Crack Propagation Analysis Using Acoustic Emission Sensors for Structural Health Monitoring Systems

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Aircraft, wind turbines, or space stations are expected to remain in service well beyond their designed performance lifetime. Consequently, maintenance is an important issue for aircraft or aerospace structures. This is accomplished through inspecting for damage at scheduled times and replacing damaged parts before failure. Ground inspections of aircraft, even using simple nondestructive testing techniques, generally require the aircraft be pulled from operation so that its components can be inspected for damage. Structural components are replaced if sufficient damage is found. Research is underway to develop a structural health monitoring (SHM) system as a means to improve the current maintenance routine. This system would consist of an array of sensors and associated analysis codes which would scan for damage in-flight and perform real time damage analysis of an aircraft’s structure. If damage is recognized long before failure occurs, then a damage tolerance and prognostic assessment could be implemented, allowing for a determination of the remaining life of components. This would ultimately lead to fewer required ground inspections. The current method of inspecting aircraft, consisting of ground inspections for damage after a set number of flight hours, works well from an aircraft safety point of view. However, an in-flight SHM system would allow for better use of components, as specific lifetimes could be determined; and, could be less costly, since an SHM system could be embedded into the aircraft structure, thereby reducing or eliminating the need to tear down the aircraft to scan for damage during the ground inspection. A novel method of implementing artificial neural networks and acoustic emission sensors to form a structural health monitoring system for metallic structures was the focus of this research. Simple structural elements similar to those in many aerospace structures were subjected to increasing static loading during laboratory tests. As the loading increased, designed cracks extended in length, releasing strain waves in the process. Acoustic emission sensors detected these strain waves, which were further analyzed through artificial neural networks. Several experiments were performed to determine the severity and location of the crack extensions in the structure. Conclusions were drawn from these experiments as the artificial neural networks could determine crack extension accurately. These artificial neural networks, coupled with acoustic emission sensors, showed promise for the creation of a structural health monitoring system for aerospace systems.

Nomenclature

\begin{align*}
\text{ANN} & = \text{Artificial neural network} \\
\text{NIAR} & = \text{National Institute for Aviation Research} \\
\text{SHM} & = \text{Structural health monitoring} \\
E & = \text{Root mean squared error} \\
O_j & = \text{Output from node } j \text{ in an artificial neural network} \\
t_k & = \text{Desired or target values for an output data set} \\
w_{ij}, \ v_{ij} & = \text{Weight for path from node } i \text{ to node } j \text{ of an artificial neural network} \\
\bar{X}_i, \ Y_i, \ Z_i & = \text{Node } i \text{ in row of input, hidden, or output layers of an artificial neural network respectively}
\end{align*}

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\[ \alpha = \text{Learning coefficient} \]
\[ \theta = \text{Angle of deviation from the plane of a crack} \]

I. Introduction

This paper contains the results of an investigation of the abilities of a passive ultrasonic scanning system, called an acoustic emission system. The focus of this research effort was for the development of a quick, accurate, and precise method of automating a structural health monitoring (SHM) system to optimize the analysis capabilities of an acoustic emission system in order to locate and assess damage in a structural component. The basic acoustic emission system was augmented with an artificial neural network analysis to provide real-time analysis of acoustic emission data measured from aircraft structural components, during routine service operations.

