Damage Detection in Adaptive Structures Using Neural Networks

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Abstract

A method is presented for determining the location and amount of damage in a structure based on active member transfer function characteristics and artificial neural networks. The method relies on using the active members, which are already present for structural control, to detect and locate damage in the structure. The neural network is trained for a number of known damage cases where the poles and zeros in the active member transfer functions are used as input training data. Two sample problems are given which demonstrate the feasibility of the method. Various simulated damage cases were run; some where the damage is within the domain of the training data and some where the damage is outside the bounds of the training data. In either case, the neural network is able to locate the damaged members and give a good estimate as to the amount of damage in the member.

Introduction

The detection of damage in structures is a topic that has considerable interest in many fields. Detecting damage in space structures subjected to the harsh environment of space could allow the repair of the structure to occur before the damage threatens the mission objectives. Offshore oil platforms constantly have problems with potential member failure in the corrosive sea environment. Buildings and bridges, where structural failure proves catastrophic, would also benefit from a reliable method of detecting and pinpointing structural damage.

In the past many methods for detecting damage in structures have relied on finite element model refinement methods [1-4]. Hajela and Soeiro [1] determined the damage present in a structure by updating the finite element model to match the static and dynamic characteristics of the damaged structure. Their method was an outgrowth of those presented in References 2 and 3 where undamaged members' section properties changed during the model update process, thus smearing the damage over a wide portion of the structure and making specific damage location difficult. Hajela and Soreiro also extended their damage detection techniques to composite structures [4] where a similar gradient-based optimization scheme was used to update the finite element model.

Other methods of detecting damage in structures rely strictly on measured data. Cawley and Adams [5] used only natural frequency data, Pandey et al [6] used mode shape curvature data, and Swamidas and Chen [7] used strain, displacement, and acceleration data to monitor and detect changes and damages in various structures. These methods require comparing measurements of the structure in the nominal (undamaged) state with those at a later date where some damage is potentially present in the structure. These methods have the drawback that they can only identify that the structure has changed; they cannot identify the location and extent of the damage.

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For space structures in particular, stringent pointing and/or slew/settle performance requirements will require some form of structural control. The latest methods of structural control utilize active members, composite members with embedded sensors and actuators [8], for controlling flexible modes. With the sensors and actuators already present for the control task, these structures are ready for the development of damage detection algorithms that rely solely on the measurements available from the active members. But the difficulty remains in processing the measurements generated by the active members and in correlating the data with actual locations and levels of damage.

Neural networks have the unique ability to be trained to recognize known patterns and classify data based on these patterns. Neural networks have been used with success for structural design tasks [9] and for classification of experimental data such as sonar target classification [10]. With proper training neural networks should be able to process the transfer function measurements from the active members, classify the data, and provide a tool for determining the location and level of damage present in a structure.

This paper presents a structural damage methodology in which only active member transfer function data is used in conjunction with an artificial neural network to detect damage in structures. Specifically, the method relies on training a neural network using active member transfer function pole/zero information to classify damaged structure measurements and to predict the degree of damage in a structure. The method differs from many of the past damage detection algorithms in that no attempt is made to update a finite element model or to match measured data with new finite element analyses of the structure in a damaged state.

Damage Detection Methodology Overview

Transfer functions taken of structures before and after some form of damage has been introduced show changes in the pole/zero spacing and, perhaps, pole/zero patterns. It is easy to see these changes when reviewing them, but it is difficult to classify them. For example, Figure 1 shows two transfer functions taken of a structure with and without damage. The differences in pole/zero spacing are small, yet detectable, to the naked eye. However, there is no convenient way to correlate the pole/zero spacing and the location and amount of damage present in the structure. Furthermore, given the transfer function of the damaged structure, no adequate method exists for locating which structural members are damaged and how much damage is present.

The method presented in this paper utilizes finite element data to simulate damage in a structure, with the resulting active member transfer functions used as input training data in an artificial neural network. The method assumes that a reasonable finite element model of the structure in the nominal configuration (i.e., without damage) is available and yields transfer functions that properly characterize the structure.

A flow diagram, outlining the details of the damage detection methodology, is shown in Figure 2. A set of members that are assumed to be at most risk within the structure are identified. These members, which may be a subset or the complete set of members within the structure, will subsequently be used to generate training data for the neural network. Each of the selected "at risk" members' cross sectional areas are varied and the resulting pole/zero information within the active member transfer functions saved. Using the pole/zero information as inputs to the neural network and the corresponding member cross sectional areas as outputs, the neural network is batch trained until a suitable level of error bound is achieved.

(Achieving this error bound is most likely an iterative process involving the number of neurons in the hidden layer, the learning rate, and the number of iterations used to train the network.) The resulting neural network weights and biases represent a mapping from pole/zero information to structural member cross sectional areas. Given a measured set of pole/zero data on a potentially damaged structure, the neural network output provides the location of the damaged members and an estimate of the cross sectional area of the damaged members.

