A Hybrid Neural Network Finite Element Scheme for Prediction of Crack Orientation on a Curved Panel

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Abstract - *A hybrid Neural Network-Finite Element scheme is developed that is able to predict crack orientation based on strain readings from a simulated sensor network on a curved panel. The simulated sensor network is achieved by extracting strain values at specific locations from a Finite Element Model (FEM) of the curved panel. Strain differences are used as training input to the model with the crack orientation angle as the target value. Early stopping is used to aid network generalization and use of 181 test cases yields good results for the correlation coefficients for testing and training. The system is intentionally designed to be computationally simple and easy to implement in a commercial setting. The use of specific blocks of the data as well as acquiring additional data would allow for more consistent predictions from the genetic algorithm.*

Keywords: Finite Element, Neural Network, strain, crack, orientation, curved panel, genetic algorithm

1 Introduction

As the majority of commercial and military fleets seek to extend the lives of their aircraft, substantially more resources are now being directed towards the prevention and management of Multiple Site Damage (MSD) due to fatigue. Many of these fleets are also examining the possibility of changing their maintenance methods and philosophy from schedule based to condition based. This relatively new approach is commonly referred to as Condition Based Maintenance (CBM). The expectation is that a CBM program would enable more effective detection of structural flaws compared to current maintenance processes and also provide opportunities to eliminate unnecessary maintenance events, thereby substantially decreasing maintenance costs. Fatigue crack orientation will play a significant role in the likelihood of MSD and/or the rate at which MSD occurs. The implementation of sensor networks in the fuselage skin that are able to detect crack orientation would be of substantial benefit to those in the aerospace community who are seeking to implement CBM programs. With the advent of nano-sensors and micro-electromechanical systems (MEMS) sensors, the idea that sensors can be placed on aerodynamic surfaces without affecting aerodynamic performance or embedded within the aircraft skin can now be taken seriously.

A neural network is a biologically inspired computational model where a network of processing elements or neurons is programmed to exhibit global behavior. Neural Networks have now been successfully used for a variety of aerospace structural applications. The dominant applications thus far include tasks such as sensor placement [1-3], damage detection [4,5], impact detection [6,7] and fatigue crack growth detection [8]. Some researchers have also applied neural networks to crack characterization. For example, Hidetoshi Fujii et al [9] used a neural network model within a Bayesian framework to model the fatigue crack growth rate of nickel based super alloys. These authors modeled crack growth rate as a function of some 51 variables and demonstrated that it was possible to estimate the isolated effect of particular variables such as the grain size, which cannot in practice be varied independently. Venkatesh et al [10] used a second fractional factorial design to minimize training error, prediction error and training time for a back propagation neural network in order to predict the elevated temperature (0.7–0.8 T_m) creep–fatigue behavior of Ni-base alloy INCONEL 690. This network showed significant improvement, for sets not previously used for training, when compared to Coffin–Manson, linear life fraction and hysteresis energy prediction techniques. Recently, Ye Lu et al [11] introduced an inverse analysis based on the artificial neural network technique for effective identification of crack damage in aluminum plates. These authors applied an information mapping approach coupled with parameterized modeling for Finite Element Analysis to constitute a damage parameter database which was used to train the neural network. The information required was dependent on an active sensor network for cross examination of lamb wave signals scattered by damage as well as a decomposition of the signals into multiple frequency regions using discrete wavelet analysis. Choubey et al [12] used natural frequencies and mode shapes obtained from FEA to determine the size and location of surface cracks in thin walled pressure vessels. The natural frequencies for different modes were used as input for an ANN (Artificial Neural Network) model. The output of the ANN model was the crack size for a particular location. These methods, while successful, would not be easy to apply without access to active resources (e.g., Piezo-electric actuators for wave generation) which are typically more expensive than passive sensors (e.g., strain gages). The use of a Neural Network that is able to detect crack orientation is therefore a natural extension of the genetic algorithm. In order to be eligible for general use, such a network however needs to be computationally efficient, simple to implement, use a minimum amount of data for training, and also be easy to integrate with other programs.

