENTAL PROCEDURE

3.1 Fabrication

Cycom® (Cytec, Woodland Park, New Jersey) 985 GF3070PW bidirectional woven prepreg cloth was used to fabricate thirty-four 10.16 x 15.24 cm (4 x 6 in) laminate coupons. The prepreg had a manufacturing defect due to misaligned fibers which were present in the weave (Figure 10). It was thought that this could prove to be a problem, as fibers misaligned in the axis of compression could buckle prematurely, increasing the variability in the compressive strength of the coupon. However, since all the coupons were manufactured the same way with the same defect, it became less of a concern but was still kept in mind. The ASTM standard D7137/D 7137M-07 for compression after impact requires the coupons to be of around 0.51 cm (0.2 in) thick.20,21 The thickness of prepreg tape suggested that a 24 ply lay-up be used to construct the coupon laminates (Figure 11). A wooden was used to keep the samples straight while laying them up. Once all 24 plies were put together, they were placed between two aluminum caul plates and held together by four C-clamps (Figure 12) and placed in the oven to cure (Figure 13) at 452.6 K (355°F) for two hours in accordance with product specifications. After curing, the oven was turned off, and the laminates were allowed to cool to room temperature in the oven. Each laminate was then removed from the oven and the aluminum caul plates removed. Four 10.16 x 15.24 cm (4 x 6 in) coupons were then cut from each laminate plate using a diamond tip wet-saw. Coupons were identified with a letter and a number; coupons coming from the same plate were given the same number but different letters (Figure 14).
Figure 10. Fabrication of laminates.

Figure 11. 24 ply lay-up on wooden jig.
Figure 12. Prepped laminate between aluminum caul plates.

Figure 13. Fabrication oven.

Figure 14. Sectioning of four 10.16 x 15.24 cm (4 x 6 in) coupons from a 24 ply laminate.
3.2 Impact Testing

Barely visible impact damage was created using the Instron (Norwood, MA) Dynatup 9200 calibrated impactor (Figure 15). The impactor was configured with a blunt 1.27 cm. (0.5 in) hemispherical tup, pneumatic brakes, and pneumatic clamps. The tup simulated a low velocity impact such as a tool dropping on the coupon. The pneumatic brakes were used to prevent repeated impacts due to bouncing of the impactor on the specimen. Pneumatic clamps were necessary to hold the laminate coupons in place during impact. The impactor was set to impact at energies ranging between 8 and 20 J. After impact the damaged area was marked with a gold metallic ink marker for easy identification. Figure 16 shows a laminate coupon that was impacted at 15 J. To the naked eye, it is difficult to see any damage. However, when an ultrasonic C-scan and X-ray image are taken of the same coupon, the damage can be seen (Figures 17 and 18). Longitudinal and transverse cracking are clearly seen at the site of impact along the weave of the composite.

Figure 15. Instron Dynatup 9200 impactor.
Figure 16. Laminate with 15 J BVID.

Figure 17. Ultrasonic C-scan image of BVID.

Figure 18. BVID X-ray image.

Longitudinal and transverse internal cracks
3.3 Compression Testing

A Tinius-Olsen (Willow Grove, PA) model 290 Lo Cap testing machine was used to compress the specimens. The Boeing CAI Test Fixture (Figure 19) was used in order to conform to ASTM standards D 7137/D 7137M-07. After securing the coupon in the compression after impact fixture, the specimen was placed in the compression machine, and the coupons were compressed at a constant rate of 17,792.9 N/min (4,000 lb/min). Upon failure, the applied force would drop from the maximum load to zero, and the machine was stopped.

Acoustic emission data were recorded during the compression test using an Envirocoustics (Physical Acoustics Cooperation, Princeton Junction, New Jersey) Pocket AE-1 acoustic emission analyzer. This handheld device employs two 150 kHz transducers (R15α A157 and A158) to collect AE data. The transducers were hot-melt glued (used in industry to mount transducers) to the specimens on the centerline 3.81 cm (1.5 in.) from the top and bottom edges of the coupon. The transducers were also taped to the compression fixture to avoid damage in case buckling failure would cause them to violently separate from the coupon. The Pocket AE analyzer also allowed for a parametric input of the load from the Tinius-Olsen machine. Equation 5 was used to convert this parametric voltage to an accurate load value.

\[
F_c = (P \cdot 30,000 + 250) \quad [lb]
\]
Figure 19. Compression test setup
This allowed the Pocket AE to match the hits that the transducers were detecting with the load that was being experienced by the specimen at the time the hit was detected. The settings for the Pocket AE are summarized in Table 2. These setting are important, as acoustic emission parameters from different materials tend to vary. The AE data given off by composite materials typically have very different parameters than those from metals. The users’ manual for the Pocket AE gives specific ranges which have to be set when using a certain type of material to avoid acquiring erroneous data. The definitions of these parameters are provided in Appendix B.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>30 dB</td>
</tr>
<tr>
<td>Sample rate</td>
<td>5 Msp</td>
</tr>
<tr>
<td>Max Duration</td>
<td>10 ms</td>
</tr>
<tr>
<td>Peak Detection Time (PDT)</td>
<td>50 µs</td>
</tr>
<tr>
<td>Hit Definition Time (HDT)</td>
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</tr>
<tr>
<td>Hit Lockout Time (HLT)</td>
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</tr>
<tr>
<td>Parametric Multiplier</td>
<td>30,000</td>
</tr>
<tr>
<td>Parametric Offset</td>
<td>250</td>
</tr>
</tbody>
</table>
CHAPTER 4

RESULTS

4.1 Data Filtering and Noise Analysis

In order to filter the data efficiently, a MATLAB code was created to eliminate erroneous data points. Hits that recorded values of zero (extremely weak hits) for energy, duration, or rise time were all removed first. Long duration hits greater than 9,800 μs were also removed, these being thought to be the multiple hit data or rubbing noise from the sides of the compression fixture. Additionally, due to the wide variety of random noise signals that occur during the progression of any type of testing, a proper noise analysis was important. In order to truly understand the acoustic signature of ambient noise, and thus remove it, five recordings of the quiescent testing environment were taken. All of these recordings were captured using the Pocket AE, with the transducers being hot melt glued to the laminates, but with no compressive loads applied and the Tinius-Olsen machine crosshead stationary. The compression machine was turned on and recordings were conducted for approximately the same duration as a typical compression test, ranging from 3 to 5 minutes. All of the AE hits for the noise recordings were then combined and the graphs shown in Figures 20-22 were constructed. This noise was thought to be the internal mechanical noise from the compression machine.
Figure 20. Hits vs. amplitude plot for all five noise recordings.

Figure 21. Duration vs. counts plot for all five noise recordings.

Figure 22. Amplitude vs. average frequency plot for all five noise recordings.
This noise signature was also plotted using an amplitude histogram which revealed a distinct low amplitude hump from about 30 to 36 decibels [dB], as shown in Figure 20. Examining the duration vs. counts graph (Figure 21), it can be seen that the majority of the noise lies within an average frequency band from 1 to 18 kHz (Recall that the average frequency of a hit is given by Equation 1). When these two parameters, amplitude and average frequency, were coupled together and plotted in an amplitude vs. average frequency graph (Figure 22), it displayed a distinct cluster of low amplitude, low average frequency noise. This plot was subsequently used for noise classification when employing the Kohonen self-organizing maps.