Active Member Description

The active members used in this work are similar to those described in References 8 and 11. Figure 3 shows a schematic of the active portion of the members. Each active member consists of a host material, either graphite composite or a metallic material, with piezoceramic sensors and actuators resident with the host material. In the case of a graphite composite host material, the sensors and actuators are usually embedded within the layup of the composite for enhanced sensing and actuation and for added protection from hostile environmental conditions. In the case of a metallic host material, the sensors and actuators can be bonded to the external surface of the host member. For the case of a truss member, where only axial sensing and actuation are required, the sensors and actuators on all four sides of the active member are tied together to cancel any imperfections in the alignment and layup of the sensors and actuators and to produce (or sense) only axial motions. On each face of the active member are two sensors; one colocated with the actuator and one nearly-colocated with the actuator. Averaging the two sensors together can give a transfer function that is advantageous for control purposes [12]. This is accomplished by varying the pole/zero spacing and pattern within the active member transfer function by changing the relative weights between the colocated and nearly-colocated sensors.

As a structure changes, the transfer functions between the actuators and the colocated and nearly-colocated sensors change. By monitoring these changes, specifically the pole/zero pattern and spacing within the transfer functions, damage to the structure can be detected.

Neural Network Description

A neural network consists of many simple elements operating in parallel. The elements were originally conceived to simulate the processes of biological systems where many processes occur in parallel. The function of the neural network is determined by the connectivity of the network and the weights assigned to the neurons. Neural networks have been used in the areas of speech interpretation, pattern recognition, and process control. One of the main features of neural networks is their ability to be trained to recognize known patterns and classify data. Once trained, the neural nets can be used to predict future outcomes or classify data when given a new set of input data.

Shown in Figure 4 is the schematic of a typical neural network. This network has a set of inputs, a single hidden layer of neurons, and a set of outputs. In general, multiple hidden layers of neurons can be used, but this point will be discussed later regarding the structural damage detection problem. The output from each neuron in the hidden layer is given by the tangent sigmoidal function

$$f(\beta) = \tanh(\beta)$$

where the input to the neuron is

$$\beta = \sum w_{ij} x_{ij} - \theta_j$$

For the tangent sigmoidal function, input values between $+\infty$ and $-\infty$ are mapped to output values between +1 and -1. Outputs from the hidden layer were linearly combined to produce the outputs of the neural network.

For the work reported on herein, the inputs consisted of the imaginary parts of the transfer function poles and zeros and the outputs consisted of the cross sectional areas of the truss members. For the generic structure with n active members, the input training data consists of 2n sets of zeros (i.e., a set of zeros for the colocated sensor transfer function and a set of zeros for the nearly-colocated transfer function), a single set of structural poles, and the feedforward voltage produced by the sensors when operating the actuators well below the dynamics of the system. This methodology has assumed that local "surge" modes of the active member are beyond the frequency band of interest.

Example Problems

Ten Bar Truss

The example structure on which the previously outlined damage detection methodology will be demonstrated is the ubiquitous ten bar truss structure shown in Figure 5. This structure has been used for many structural optimization methodology demonstrations including one utilizing neural networks [9]. The nominal design for the structure without active members typically consists of all ten aluminum members having a cross sectional area of 1.0 in^2. Active members were substituted for element number 1 (the bottom root longeron) and for element number 8 (the upwardly pointing root diagonal). The piezoceramic sensors and actuators were designed to have matched stiffness to the local region of placement. This involved cutting the aluminum portion of the active truss members so that the overall stiffness characteristics of the active member approximately match those of the inert aluminum members. The ten bar truss structure with this baseline design has the natural frequencies of 13.6, 39.0, 40.2, 75.6, 82.3, 93.0, and 94.0 Hz.

Transfer functions between the active member actuators and sensors were generated. A typical set of transfer functions for the two active members is shown in Figure 6. Note that the colocated sensor in either case has a relatively large feedforward term when compared with the nearly-colocated sensor. This feedforward term gives an indication of the stiffness of the active member relative to the remainder of the structure. Thus it can be used as an indicator of the health of the active member itself. In addition, the location of the poles and zeros gives an indication of the health of the remainder of the structure.

Input training data for the neural network consisted of the level of feedforward at the four sensors as well as the imaginary parts of the transfer function poles and zeros. Output training data for the neural network consisted of the cross sectional areas of each of the ten bars in the truss. Additional training sets were obtained by decreasing the stiffness of a member of the truss by a known amount and presenting the resulting input and output training data, as described above, to the neural network.

All results presented below were obtained using a neural network with a single hidden layer of 9 tangent sigmoidal neurons. Additional configurations of neural networks were trained and used to locate and predict the damage in the ten bar truss, but did not achieve better results than the single layer, 9 neuron network. Two networks that achieved approximately equivalent results were a double layer network (with 5 and 4 tangent sigmoidal neurons) and a single layer network with 17 log sigmoidal neurons.

