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Material Property Identification of Composite Plates Using Neural Network and Evolution Algorithm

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I. Introduction

THE baseline material properties of composite materials are susceptible to errors due to various defects during the manufacturing and operation. Thus, accurate estimation of the actual material properties is absolutely necessary for accurate numerical analysis. In the present Note, an efficient and accurate procedure is presented for the nondestructive material property identification of composite plates.

One of the popular nondestructive tests to identify material properties of composite structures is to utilize dynamic responses such as natural frequencies and mode shapes. Dynamics updating problems are solved by inverse procedures,[1–6] where perturbation methods based on the Taylor series expansion is usually adopted. Optimization techniques based on the conjugate-gradient method have been introduced that minimize the error norm of measured data and numerical results.[5] However, because the mass matrix is not updated, the material properties may be distorted due to the inaccuracies in the mass matrix.[6] Although the accuracy of the predicted dynamic behaviors may be enhanced by considering the dynamic response data, the evaluated static behavior is prone to error. With inclusion of static data in the update process, these difficulties could be relieved.[7]

Recently neural networks have drawn attention due to their powerful capabilities of pattern recognition, classification, and function approximation. A neural network has been utilized for the identification of material properties and damage detection by recognizing patterns of dynamic behavior and modal parameters.[8] Because the neural network does not require an explicit equation relating input data and output results, it can be utilized to solve complex inverse problems without calculation of the sensitivity, where the influence of certain parameters on the mass and stiffness of the structures is not obvious. Accurate prediction with neural networks usually requires many training input/output patterns, resulting in a large amount of computing time. This is one of reasons why most research is limited in application of neural network to simple problems.

In this Note, a neural network and an evolution algorithm are combined for the efficient prediction of material properties of structures. The neural network can make accurate predictions by using a small number of training data sets that is carefully selected through the evolution process.[9] The present method is a simple algorithm, shows rapid convergence, and does not require sensitivity computations. The applicability of the proposed method for the identification of the material properties of composite plates and the accuracy of the numerical analysis of static and dynamic behaviors using the identified material properties are investigated. The identification of material properties is accomplished by minimizing the difference between experimental measurements and the corresponding values of the dynamic responses and the static deflection obtained by the finite element analysis. The measurements of both static and dynamic responses ensure reliability in the prediction of the static as well as dynamic behavior. Accuracy and applicability of the present method are demonstrated by both numerical and experimental tests of carbon-fabric composite plates.

II. Optimization Using Neural Network and Evolution Algorithm

In the present study, the neural network, combined with the evolution algorithm, is used for the identification of material properties of composite structures. The neural network plays the role of approximating and recognizing the complex relationship between input patterns and output patterns. Figure 1 shows the prediction using the neural network. The input patterns consist of natural frequencies and static deflection, whereas the output patterns consist of the normalized material properties of the composite structures. The training input/output pairs are generated by finite element analysis of the composite structure. However, to obtain an accurate neural network prediction, a large amount of training data is required. The computational costs to generate such large training patterns and to train such large patterns would be very expensive. Therefore, in this work, we introduce an evolutionary procedure, where qualified training data are chosen for the neural network using a simple evolution algorithm. With such an evolutionary procedure, computational costs in training the neural network, as well as in generating the training patterns, can be substantially reduced.

An evolution algorithm is employed to aid in acceleration of the convergence of the neural network learning and in enhancement of the accuracy of the identified material properties. The criterion for the selection process is to minimize the error norm given as follows:

$$E = \left[\sum_i \left(\frac{w_i - w_i^0}{w_i^0} \right)^2 - \left(\frac{\delta - \delta^0}{\delta^0} \right)^2 \right]^{0.5} \tag{1}$$

where w_i and w_i^0 are the eigenvalues of the dynamic problem obtained numerically and experimentally, respectively, and δ and δ^0 are the numerical and experimental deflections, respectively. The scheme of optimization is shown in Fig. 2.

III. Identification Procedure

A schematic flowchart of the procedure is given in Fig. 2. The identification procedure is composed of the following processes.

First, k input/output pairs are generated for the initial neural network training. Note that k sets of initial vectors $\boldsymbol{X}_i$, $i = 1, \ldots, k$, are chosen from $U(a, b)^n$ as the output vector of the neural network, where $\boldsymbol{X}_i$ is a random vector, whose components are the normalized material properties. $U(a, b)^n$ denotes n-dimensional uniform distribution ranging over $[a, b]$. The corresponding input vector is the natural frequencies w_i and the static deflection δ obtained by the finite element method using the material properties of $\boldsymbol{X}_i$.