This work seeks to implement an ANN algorithm that uses training parameters obtained from static Finite Element Model outputs. Direct use of strain differences for training allows for a reduction of data translation steps thereby increasing processing speed. The simplicity may result in reduced accuracy relative to the more sophisticated approaches previously mentioned. However, if a comparison is made with current "blind" maintenance methods, the suggested method becomes a powerful tool that may reduce maintenance costs for aircraft carriers. Also, the required accuracy for identification of the crack orientation may be relatively low in order to diagnose MSD growth rate. The objective is therefore to develop a practical sensor network and an associated predictive algorithm that act as a single system which is able to signal the carrier of impending multiple site damage. Knowledge of crack orientation will enable more accurate predictions of MSD. The models discussed can be developed quickly with commercially available Finite Element and mathematical programming software, and utilized by end users who are not necessarily experts in either method.

2 Method Overview

A suitable sensor pattern is devised based on the expected strain gradients that might be caused by fatigue cracks due to load history and cyclical pattern. A typical fuselage panel will be loaded as shown in Fig. 1. The combination of cabin pressurization/depressurization and flight loads will result in cyclical loading which, after thousands of flight cycles, may lead to the formation of micro-cracks.

Strain output locations were chosen such that the strain differences would be most significant when the crack is oriented along either the longitudinal or the transverse direction. The circumferential and longitudinal strains at each sensor location (eight locations) were recorded. For every i^{th} sensor location, there will be $i-1$ new connections between each location. Therefore the number of strain differences, S, that could be obtained by measuring strains at n locations is given by Eqn. 1,

$$S = \sum_{i=1}^{n} i - 1 \qquad (1)$$

For eight strain locations, we therefore have 28 possible strain differences. In order to specify crack orientation, we define the angle, α, (shown in Fig. 1) as the angle which the crack makes with the longitudinal direction. This angle was varied in one degree increments and strain differentials were recorded for each variation. The Back-Propagation Neural Network was generated in order to predict the crack orientation based on strain input.

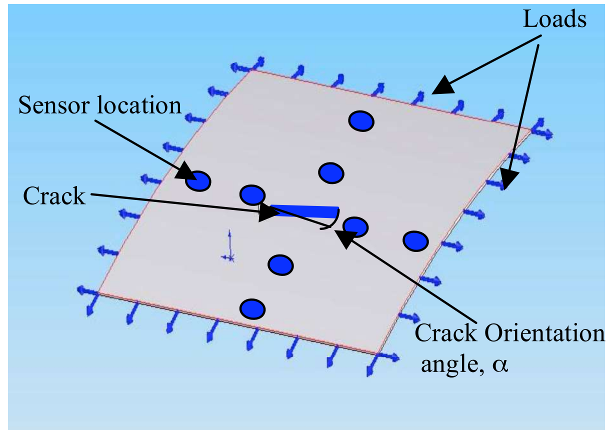

Figure 1. Typical fuselage panel loading.

2.1 Finite Element Model

A Finite Element (FE) model of the curved fuselage panel was developed using the commercial FE software CosmosWorks [13]. Loading was applied transversely as shown in Fig 2. The model was discretized with 1804 thin shell parabolic triangular elements with 3734 nodes, each node having six degrees of freedom. The Young's Modulus and Poisson's ratio used were 72.4 GPa and 0.33 respectively, simulating aluminum 2024-T3. An initial crack length of 12.7 mm or ½ inch was chosen with panel dimensions of 30.48 mm×30.48 mm×1.905 mm. No crack growth algorithm was used as only the static FE case results were of interest. The curvature of the panel about the longitudinal axis was chosen to be 1.145×10^{-3} mm^{-1}.

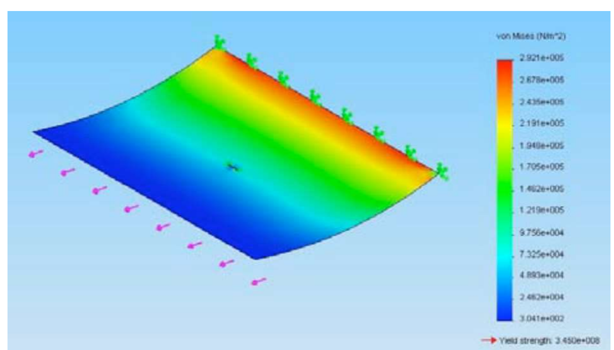

Figure 2. FE model of curved panel with transverse crack.