Table 1 contains a list of the simulated damage cases that were run on the ten bar truss structure. The resulting neural network predictions of the member cross sectional areas are also given in Table 1 and presented pictorially in Figures 7 through 9. Test Case 1 represents a condition where a single member was damaged (i.e., member number 4). This type of damage is within the domain of the training data and gives an indication of the adequateness of the training of the neural network. The damage assessment from the neural network indicates that member 4 is damaged and the predicted level of damage, $A_4 = 0.74$, compares well with the actual level of damage used to generate the damaged structure transfer functions (see Figure 7). The network also predicts slight damage to members 2 and 9 that is a result of the static indeterminacy in the ten bar truss. Test Cases 2 and 3 represent multiple member damage conditions where 2 and 3 members are damaged simultaneously, respectively. These types of damage are outside the domain of the training data of the neural network. Nonetheless, the neural network pinpoints the damage very well for both cases (see Figures 8 and 9). In addition, the level of damage is predicted within a few percent for Test Case 2 and within approximately 8% for Test Case 3.

Twenty Five Bar Transmission Tower

A second example structure for demonstrating the damage detection methodology is the twenty five bar transmission tower shown in Figure 10. This structure has been used in a number of design optimization studies and has behavior closer to realistic structures that would benefit from the damage detection algorithm than the ten bar truss structure.

Initially the twenty five bars in the truss were linked to produce four "design variables". The lateral batten across the top of the tower was designated as an independent design variable, the eight upper diagonals were linked to a second independent design variable, the four mid-tower battens were linked to a third independent design variable, and the lower ten inert diagonals were linked to a fourth independent design variable. The cross sections of the two active members, located in the lower diagonals as shown in Figure 10, were held fixed in generating the training data.

A baseline set of transfer functions between the actuators in the active members and both the colocated and nearly-colocated sensors were obtained. A typical baseline transfer function is shown in Figure 11. Each design variable was then perturbed and the resulting structural poles and active member transfer function zeros recorded for use in training the neural network. A typical perturbed transfer function is also shown in Figure 11. As in the case with the ten bar truss, small, but distinguishable, differences can be seen in the transfer functions. Without the neural networks, no existing methodology can take these differences and determine the location and amount of damage present in the structure.

A neural network with a set of input neurons, two layers of hidden neurons, and a single layer of output neurons was batch trained with the baseline and perturbed structure data. The input layer contained forty neurons corresponding to 8 poles and 32 zeros. The two hidden layers contained 7 and 5 neurons each, while the output layer contained four neurons corresponding to the cross sectional area of each independent design variable. The neural network was batch trained until the network had approximately converged to its "best" solution (i.e., 8000 epochs of training). Examining the trained neural network indicated that predictions of damage in design variables 2 through 4 should be relatively good. Predictions for damage in design variable 1 would produce some inaccuracy because the neural network has not converged to the weights that yield high quality estimates. This failure to converge is due to the fact that design variable 1 does not have a great influence on the first 8 modes of the structure (i.e., the modes that were used to train the neural network). Using additional modes for training the neural network could alleviate this difficulty.

Three cases of simulated damage were run on the truss and compared with the predictions made by the trained neural network. These three cases are given in Table 2 and correspond to: Case 1) 25% reduction in stiffness in design variable 2 only; Case 2) 5% reduction in design variable 2 and a 25% reduction in design variable 4; and, Case 3) 5% reduction in the active member stiffness. The first case corresponds to an extrapolation of the training data, the second corresponds to a combination and extrapolation of training sets, and the third corresponds to the presence of damage in the structure that was outside the domain of the training data.

The results of these three case are given in Table 2 and shown pictorially in Figures 12 through 14. For Case 1, the neural network is able to locate the damaged member and give a reasonable estimate of the damage. The network predicts a 35% stiffness reduction in design variable 2 as compared with the actual reduction of 25%. However, the neural network tended to smear the damage across design variables 3 and 4. This smearing effect is due to the inadequacy of the training data in representing damage to design variable 1. (The neural network predicts some increase in stiffness for variable 1 and counteracts this with a smeared reduction in the remaining design variables.) For Case 2, a reasonable prediction of the damage to design variables 2 and 4 is given, along with the same difficulty associated with design variable 1 as seen in Case 1. In Case 3, the neural network recognizes that the damaged structure does not include damage to any of the 4 design variables. Though damage is present in the structure, with a moderate movement of the transfer function poles and zeros, the neural network successfully predicts that the four design variables that it can accurately classify are undamaged. In this case, the neural network does not try to smear the damage across the design variables, preferring instead to correctly recognize design variables 1 through 4 as undamaged.

Conclusions

A methodology for detecting damage in structural systems has been described. The method utilizes the active members that are already present for a controlled structure in conjunction with a trained artificial neural network. Two numerical examples demonstrated the feasibility of the method by pinpointing the damaged members and by giving a very good estimate regarding the level of damage present for each member. Better estimates of the levels of damage could be obtained if training data that encompasses the majority of most likely damage scenarios is used.

The damage detection methodology presented herein is potentially applicable to a wide range of structures where sensor/actuator transfer function pole and zero information is available. Though demonstrated only on simple truss structures, the method could be applied to bending active members or to active plate and shell structures. The keys to making the problem tractable for larger problems are adequately identifying the areas of the structure at high risk for potential damage and including enough pole/zero information in the training of the neural network.

The numerical results from both the 10 bar truss and the 25 bar transmission tower demonstrate the feasibility of the method for detecting and locating damage within structures. The neural network was able to locate patterns of damage even for cases where the damage was outside the domain of the training data.

