[5]Teske, M. E., Bowers, J. F., Rafferty, J. E., and Barry, J. W., "FSCBG: An Aerial Spray Dispersion Model for Predicting the Fate of Released Material Behind Aircraft," *Environmental Toxicology and Chemistry*, Vol. 12, No. 3, 1993, pp. 453–464.

Material Model for Composites Using Neural Networks

R. M. V. Pidaparti* and M. J. Palakal†
Purdue University, Indianapolis, Indiana 46202

Introduction

ADVANCED materials such as composites are being used in a variety of engineering applications. These composites exhibit complex behaviors such as anisotropy, microcracking, fiber breakage, etc. Constitutive equations are being developed to describe these complex behaviors using some mathematical rules and expressions based on either experimental data or a theory. The constitutive equations describe the relationship between stresses and strains. A new computational paradigm using Artificial Neural Network provides a fundamentally different approach to the derivation and representation of composite material behavior relationships. Neural network (NN) is a paradigm for computation and knowledge representation inspired by the neuronal architecture and operation of the brain.[1,2]

There have been considerable research efforts in different applications of NN: signal processing,[2] robotics,[3] structural analysis and design,[4] and pattern recognition[5,6] to name a few. Other related work in the use of NN for effective modeling of complex, highly nonlinear relationship among data sets can be found in Ref. 7. The resurgence of earlier research in NN has facilitated the development of a totally different approach to the derivation and representation of material behavior. With this new approach, the knowledge of the material's behavior is captured within the connections of a self-organizing NN that has been trained with experimental data. Recently, the stress-strain behavior of concrete material under the plane stress condition was modeled with a back-propagation (BP) neural network.[8]

A neural-network-based material model is developed as an alternative to mathematical modeling of composite material behavior. Neural-network-based modeling solutions are better than conventional methods, such as nonlinear regression analysis, etc., for handling unknown data sets, large dimensional data sets, and noisy data. In this Note, the nonlinear stress-strain behavior of ($\pm\theta$) graphite-epoxy laminates under monotonic and cyclic loadings is modeled with a back-propagation neural network. The NN predicted stress-strain behavior is compared to the experimental data for both monotonic and cyclic loadings.

Neural-Network-Based Material Model

The underlying rationale for developing a neural-network-based material model is to train a back-propagation neural network to map the stress-strain relationship on the results of experimental data for a material. The trained network would contain sufficient information about the material behavior. This trained network could be qualified as a material model when the network is able to reproduce the trained experimental data and also the untrained experimental data for generalization. In general, the material behavior might be complex, exhibiting nonlinear characteristics in stress-strain behavior, anisotropy, fiber breakage, etc. As a first attempt, the neural network can also be based on traditional mathematical models if no experimental data is available. Since the material behavior of graphite-epoxy composites is highly nonlinear and exhibit stiffening and softening behavior for various fiber angles,[9] the input data to the network must have sufficient information about the material behavior.

Graphite-epoxy laminates were chosen as a first example of material modeling with neural network for composite materials. In the present study, a back-propagation neural network is developed for predicting the nonlinear stress-strain behavior of ($\pm\theta$) graphite-epoxy laminates. More details regarding the BP learning algorithm can be found in Refs. 6-7. The BP network gives the input/output relation in the form of a functional fit for a set of data points. Currently there are no rules available in the literature for determining the NN architecture (as this question is under research). The architecture used in this study was based on empirical results. The back-propagation NN developed in this investigation has one input layer with three nodes, two middle layers with 17 processing elements each, and one output layer with one node (3- 17- 17- 1) (see Fig. 1a). The input parameters chosen in this study are fiber angle, initial stress, and incremental stress, and the output is the total strain. There might be other possibilities: for example, the input parameters can be fiber angle, initial strain, and incremental strain, and the output can be the total stress. The present results are assumed to be stress controlled, i.e., stress as input and strain as output. There are two main phases involved in this neural-network-based modeling: learning and testing.