Second, material property is predicted using the neural network. The neural network trained by the k input/output patterns predicts

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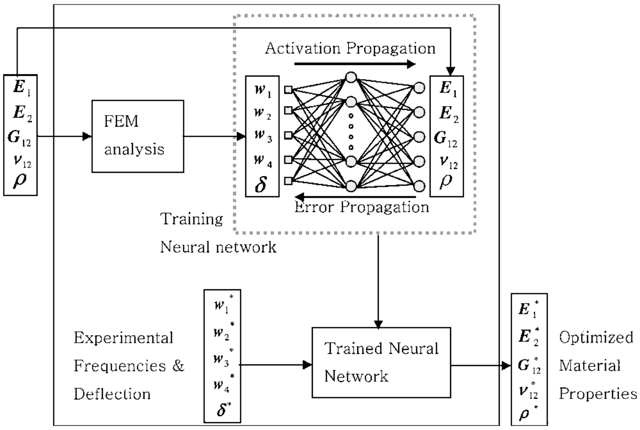

Fig. 1 Prediction using the neural network.

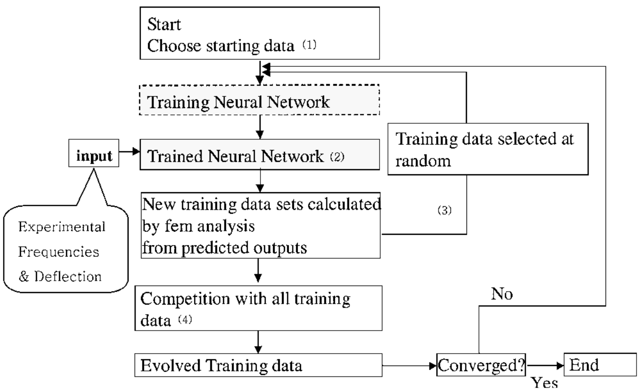

Fig. 2 Optimization algorithm using the neural network and evolution.

the material properties X_0 from the natural frequencies w_i^0 and static deflection δ^0 obtained experimentally.

Third, m new input/output patterns are created from the $k+1$ existing input/output patterns (k random patterns plus the experimental result from step 2). To create each of the m extra input/output pairs, k input/output pairs among the $k+1$ pairs are selected for the neural network training. The output vector X_{k+i} of the newly created pair is obtained by the neural network prediction using the input vector of the experimental values w_i^0 and δ^0. The input vector of the newly created pair is obtained by finite element analysis using X_{k+i} as the material properties. The newly created input/output pairs tend to be more qualified data for the neural network training because they are closer to the optimized value.

Fourth, the $k+m$ training patterns produced undergo competition. The k training patterns that minimize Eq. (1) survive as parents for the next generation, and the remaining m patterns are discarded. This process (second–fourth steps) is repeated. The evolution process is terminated if $|X_i^B - X_i^W|$ is less than some specified value. X_i^B and X_i^W are the most fit and the most unfit training patterns, respectively. The most fit data are the ones closest to the experimental value.

As described, the evolution algorithm adopted plays the role of selecting the most qualified data set for the neural network training to reduce drastically the overall computational cost. When the present method of neural networks is used in conjunction with the evolution algorithm, accurate material properties can be identified utilizing single set of experimental results of natural frequencies and static deflection.

IV. Numerical and Experimental Studies

Several numerical and experimental tests were conducted to validate the effectiveness of the proposed procedure. Among the results, two representative examples are presented. For the numerical studies, a composite plate of stacking sequence of $[0]_{8T}$ clamped on one end is selected. The baseline material properties are shown in Table 1. For identification, the normalized material property vector has the following values:

Table 1 Baseline material properties of carbon fabric composite

Property	Value
E_1^0	65.19 GPa
E_2^0	65.19 GPa
G_{12}^0	3.92 GPa
ν_{12}^0	0.058
ρ^0	1448 kg/m^3

Table 2 Prediction of material properties for composite plate $[0]_{8T}$

Method	E_1/E_1^0	E_2/E_2^0	G_{12}/G_{12}^0	ν_{12}/ν_{12}^0	ρ/ρ^0
Objective	0.7	0.8	0.8	0.9	0.95
Neural network	0.7043	0.8066	0.7963	1.0419	0.9523
Neural network and evolution	0.6992	0.7976	0.7991	0.9543	0.9488

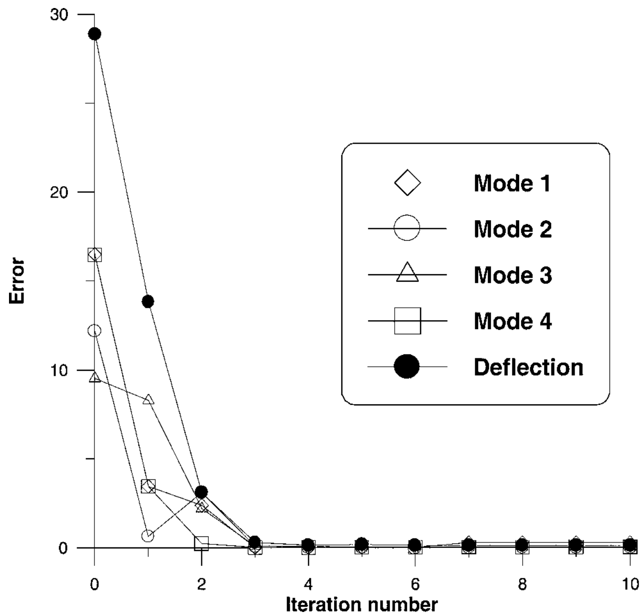

Fig. 3 Error history of frequencies and deflection for carbon fabric composite $[0]_{8T}$.

