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Abstract

Artificial neural networks can provide improved computational efficiency relative to existing methods when an algorithmic description of functional relationships is either totally unavailable or is complex in nature. For complex calculations, significant reductions in elapsed computation time are possible. The primary goal of this project is to demonstrate the applicability of artificial neural networks to composite material characterization. As a test case, a neural network has been trained to accurately predict composite hygral, thermal, and mechanical properties when provided with basic information concerning the environment, constituent materials, and component ratios used in the creation of the composite. A brief introduction on neural networks is provided along with a description of the project itself.

Introduction

Artificial neural networks may take varied forms and are applicable to a wide variety of problems. A number of applications were investigated by Berke and Hajela [Reference 1] in structural optimization and a number of other applications were suggested including computational material characterization problems. Applications pertaining to the engineering problems can be found in reference 2. The modeling of the material behavior for conventional isotropic materials using knowledge based artificial neural net works is the subject of references 3 and 4. The present project investigates the applicability of neural networks to the analysis of composite materials. The ultimate goal is to apply neural network simulation to composite material characterization problems in which the computation times are unacceptably large. However, the immediate goal is simply to demonstrate that neural networks are capable of performing the necessary types of basic calculations.

For this purpose, the functional relationships defined by the micromechanics embedded in the computer code, ICAN (Integrated Composites Analyzer) [5] have been partially duplicated in a neural network. ICAN is an in-house developed computer code which performs micromechanics, macromechanics, and laminate analysis of composite materials. ICAN's inputs are constituent material properties, factors reflecting the fabrication process, and the laminate configuration. A number of constituent material properties are maintained in ICAN's dedicated resident database. ICAN outputs are the various ply and composite properties, the composite/ply response to different types of loading, and various composite stress analysis results with predictions for failure . ICAN performs its own calculations very efficiently and is not the best candidate for replacement by a neural network. Its computations have been simulated here primarily as a demonstration of the applicability of neural networks to material characterization appropriate to composite mechanics.

Fundamental Neural Network Concepts

Neural network simulations represent attempts to mirror biological methods of information processing. The fundamental concept is that of a neuron, a biological cell which receives electrical or chemical inputs from one or many sources and processes those inputs to generate a unique output. The output may, in turn, be passed on to other neurons. Figure 1 provides a simplified view of a neuron. It has been artificially oriented so that all of its inputs enter at the right of the cell body, its unique output mechanism emanates from the left, and its output is passed on to other neurons to the left of the body. Real neurons are not always so predictably organized.

Probably, the most interesting fact about neurons is that they can change with experience the way they respond to the inputs they receive. In other words, they can "adapt" or "learn." Consequently, when presented the same inputs in the future, they may generate an entirely different output response than the one they are currently generating. Neurons can differ greatly in physical structure, in their ability to adapt, and in their method of adaptation. Some neurons do not adapt at all, and some adapt in different ways than others. This report will deal with artificial neurons which adapt by changing the degree to which they "weigh" or count each of their inputs before summing them together to determine their output. The biological neurons upon which they are based adapt by chemically increasing or decreasing the "connection strength" to each of their inputs. The connection strengths in the artificial neurons are frequently referred to as "weights". For further discussion on this subject reference [6] may be consulted.

The term "neural network" refers to a collection of neurons and the biological connection material and connection strengths between them. It is also frequently used to describe a computer simulation of such a biological entity. Figure 2 shows an idealized neural network where the artificial neurons are shown as circles, the connections as straight lines, and the connection strengths (or weights) are calculated during the learning process. During forward propagation of input data the sums of products of input and weights from other neurons are presented to an "activation function" of the neuron, usually the sigmoid function with asymptotes of zero and one at minus and plus infinity respectively. The output of such a neuron is then between zero and one requiring scaling of the output and preferably also the input vectors to values between those two limits. Most codes perform the scaling automatically making it transparent to the user.