A. Acoustic Emission

As a crack propagates in a material, molecular bonds are broken, releasing small amounts of energy. The energy released spreads throughout the surrounding material in the form of strain waves, similar to beat pulse waves. These waves are minute deformations in the material with wave frequencies in the ultrasonic range (500 kHz to 3 MHz). Generally all structural deformations transmit some form of energy into the material, including plastic yielding and impact events, resulting in waves similar to those of crack growth. Piezoelectric ceramic materials have been created that can detect those strain waves. These materials are unique in that a voltage is produced in the material, when it is deformed. Ultrasonic sensors created from this piezoelectric material are sensitive enough to produce the small voltages generated by very small deformations, which is then recorded into a computer database for further analyses. The passive system differed from an active ultrasonic testing system in that no strain waves, or deformations, were produced by actuators and transmitted to the structural component. The acoustic emission system was configured to only receive waves, generated by other sources, such as crack extensions or impact events, within the structural component under investigation; however, the detections can still be quite complex due to how strain waves travel in solid structures.\(^1\)\(^-\)\(^3\). The recorded voltage time histories were then broken down into characteristics of the waves, such as amplitude, rise time, and duration, using software provided by Physical Acoustics Corporation\(^4\) with the acoustic emission sensors. These characteristics of the waves were recorded with a network of sensors and analyzed via different software methods through MATLAB and NeuralWorks to determine if cracks were present and growing, and whether the structural component should be replaced. A custom designed artificial neural network was used for the post processing analysis of the detected waves of this study.

The energy released during the deformation of a material has been shown to occur at two stages of the deformation. One is at the onset of plastic deformation, and the other when fracture occurs. This can be illustrated using the results of a simple test, performed at the National Institute for Aviation Research (NIAR). A metallic coupon was subjected to a monotonically, increasing pseudo-static tensile load, with one acoustic emission sensor attached. The results of the test to failure are presented in Figure 1. The stress-strain curve, illustrated as the solid line in the figure, follows the normal convention of being linear to the yield point and nonlinear thereafter. Each of the discrete points on the plot is a measurement of the energy of each strain wave detected during the test. At the yield strength of around 1700 lb. and displacement of 0.133 in., some strain waves were detected and recorded. At the point of fracture, more strain waves were detected with similar levels of energy. At the instant of final fracture two strain waves with large energy were measured. Thus the two main states associated with released strain waves detectable by an acoustic emission system, are at the onset of plastic deformation and at the point of fracture. The research reported in this paper involved an examination of the energy of strain waves produced at a crack tip at the instant

![Figure 1. Correlation of the detected strain waves and the load-displacement curve of a uniaxially loaded metal sample with single acoustic emission sensor. Individual points are the energies associated with individual strain waves detected by sensor](image-url)
of extension to determine the severity of the fracture. A second theory was proposed and observed that might provide a method to better locate growing cracks in structures by accounting for the presence of the plastic zone in the vicinity of the crack tip.

Energy is released within a material for two different transition events, when the deformation of the material changes from pure elastic deformation to a combination of elastic and plastic deformation, and at the point of crack extension associated with fracture. This energy is detectable by acoustic emission sensors. The amount of energy released by a fracture is generally far greater than the amount accompanying plastic deformation. However, both instances occur for growing cracks. The tip of a crack is the site for very large stresses. Before the crack extends, a region or zone of plastic deformation is achieved in the vicinity of the crack tip. This plastic region can be approximated, using Von Mises criterion to determine the boundaries of the plastic zone. For the thin-walled structures of this research, the plastic zone covered a very small region near the crack tip and was the focus, while the major portion of the structure undergoes purely elastic deformation.

As a crack initiates in the material, the plastic zone at the tip is quickly formed. As loading to the structure is increased, the crack will increase in size as illustrated in Figure 2a. Thus at any increment of crack propagation, a crescent shaped region of new plastic deformation is created as illustrated in Figure 2b. This shape may vary for fatigue loading, but for simplicity, a basic shape can be examined.

