Damage Detection in Electrically Conductive Structures

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Summary

An experimentally verified technique to predict damage in electrically conductive structures using electric potential measurements in conjunction with an artificial neural network inversion scheme has been developed. This scheme is applicable to any electrically conductive structure of moderate resistivity, including composite structures, electroactive membranes, and conductive polymers. Experimental results are presented for conductive polymer specimens, using both an approach where the location and size of the damage are predicted, and one where the damage is mapped onto a grid of cells.

Introduction

Detection and location of damage is an impetus behind many electrically based structural health-monitoring technologies [1-4]. Although several previously developed methods have been successful for some purposes, none have been sufficiently general to apply to the detection of damage in large conductive membrane structures for space applications. To address the inadequacies of the previous methods, an electric potential technique in conjunction with an artificial neural inversion scheme has been developed to predict damage. In this case, damage is linked to a reduction in the conductivity, as would be appropriate for a tear in an electroactive membrane or fiber breakage in a composite laminate structure. The scheme consists of a feed-forward, back-propagation multi-layer neural network that determines the damage state and configuration from the electric potential values at the boundary. The training data for the neural network is obtained through numerical experiments using the boundary element method. A method is also discussed for determining which of the voltage measurements obtained from the specimen should be used considering the significant systematic error caused by inhomogeneity and anisotropy, as well as the unknown material resistivity.

Damage Prediction Method

To perform the theoretical voltage predictions needed for both generating training data for the neural networks and for processing experimental data, a Boundary Element Method (BEM) code was developed in MATLAB. This code is capable of modeling anisotropic two-dimensional bodies composed of multiple materials with distributed current sources or sinks, and has been validated against

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the commercial finite element analysis program, ANSYS. Further details of this BEM code can be found in the authors' previous paper [5].

All neural network calculations were performed using MATLAB's Neural Network Toolbox; for more information on the toolbox, comprehensive documentation is provided by The Mathworks [6]. The neural networks were trained using the "trainscg" function, which implements a scaled conjugate gradient algorithm to optimize the weights and biases of the network. Network architecture is described in a later section.

For this scheme, the specimen is fitted with a set of electrodes around its perimeter; a fixed current is run successively between each distinct pair of electrodes, except for a reference electrode, and the resulting voltages at all electrodes are measured with respect to the reference electrode. This tactic of measuring voltages with respect to a particular electrode was developed because of difficulties with large, highly variable contact resistances at the electrodes. Since the reference electrode never carries current, its voltage potential is equal to that in the test specimen, so that voltages measured with respect to it are independent of contact resistances (except for the voltages of the source and sink electrodes). Using this scheme for N electrodes, (N-1)(N-2)(N-3)/2 useful voltage measurements are available to the network.

Comparison of the voltage readings for an undamaged specimen to their theoretical values shows a large amount of systematic error, even with the effects of contact resistances nullified. This error is due to small imperfections in the material and geometry. To determine which data should be used for the damage prediction, the ratio of the experimentally determined voltage to the theoretical voltage is taken for each measurement; these values are then sorted, and only those measurements that fall within 3.5% of the median are retained. A scale factor between the experimental and theoretical results is then obtained as the average of the remaining ratio values. Finally, only the source/sink/measurement sets whose experimental voltages fall within 1% of the scaled theoretical values are downselected for use in damage prediction. Although this method of selecting which data to use is somewhat ad hoc, it relies only on measurements of the undamaged structure, and therefore could still be realistically used on an actual part. This procedure also serves as a mechanism for allowing slight material anisotropy, inhomogeneity, and dimensional manufacturing tolerances in "real life" structures.

Two different representations of the damage were used to form the target data sets for the neural networks. The first used the location and radius of a circular cutout as its representation; only a fairly small neural net is required to obtain good results with this approach, but it is limited to only a single damage site. The second representation maps the damage onto a square grid of cells with 30 cells on a side; each cell is assigned a value from 0 to 1 according to the fraction of the cell not covered by the damage.

Once the data to be used have been selected, a feed-forward neural network is trained using theoretical data for damaged specimens. The damage sites for the training data are randomly located uniformly throughout the specimen, and the damage size is also random, with a uniform distribution of sizes from 10% to 20% of the total dimension of the specimen. All actual damage in the experimental specimens fell within this size and location range. For a neural net trained for the location/radius representation, circular damage cutouts were used in the theoretical damage cases; for the cell grid representation, rectangular damage cutouts were used to facilitate projecting the damage onto the cell grid, with the width and height of the damage allowed to vary independently. Since the experimental data display random as well as systematic error, Gaussian noise was added to the training data. The standard deviation of the noise added to each measurement in the training data was scaled from the standard deviation of the experimental measurement on the undamaged specimen. This provides the network with highly realistic data sets to train from. Finally, before training, each input and target datum was normalized to a mean of zero and a standard deviation of unity; the input data was also subjected to a principal component analysis, and only those components contributing more than 0.1% of the total variation in the data set were retained.