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Table 1. Simulated Damage Test Cases - Ten Bar Truss

	Test Case 1		Test Case 2		Test Case 3	
Member Number	Actual Area	NN Area	Actual Area	NN Area	Actual Area	NN Area
1	1.00	1.00	1.00	0.98	1.00	1.05
2	1.00	0.92	1.00	1.00	1.00	0.96
3	1.00	0.99	0.80	0.82	0.80	0.88
4	0.75	0.74	1.00	0.99	1.00	1.05
5	1.00	1.02	1.00	0.99	1.00	1.00
6	1.00	0.98	1.00	1.02	0.80	0.85
7	1.00	0.99	0.95	0.95	1.00	0.92
8	1.00	1.07	1.00	0.99	1.00	1.11
9	1.00	0.98	1.00	1.00	1.00	0.95
10	1.00	1.02	1.00	1.00	0.70	0.76

Table 2. Simulated Damage Test Cases - Twenty Five Bar Tower

	Test Case 1		Test Case 2		Test Case 3	
Member Number	Actual Area	NN Area	Actual Area	NN Area	Actual Area	NN Area
1	1.00	1.04	1.00	0.91	1.00	0.97
2	0.75	0.65	0.95	0.93	1.00	1.00
3	1.00	0.95	1.00	0.96	1.00	1.00
4	1.00	0.92	0.75	0.67	1.00	1.00