![Figure 2. Crack tip and plastic zone for a thin plate](image)

Borrowing an idea from the distributed point source method for approximating wave sources in a material, suppose each molecular change is a point source of infinitesimally small diameter, which releases a strain wave into the surrounding area. These point sources could be placed close together, forming a wave front with a specific geometric shape. Overlapping waves will start to cancel one another as the distance between the point sources becomes smaller through the superposition principle. As the number of point sources increases to infinity and the distance between points approaches zero, the geometric shape of the wave becomes continuous and smooth. Waves will travel outward with this smooth shape in a direction normal to the boundary of the shape. This idea is illustrated below in Figure 3, using a line as an example. This idea was originally used for generating wave shapes by piezoelectric actuators. However, this idea may also be applied to a point sources not generated by an actuator, but rather the crescent shape of the new plastic region formed during crack growth. The thicker region of the crescent shape, near the horizontal axis in Figure 2b, contains more energy than at the sharp, pointed tip of the new plastic zone. Thus acoustic emission sensors ahead of the tip of the growing crack will detect strain waves of higher magnitude of energy, when compared to sensors detecting the same wave above or behind the growing crack wave (see Figure 4). Based on the direction of the growing crack, a wedge shape of intensity or magnitude of energy can be drawn, protruding outward from the crack tip.

![Figure 3. Distributed point source method idea illustrated](image)
In other words, the wave energy values detected increase as $\theta$ reaches 0. This allows for a line-of-sight principle to be applied to triangulation methods to compare detections of multiple sensors resulting from the same wave. 

While a crack grows, the material surrounding the tip is in plastic strain. Strain waves propagating through the elastic region of the material will be characterized by a rapid deformation followed by a return to the undeformed configuration; whereas strain waves propagating through a region of elastic/plastic deformation will produce some plastic deformation, even for the minute deformations produced by strain waves. Because of this plastic deformation, the strain waves are dampened and reduced in amplitude when they reach an acoustic emission sensor. This effect, along with the theory of distributed point sources within a new plastic region, strengthens the notion of directional strain waves propagating from a crack tip during crack extension.

**B. Artificial Neural Network**

In the nervous system of animals, networks of passive sensors detect damage within the body. Once damage is detected, the system reacts by sending signals to the brain for further analysis of the situation. More intense signals are generated for larger damage that identifies the specific location of the damage. A similar idea for a passively scanning SHM system for an aircraft has been studied for this paper. That is, as a crack grows in a structural component, the amount of energy released as strain waves is linked to the size of the crack propagation. For large crack growth, more energy is released, and thus more intense strain waves are detected by an acoustic emission system.

An artificial neural network (ANN) is an analysis system that emulates the process of the brain of humans and other animals in that a set of inputs is analyzed to obtain a desired output set. This process allows for quick, but approximate, analysis to complex problems and systems. An ANN utilizes pattern recognition and rapid analysis for approximations of varying data sets. It is fault and noise tolerant and can account for some unknown variables and errors in the data and still achieve a desired output. The ANN was an attractive candidate system to analyze the complex ultrasonic waves, traveling through the material, due to the presence of non-related noise and other unaccounted or unknown variables. An ANN was sought to mimic the ability of an animal nervous system to determine the location and extent of damage. Previous research has found damage detection to be a suitable application for ANN as well.

Artificial neural networks were created around the same time as serial computers. These networks are composed of algorithms to mimic the thought processes of an organic brain to analyze a set of inputs in order to obtain a desired output set. Through a fuzzy logic system, the human thought process was emulated mathematically with a network of connected nodes and adjustable weighted values on the paths connecting the nodes, which can establish a relationship of a set of input variables to a set of output variables. Similar to a human brain, this network can be “taught” the relationship of inputs to outputs using example sets of inputs and outputs. After a sufficient number of examples have been introduced, the network can then be used to determine a trained approximation for the output associated with a new input set within the range of the examples used for training. This process approximates the output set, using “fuzzy” logic. The true power of a neural network is demonstrated when used to evaluate complex problems. Because of the training process of neural networks, a complex relationship of inputs to outputs can be found quickly, accurately and precisely if taught well. The advantages offered by the neural network when applied to a structural health monitoring system of ultrasonic sensors allow for quick assessment of the complex strain wave signals generated by the piezoelectric signals. This would result in an accurate, almost real-time damage assessment of structural components, which may occur when in-service. The focus of the research of this paper consisted of using artificial neural networks to analyze the output of an ultrasonic testing system, being considered as a principal element of a structural health monitoring system for aircraft.
The concept of an artificial neural network was introduced by McCulloch and Pitts in the 1940’s. Rumelhart, Hinton and Williams provided significant improvements of the procedure by including increased learning and solving abilities for complex problems, during their work in the 1980’s. Through these studies, a neural network process was developed, which was suitable for application in the ultrasonic testing addressed in this research. Similar to control theory, the network created was called a feed-forward network, where all connections between nodes are one directional, as illustrated in Figure 5.