The different levels shown in figure 2 are referred to as "layers." The lower layer is called the "input layer" and the upper one the "output layer." The layer in the middle is called a "hidden layer." There can be several hidden layers in some applications. A network with no hidden layer is referred to as a "flat" network and may not have enough flexibility to capture the physical behavior with sufficient accuracy. Depending upon the problem in hand a successful neural net may have one or more hidden layers. The network shown in figure 2 might be described as a "3:2:4 feed forward" network, to reflect its layer and connection structures. The sizes of the input and output layers are clearly dictated by the nature of the problem. The number and size of the hidden layers may be selected by the user. A hidden layer is frequently chosen to be as small as possible (to minimize the total number of computations in the network) without being so small that the ability of the network to "learn" and to "generalize" the desired behavior is impaired. A good starting value for the number of nodes in hidden layer is an average of the number of input and output variables.

This project deals with "trainable" neural nets. Such networks are mathematical entities whose design is motivated, to some extent by biological processes, but which follow strictly defined rules of behavior. The process by which a neural network's weights (connection strengths) are established is referred to as "training." In order to train an artificial neural network, there must be a substantial quantity of data available. The data is provided to the network in the form of training pairs, vectors of information consisting of independent input values and their associated output results. For example, one training pair for the Exclusive Or function, XOR, might be: (1,1,0) indicating that when the two inputs "1" and "1" are provided, the correct result is "0." Clearly, the form of a training pair may vary from one network to another, depending upon the number of inputs and the number of outputs.

Training pairs are repeatedly presented to the network, and the network adapts its weights using its adaptation formula. The adaptation formula is designed so that each modification of the weights will move the network to a state where it would be more likely to generate the correct response to the current training pair when provided the inputs of that training pair. The adaptation scheme used in this project is the most common one, "delta error back propagation." In error back propagation, the modifications of the weights are accomplished so as to perform a "steepest descent" reduction of the sum of the squares of the differences between the generated outputs and the desired outputs as indicated in the training pairs. The details of the adaptation scheme will not be discussed here. It has been thoroughly described by Rumelhart, Hinton, and Williams [7].

The simulations reported here have been accomplished using NETS [reference 8], version 2.0, a public domain back propagation package. Numerous implementations of back propagation are commercially available.

Project Details

ICAN uses more than thirty constituent properties, fabrication process related variables and environmental conditions as input to generate thirty-seven composite properties. This project has introduced increasing numbers of variables using a three stage approach. The first and second stages of the project have focused on the four input variables. They are the fabrication process related variables and the environmental conditions. The fabrication process related variables are the fiber volume ratio and the void volume ratio. The environmental conditions considered are the use temperature, and the absorbed moisture content by the composite. Three typical composite systems are chosen in the study. They are the S-Glass/Epoxy, AS-Graphite/Low Modulus Low Strength Matrix, and P-75 fiber/High Modulus High Strength Matrix composite systems. The constituent properties for all the materials involved are resident in the dedicated databank of ICAN. For the first stage, four different neural networks have been trained, each predicting the composite properties with only one of the four variables being permitted to vary and all other variables remaining fixed. In the second stage, the four variables have been permitted to change simultaneously. All input constituent properties have varied in the third stage.

Stage 1

The stage 1 simulations have served as a test situation in which the basic data generation and training techniques of the project could be developed and tested. Despite the fundamental simplicity of the results shown here, a major portion of the project effort was expended on these tasks. The stage 1 input variables are the fiber volume ratio, the void volume ratio, the use temperature and the moisture content. The outputs are unidirectional composite ply properties. Four different networks, each corresponding to a particular ICAN input variable, were trained in the first stage. In anticipation of stage two, a 4:15:37 feed forward structure was utilized, even though only one input variable was non-constant in the training of a given network. Table 1 summarizes the results. For each of the four variables, training data, consisting of sixteen ICAN runs was used to train the network. The trained network was then applied to sixteen test cases, where the variable in question varied randomly within the range of values used in the training cases. The ranges were chosen to include all reasonable possibilities.