Hits in the high decibel region were also acquired, but these were noises created by the researchers to understand the sensitivity of the transducers. Such noise was not generated nor observed during actual testing. After conducting the noise analysis, it was very simple to distinguish the difference between noise and genuine AE data from the specimen. Figure 23 shows a duration vs. counts plot in which the noise average frequency band is easily separated from the specimen data. Additionally, Figure 24 shows an amplitude histogram for the same specimen. Here the low amplitude noise readily stands out from the specimen data.
Figure 23. Duration vs. counts plot showing the difference between noise and specimen data.

Figure 24. Hits vs. amplitude plot showing the difference between noise and specimen data.
4.2 Failure Loads

Once testing was completed and all of the failure loads were acquired, Figure 25 was plotted in order to visualize how the coupons were affected by the varying impact energies. It can clearly be seen that as impact energy increases, the residual CAI failure load of the laminates is affected in a parabolic fashion. A significant amount of variability is observable, but this is to be expected given the nature of composite materials and the manner of fabrication. Of noteworthy importance is the control specimen (not shown in the figure), which was not impacted, and reached the maximum compressive load of the Tinius-Olsen Lo Cap testing machine of 32,000 lbs without failing. It was not imported into the graph, as its final compressive failure load was not reached and thus would distort the plot. The parabolic nature of the compressive failure load was expected, because as impact energy increases, the type of impact damage changes from barely visible to a high velocity impact that penetrates the surface. This penetration creates a circular indentation which is thought to inhibit slip between plies. This effect would then increase rather than decrease the compressive strength. Added into the graph are the best fit parabola $P_{cu} = 39,877 - 2,657a + 82b$ and the B-basis allowables for the composite coupons. The latter is the tolerance interval within which it can be stated with 95% confidence that 90% of all future CAI failure loads will lie. Appendix D contains a table with all the given impact damage levels and their corresponding failure loads.
Of further importance, although the control specimen did not fail, the acoustic signature it exhibited during compression was very similar to those of the majority of the other specimens. This is important, because it means that mechanisms that occur very close to failure, such as large fractures and crack jumps, are not audible in the 30 to 100 dB range used in this experiment: they typically have higher amplitudes. These types of higher amplitude hits are not recorded by the Pocket AE. Knowing this was helpful when distinguishing between failure mechanisms in the AE data.
4.3 Failure Mechanisms Prevalent in Composite Materials

For the purposes of this research, failure mechanisms will be analyzed in composite coupons of constant thickness subject to low energy impact damage and compression tested in accordance with the relevant ASTM standards. Since this research primarily involves BVID, only a certain number of failure mechanisms occur during impact. In such low energy impacts, matrix crushing and cracking are visible around the circumference of the blunt impactor. The material used to fabricate the laminates was a bidirectional (0°/90°) woven prepreg; therefore, barely visible longitudinal and transverse cracks (Figure 18) were noticed along these fiber directions, coupled with fiber splits. Due to the penetrating force of the impactor, minimal (yet visible) outward fraying of the fibers was seen on the back side of the coupons with internal micro/macro-fiber breaks. This occurred at the epicenter of the impact where the most force was applied. Inter-ply slipping with micro-delaminations is also caused due to the shearing and outward bending of the plies around the impact site. This BVID acts as a stress concentration and thus a weak point for a composite plate or panel placed under fatigue or compression. Since the matrix is thought to bear most of the load in compression, this has a great effect on the compressive strength of the laminate, reducing it by as much as 60 percent.

When a composite undergoes compression, a series of failure mechanisms occur. First is the dominant mechanism of matrix cracking (Figure 26), the extent of which depends upon the ductility of the matrix. Cracks propagate faster in a brittle matrix than in a relatively softer, more ductile matrix. Cracks occur in the matrix and between the fiber-matrix interfaces, propagating along and around the fibers as the local stress increases.
These minute cracks propagate into micro-delaminations and fiber matrix debonding (Figure 26). Due to fusion of the plies by the matrix during manufacture, micro-fiber breaks also occur as cracks propagate along these interfaces (Figures 26 and 27). With the further application of stress, these micro-fiber breaks lead to macro-fiber breaks coupled with matrix cracking (Figure 28). Further, micro-delaminations lead to macro-delaminations and the outward bending and splitting of the laminates (Figure 29). This causes further shearing of the plies, and ultimately leads to final failure of the plate, as fiber bundles break and large crack jumps propagate throughout the laminate. Failure begins at the site of impact and propagates in a transverse direction perpendicular to the compressive load. Depending upon the ductility of the plies, delaminations will occur with outward bowing of the plies, leading to buckling. Because the resin content for these laminates was about 35 to 39 percent, no outward bowing or buckling was visualized herein, but large cracks, ply splitting, and fiber breakage were observed at failure.  

Figure 26. Microscopic image of an impacted plate showing matrix cracking and fiber matrix debonding.

Figure 27. Microscopic image of an impacted plate showing a micro fiber break.
Matrix Cracking and Macro Fiber Breaks

Figure 28. Microscopic image of failed plate showing matrix cracking and macro fiber breaks

Macro Delaminations

Figure 29. Microscopic image of a failed plate showing macro-delaminations.
4.4 Failure Mechanism Classification Through Graphical Analysis

As previously discussed, the main failure mechanisms which are expected to occur in graphite/epoxy composites undergoing compression are matrix cracking, micro- and macro-delaminations, and fiber breaks. Additionally, large fractures and crack jumps will occur just before failure. The amplitude ranges produced by the various failure mechanisms can be seen in Figure 30. This chart, which was produced by the Mistras Group Inc. (formerly Physical Acoustics Corporation), shows the possible sizes and magnitudes of typical acoustic emission sources. It must be stated that this chart provides only the general amplitude ranges and that specific values may vary significantly with material and test configuration. Matrix cracking (circled in red), is thought to occur at a lower decibel range; between approximately 20 and 60 dB, depending upon the specimen. Delaminations (circled in yellow), are thought to have slightly higher magnitude range, approximately 50 to 70 dB. Even louder are fiber breaks, in the approximate range between 70 and 100 dB. Again large fractures and crack jumps are typically thought to produce acoustic emissions higher than 100 dB. Since this project was only concerned with CAI failure load prediction and not failure analysis, all AE data over 100 dB were not considered. Although Figure 30 is thought to provide only general ranges, it is very helpful when analyzing amplitude histograms of AE data. The most important thing to note is that the possible failure mechanisms such as matrix cracks are of the lowest decibel range, followed by delaminations, and then fiber breaks.
Figure 30. Sizes and magnitudes of typical AE sources.\textsuperscript{15}

The first graph to be discussed will be amplitude vs. time as shown in Figure 31 for Coupon 23A. The time scale is from the start of the test all the way to failure. Note that in the first half of the test, the vast majority of the hits occur in a range thought to be consistent with matrix cracking. There are a few hits of higher amplitude, but they are relatively sparse and thought to be occurrences of micro-delaminations. Matrix cracking, as this range is assumed to be, occurs evenly across the time scale. At the beginning of the second half of the test, hits in the range consistent with delaminations become more frequent. Additionally, hits in the range consistent with fiber breaks also begin to occur, becoming more prevalent as the test proceeds to failure. While Figure 30 was useful for providing the amplitude ranges to be expected for different mechanisms, amplitude vs. time graphs show when the mechanisms actually do occur during the test. Appendix E contains similar graphs for each coupon tested. Some samples have a slightly different
amplitude distributions from start to the end of the test with the higher amplitude mechanism occurring earlier in the test rather than towards the end. This may be due to the fact that composites have a lot of variability and the manufacturing process used in this project was not set to industry standards. The manufacturing defect in the prepreg and fabrication defects created during the manufacture of the coupons could also be a contributing factor.