An ANN is a system of connected nodes, activated when sufficient incoming signals are received. Each node has a binary activation of active or not, that is, 1 or 0 respectively, along with partial activations between 0 and 1 to account for approximations, or “fuzzy logic.” If a node is activated, it sends a signal to the next set of nodes. Each connection between a node and the next layer of nodes has a weighted value as well, affecting how the outputs of each node affect the next receiving node. The system then “learns” from training examples by optimizing these inter-nodal weights to obtain an ideal input to output operation. The architecture of the networks used in this investigation was a simple one-way network, consisting of layers of nodes, which affect the next layer. No signals were sent backward through the network, so that the process is not time dependant, and thus most suitable for this problem. The input variables form their own, first set or layer of nodes in the network, then several sets of nodes, called hidden layers, follow. Figure 5 illustrates a feed-forward network with only one hidden layer; however, multiple hidden layers may be added as well. The final layer of nodes is the output set, representing the output of the entire network.

ANN’s optimize these inter-nodal weights by "learning" a data set of inputs to outputs, using a training data set. This is usually a general sweep of combinations of inputs to outputs, which the network would encounter in operation. The neural network, once taught a set of inputs to outputs, is then used with data sets, which fall within the range of the learning data set. The advantage of the neural network lies in its ability to use this learning procedure to approximate outputs associated with approximate inputs, which would otherwise require a strenuous, time-consuming method to determine the appropriate input/output relationship. Crack detection in an aircraft SHM system requires fast, accurate detection and analysis of the condition of structural components in flight to assure that damage is recognized before structural failure.

Each node of the network follows a mathematical model represented by Eq. (1) below, where function, $f$, is a sigmoid function and the notation is taken from that of Figure 5.

$$O_k = f\left(\sum_{j=1}^n w_{kj} \cdot Z_j\right)$$  \hspace{1cm} (1)

Here, the sum of the weighted outputs of the hidden layer, $Z_j$, which are connected to node $k$ in the output layer, go into an activation function, which then becomes the output for node $k$ in the output layer, $O_k$. This equation is the mathematical model for a node in the output layer, but it also applies to all other nodes in previous layers as well. Unlike serial or digital computers, where the activation function is limited to a hard threshold of on or off (1 or 0 respectively), neural networks allow for smooth transitions, resulting in better approximations of similar functions.

Adjustment of the weights between the nodes comes about through a method presented by Rumelhart, Hinton and Williams, which involves using the error between the desired outputs, $t_k$, and the output obtained by the network, $O_k$, to adjust the weights, $w_{kj}$ of Figure 5 and Eq. (1), using Eq. (2) below.

$$\Delta w_{kj} = \alpha \cdot Z_j \left( t_k - O_k \right) f'\left(\sum_{j=1}^n w_{kj} \cdot Z_j\right)$$  \hspace{1cm} (2)

$$w'_{kj} = w_{kj} + \Delta w_{kj}$$
This process, based upon an optimization method of adjustment by way of greatest descent, uses a learning curve rate, designated as $\alpha$ in Eq. (2), to adjust the weights slowly. The error values for the output layer, shown in the brackets in Eq. (2), are transmitted backwards through the network in a similar way as described in Eq. (1) to determine the error values for the hidden layer. Once the error values have been determined, the weight adjustments can be obtained for other connections within the network. Through many iterations of the training data set, the weights within the neural network can be optimized.