Learning

Learning or training involves presenting the network with the experimental data so that it correctly reproduces the total strain when presented with the current states of stress and incremental stress by modifying its weights. Learning also involves the transformation of the stress-strain data into the network as input and output, and presenting this information repeatedly to the network. It is discovered that an effective way to train the neural network is to present the data in normalized form, In this study, the fiber-angle values in the data set were normalized between 1.0 and 12.0 while

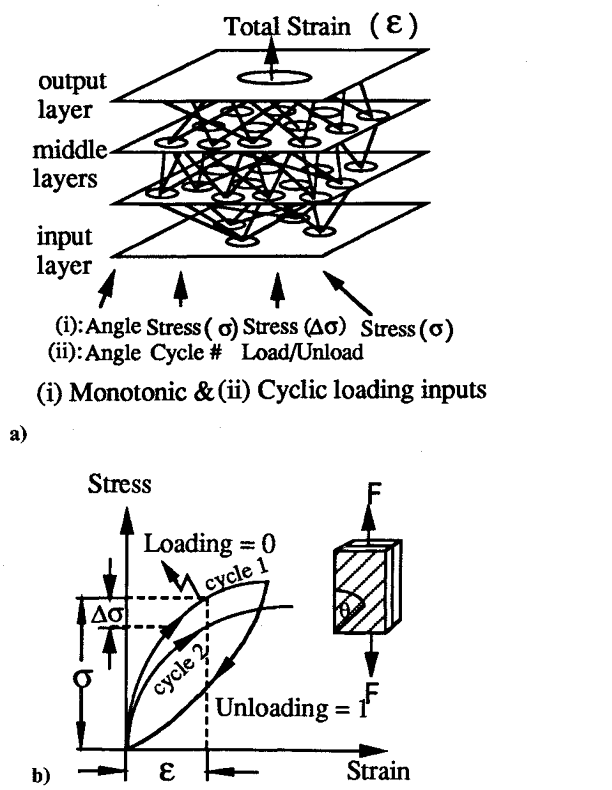

Fig. 1 Neural network representation for monotonic and cyclic stress-strain behavior: a) architecture and b) typical stress-strain behavior.

Received June 26, 1992; revision received Feb. 8, 1993; accepted for publication Feb. 28, 1993.

*Associate Professor, Department of Mechanical Engineering, 723 West Michigan Street. Member AIAA.

†Assistant Professor, Department of Computer Science, 723 West Michigan Street.