Perhaps a better way to visualize failure mechanism trends in the acoustic emission data is through amplitude histograms. Figures 32-35 show amplitude histograms for Coupon 1A for the various segments of the loading. This sample was selected because of its relatively low external noise content. Figure 32 shows the AE activity from 0-25% of the failure load with multiple ranges of 5, 15 and 25% data being plotted on the same graph.
to visualize the changes that occur for each failure mechanism. Figure 33 is from 30-50%, Figure 34 is from 55-70%, and Figure 35 is from 75-100%. Recall that for hits vs. amplitude graphs of AE data, failure mechanisms appear as approximately normally distributed humps. Consistent with the amplitude vs. time graph (for a different coupon), the first loading segment (0-25% of the failure load) includes mainly matrix cracking. There are a few hits of higher amplitude, but as in the amplitude vs. time graph, they are very sparse. During the second segment (30-50% of the failure load), matrix cracking continues to occur at a seemingly constant rate, while higher amplitude hits, assumed to be micro-delaminations, become more common. Here hits above 70 dB, assumed to be a combination of macro-delaminations and fiber breaks, are virtually nonexistent. In the final loading segment (75-100% of the failure load), however, most of the highest amplitude hits occur. In this loading segment, matrix cracking and micro-delaminations occur at an increased rate. Analyzing these histograms from a time perspective is useful because it makes the growth of individual mechanisms and their respective amplitude ranges more observable. Later each of these mechanisms will be distinguished quantitatively using a Kohonen self-organizing map (SOM), but this classification must have a baseline – an expected outcome from which to compare results. Watching the mechanism distributions grow across the entire range of the test provides this baseline.
Figure 32. Hits vs. amplitude graph for 0-25% of failure load.

Figure 33. Hits vs. amplitude for 30-50% of failure load.
Figure 34. Hits vs. amplitude for 55-70% of failure load.

Figure 35. Hits vs. amplitude graph for 75-100% of failure load.
4.5 Failure Mechanism Classification Through Kohonen Self-Organizing Maps

As stated previously, the purpose of this project was to predict after-impact compressive failure loads using backpropagation neural networks. The other part of the research was to determine whether classifying the data quantitatively into separate failure mechanisms, as well as removing external noise, yielded better prediction results. In order to accomplish this, Kohonen SOMs were created and optimized to produce results consistent with the graphical analysis previously discussed.

Kohonen SOM construction and operation was accomplished using *Neuralworks Professional II/Plus* software (NeuralWare, Carnegie, PA). Default settings were used, except for the number of Kohonen layer PEs the network would contain. This was determined through experimentation to match the number of failure mechanisms present. After considerable trial and error, it was determined that the SOM would best classify the various failure mechanism signals using the AE parameters amplitude and average frequency. Alternative analyses were conducted using amplitude, energy, and duration, but the best results were produced using the former combination. It was also beneficial to optimize the neural network to run on the least number of AE parameters. Using amplitude, average frequency, energy and other separate parameters during testing resulted in the same type of plots acquired from the network tested on very few parameters. Recall that average frequency is equal to the counts of a hit divided by its duration, so this parameter is in actuality a combination of these two AE parameters. Next the amplitude and average frequency values from each hit from the samples were combined to create a single file which the network used to adjust the weights between the
Values from each of the 34 samples were then used to make individual testing files, which revealed slightly varying outputs for each coupon. As for the number of Kohonen layer PE’s, training iterations were performed with as few as 2 to as many as 20 PEs. Graphs were created for every variation of PEs in the network. Recall that the number of Kohonen layer PEs will equal \(2n+1\) times the number of choices or clusters of data the network is given for classification. This SOM was configured to assign an X-Y coordinate to input vectors with similar amplitudes and average frequencies. The number of Kohonen PEs determined the number of distinct amplitude and average frequency ranges to which an input vector could be classified. It was soon realized that after the number of PEs had been varied, the graphs had generally the same range of amplitudes corresponding to the same generalized failure mechanisms. The amplitude ranges for low amplitude noise, micro-delaminations, and the combination of macro-delaminations and fiber breaks stayed approximately the same.

In a complex classification problem such as composite failure mechanisms, a SOM by itself cannot determine the ideal failure mechanism distributions; rather, it will provide ranges of similar data, which the engineer must interpret to determine plausible mechanism distributions. For this research, the best results were obtained using 14 Kohonen layer PEs (or data ranges), then combining the output into 4 distinct groupings: low amplitude noise, matrix cracking, micro-delaminations, and a combination of macro-delaminations and fiber breaks. Figure 36 is a visual representation of the optimal network configuration, while Figure 37 is an amplitude histogram showing classification results for the same coupon 23A shown in Figure 31. Note that in the amplitude
histogram, the noise range is identical to the range experienced in the noise analysis (Figure 20), and the three distributions of composite AE failure mechanism data nearly mirror those experienced in Figures 32-35. All this was after an iterative process in which the 14 separate ranges were combined into 4 plausible failure mechanism groupings. Specifically, the humps thought to be external noise, micro-delaminations, and the combination of macro-delaminations and fiber breaks were left unchanged – they are possibly unique ranges that were output by the SOM. The other eleven ranges of data were combined to produce the dominant hump denoted as matrix cracking. This suggests that within the mechanism of matrix cracking, there may be 11 different modes of cracking or possibly 11 different specimen resonances, each emitting slightly differing acoustic signatures. It could also be possible that as the PEs were increased, the SOM itself found unique characteristics in the data of low amplitude noise, micro-delaminations, and the combination of macro-delaminations and fiber breaks, and could only further divide the data considered as matrix cracking into clusters.

![Figure 36. Optimal SOM configuration for amplitude and average frequency classification.](image)

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Figure 38 is an amplitude vs. average frequency graph of the same sample (Coupon 23A) showing the classified data. Again, the cluster of data points determined to be external noise is strikingly similar to the cluster from the noise recordings shown in Figure 22. The other three clusters, slightly overlapping, are logically sound due to the fact that failure mechanisms in composites are coupled with each other and do not occur separately. Matrix cracking, due to its various modes and corresponding acoustic signatures, will be experienced over a wider range of average frequencies. However, delaminations and fiber breaks, which typically occur towards the end of the test, are rapid and energetic, thereby giving of lesser number of acoustic emissions than that of matrix cracks which occur more slowly and continuously throughout the test. Therefore, it will typically occur in somewhat narrower a range, explaining the smaller clusters of data in the higher amplitude ranges.

Also on from analyzing the energy versus amplitude graph of Figure 39, there is a distinct increase in energy with increases in amplitude. Even though energy was not an input to the SOM, the clusters show that they have been separated by distinct ranges of energy. It can be seen that macro-delaminations and micro/macro fiber breaks generate a lot more energy than matrix cracking which makes sense physically.
It is important to state again that although SOMs are incredibly useful for data classification, they must be accompanied by a sound knowledge of the physics involved. Additionally, for this project’s scope, classification alone is not the end goal; rather, it was hoped that classifying the AE failure mechanism data would lead to more accurate prediction results.
Figure 38. Amplitude vs. average frequency graph of data classified by a SOM.