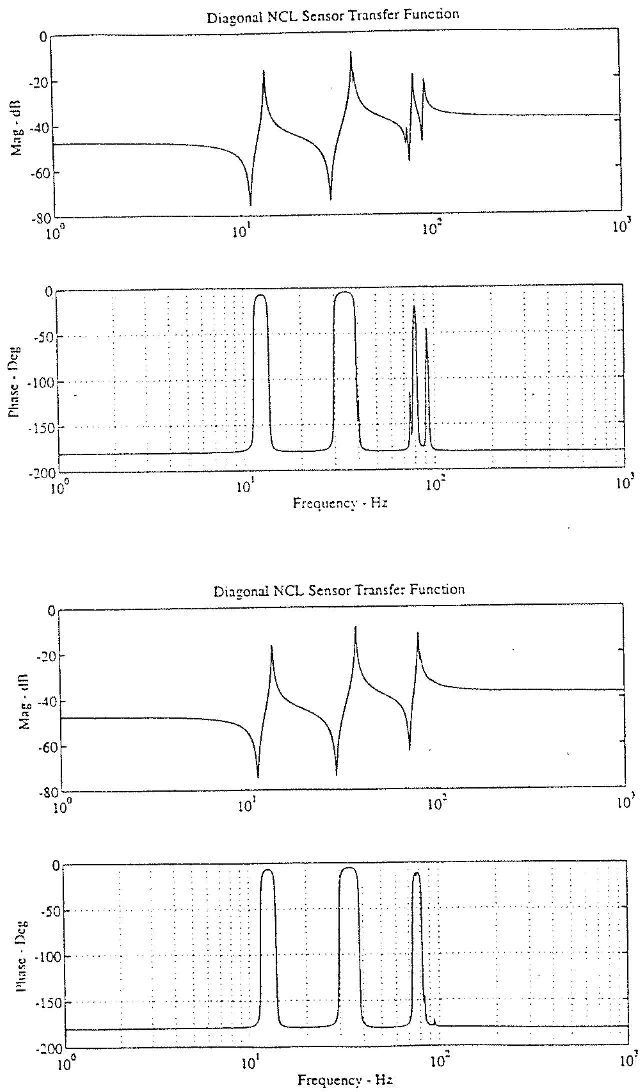

Figure 1. Typical Undamaged and Damaged Structure Transfer Functions

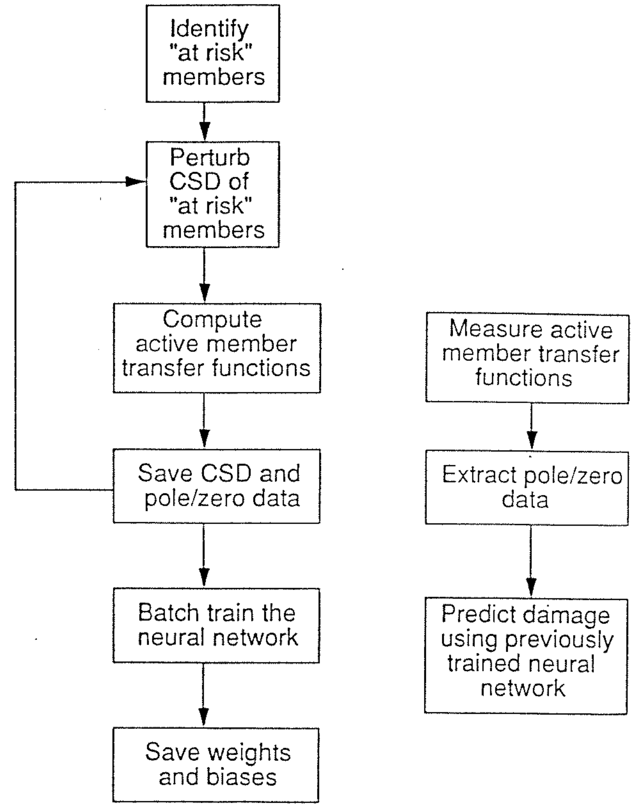

Figure 2. Structural Damage Detection Flow Diagram

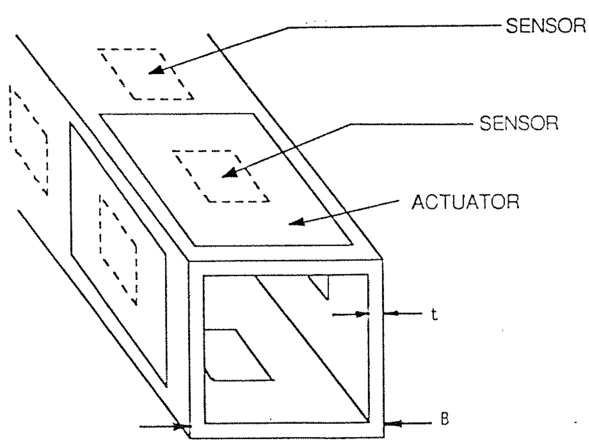

Figure 3. Typical Active Member Schematic

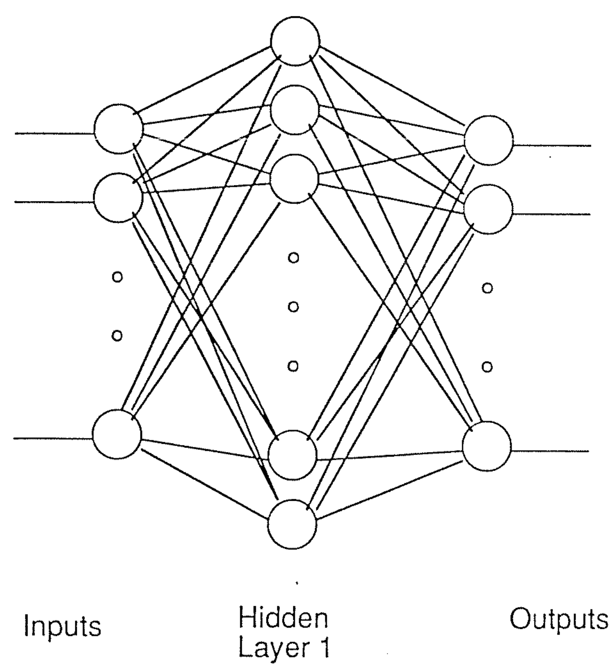

Figure 4. Generic Neural Network Layout