Networks trained for the location and radius scheme had 120 log-sigmoid neurons in each of two hidden layers, and 3 linear neurons in the output layer; cell grid networks used a similar architecture, with 270 log-sigmoid neurons in each of two hidden layers and 900 linear neurons in the output layer. One thousand total damage cases were used in the training process, with five-sevenths of the cases forming the actual training set, one-seventh for the test set, and one-seventh for the validation set, which was used for early stopping to prevent overspecialization.

A flowchart of the damage detection process is presented in Figure 1; note that all steps up to and including training the neural network can performed before the structure is put into service. Damage occurring while the structure is in use could thus be detected simply by taking voltage readings and applying the neural network. Because the application of the trained NN is computationally inexpensive, this method could be used for continuous monitoring.

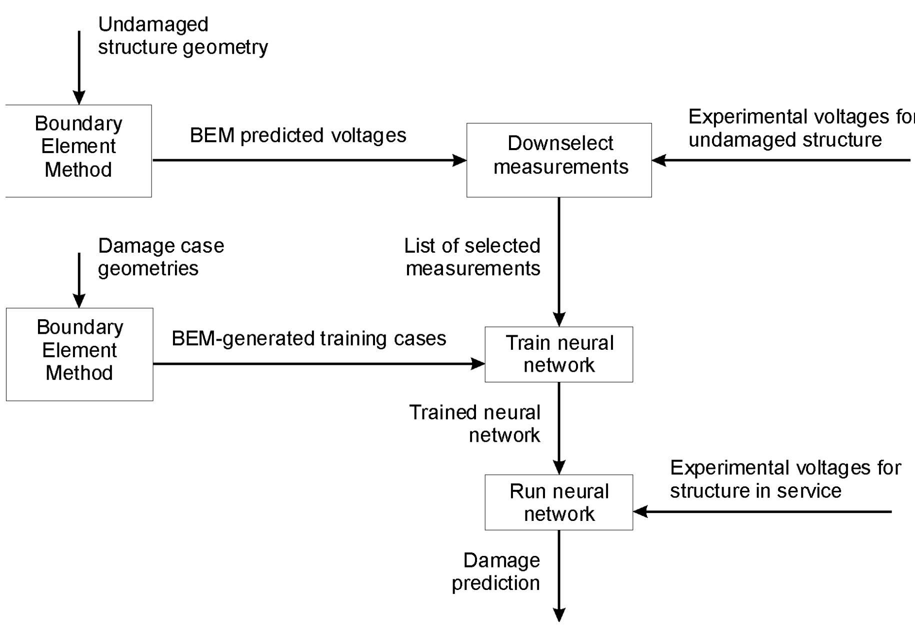

Figure 1. Flowchart of damage detection process.

Experimental Results And Discussion

Experimental runs were conducted to verify that this scheme could accurately detect a cutout in an appropriate test specimen. To accomplish this, nominally isotropic and homogeneous sheets of UHMW polyethylene filled with carbon black were used as the conductive structures. This material provides moderate electrical conductivity as well as durability and ease of working. The specimens used were 12 inches square by 1/8 inch thick; the results of the analysis indicated a sheet resistivity of approximately 1350 Ω/square. Electrodes were created by driving sixteen 0.035-inch diameter steel nails through the specimen, spaced around the perimeter 0.5 inch inward from the edge and 2.4 inches apart. These nails were then attached to wires connected to the data acquisition system. An Agilent 34970A data acquisition/matrix-switch unit was used to provide current source and sink switching, and to collect voltage data.

Damage predictions were obtained for four different representative damage cases. For each originally undamaged case, ten separate sets of voltage measurements were taken in order to obtain the standard deviation of each measurement; the mean of these data sets was used in downselecting the measurements to be used with the neural networks. The voltages input to the neural networks were also the mean of ten sets of measurements on each damaged specimen in order to decrease the effect of random error. Since the standard deviations of the voltage measurements for the undamaged specimens were typically on the order of 10^{-3} or less of the measurements themselves, however, one set of measurements would likely suffice. All specimens had roughly 100 to 140 measurements retained after downselection, out of 1365 total.

Results obtained using the location/radius representation are shown in Table I. The location and radius predictions from the neural network agree well with the actual location and size of the damage for damages of multiple sizes located at various points in the specimen. Note that the neural network performs well for damage at the exact center of the specimen, where this technique is least sensitive.

Results for the cell grid representation are given in Figure 2. The neural network results display a significant amount of noise, which is present even for BEM-generated inputs. However, the predicted damages are the only prominent features, and their locations and extent agree well with the actual damages in the specimens. It is also interesting to note that the cell grid networks have no difficulty detecting circular damage even though they were trained with rectangular damage cases. The electrodes are also shown in Figure 2.

Table I. Damage prediction results for location/radius representation.