Figure 39. Energy vs. amplitude graph of data classified by a SOM.
4.6 After-Impact Load Prediction Using Backpropagation Neural Networks

![Figure 40. Amplitude histogram with data up to 50% of the failure load.](image)

In order to predict the CAI failure load in the coupons, backpropagation neural networks (BPNNs) were constructed and optimized using the same software as for the SOMs – *Neuralworks Professional II/Plus* (NeuralWare, Carnegie, PA). In the training phase, the networks were trained by normalizing 24 of the coupons’ amplitude distributions (containing data up to 50% of the failure load) as the inputs. The known failure load for each of these coupons was also input to the network. The network then updates the weights between the PEs until the output failure load comes within a certain percent error of the actual failure load, at which point the ANN is considered to be trained. In the testing phase, the networks were tested using the amplitude histograms from the other 10 samples, with the corresponding failure loads being predicted. As seen in Figure 41, two general BPNN architectures were used, and various network parameters were optimized for each configuration until the most accurate predictions were reached. Again Appendix
D contains all the impact damages with their corresponding failure loads. Shaded in a darker color are the random samples chosen for testing the BPNN. In the first configuration, the input layer contained 72 PEs, one for each amplitude decibel level between 30 dB and 100 dB, plus one for the actual failure load (during the training phase only). The number of hidden layer PEs was varied from 7 to 15 to find the optimum value, and the output layer consisted of a single PE, the predicted CAI failure load. At this point the input data were not classified and therefore still contained external (specimen/test fixture rubbing) noise.

1. **Unclassified Data**
   (Includes external noise)

2. **SOM Classified Data**
   (External noise removed)

Figure 41. Two different BPNN configurations.
For the second configuration, the input layer contained 214 PEs. As previously mentioned, the effects of classifying data into failure mechanisms before inputting it into a BPNN were explored. Thus, amplitude distributions from each individual mechanism were used as inputs. The data classified as external noise was removed, leaving three amplitude distributions, one for matrix cracking, one for micro-delaminations, and one for the combination of macro-delaminations and fiber breaks. As before, the actual failure load was also an input (for training), the number of hidden layer PEs varied between 7 and 15, and the sole output PE was the predicted failure load. The two different configurations or neural network architectures are shown in Fig. 41.

It was found that the three most influential parameters in a BPNN are the number of hidden layer PEs, the learning coefficient, and the RMS error of the output. The learning coefficient determines how fast the network weights are adjusted, and the RMS error determines how tightly the network trains. If the BPNN trains too tightly, when new data are presented, the prediction errors will tend to be large. Alternatively, if it does not train tightly enough, there is little chance for an accurate prediction. This could occur if the new data had considerable variance when compared to the data the network was trained on. Thus, several iterations were conducted in order to arrive at the optimal neural network training parameters. Additional training parameters having lesser effects include F’offset, learning coefficient ratio, momentum, and transition point. The number of hidden layer PEs was varied from 7 to 15 (9 possibilities), the learning coefficient was varied between 0.1, 0.05, 0.01, and 0.005, and the RMS error was varied between 10%,
15%, and 20%. This involved 108 possible combinations for each of the two configurations.

After the optimization process was completed for each configuration, the lowest maximum prediction error was found to be 15.89% for the unclassified data. This was with a network containing 15 hidden layer PEs, a learning coefficient of 0.01, and an RMS error of 20%. On the other hand, for the classified data with the noise removed, the lowest maximum error was reduced to -11.65%. This network contained 9 hidden layer PEs, had a learning coefficient of 0.005, and an RMS error of 10%. After approximately 65 more iterations attempting to optimize the minor parameters for the second configuration, the maximum error was ultimately reduced to -11.53%. These results are summarized in the flowchart of Figure 42.

Figure 42. BPNN optimization flowchart.
Tables 3 and 4 contain the best failure load prediction results for the two different architectures. It can be seen that although some individual samples experience better results in the unclassified data network, the overall average error and worst case error are much lower for the SOM classified data network.
Table 3. Optimal network parameters and prediction results for unclassified data (contains external noise).

<table>
<thead>
<tr>
<th>Network Configuration</th>
<th>Sample</th>
<th>Actual Failure Load</th>
<th>Predicted Failure Load</th>
<th>Percent Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1A</td>
<td>22583</td>
<td>21417.30</td>
<td>-5.16%</td>
</tr>
<tr>
<td></td>
<td>5A</td>
<td>19916</td>
<td>20427.09</td>
<td>2.57%</td>
</tr>
<tr>
<td></td>
<td>7A</td>
<td>20434</td>
<td>21708.90</td>
<td>6.24%</td>
</tr>
<tr>
<td></td>
<td>14A</td>
<td>20975</td>
<td>18238.17</td>
<td>-13.05%</td>
</tr>
<tr>
<td></td>
<td>16A</td>
<td>17410</td>
<td>18302.97</td>
<td>5.13%</td>
</tr>
<tr>
<td></td>
<td>26C</td>
<td>20729</td>
<td>23918.20</td>
<td>15.39%</td>
</tr>
<tr>
<td></td>
<td>23A</td>
<td>17322</td>
<td>20075.31</td>
<td>15.89%</td>
</tr>
<tr>
<td></td>
<td>24B</td>
<td>19782</td>
<td>21324.04</td>
<td>7.80%</td>
</tr>
<tr>
<td></td>
<td>25B</td>
<td>21749</td>
<td>19750.56</td>
<td>-9.19%</td>
</tr>
<tr>
<td></td>
<td>27D</td>
<td>18742</td>
<td>19825.08</td>
<td>5.78%</td>
</tr>
</tbody>
</table>

Table 4. Optimal network parameters and prediction results for SOM classified data (external noise removed).

<table>
<thead>
<tr>
<th>Network Configuration</th>
<th>Sample</th>
<th>Actual Failure Load</th>
<th>Predicted Failure Load</th>
<th>Percent Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1A</td>
<td>22583</td>
<td>24634.3</td>
<td>9.08%</td>
</tr>
<tr>
<td></td>
<td>5A</td>
<td>19916</td>
<td>18183.8</td>
<td>-8.70%</td>
</tr>
<tr>
<td></td>
<td>7A</td>
<td>20434</td>
<td>19293.8</td>
<td>-5.58%</td>
</tr>
<tr>
<td></td>
<td>14A</td>
<td>20975</td>
<td>22283.4</td>
<td>6.24%</td>
</tr>
<tr>
<td></td>
<td>16A</td>
<td>17410</td>
<td>19040.2</td>
<td>9.36%</td>
</tr>
<tr>
<td></td>
<td>26C</td>
<td>20729</td>
<td>18817.7</td>
<td>-9.22%</td>
</tr>
<tr>
<td></td>
<td>23A</td>
<td>17322</td>
<td>15324.0</td>
<td>-11.53%</td>
</tr>
<tr>
<td></td>
<td>24B</td>
<td>19782</td>
<td>18400.4</td>
<td>-6.98%</td>
</tr>
<tr>
<td></td>
<td>25B</td>
<td>21749</td>
<td>21084.2</td>
<td>-3.06%</td>
</tr>
<tr>
<td></td>
<td>27D</td>
<td>18742</td>
<td>20099.4</td>
<td>7.24%</td>
</tr>
</tbody>
</table>

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CHAPTER 5
CONCLUSIONS

The main goal of this research was to develop a technique for accurately predicting the residual compressive loads of impact damaged graphite/epoxy composite coupons. Acoustic emission was useful for this purpose because it goes beyond manufacturing defects, flaws and stress concentrations and only acquires important data from a failing composite. Using these acoustic signatures, failure mechanisms of these composite laminates were classified fairly accurately. Additionally, two distinctly different acoustic signatures were distinguishable from the graphs plotted for AE data analysis — one for noise, and one for genuine AE failure mechanism data. This is an important factor, as many past researchers ignored these noise signatures in their analyses, which doubtless increased their prediction errors. Using a MATLAB code to remove possible long duration AE fixture rubbing hits plus other erroneous data created during compression, and SOMs to remove the external noise created by the compression machine, proved to be much more accurate. Thus, using a combination of SOMs and BPNNs for prediction reduced the prediction error from a worst case of 15.89% down to -11.53%. While previous researchers used different parameters like amplitude, duration, rise time and energy together to classify failure mechanism in acoustic emission data, after much trial and error this research streamlined the process to using just two AE parameters, amplitude and average frequency, to achieve a highly accurate SOM classification.