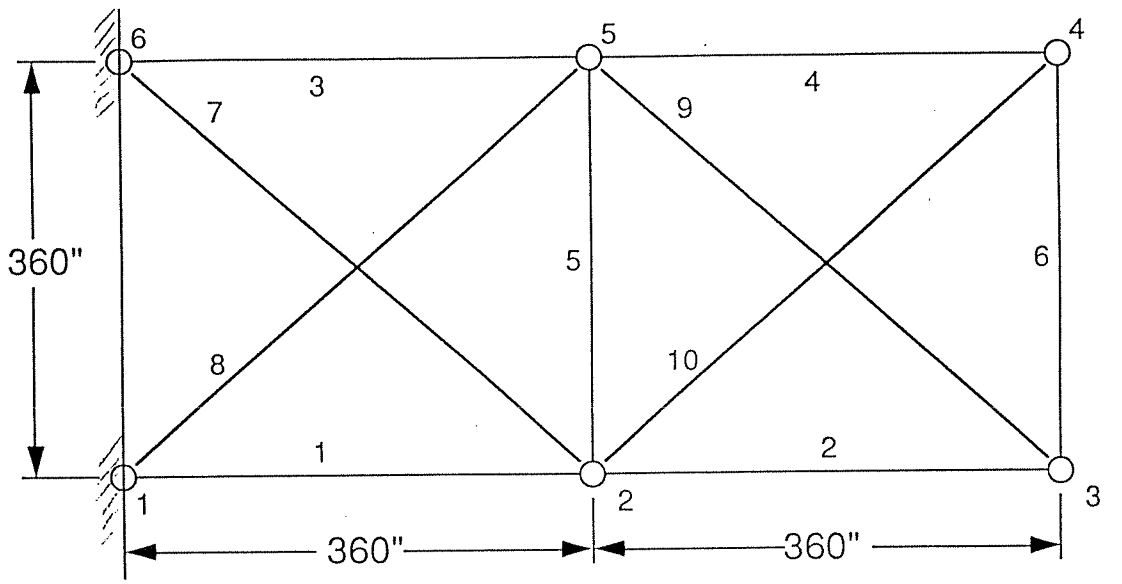

Figure 5. Ten Bar Truss Example Structure

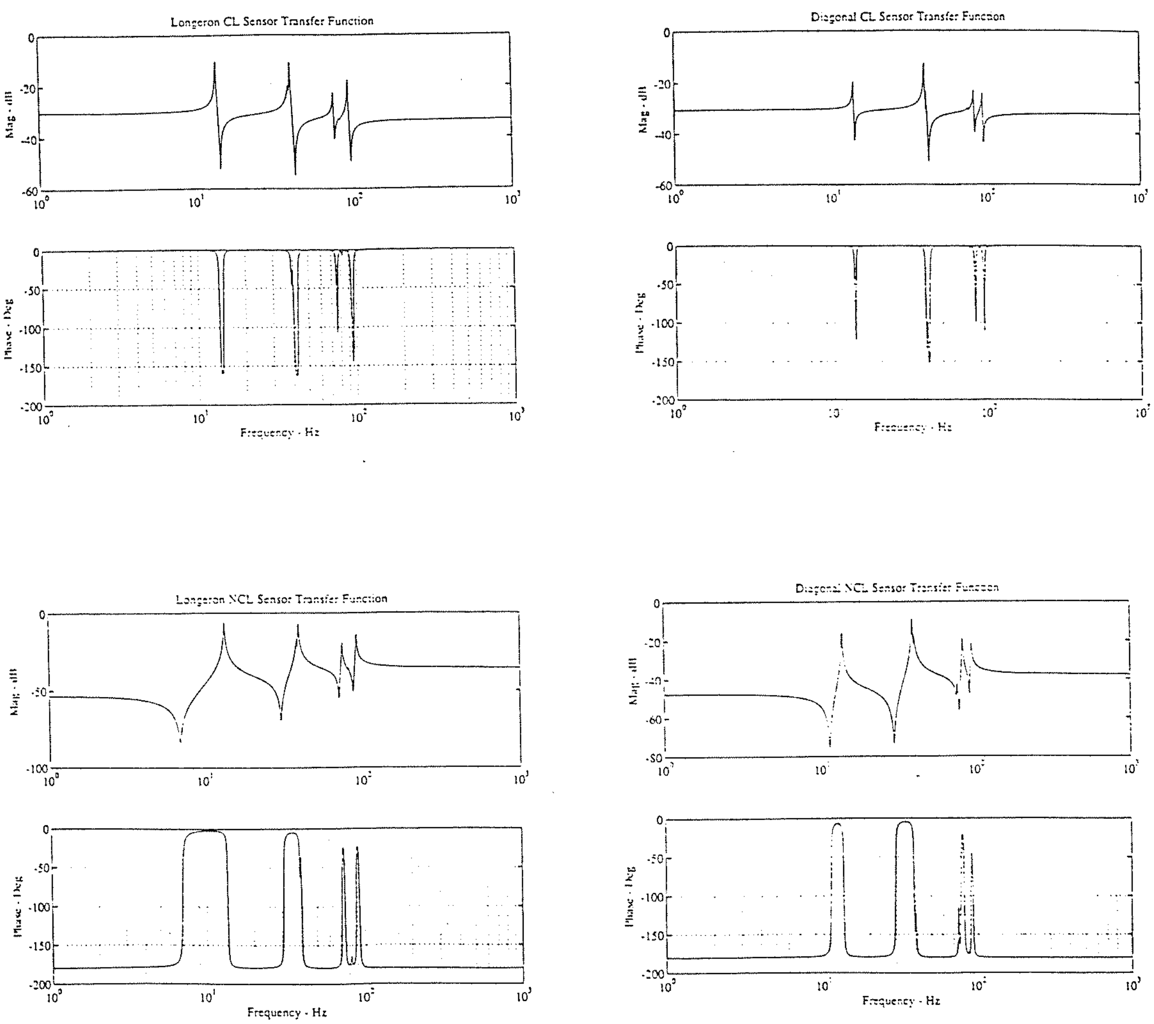

Figure 6. Ten Bar Truss Active Member Transfer Functions

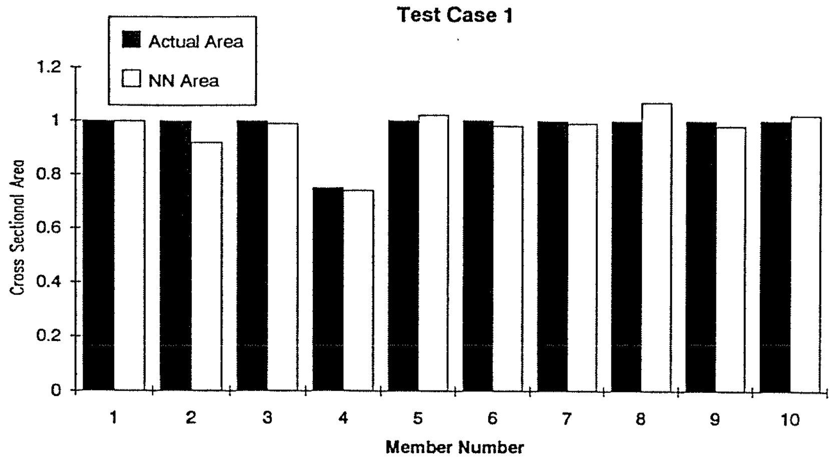

Figure 7. Actual and Predicted Cross Sectional Areas - Test Case 1

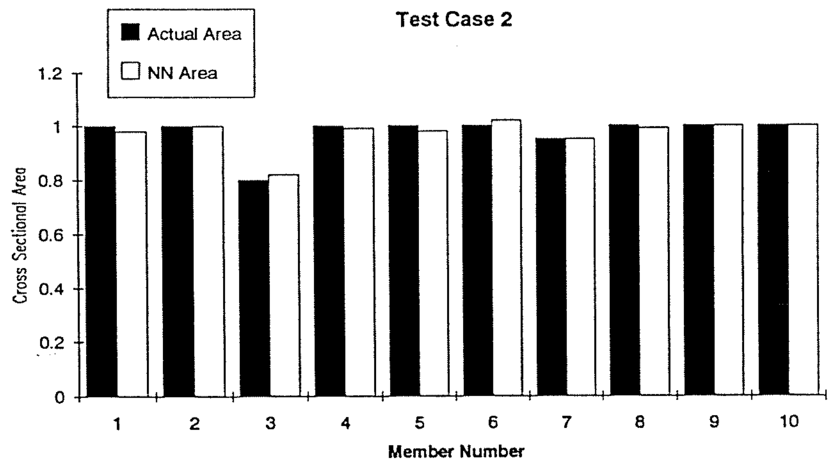