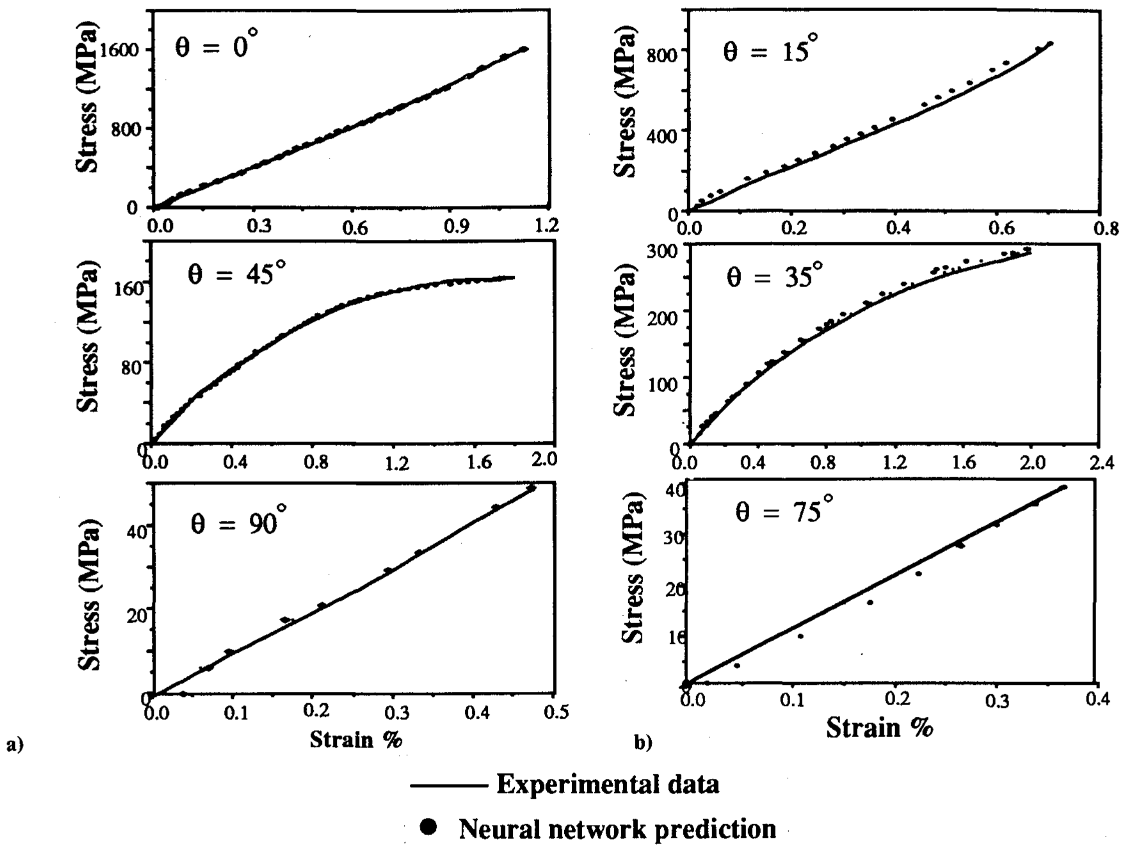

Fig. 2 Comparison of neural network predictions with experimental data for graphite-epoxy (±θ) laminates under monotonic loading: a) trained data and b) untrained data.

the initial and incremental stress and expected total strain were normalized between 0.1 and 0.9. Normalization between 1.0 and 12.0 for the fiber-angle values allowed the trained neural network to generalize better, and hence it generated more accurate results during the testing process. A Sigmodial transfer function, a learning coefficient of 0.7, and a momentum term value of 0.85 were used in the learning algorithm. The training data set consisted of 959 data points.

Testing

Testing refers to how the network globally processes input data at its input layer and generates an output at its output layer. The testing process in this study involved specifying the fiber angles, initial and incremental stresses for which the trained network will predict the corresponding total strain for trained data as well as for untrained data.

The stress-strain curves for (±θ) graphite-epoxy laminates were initially digitized using a digitizing tablet and this data was used for training the BP network. The network was trained with 0-, 25-, 35-, 45-, 55-, 60-, and 90-deg fiber angles for 25,000 iterations. The network is tested with 15-, 20-, 30-, 40-, 50-, and 75-deg fiber angles after the training phase has been completed. The learning and testing procedures were implemented on a SUN/Sparc2 System.

Results and Discussion

Representative results for trained data showing the stress-strain behavior for 0-, 45-, and 90-deg fiber angles are given in Fig. 2a. It can be seen from Fig. 2a that the network was able to learn the relationship between stresses and strains for the fiber angles under consideration. A good agreement is found for other angles in the trained data as well. Figure 2b shows the results of the stress-strain curves for untrained 15-, 35-, and 75-deg fiber angles. It can be seen from Fig. 2b that the back-propagation neural network predictions are in good agreement with the experimental data.

Also a good agreement is found for 20-, 30-, 40-, and 50-deg fiber angles. It is interesting to note that the stress-strain behavior change from stiffening ($\theta<20$) to softening ($\theta>20$) is also predicted by the neural network. Different numerical experiments were carried out by varying the training set, number of iterations, and number of nodes in the hidden layer, to achieve the present results.

Four different neural network configurations having 17, 21, 25, and 29 processing elements in each hidden layer were studied. The results of these studies indicate that overall the 3-17-17-1 and 3-25-25-1 networks predict reasonably well for all of the fiber angles considered. Based on the studies conducted, it can be concluded that the NN predictions are sensitive to the training data for different fiber angles when the material is changing from stiffening to softening behavior.