In conclusion, using acoustic emission NDT and artificial neural networks to classify failure mechanisms and predict compressive failure loads for this research proved highly
successful. The combination of these two methods could be used on real world aircraft to predict the failure loads associated with impact damaged parts without knowing a priori the level of impact damage. Moreover using AE, these predictions could be made in service.
CHAPTER 6
RECOMMENDATIONS

For future projects, perhaps more sample coupons could be made and tested on a single network: the more the coupons tested, the better the network will be able to analyze different patterns in the AE failure mechanism data. A network trained and tested on two or three different composite materials could also be tested to see if it can analyze the data the same way it does for one type of material. If this was successful, then a combination of materials could be analyzed for different acoustic signatures using a backpropagation neural network to achieve error predictions results below the desired ±15%. This same aspect could be applied to the Kohonen self-organizing maps to analyze the different failure mechanisms in different composite materials using the same network. Another type of compression fixture could be used to analyze size versus CAI loads and failure mechanisms. Different sized coupons may change the CAI loads, and acoustic emission signatures when compared to this project and possibly even the sequence of failure mechanisms.

More work could be applied to formatting a specific equation for the different failure mechanisms obtained from the SOM. Research would have to be done as to how much data are needed from each failure mechanism from each coupon for accurate prediction. This would be a little challenging, as from the data obtained herein, there was very little consistency between the failure mechanisms of the different coupons. However, there might be a solution to this using the average frequency vs. RA value plot. It may better
cluster the data into specific groups, which could be helpful to future researchers who want to further investigate failure mechanism classification.


APPENDIX A: MATLAB CODE FOR DATA FILTERATION

%%%%%%%%%%
% THIS PROGRAM WAS WRITTEN BY ANTHONY MICHAEL GUNASEKERA TO READ ACOUSTIC
% EMMISION DATA FROM EXCEL FILES AND ARE FILTERED ACCORDINGLY TO THE
% REQUIREMENTS OF THE PROJECT
%%%%%%%%%%

%CLEAR ANY OLD DATA IN MATLAB MEMORY
clear;
clc;

% FILES TO BE READ BY THE PROGRAM (GIVEN BY USER)
fileName_input = { '24A', '8JkA', '24B', '24C', '24D', '25A', '25B'...
                  '27D', '12C', '13C', '14C', '15C', '16C', '17C', '18C', '19C', '20C', '21C', '22C'};

% NEW GENERATED FILE NAME (ADDS THIS NAME TO THE ORIGINAL FILE NAME)
fileName_output = strcat(fileName_input,'30db9.8msc250frq');
for i=1:1:length(fileName_input)
    clear a freq new_freq new_a counts duration energy max_load

% READING EXCEL FILES (CAN BE CHANGED TO READ NEWER VERSIONS OF EXCEL)
a = xlsread(strcat(fileName_input{i},'xls'));
Risetime =a(:,4);
Counts =a(:,5);
Duration =a(:,7);
Energy =a(:,6);
Load =a(:,9);
Amplitude =a(:,8);

% CALCULATING AVERAGE FREQUENCY
freq=round(counts./(duration.*1e-6)/1000);

% DURATION RANGE
min_d=1;
max_d=9800;

% FILTERING DATA BY DURATION WITHIN THE GIVEN RANGE
for j=length(freq):-1:1
    if((duration(j,:)<min_d) | (duration(j,:)>max_d) && j>0)
        risetime(j,:)=[];
        counts(j,:)=[];
        duration(j,:)=[];
        energy(j,:)=[];
        load(j,:)=[];
        amplitude(j,:)=[];
freq(j,:) = [];  
a(j,:) = [];  
end  
end  

% AMPLITUDE DATA RANGE  
max_dB=100;  
min_dB=30;  

% FILTERING DATA BY AMPLITUDE RANGE  
for j=length(freq):-1:1  
  if ((amplitude(j,:)<min_dB) | (amplitude(j,:)>max_dB) & & j>0)  
    risetime(j,:) = [];  
    counts(j,:) = [];  
    duration(j,:) = [];  
    energy(j,:) = [];  
    load(j,:) = [];  
    amplitude(j,:) = [];  
    freq(j,:) = [];  
    a(j,:) = [];  
  end  
end  

% FREQUENCY RANGE  
max_freq=250;  
min_freq=0;  

% FILTERING DATA BY FREQUENCY RANGE  
for j=length(freq):-1:1  
  if ((freq(j,:)<min_freq) | (freq(j,:)>max_freq) & & j>0)  
    risetime(j,:) = [];  
    counts(j,:) = [];  
    duration(j,:) = [];  
    energy(j,:) = [];  
    load(j,:) = [];  
    amplitude(j,:) = [];  
    freq(j,:) = [];  
    a(j,:) = [];  
  end  
end  

% REMOVES ANY ZERO ENERGY HITS  
for j=length(freq):-1:1  
  if (energy(j,:)<1)  
    risetime(j,:) = [];  
    counts(j,:) = [];  
    duration(j,:) = [];  
    energy(j,:) = [];  
    load(j,:) = [];  
    amplitude(j,:) = [];  
    freq(j,:) = [];  
    a(j,:) = [];  
  end  
end
% REMOVES ANY ZERO RISTIME HITS
for j=length(freq):-l:1
    if (risetime(j,:)< 1)
        risetime(j,:) =[];
        counts(j,:) =[];
        duration(j,:) =[];
        energy(j,:) =[];
        load(j,:) =[];
        amplitude(j,:) =[];
        freq(j,:) =[];
        a(j,:) =[];
    end
end

% ASSIGNING ALL DATA TO SPECIFIC COLUMNS FOR EXCEL
for j=1:length(freq)
    new_a(j,1) = counts(j);
    new_a(j,2) = duration(j);
    new_a(j,3) = energy(j);
    new_a(j,4) = load(j);
    new_a(j,5) = freq(j);
    new_a(j,6) = amplitude(j);
    new_a(j,15)= risetime(j);
end

% DISPLAYS AMPLITUDE DISTRIBUTION (COLUMN 7 AND 8 ON SPREAD SHEET)
for j=1:(max_dB-min_dB+1)
    new_a(j,7)=min_dB+j-1;
    new_a(j,8)=0;
end

for k=1:(max_dB-min_dB+1)
    for c=1:length(new_a)
        if (new_a(c,6)==new_a(k,7))
            new_a(k,8)=new_a(k,8)+1;
        end
    end
end

% DISPLAYS FREQUENCY DISTRIBUTION (COLUMN 9 AND 10 ON SPREAD SHEET)
for j=1:(max_freq-min_freq+1)
    new_a(j,9)=min_freq+j-1;
    new_a(j,10)=0;
end

for k=1:(max_freq-min_freq+1)
    for c=1:length(new_a)
        if (new_a(c,5)==new_a(k,9))
            new_a(k,10)=new_a(k,10)+1;
        end
    end
end
%WRITES A NEW EXCEL FILE FOR EACH SAMPLE WITH FILTERED DATA
xlswrite(strcat(fileName_output(i),'.xls'),new_a);
length(new_a)
end
APPENDIX B: AE, BPNN AND SOM DEFINITIONS

The following terms were used in the thesis and they are explained as follows:

**Max duration** is used to specify the maximum length of a hit, in the event that it would not end normally due to continuous emission.