For the purposes of this study, the training was conducted by repeatedly introducing a training set of input to output data to the neural network, until an RMS error, $E$, reached a minimum value. Using $q$ data sets within the training routine, the error was found, using the following equation.

$$E = \sqrt{\frac{1}{q} \sum_{i=1}^{q} \sum_{k=1}^{k} (t_i - O_i)^2}$$  

(3)

After the entire collection of training sets was used in adjusting the weights once, called an epoch, an RMS error was computed. The network was then constrained to learn for a specific number of epochs before ending the training process. The number of epochs required was large enough to find a minimum RMS error point for the training sets.

Although artificial neural networks have been in existence since the 1950’s, they have not been integrated into the structural health monitoring or nondestructive testing field. Only recently has research shifted to ANN’s as a post-processing solution. The research in this paper offers another use for artificial neural networks and their application with an acoustic emission.

II. Experiment

Several experiments were performed on flat aluminum panels (Al 2024-T3) to determine the ability of an artificial neural network to analyze damage within a structural element. Two different panels were designed and used; one with a width of 6 in. and a thickness of 0.032 in. and another with dimensions of 4 in. wide and 0.05 in. thick. Flat, thin panels were used to simplify the experiments. Two different methods were investigated to utilize a neural network to determine the severity, or extension length, of the crack growth and the position of a crack tip. These experiments are reported on in sections A) and B) below, respectively.

A. Magnitude of Crack Extension

Figure 6 below contains drawings that detail the dimensions of the two different test panels used in the experiments. The panel, shown in Figure 6a was subjected to a uniaxial tensile load to initiate crack extension in order to measure the magnitude of an increment of crack growth. An initial crack was cut into the panel from one of the side edges in the testing region and then the panel was statically loaded with an MTS Sintech 5/G machine through a pin and clevis setup as illustrated in Figure 7. The loading was gradually increased, until crack extension occurred. The crack length was measured at specific load intervals by an observer, using digital calipers. These

![Figure 6. Dimensions of test panels used for experiment. Al 2024-T3 panels with a thickness of 0.032”](image)
measured crack lengths were used to create a learning data set for an artificial neural network. Likewise, they were used to compare the calculated values of a neural network relative to the actual measured values. The acoustic emission sensors, located as shown in Figure 7, continuously monitored for any crack growth during the increasing-load process. The recorded acoustic emission signals were later used for analysis with an artificial neural network. Only two sensors were used for this test, since crack growth size and severity were desired and not the positioning of the crack (see Figure 7b). The sensors were placed at similar positions away from the crack tip to avoid any effects of plastic zone deformation as well as confirm the sensors were functioning properly.

A neural network analysis program could not be added to the Physical Acoustics software used to measured crack lengths were used to create a learning data set for an artificial neural network. Likewise, they were used to compare the calculated values of a neural network relative to the actual measured values. The acoustic emission sensors, located as shown in Figure 7, continuously monitored for any crack growth during the increasing-load process. The recorded acoustic emission signals were later used for analysis with an artificial neural network. Only two sensors were used for this test, since crack growth size and severity were desired and not the positioning of the crack (see Figure 7b). The sensors were placed at similar positions away from the crack tip to avoid any effects of plastic zone deformation as well as confirm the sensors were functioning properly.

A neural network analysis program could not be added to the Physical Acoustics software used to
measure the strain waves in the test samples. Therefore, the measured strain wave data were exported and post-processed. A dataset was created with the acoustic emission software, the measured elapsed time, and the wave characteristics for analysis. The commercial software, NeuralWorks, was used to create the neural network to generate the datasets. A MATLAB program was created to simulate receiving the strain waves over time.