A different network architecture was used to model the cyclic stress-strain behavior of (±θ) graphite-epoxy laminates. The input to the NN included the fiber angle, cycle number, index (1 or 0) for loading and unloading, stress, and the output from the network is the total strain (see Fig. 1b). Thus, there are four processing units in the input layer and one processing unit in the output layer. Two hidden layers, each with 17 processing elements (4-17-17-1), were used as in the case of monotonic loading. The training data set consisted of 180 data points. The learning coefficient and momentum term values used are the same as in the monotonic loading experiment.

The experimental data of Lagace[9] for (±θ) graphite-epoxy laminates for θ=0-, 30-, and 50-deg orientation were used in training the NN as no other data is available in the literature. The data for fiber angle and total stress were normalized between 1.0 and 12.0, and 0.1 to 1.2, respectively. The network converged at approximately 10,000 iterations. Figure 3 shows a comparison of cyclic stress-strain behavior between NN predictions and experimental data. A good agreement is seen. This study shows that a NN can be effectively used to represent cyclic stress-strain behavior of composites. From a series of tests conducted to predict the cyclic stress-strain behavior, it is concluded that more experimental data is needed for the network to generalize the behavior correctly. Since there is no other experimental data available for these lami-

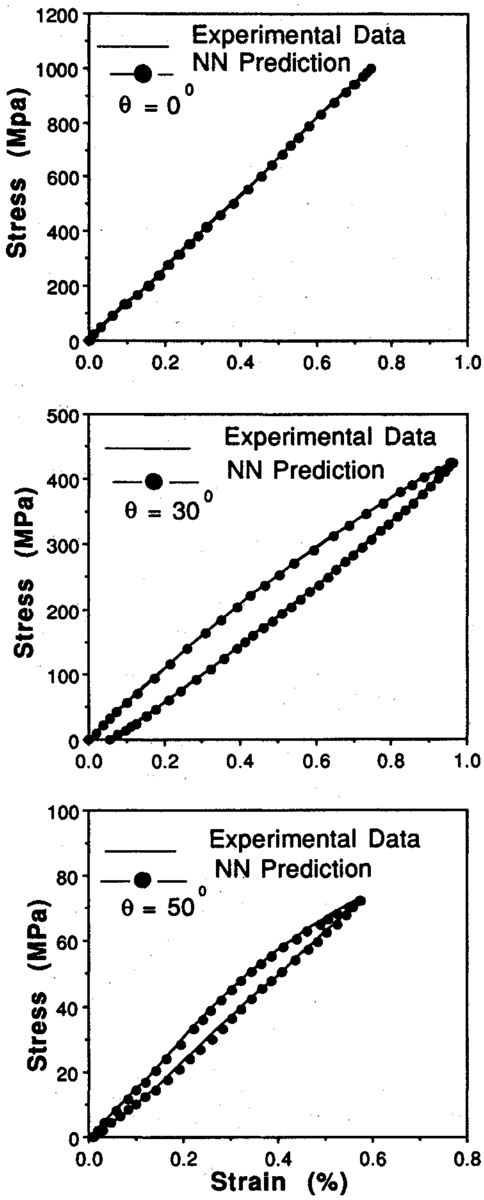

Fig. 3 Comparison of neural network predictions with experimental data for graphite-epoxy ($\pm\theta$) laminates under cyclic loading for trained data.

nates in the literature, no other predictions are made for the cyclic stress-strain behavior.

Concluding Remarks

Two different back-propagation neural networks were developed to represent the nonlinear stress-strain behavior of ($\pm\theta$) graphite-epoxy laminates under monotonic and cyclic loadings. The NN predictions for both monotonic and cyclic loadings are in good agreement with the experimental data obtained from the literature. These preliminary results support the use of a NN approach to composite material modeling. The network developed in this study aids in identifying important aspects of the stress-strain behavior, such as breaking stress, fracture stress, etc. This approach can also be used to predict failure mechanisms.

Acknowledgments

The first author thanks P. A. Lagace of MIT for providing the list of papers on graphite-epoxy composites and Moffit Othman for assisting with the neural network experiments. This research was supported by an internal grant from the Faculty Development Office of Indiana University/Purdue University at Indianapolis.