**Sample rate** is the rate at which the data acquisition board samples waveforms on a per second basis. The sample rate of 1 MSPS (mega sample per second) means that one waveform sample is taken micro second. The sample rate of 2 MSPS means that one waveform sample is taken every half a micro second.

PDT, HDT and HLT are timing parameters of the signal measurement process.

**Peak definition time (PDT)** ensures correct identification of the signal peak, for risetime and peak amplitude measurements. 20 to 50 μ seconds is the normal range for a composite material.

**Hit definition time (HDT)** ensures that each AE signal from the structure is reported as one and only one hit. 100 to 200 μ seconds is the normal range for a composite material.

**Hit lockout time (HLT)** ensures that spurious measurements during the signal decay are avoided and the data acquisition speed can be increased. 300 μ seconds is the normal range for a composite material.

**Competitiveness:** Describes the way in which the processing element attempts to control learning through either a cooperative or suppressive relationship with the other processing elements.
**Coordinate Layer:** If you would like an XY output, make sure this is checked, as well as setting your output layer to two. The SOM will attach an XY value between -1.0 and 1.0 to each input value. This is useful for organizing the AE data later.

**Epoch:** Is used for all learning rules except Delta-Rule and it correspond to the number of inputs from the input or training file.

**F' Offset:** Corresponds to a value added to the derivative of the transfer function prior to calculating the value to backpropagate from each PE.

**Hidden Layers:** This sets the number of PEs in the hidden layer, should you choose to have one. This is where most of the mathematical calculations take place. This is necessary in backpropagation neural networks, but not self-organizing maps. Leave it zero.

**Inputs:** This is the number of inputs you are classifying with; the number of dimensions your input vectors and weight vectors will have. Since we are using amplitude and duration, this number is two.

**Learning Coefficient:** Remember this from the theory section? This is the rate the SOM adjusts the PEs, corresponding to the learning rate for each of the hidden layers and the output layer. Too high, too much overshoot. Too low, and it takes too long to learn. There are three boxes for this, one for each possible layer. Leaving them at the default settings is probably a good idea.

**Learn Rule:** Specifies how connection weights are changed during the learning process. In this tutorial, Normalized-cumulative delta-rule was used. It is a rule which accumulates weight changes and updates the weights at end of epoch. It is normalized so that the learning rate is independent of the epoch size.
Learning Coefficient Ratio: The learning coefficient is reduced by this magnitude in order to “slow the learning down” and hone in on specific weights vector values.

Momentum: Becomes useful in configuring the learning and recall schedules for the hidden and output layers.

Neighborhood: The options are diamond, square, and alternating. If you have a network that is more than a few PE’s in each direction, this will determine how the network measures the neighborhood width – horizontally/vertically or diagonally. For our SOMs, we always used 1 column, so this was not a factor

# Rows and # Columns: This will define your Kohonen layer. If you want a 100 PE Kohonen layer, you could do 10 X 10 or 20 X 5, it really should not make a difference. Think of it as the “number of buckets” you are allowing the SOM to classify your data into. Since we are working with composites, and are trying to tailor the Kohonen PEs to the number of failure mechanisms, we experimented with 4-10 rows, and always used 1 column.

# SOM Steps: This value sets the number of learning iterations for the Kohonen layer. If you choose the Set Epoch From File button, it will automatically be set to 30 times the number of input vectors. You have to specify the training file before you set the epoch from it, though.

Output Layer: This allows a mapping network at the output of the SOM. In other words, we can have an XY output attached to each input vector. Set this to two.

Transfer Function: menu allows you to specify a transfer function that is used for all layers in the network. It is suggested to use the hyperbolic tangent transfer function. This function is a very flexible non-linear function which is also continuous and differentiable.
Supervision: Relates to how the network is trained; they are either unsupervised (like Kohonen Self Organizing Maps) or supervised (as will be seen in BPNN). A supervised network requires information about the desired outcome in order to learn, while an unsupervised network trains itself through the use of competitive learning. Supervised learning also means the network has some input present during training to tell it what the correct answer should be. Conversely, the unsupervised learning means the network has no such knowledge of the correct answer and thus cannot know exactly what the correct response should be.
APPENDIX C: SOM LEARNING EXAMPLES

A simple example to how a SOM can be used is to separate a basket of fruit. The basket contains three different types of melons and citrus fruit. The user can input the different sizes of fruit as one of the inputs. Therefore the SOM will try and classify the fruit basket and will probably get two distinct groups. More inputs can be also inputted by the user, for example color or any other specific trait that corresponds to the particular fruit. The network will then assign certain weights or coefficients to these inputs and through certain mathematical calculations will pick two distinct traits (in data form) that will be used to separate and cluster data, if the user has specified two distinct groupings. If more clusters or groups are required, then the network will analyze the data inputted for these traits and try and find more distinct differences. Since all the data is interconnected to each other in the Kohonen layer, which performs all the calculations, it will start comparing the data and looking for data with similar characteristics with similar calculated weights.

Through iteration these weights are also updated to try and hone in on the exact group of weight in the cluster that corresponds to the distinct trait that was used to separate the data. If the user wanted to separate the data further, they could specify exactly how many clusters they want. In the case of the fruit basket they could specify as many as six different clusters (recall the basket contains six different types of fruit). If the user really did not know how many types of fruit there are, a trial and error process of running the program, changing the number of clusters required and then observing the data to distinguish if the clusters of data have a general uniqueness or are mixed in with other data from other groups. Sometimes the SOM will split the
same group into two clusters if excess clusters are specified by the user, due to the marginal difference in data. This is not a problem as the user can then reduce the number of clusters required or add the two different clusters together as they originally used to be one group. This is only possible if the user knows what the data looks like and can justify the addition of the two groups.

**Simple mathematical calculation of a SOM.**

In this simple example, three input vectors will be attached to a Kohonen layer of 10 PEs. This means that there will be 30 weight vectors in total. The neighborhood factor will be set at 2, and the learning coefficient $\alpha$ will be 0.5. That way, the SOM will be able to learn the data relatively fast. By going step by step through the learning process, it will be easy to see how the weight vectors adapt to the inputs. Shown below are the three input vectors, where $X(N) = (x_1, x_2, x_3)$.

\[
X(1) = (0.800 \ 0.500 \ 0.100) \\
X(2) = (0.400 \ 0.900 \ 0.200) \\
X(3) = (0.200 \ 0.000 \ 0.600)
\]

To assist in the demonstration, the weight vectors between a given Kohonen PE and all three input vectors will be the same. That way, it can be seen how the weight vectors change based on the difference in input vector. The initial, randomly assigned weight vectors are given in the following matrix, where $W(N)_{ij0}= (w_{1,j0}, w_{2,j0}, ..., w_{3,j0})$. Note that the “0” after the “ij” refers to the epoch number. Thus, the first set of weight vectors will be $W_{ij0}$

\[
W(1,2,3)_{ij0} = \begin{pmatrix} 
0.200 & 0.000 & 0.600 & 0.600 & 0.100 & 0.300 & 0.400 & 0.900 & 0.200 & 0.700 \\
0.200 & 0.700 & 0.400 & 0.700 & 0.000 & 0.500 & 0.100 & 0.700 & 0.800 & 0.300 \\
0.300 & 0.200 & 0.700 & 0.800 & 0.500 & 0.100 & 0.800 & 0.200 & 0.700 & 0.400 
\end{pmatrix}
\]
The first calculation, using Equation (3) is shown below. Note that in the term $D(N_n)$, the larger number refers to which input vector the distance is calculated for, and the subscript refers to the Kohonen PE.