The strain wave data were received continuously over time. For an artificial neural network input data set, a small time interval was used for determining the increment of crack growth associated with the large number of strain waves detected over the short period of time of the crack extension. The energy values from each detected wave were placed into a 10 bin histogram. The output consisted of the change in crack growth, or difference from initial size to final size over that time step. These input and output datasets were used in the network architecture, shown in Figure 8 above. Experimenting with different network architectures, two hidden layers were found to increase precision and accuracy of the output values, while minimizing the processing time of the network. This neural network system proved to work well for predicting the magnitude of crack growth for a flat panel.

B. Crack Positioning

Four acoustic emission sensors were used for the crack positioning experiment. These were placed in a line, parallel to the plane of the edge crack (see Figure 7c). This positioning allowed for sensors to lie ahead of the crack front and other sensors to be behind the crack front. The purpose of this experiment was to determine the validity of the theory described earlier relative to the influence of the plastic zone on the characteristics of the strain waves in the structure.

III. Results and Discussion

The crack extension calculated by an artificial neural network (ANN), using the measured acoustic emission strain wave data was compared with the actual measured crack extension for both training and testing data sets. The abilities of the ANN were assessed using an RMS error of mapping inputs to outputs. The concept of plastic zone interference on the release of strain waves into the material was examined as well, leading to possible future research. The neural networks created for this research were capable of detecting the actual values both accurately and precisely.

A. Magnitude of Crack Extension

Training Data Sets: The MTS machine was configured to increase the displacement in the test section at a rate of 0.01 in/min, resulting in the tensile load necessary to produce this displacement. The instrumentation of the MTS machine tracked the loading force applied to the test specimen, as well as, the applied displacement of one end of the specimen with respect to the other as a function of time. At some load value the crack increased in size as evidenced by a sudden drop in the force applied and a corresponding sudden increase in the number of strain waves detected by the acoustic emission system. In addition any crack extension greater than 0.05 in. was audible to the observers of the experiment. As soon as these phenomena were detected, the MTS machine was manually turned off, so that the displacement did not increase further and the applied load went to zero. The crack length was measured, using a digital calipers and the displacement of the load heads were reset to the original position. This process allowed for acoustic emission detections for a series of finite increments of crack growth, which could then be used for a training set for an artificial neural network to identify a crack extension event.

The data contained in Figure 9 illustrate the results for one of the experiments using the method described above. For this case, crack growth began around 396 sec after the initiation of the applied load. Sudden decreases in load indicate instances of crack extension. As shown in Figure 9b, there were five different instances where increments of crack growth occurred (390sec, 393sec, 395.2sec, 397sec, 398sec). Since the measured crack size was only possible before and after loading was applied to the panel, the percentage of the total crack growth at each instance was estimated, such that the cumulative crack growth equaled the measured change of the crack lengths.
Once increments of crack growth were estimated for each intermediate time step, the entire elapsed time from the beginning of loading was broken down into eight second intervals of time, or time windows. A sliding time window for real-time monitoring was created that stepped through time at a step of 1.6 seconds. This procedure allowed for multiple readings from the same detection (see Figure 10). Within each time window, multiple detections could be observed. These were normalized into a histogram of the data within the time window, thus removing any time dependence. A histogram was made of 10 bins, grouping the values of the energy value of each strain wave between zero and a normalized maximum value. The energy value had exponential characteristics, so a logarithmic scale was used. Some strain waves had an energy value of zero. Thus the logarithmic value was not taken of these values. Finally each time value was provided a crack growth amount and a grouping of either crack growth present or not. Four examples of the final data sets are provided in Table 1 below.

Two artificial neural networks were created for two separate purposes. Both neural networks used the ten histogram bin values as input sets. The first network was designed to a self-organizing map architecture. This network was used to classify each time window into two groups; “yes” crack growth was present, or “no” crack growth present. This was accomplished with a network with a Kohonen layer of 20 nodes x 20 nodes. The neighborhood started at 15 nodes and was decreased with each epoch until grouping was complete. These nine experiments were used to train this network into the two groups. The Kohonen layer was then connected to two output nodes, each representing either “yes” or “no” to crack growth. The connections between the Kohonen layer and the output nodes used a back-propagation method, were trained with the Delta rule, and used hyperbolic tangent activation functions. The purpose of this network was to filter out noise from strain waves corresponding to crack growth.