References

[1]Rumelhart, D. E., Hinton, G. E., and McClelland, J. L., "A General Framework for Parallel Distributed Processing," *Parallel Distributed Processing, Vol. I: Foundations,* The MIT Press, Massachusetts, 1986, pp. 45–76.

[2]Rumelhart, D. E., and Zipser, D., "Feature Discovery by Competitive Learning," *Cognitive Science,* Vol. 9, 1985, pp. 75–112.

[3]Handelman, D. A., Lane, S. H., and Gelfand, J. J., "Integrating Neural Networks and Knowledge-Based Systems for Intelligent Robotic Control," *IEEE Control Systems Magazine,* April 1990, pp. 77–86.

[4]Hajela, P., and Berke, L., "Neurobiological Computational Models in Structural Analysis and Design," *Proceedings of 31st AIAA Structures, Structural Dynamics, and Materials Conference,* Huntsville, AL, April 1990, pp. 345–355.

[5]Palakal, M., and Zoran, M. J., "A Neural-Network-Based Learning System for Speech Processing," *Expert Systems with Applications: An International Journal,* Pergamon Press, New York, 1990, pp. 59–71.

[6]Lippmann, R. P., "An Introduction to Computing with Neural Nets," *IEEE, Acoustic, Speech, and Signal Processing Magazine,* Vol. 4, No. 2, 1987, pp. 4–22.

[7]Freeman, J. A., and Skapura, D. M., *Neural Networks: Algorithms, Applications, and Programming Techniques,* Addison Wesley, New York, 1991.

[8]Ghaboussi, J., Garrett, J. H., Jr., and Wu, X., "Knowledge-Based Modeling of Material Behavior with Neural Network," *Proceedings of ASCE, Journal of Engineering Mechanics,* Vol. 117, No. 1, 1991, pp. 132–153.

[9]Lagace, P. A., "Nonlinear Stress-Strain Behavior of Graphite/Epoxy Laminates," *AIAA Journal,* Vol. 23, No. 10, 1985, pp. 1583-1589.

Postbuckling Analysis of Composite Laminated Cylindrical Panels Under Axial Compression

J. H. Kweon* and C. S. Hong†
Korea Advanced Institute of Science and Technology, Kusong-Dong, Yusong-Gu, Taejon 305-701, Korea

Introduction

In designing shell-type structures, the buckling and postbuckling behaviors have been considered as the important issues. Specifically, the composite cylindrical panel has been an object of great interest in the weight-sensitive structures due to its high specific stiffness and strength.[1–5] Unlike the flat plate, the cylindrical panel has the limit points on the equilibrium path. The limit point and numerical problems related to that have been the obstacles to the postbuckling analysis of cylindrical panels, and a great number of numerical schemes have been proposed to overcome these problems. The most widely used scheme is the arc-length method.[6]

In this Note, the postbuckling behavior of composite laminated cylindrical panels with various stacking sequences under compression is investigated by the nonlinear finite element method. For the finite element analysis, the updated Lagrangian formulation and the eight-node degenerated shell element are used. An improved load-increment method based on the arc-length scheme is proposed for the postbuckling analysis. Experiments are conducted to verify the validity of the present analysis for a cross-ply laminate.

Finite Element Formulation

At an arbitrary $(n + 1)$st equilibrium state, the principle of virtual work is expressed as

$$\iiint_{V^{n+1}} \sigma_{ij}^{n+1}\delta e_{ij}^{n+1}\,\mathrm{d}V = \iiint_{V_f^{n+1}} f_i^{n+1}\delta u_i^{n+1}\,\mathrm{d}V + \iiint_{S_T^{n+1}} T_i^{n+1}\delta u_i^{n+1}\,\mathrm{d}S \tag{1}$$

Received Aug. 25, 1992; revision received Feb. 15, 1993; accepted for publication Feb. 28, 1993.

*Research Assistant, Department of Aerospace Engineering.
†Professor, Department of Aerospace Engineering. Member AIAA.