\[
D(l_i) = \sqrt{(w_{i1} - x_1)^2 + (w_{i2} - x_2)^2 + (w_{i3} - x_3)^2}
\]

\[
D(l_5) = \sqrt{(0.200 - 0.800)^2 + (0.200 - 0.500)^2 + (0.300 - 0.100)^2} = 0.700
\]

The calculated distances for all 30 weight vectors are shown below. Note that the fifth PE contains the shortest Euclidean distance, and thus becomes the winning PE. This value is shown in bold.

\[
\begin{align*}
D(l_1) &= 0.700 & D(l_2) &= 0.735 & D(l_3) &= 0.361 \\
D(l_2) &= 0.831 & D(l_3) &= 0.447 & D(l_4) &= 0.831 \\
D(l_3) &= 0.640 & D(l_4) &= 0.735 & D(l_5) &= 0.574 \\
D(l_4) &= 0.755 & D(l_5) &= 0.663 & D(l_6) &= 0.831 \\
D(l_5) &= 0.949 & D(l_6) &= 0.424 & D(l_7) &= 0.141 \\
D(l_6) &= 0.500 & D(l_7) &= 1.00 & D(l_8) &= 0.714 \\
D(l_7) &= 0.900 & D(l_8) &= 0.589 & D(l_9) &= 0.300 \\
D(l_8) &= 0.245 & D(l_9) &= 0.548 & D(l_{10}) &= 1.068 \\
D(l_9) &= 0.900 & D(l_{10}) &= 0.548 & D(l_{11}) &= 0.806 \\
D(l_{10}) &= 0.374 & D(l_{11}) &= 0.700 & D(l_{12}) &= 0.616
\end{align*}
\]

Now that the winning PE has been determined, the first set of new weight vectors can be calculated. Recall Equation 4, noting that the learning coefficient $\alpha$ is 0.5. With a neighborhood factor of two, the weights attached to the winning PE, as well 2 PEs in either direction will have new weights calculated. A sample calculation using Equation 4 is shown for the weight vector between the first element of the first input vector, and the third PE.
\[ W_{\text{new}} = W_{\text{old}} + \alpha(X - W_{\text{old}}) \]
\[ W(1)(i = 3, j = 1)_1 = 0.6 + 0.5(0.8 - 0.6) \]
\[ W(1)(i = 3, j = 1)_1 = 0.7 \]

The weight vectors after the first complete epoch are shown below. The updated vectors are shown in bold.

\[
W(1)_{ij} = \begin{pmatrix}
0.200 & 0.000 & 0.700 & 0.700 & 0.450 & 0.550 & 0.600 & 0.900 & 0.200 & 0.700 \\
0.200 & 0.700 & 0.450 & 0.600 & 0.250 & 0.500 & 0.300 & 0.700 & 0.800 & 0.300 \\
0.300 & 0.200 & 0.400 & 0.450 & 0.300 & 0.100 & 0.450 & 0.200 & 0.700 & 0.400
\end{pmatrix}
\]

\[
W(2)_{ij} = \begin{pmatrix}
0.200 & 0.000 & 0.500 & 0.500 & 0.250 & 0.350 & 0.400 & 0.900 & 0.200 & 0.700 \\
0.200 & 0.700 & 0.650 & 0.800 & 0.450 & 0.700 & 0.500 & 0.700 & 0.800 & 0.300 \\
0.300 & 0.200 & 0.450 & 0.500 & 0.350 & 0.150 & 0.500 & 0.200 & 0.700 & 0.400
\end{pmatrix}
\]

\[
W(3)_{ij} = \begin{pmatrix}
0.200 & 0.000 & 0.400 & 0.400 & 0.150 & 0.250 & 0.300 & 0.900 & 0.200 & 0.700 \\
0.200 & 0.700 & 0.200 & 0.350 & 0.000 & 0.250 & 0.050 & 0.700 & 0.800 & 0.300 \\
0.300 & 0.200 & 0.650 & 0.700 & 0.550 & 0.350 & 0.700 & 0.200 & 0.700 & 0.400
\end{pmatrix}
\]

After completing the cycle a second time, it can already be seen that the values in the weight vectors are approaching the values of the input vectors. Recall that \(X(1) = (0.800, 0.500, 0.100)\), \(X(2) = (0.400, 0.900, 0.200)\), and \(X(3) = (0.200, 0.000, 0.600)\). The winning PE and the influenced weight vectors are consistent with the first epoch.

\[
W(1)_{ij} = \begin{pmatrix}
0.200 & 0.000 & 0.750 & 0.750 & 0.625 & 0.625 & 0.700 & 0.900 & 0.200 & 0.700 \\
0.200 & 0.700 & 0.475 & 0.550 & 0.375 & 0.500 & 0.400 & 0.700 & 0.800 & 0.300 \\
0.300 & 0.200 & 0.250 & 0.275 & 0.200 & 0.100 & 0.275 & 0.200 & 0.700 & 0.400
\end{pmatrix}
\]

\[
W(2)_{ij} = \begin{pmatrix}
0.200 & 0.000 & 0.450 & 0.450 & 0.325 & 0.375 & 0.400 & 0.900 & 0.200 & 0.700 \\
0.200 & 0.700 & 0.775 & 0.850 & 0.675 & 0.800 & 0.400 & 0.700 & 0.800 & 0.300 \\
0.300 & 0.200 & 0.325 & 0.350 & 0.275 & 0.175 & 0.350 & 0.200 & 0.700 & 0.400
\end{pmatrix}
\]
After the fourth epoch, the weight vectors have clearly begun to cluster around the input vectors.

A three-dimensional graph showing these clusters is shown in Figure 43.
After ten epochs, it was seen that the clusters were all located exactly at the same coordinates as the input vectors. This can be primarily attributed to the relatively high learning coefficient of 0.5. Also, only half of all the weight vectors were influenced. This is because the same PE was the winning PE each time, and due to the neighborhood factor of two, the same five PEs were influenced during each epoch. If there were more input vectors than Kohonen PEs, and a wider spread of data, more of the weight vectors would have been prone to shifting. This example provides an excellent way of seeing how the learning process of SOMs actually takes place.
## APPENDIX D: CAI FAILURE LOADS