2.2 Neural Network

The biological nervous system consists of billions of processing elements called neurons. Each neuron is connected to thousands of other neurons and communicates with them via electrochemical signals. Neurons continually receive input signals as well as target signals as we learn and observe phenomena. After numerous input/target pairs are provided, the neurons develop complex relationships such that targets can be predicted based on previously recorded input signals. In many cases new connections are established or deleted as the neurons minimize the difference between the observed target value and its own predicted value.

For an ANN, this process is simulated computationally. The ANN is a subset of genetic algorithms which use optimization techniques based on biological evolutionary concepts such as reproduction, mutation, recombination and selection. An ANN consists of several elements or neurons acting in parallel. Mathematical inputs are summed at each neuron and a threshold condition involving a transfer function is applied to this sum. The mathematical result determines the nature of the neuron output. Training is performed by adjusting the values of the connections (weights) between elements. During training, the error between the network output and the target is minimized until the network output matches the target. The process is shown in Figure 3. One commonly applied minimization technique is the method of least squares.

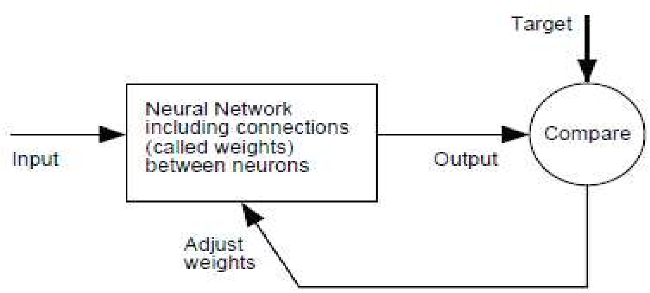

Figure 3. Neural Network (MATLAB documentation).

The network training was performed using the 'Neural Network Toolbox' available with MATLAB (version 6.0) software [14]. Su [15] demonstrated that ANN models with two hidden layers are adequate for most structure-related analysis of damage identification. A single layer was initially chosen in order to minimize complexity and maintain the advantage of low computational cost. However accuracy increased with increasing the number of layers up to three, therefore three hidden layers were eventually used. The log-sigmoid transfer function, *f(s)*, shown in Eqn. 2, was used between all layers except the final hidden layer and the output layer. The linear transfer function, *g(s)*, shown in Eqn. 3 was used for the latter.

$$f(s) = \frac{1}{1+e^{-\beta s}} \tag{2}$$

$$g(s) = s \tag{3}$$

In Eqn. 2, β is a slope parameter. For network training, the weights and biases of the network were updated only after the entire training set was applied. Changes in weights and biases were determined by summing the gradients calculated at each training example. The performance function used (denoted as *mse* in Eqn. 4) was the mean of the sum of squares of the network errors, typical of feed-forward networks.

$$mse = \frac{1}{N}\sum_{i=1}^{N}\left(t_i - a_i\right)^2 \tag{4}$$

The parameters t_i, a_i are the network target and output values, respectively, while N represents the number of cases. Regularization of the performance function through addition of the mean of the sum of squares of the weights and biases did not appear to improve network results. The Levenberg-Marquardt algorithm was used to train the network due to its fast training time and a history of successful use in similar structural applications. Generalization was achieved via the method called early stopping, in which the data is divided into three sets. One set was used for training (70%), another for validation (15%) and the third set used for testing (15%). These sets were randomly sampled from the data set.

The network inputs were the 28 strain differences obtained from the FE model. The output was the crack orientation (angle) associated with the set of 28 strain differentials. Since the angle was varied from 0 to 180 degrees in one degree increments, there were 181 cases available for training, validation and testing. All hidden layers contained 10 neurons each. Increasing the amount of neurons beyond this did not result in improved network performance. A schematic of the network is shown in Fig. 4.