Figure 8. Actual and Predicted Cross Sectional Areas - Test Case 2

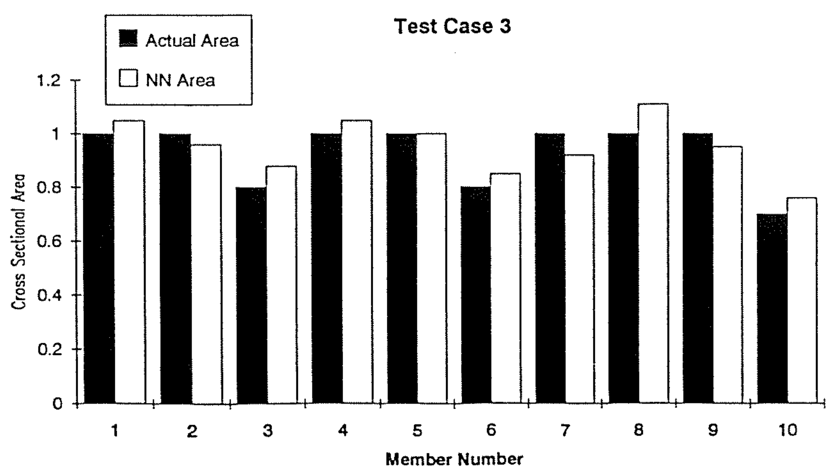

Figure 9. Actual and Predicted Cross Sectional Areas - Test Case 3

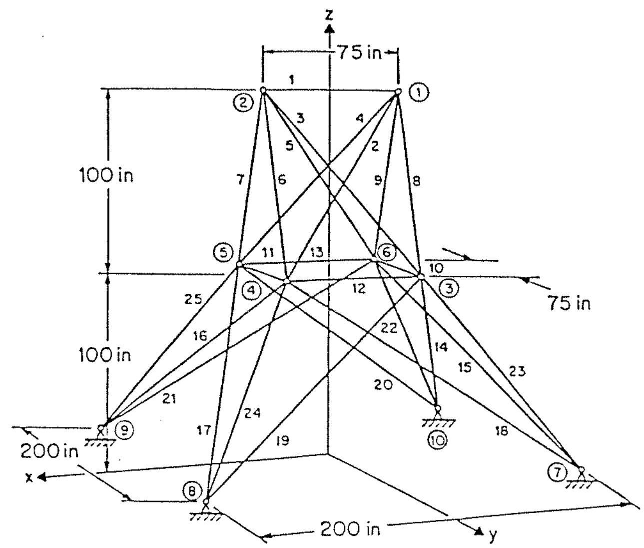

Figure 10. Twenty Five Bar Transmission Tower

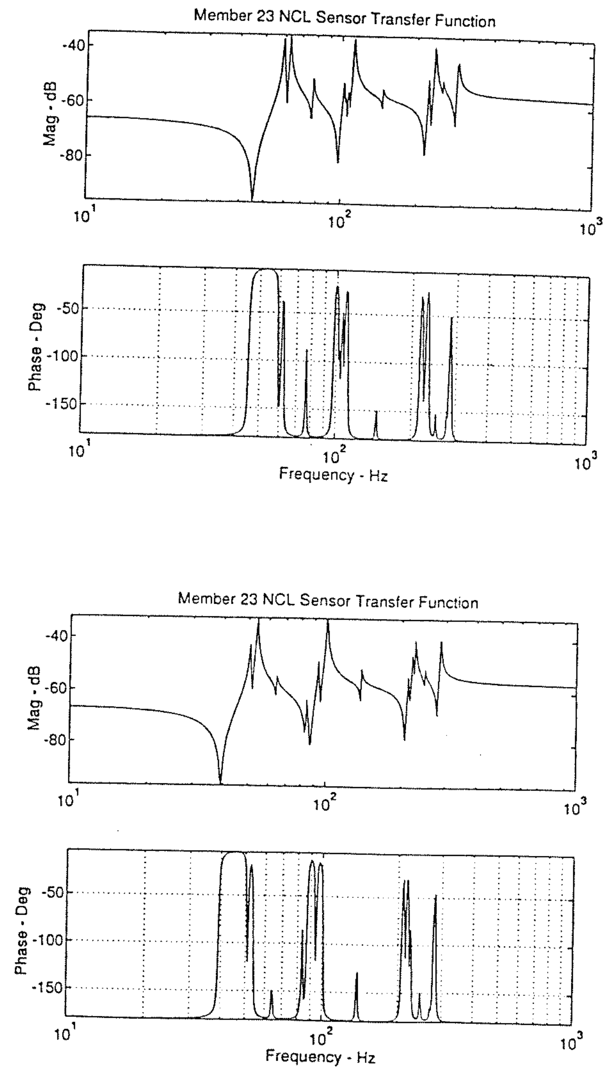

Figure 11. Baseline and Perturbed Active Member Transfer Functions