	Actual damage			Neural net prediction		
	X (in)	Y (in)	Radius (in)	X (in)	Y (in)	Radius (in)
Case 1	8.125	7.0	1.0	8.5990	7.3348	0.9128
Case 2	6.0	6.0	1.0	5.9973	5.9264	1.0342
Case 3	3.1875	4.0	0.75	3.0633	4.0087	0.8673
Case 4	4.0	8.0	0.75	4.0263	7.7176	0.7927

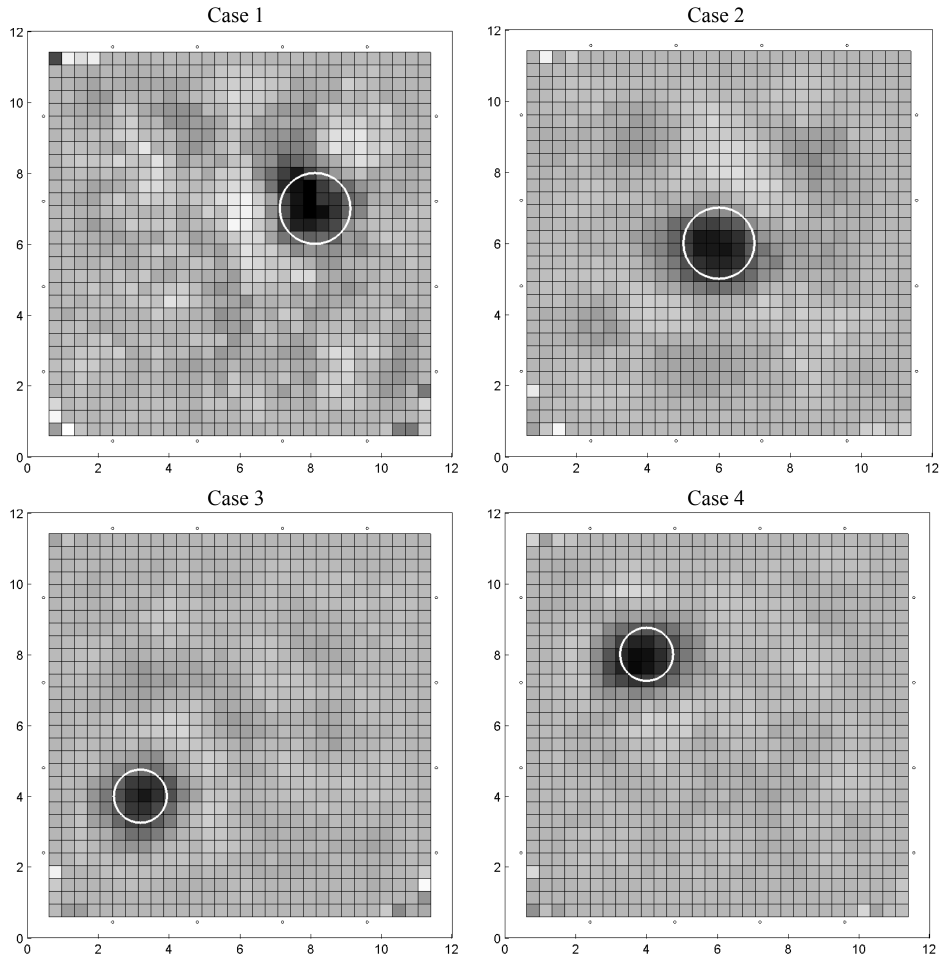

Figure 2. Damage results for cell grid representation. The white circle indicates the actual damage. Results range from 1.4 (white) to 0 (black).

Conclusions

A technique using the electric potential of a structure in conjunction with an artificial neural network inversion scheme has been developed to predict damage in electrically conductive structures. Damage is linked to a reduction in the conductivity, as would be appropriate for a tear in an electroactive membrane or fiber breakage in a composite laminate structure. The scheme consists of a feed-forward, back-propagation multi-layer neural network that determines the damage state and configuration from the electric potential values at the boundary of the domain. The training data for the neural network is obtained through numerical solution of the resulting electrostatics problem using the Boundary Element Method (BEM); damage is represented either by a circular cutout whose location and radius are to be determined, or by a grid of cells, with a value equal to the fraction of the cell not covered by the damage.

To deal with the large amount of systematic error present in the data, the experimentally determined voltage readings taken from the specimen before it is damaged are compared with the theoretical voltage readings obtained from BEM calculations. A scale factor between BEM and experiment is obtained from the ratios of experimental to BEM voltages, and only those readings whose undamaged values are within 1% of the scaled BEM values are retained for use in damage prediction.

Experimental results indicate that neural networks trained to both damage representations can accurately detect damage in conductive polymer structures. Networks trained for the location/radius representation tended to somewhat overestimate the damage size; networks trained for the cell grid representation showed a significant amount of noise, including some Gibbs phenomenon-like features, but were able to accurately locate the damage.

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