**Table 1. Example data sets of histogram values and respective crack growth sizes. Time listed is for the start of the time window**

<table>
<thead>
<tr>
<th>Time (sec)</th>
<th>Histogram Values</th>
<th>Crack Growth present (“yes”, “no”)</th>
<th>Crack Growth Size (in)</th>
</tr>
</thead>
<tbody>
<tr>
<td>381.80</td>
<td>0 0 0 1 0 0 1 0 0 0</td>
<td>0 1</td>
<td>0</td>
</tr>
<tr>
<td>383.40</td>
<td>0 0 1 2 1 0 0 0 0 0</td>
<td>0 1</td>
<td>0</td>
</tr>
<tr>
<td>391.40</td>
<td>1 6 7 4 7 0 1 0 0 0</td>
<td>0 1</td>
<td>0.1495</td>
</tr>
<tr>
<td>396.20</td>
<td>9 4 1 3 1 2 0 0 0 0</td>
<td>0 1</td>
<td>0.0299</td>
</tr>
</tbody>
</table>

**Figure 9. Example of test results for panel load to onset of crack extension**

**Figure 10. Example of sliding time window used for experiment.**
With this first network completely trained a second neural network was constructed. This network used the histogram values to determine the crack growth size in inches. This network was trained on the nine experiments, using only the time windows where crack growth was present. This network consisted of a back-propagation network with two hidden layers of five nodes each. Again, Delta rule training was used along with hyperbolic tangent activation functions. The results of the training process are present in Figure 11, below. From the nine experiments, 106 data sets contained one of the defined crack growth times. From this, 85 were used to train the neural network and the remaining 21 were used to test the abilities of the network. The network was trained for 50,000 epochs, or iterations through the data sets. Figure 11 below shows the results for the trained and testing data sets, used in the neural network. The top plots show the target or desired values, while the lower plots show the values predicted by the neural network, once taught. The vertical axis of the plots shows the crack growth value, while the horizontal axis is just the order of how the data sets were stored. The overall shape of the plots in the upper part of the figure should be the exact same shape as those in the lower part of the figure. Due to complexities, these plots vary slightly, but are close to the desired values. This showed promise for the ability of a neural network for health monitoring due to the very small differences between the target crack growth values and the neural network values.

**Figure 11. Results of training an artificial neural network to determine the magnitude of crack growth.** Upper plot shows the desired values, while the lower plot shows the approximation for the fully trained network.

**Testing Data Sets:** Once the two artificial neural networks were created and fully trained, the next step was to use these in a situation, where data sets not previously presented to the networks were used. To accomplish this task, a tenth experiment was conducted. However, for this experiment, the MTS machine was not stopped at the initiation of crack growth, but instead allowed to continue increasing displacement over an extended time. The experiment was finally stopped around the 800 second mark. The detections of strain waves for this experiment are reported in the figure below. Only the initial and final crack lengths were measured for this experiment, but some conclusions could be drawn from the data. The panel failed at around 360 sec, where the crack grew large. The crack then slowly increased in size, until

**Figure 12. Strain wave detections of acoustic emission sensors from a panel under tensile loading.** Initial crack extension occurred around 360 seconds, and continued under displacement control.
the loading was halted. The total increase in crack size was measured to be 0.972 in.

The results shown in Figure 12 indicate that there was a great deal of noise and strain waves detected after the crack extension was initiated. This data set was evaluated using the neural networks, using time windows similar to those of the training sets. Histograms were made of ten bins each with the same range as before. This new data set was first used in the self-organizing map network. Here the outputs of the network categorized each histogram into either crack growth or noise present. The data sets determined to be crack growth and not noise were then used in the second neural network. This network then determined the size of the increment of crack growth over the time window.