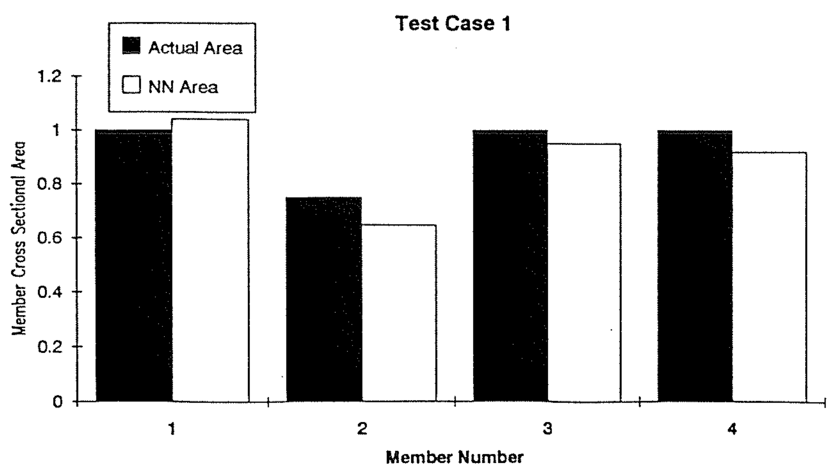

Figure 12. Actual and Predicted Cross Sectional Areas - Test Case 1

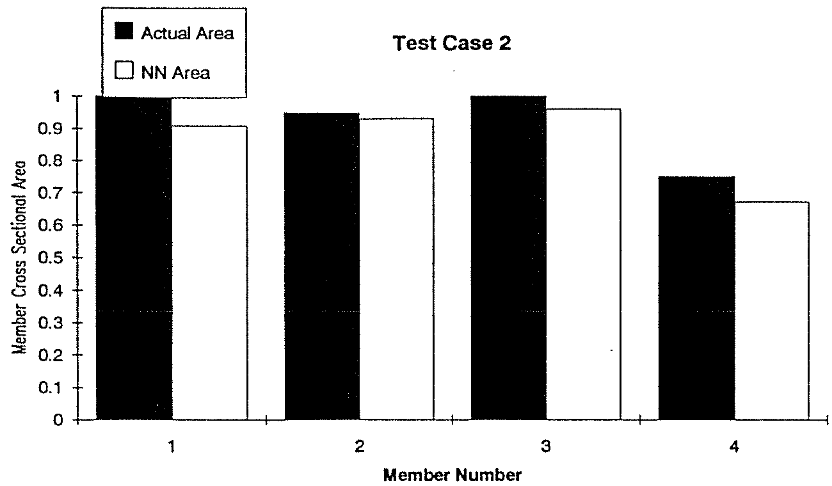

Figure 13. Actual and Predicted Cross Sectional Areas - Test Case 2

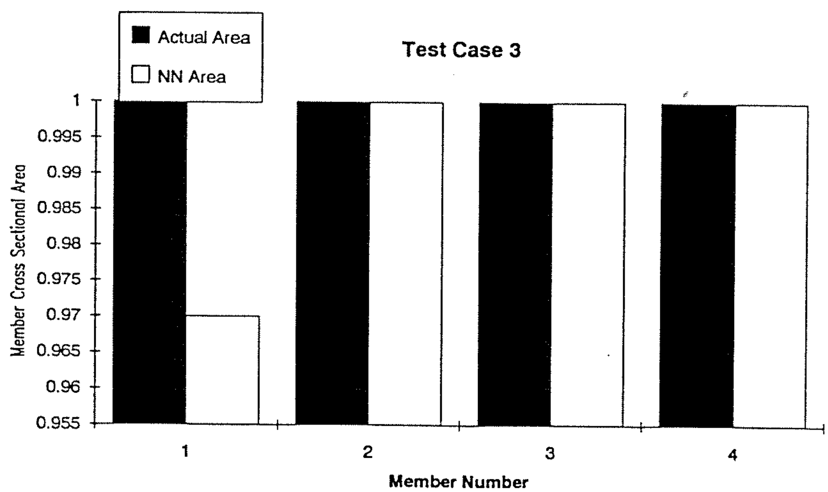

Figure 14. Actual and Predicted Cross Sectional Areas - Test Case 3