$$X_i = \left[E_1/E_1^0, E_2/E_2^0, G_{12}/G_{12}^0, \nu_{12}/\nu_{12}^0, \rho/\rho^0\right] \tag{2}$$

where the superscript 0 refers to the baseline material properties. Also, for neural network training, the four lowest natural frequencies and the static tip deflection subjected to static loading were used. The number of the initial input/output pairs, k, is 5, and the number of additional pairs introduced during the evolution algorithm, m, is 4.

In the first case, we tried to simulate the whole procedure numerically to validate the effectiveness of the procedure by assuming specific material property apart from the baseline property and tried to identify the values using the proposed procedure. This is a verification test because the exact material properties are known, although not visible to the numerical algorithm. The results (Table 2) are compared with the identified value using neural network alone. Note that the neural network alone has the potential of predicting an accurate estimation of the material properties by recognizing the patterns of the training samples. However, to get an accurate estimation, more than 200 training samples were required, whereas about 20 training sets were used altogether with the present method. All in all, the saving in the computational cost was about 70%.

In the second case, the material properties are identified using the actual experimental results. With the use of the identified material properties, the static dynamic responses are reevaluated using the finite element method. Figure 3 shows the natural frequencies and

Table 3 Errors of frequencies and static deflection for carbon fabric composite $[0]_{8T}$

Mode	Test, Hz	FDUB,[a] Hz	Error, %	FDUP,[b] Hz	Error, %
1	66.25	72.3	9.1	66.28	0.038
2	130	127.8	−1.7	129.8	−0.15
3	416.3	452.9	8.8	415.3	−0.25
4	518.8	539.2	3.9	520.0	0.25
5	990	1065.6	7.6	982.3	−0.7
Static deflection, mm	−0.68	−0.61	10.3	−0.677	−0.034

[a]Frequencies and deflection using baseline material properties.
[b]Frequencies and deflection using prediction material properties.

the static deflection errors during the evolution process. Table 3 shows the results of the natural frequencies and static deflection obtained using the finite element method based on the identified material properties. Examination of the error between the experimental data and the numerical data reveal noticeable improvement in accuracy of the present procedure from results based on the baseline material properties.

V. Conclusions

An effective nondestructive procedure for the identification of material properties of composite structures was presented. The combined method using neural networks and an evolution algorithm effectively identifies the material properties. The neural network plays the role of recognizing the input/output patterns and predicting an accurate estimate of the actual material properties, and the evolution algorithm plays the role of providing the neural network with qualified training patterns to enhance the performance of the neural network while reducing the computational costs. The proposed procedure is computationally economic and simple to implement compared with other sensitivity-based schemes because the approach does not require the computation of the sensitivity coefficients. Numerical and experimental studies were made for the assessment of the accuracy and effectiveness of the proposed procedure. Reanalysis results using the finite element method based on the identified material properties were compared with the experimental results. Based on the numerical and experimental studies conducted herein, it can be concluded that more accurate dynamic and static responses of structures can be evaluated by numerical analysis using the material properties identified by the proposed procedure.

Acknowledgments

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Errata

Linear Instability of Laterally Strained Constant Pressure Boundary-Layer Flows

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WHILE studying the nonparallel aspect of this problem (Tyagi, P. K., "Linear Instability of Laterally Strained Constant Pressure Boundary Layer," M.Sc. Thesis, Dept. of Aerospace Engineering, Indian Inst. of Science, Bangalore, India, 2001), we came across an error in our recently reported result, which was based on the parallel flow approximation. We sincerely regret such an unintentional error.

The nonparallel linear instability equation is found to be the same as that for the Blasius flow. The momentum equation (6) in our earlier analysis shows that, compared to two-dimensional flows, the Reynolds number is changed by the nondimensional divergence/convergence factor, $A/(A+x)$; this factor is <1 and >1 for diverging and converging flows, respectively. Therefore, the linear instability of a constant pressure diverging/converging flow will correspond to that for the Blasius flow at a correspondingly reduced/increased Reynolds number. That is, a diverging flow will be more unstable than the two-dimensional Blasius flow. Similarly, a converging flow will be more stable than the two-dimensional Blasius flow.