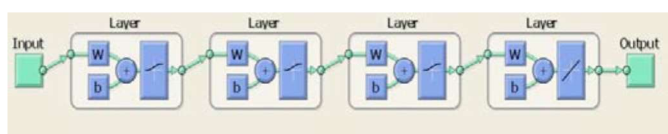

Figure 4. Feed-forward Network schematic for crack orientation.

3 Results

Application of linear regression of the ANN training output relative to the 127 target values (70%) resulted in the equation Output=0.66*Target+27 with an R-squared value of 0.83. In linear regression, the R-squared or coefficient of determination is defined using Eqn. 5.

$$R^2 = \frac{\sum_i \left(t_i - a_i\right)^2}{\sum \left(t_i - \bar{t}\right)^2} \tag{5}$$

where $\bar{t}$ is the mean of the target values. The R-squared magnitude will be between 0 and 1; the closer it is to one the stronger the linear relationship between the target values and the output values. This plot is shown in Figure 5. Linear regression analysis was also applied to the ANN output values relative to the 27 test values (15%). Note that the test values were not used in the training of the network. The resulting equation had an R-squared value of 0.74. This result is shown in Figure 6. Increasing the percentage of test value data generally resulted in better network performance for test values, however the performance for training output would decrease. Since the training set was randomly selected from the data set, the R-squared values varied with each new training. R-squared values varied between 0.51 and 0.93 for the training data and 0.43-0.85 with the test data. When training the network with selected blocks of data, results were more consistent.

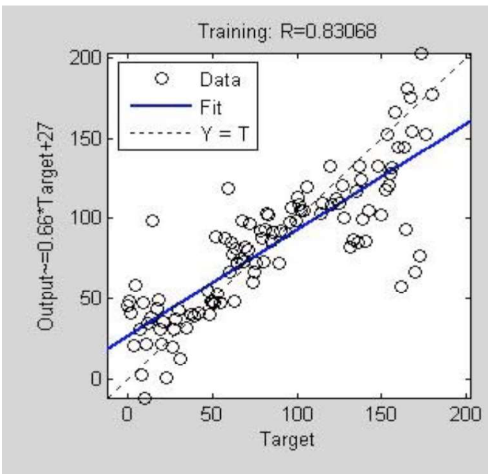

Figure 5. ANN output values vs. target values.

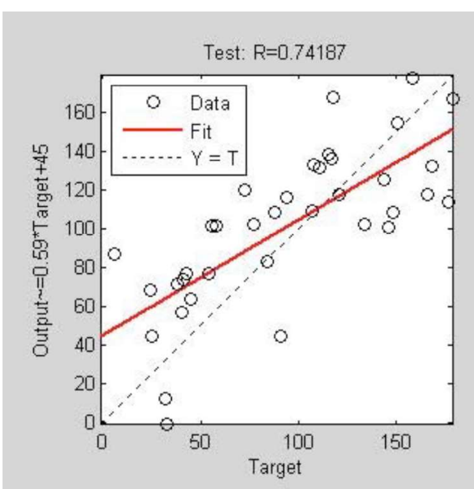

Figure 6. ANN output values vs. test values.

4 Conclusion

A Hybrid Neural Network-Finite Element system has been developed that predicts crack orientation at the center of a curved panel reasonably well. Utilization of early stopping in order to provide generalization for the three layer feed-forward network was an effective tool in testing network performance. Use of 28 strain differences obtained from 8 sensor locations provided enough data to train the Feed forward ANN, yielding an R-squared average of approximately 0.8 for training and test results correlation. More data is recommended for more consistent and accurate predictions. Specific blocks of data provide for better network training than randomly chosen data blocks.

The process outlined is a necessary first step in the development of a smart system that is able to provide real time crack identification information. Though actual strain differences will differ from the FE predicted values, the success of the simple network demonstrates that a low cost genetic algorithm coupled with strain gage readings may be successful in the prediction of crack identification characteristics. For future work, the author intends to add the material and geometrical properties as input parameters and crack length as a second output for the ANN.

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