This experiment used two separate channels, or sensors. The data from each channel were separated and run through the two networks. Figure 13a below contains plots of the results of the networks in terms of crack length. As time increased in the experiment the total crack length increased. Finally an average of the two signals was taken to find a net crack length value. This average crack growth length is illustrated again in Figure 13b along with the load history. The crack length followed the trend, predicted by the shape of the loading curve. A sudden increase in the length of the crack occurred at the time crack extension began, and the crack slowly increased in size as the controlled displacement of the MTS machine continued. The final cumulative crack length computed using the neural network system was 0.1 in. less than the measured value of the actual crack length. This difference was considered to be an acceptable approximation for the purposes of this experiment.

**B. Crack Location and Plastic Phenomenon**

The proof of concept was examined in this experiment. Due to limited data and knowledge of the wave properties, this process will need to be explored in future studies. Further testing and research will be performed by locating the position of actual crack propagation. Since energy is released at the crack tips, these will be the positions located by the neural network, allowing the entire crack to be determined as the distance between the two close crack tips. This network will then be coupled with a crack severity neural network to determine the ability of neural networks to assess damage detected by an acoustic emission system.

The following figure (Figure 14) contains the signal detections from four AE sensors, placed in a line. The actual sensor placements

**Figure 13. Crack growth length over time, approximated by neural networks.**

**Figure 14. Crack location and sensor placement. Plastic zone is shown around the propagating crack tip.**
and crack position are illustrated in the figure. The plastic zone is shown to increase in size, until the final crack length of 1.98 in. For each increment of crack growth, a single detectable strain wave was produced, and is shown in Figure 15. For this experiment, the amplitude of the strain wave was the characteristic of the wave used for comparison. As the crack grew, the single strain wave was detected by each of the four sensors. For crack growths before the final increment measured, the detected amplitudes of the strain waves remained close to one another. However, for the large extension of the crack tip the detected amplitudes of the strain wave became skewed. As shown in Figure 15c sensors 2 and 3, the sensors closest to the crack tip, received the highest amplitude waves with sensor 1 detecting the third largest amount. The waves detected by sensor 4 had smaller amplitudes, compared to the other three sensors. These measured observations support the theory presented earlier regarding the effects of location of the crack tip and growth direction relative to the position of the sensor.

Figure 15. Strain wave detections from crack propagation.

Further, if this trend is recognizable to an observer of the experiment, than an artificial neural network should be able to deduce a similar trend and be able to predict location of a crack by the amplitude of the detected wave. With multiple sensors of known positions detecting the same waves, a comparison between amplitude magnitudes could be used to determine the location of the crack tip in a structure. Future study will involve combining the severity artificial neural network and a new neural network to perform the location of the crack tip, using this phenomenon.

IV. Conclusion

A novel method of implementing artificial neural networks and acoustic emission sensors to form a structural health monitoring system for metallic structures was presented. Flat aluminum panels, similar in thickness to those found in many aerospace structures, were subjected to increasing static loading during laboratory tests. As the load increased, a crack in the panel increased in size, releasing strain waves into the material. These waves were then detected by acoustic emission sensors, and artificial neural networks were implemented to analyze the strain waves. From a feed-forward neural network, the crack length could be approximated with decent precision. A theory of plastic zone interference with strain waves released was also observed during the analysis of the experimental analysis. Through a second experiment, sensors placed behind the crack front were found to detect waves with smaller amplitudes than the sensors placed in other locations. Future study will involve using this knowledge to train, or teach, an artificial neural network to determine the location of a growing crack based on this difference in amplitude. These two artificial neural networks, coupled with acoustic emission sensors, form the initial stages of the development of a structural health monitoring system for aerospace systems with the capability of determining damage severity and locations within structures.

V. Acknowledgments

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VI. References

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