Table 5. CAI failure loads

<table>
<thead>
<tr>
<th>Sample</th>
<th>Impact Damage (J)</th>
<th>Actual Failure Load (lb)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1A</td>
<td>8</td>
<td>22583</td>
</tr>
<tr>
<td>2A</td>
<td>8</td>
<td>24498</td>
</tr>
<tr>
<td>4A</td>
<td>10</td>
<td>20162</td>
</tr>
<tr>
<td>5A</td>
<td>10</td>
<td>19916</td>
</tr>
<tr>
<td>23C</td>
<td>10</td>
<td>22470</td>
</tr>
<tr>
<td>24A</td>
<td>10</td>
<td>24195</td>
</tr>
<tr>
<td>25A</td>
<td>10</td>
<td>21815</td>
</tr>
<tr>
<td>26A</td>
<td>10</td>
<td>22190</td>
</tr>
<tr>
<td>7A</td>
<td>12</td>
<td>20434</td>
</tr>
<tr>
<td>8A</td>
<td>12</td>
<td>20827</td>
</tr>
<tr>
<td>24B</td>
<td>12</td>
<td>19782</td>
</tr>
<tr>
<td>25B</td>
<td>12</td>
<td>21749</td>
</tr>
<tr>
<td>25D</td>
<td>12</td>
<td>17249</td>
</tr>
<tr>
<td>10A</td>
<td>13</td>
<td>18163</td>
</tr>
<tr>
<td>11A</td>
<td>13</td>
<td>17226</td>
</tr>
<tr>
<td>13A</td>
<td>14</td>
<td>18660</td>
</tr>
<tr>
<td>14A</td>
<td>14</td>
<td>20975</td>
</tr>
<tr>
<td>16A</td>
<td>15</td>
<td>17410</td>
</tr>
<tr>
<td>17A</td>
<td>15</td>
<td>16685</td>
</tr>
<tr>
<td>19A</td>
<td>16</td>
<td>15805</td>
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<tr>
<td>20A</td>
<td>16</td>
<td>16734</td>
</tr>
<tr>
<td>24C</td>
<td>16</td>
<td>17944</td>
</tr>
<tr>
<td>26B</td>
<td>16</td>
<td>20833</td>
</tr>
<tr>
<td>27B</td>
<td>16</td>
<td>18825</td>
</tr>
<tr>
<td>27D</td>
<td>16</td>
<td>18742</td>
</tr>
<tr>
<td>23A</td>
<td>18</td>
<td>17322</td>
</tr>
<tr>
<td>22A</td>
<td>18</td>
<td>19503</td>
</tr>
<tr>
<td>25C</td>
<td>18</td>
<td>20010</td>
</tr>
<tr>
<td>26C</td>
<td>18</td>
<td>20729</td>
</tr>
<tr>
<td>27A</td>
<td>18</td>
<td>20255</td>
</tr>
<tr>
<td>27C</td>
<td>18</td>
<td>18986</td>
</tr>
<tr>
<td>4B</td>
<td>20</td>
<td>19175</td>
</tr>
<tr>
<td>24D</td>
<td>20</td>
<td>17250</td>
</tr>
<tr>
<td>26D</td>
<td>20</td>
<td>20024</td>
</tr>
</tbody>
</table>
Amplitude vs. Average Frequency

Duration vs. Counts
Coupon 5A - Hits vs. Amplitude

Hits vs. Average Frequency
Amplitude vs. Average Frequency

Duration vs. Counts
Coupon 7A - Hits vs. Amplitude

Hits vs. Average Frequency
Amplitude vs. Average Frequency

Duration vs. Counts
Amplitude vs. Average Frequency

Duration vs. Counts
Coupon 19A - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 20A - Hits vs. Amplitude

Hits vs. Average Frequency
Amplitude vs. Time

Amplitude (dB) vs. Time
Coupon 22A - Hits vs. Amplitude

Hits vs. Average Frequency
Amplitude vs. Average Frequency

Duration vs. Counts
**Amplitude vs. Average Frequency**

- **Y-axis:** Amplitude (dB)
- **X-axis:** Average Frequency (KHz)

**Duration vs. Counts**

- **Y-axis:** Duration (microsec)
- **X-axis:** Counts
Amplitude vs. Average Frequency

Duration vs. Counts
Amplitude vs. Time

Amplitude (dB)

Time
Amplitude vs. Average Frequency

Duration vs. Counts
Amplitude vs. Time

Amplitude (dB)

Time
Coupon 25A - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 25C - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 26A - Hits vs. Amplitude

Hits vs. Average Frequency
Amplitude vs. Average Frequency

Duration vs. Counts
Amplitude vs. Time
Amplitude vs. Time

Amplitude (dB) vs. Time
Amplitude vs. Average Frequency

Duration vs. Counts
APPENDIX F: PLOTS FOR NOISE TEST DATA

Noise Test - Hits vs. Amplitude

Hits vs. Average Frequency
APPENDIX G: PLOTS FOR SELF-ORGANIZING MAP FOR 100 PERCENT OF DATA WITH NOISE

Coupon 1A S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 14A S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 17A S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Amplitude vs. Average Frequency

Duration vs. Counts

- Noise
- Mech 1
- Mech 2
- Mech 3-4
Coupon 19A S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency

Average Frequency (KHz)

Noise
Mech 1
Mech 2
Mech 3-4
Coupon 20A S.O.M Distribution - Hits vs. Amplitude

 Hits vs. Average Frequency
Coupon 24A S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 24B S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 25C S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 26D S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 27B S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
Coupon 27D S.O.M Distribution - Hits vs. Amplitude

Hits vs. Average Frequency
APPENDIX H: PLOTS FOR SELF-ORGANIZING MAP FOR 50 PERCENT OF DATA WITH NOISE

Coupon 1A S.O.M Distribution - Hits vs. Amplitude

Coupon 2A S.O.M Distribution - Hits vs. Amplitude
Coupon 8A S.O.M Distribution - Hits vs. Amplitude

Coupon 10A S.O.M Distribution - Hits vs. Amplitude
Coupon 25C  S.O.M Distribution - Hits vs. Amplitude

Coupon 25D  S.O.M Distribution - Hits vs. Amplitude
Coupon 27A  S.O.M Distribution - Hits vs. Amplitude

Coupon 27B  S.O.M Distribution - Hits vs. Amplitude
Figure 44. Microscopic image of an impacted plate showing matrix voids and cracking.

Figure 45. Microscopic image of an impacted plate showing matrix cracking.
Figure 46. Microscopic image of an impacted plate showing fiber bundle splits.

Figure 47. Microscopic image of an impacted plate showing fiber bundle splits and matrix voids.
APPENDIX I: COMPOSITE ROLL DEFECT LOG

<table>
<thead>
<tr>
<th>Footage From</th>
<th>Defect Number</th>
<th>Minor Defect Area SQ IN</th>
<th>Major Defect Allowance LFT</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core 90</td>
<td>Roll End 90</td>
<td>14</td>
<td></td>
<td>Misalignment - Fill Yarns</td>
</tr>
<tr>
<td>180</td>
<td>6</td>
<td>14</td>
<td></td>
<td>Misalignment - Fill Yarns</td>
</tr>
</tbody>
</table>

CYCOM: 985 GF3070PW-60°, Resin Content 35-39%

Modified epoxy resin on structural carrier

WARNING! MAY CAUSE ALLERGIC SKIN REACTION

The following components of this product are listed in accordance with right-to-know laws.
CAS NO. COMPONENT
037782-42-5 Graphite
089192-01-1 Aramid Fiber
000097-06-1 Epoxy Resin(s)

WIDTH OF PRODUCT 60"

TOTAL LENGTH 180 LFT 60 LYD

ALLOWANCE FOR DEFECTS 0 LFT 0 LYD

ACCEPTABLE MATERIAL 180 LFT 60 LYD

DEFECTS
1. Impurities
2. Dry Areas
3. Area of Non-uniformity
4. Incomplete Impregnation
5. Cured Resin
6. Hard Spot
7. Color Difference
8. Folded Selvage
9. Yarn Splices
10. Twisted Yarns
11. Wrinkles or Puckers
12. Resin-Rich Area
13. Misalignment - Warp Yarns
14. Misalignment - Fill Yarns
15. Unwetted Fibers
16. Fiber Balling
17. Width
18. Straightness of Edge (Tape)
19. Cut
20. Gap
21. Stop Mark
22. Other (describe in comment section)
23. Splice

HG-8000 White Copy-Customer
Yellow Copy-Inspection