The neural network created for each variable predicts results in the test cases with an RMS error below 1.2 percent. In fact, for all variables except the fiber volume ratio, the RMS errors are well below 0.5 percent. Experiments with additional training data and increased training time have not resulted in significant improvement over the results shown in Table 1.

Stage 2

As mentioned earlier, Stage 2 of the project involved training a network which uses all four of the preceding variables as input. Experiments in this stage involve a 4:15:37 feed forward network. Training data consist of 625 ICAN test cases, where each of the four variables takes on five evenly spaced values across an appropriate fixed range. The test data consist of an equal number of ICAN data sets, where the four variables each have values which are randomly selected from within their fixed range. The trained neural network predicts the thirty-seven composite properties with an RMS error of approximately one percent.

In addition to the evenly spaced training data used in the second stage, some training has been done with randomly selected data. The randomly selected training data produce essentially the same outcome as the evenly spaced data. The only observable difference is that, when training to a one percent RMS error, the evenly spaced data provide a slightly more difficult training standard but also produce slightly more accurate results on the randomly selected test data. This probably results from the fact that the output functions are, for the most part, monotonic in the variables and the evenly spaced data always included the extreme values. Even when using the evenly spaced data, the order of the pairs in the training set has been randomized. This technique is commonly used to improve the speed at which a network learns.

All experiments described to this point have involved an intermediate modulus, high strength matrix with glass fiber. To guarantee that the ability to train is not unique to this material combination, additional stage two training has been accomplished with other materials. Descriptions of the component constituents for the various composites are shown in Table 2 with the RMS accuracy of their appropriate test data. The networks for each composite have been exposed to their training sets 250 times. As the table shows, no significant difference in predictive capability has been discovered in the additional models. Because of the common training approach, this also suggests that the relative levels of training difficulty are comparable.

Sample results from this study for S-Glass/Epoxy composite system are shown in Tables 3a and 3b. The results are the ply properties for a unidirectional ply. Table 3(a) gives a description of all the 37 composite ply properties with the appropriate units in which they are defined. Three different arbitrarily chosen sets of fabrication variables (fiber volume ratio and void volume ratio) and environmental conditions (the use temperature and the moisture content) are fed through the trained net and the results are compared with those predicted by ICAN. These are shown in Table 3(b). It can be concluded from these results that with the exception of the longitudinal coefficient of thermal expansion (No. 10), the trained net has captured the hygro-thermo-mechanical behavior of the S-Glass/Epoxy composite system. The maximum error in the coefficient of thermal expansion (CTE) is about 10%. Similar trends are noticed in the predictions of properties for the other two composite systems as well. It appears that the vast differences in the orders of magnitude between the CTE's and some of the other properties causes a precision problem. This sort of difficulty may be overcome by artificially raising the magnitudes of those properties so as to be able to carry more digits and avoid any precision related problem. The difficulties induced by large differences in the order of magnitude of the variables involved will be investigated in subsequent efforts.

As an additional exercise several Input/Output pairs of the 3-D composite properties for a $[\pm 10^\circ]_s$-Glass/Epoxy composite laminate have been generated and a net was trained to approximately one percent accuracy. The results from this study are shown in the Table 4. Once again the neural net predicted values are in excellent agreement with ICAN predictions.

Stage 3

Stage 3 of the project has resulted in a neural network which predicts composite properties when all ICAN constituent properties are permitted to vary. Variables controlling the fabrication process (including the four variables studied in the first two stages) have been maintained at fixed values. A 31:50:37 network structure has been utilized to guarantee simplicity and adequate training flexibility for stage 3 simulations. However, it is probably less efficient in both training time and computational accuracy than a more sophisticated network with more hidden layers with less connectivity (fewer nodes in each layer).

The network has been trained on 500 cases in which all constituent input properties were randomly chosen over ranges to cover the set of reasonable values for the variables in question. The 500 test cases have been similarly selected. The RMS error on the test cases is 1.08 percent. Table 5 gives results for a typical stage three problem. The RMS error on this particular problem is 1.2 percent, somewhat higher than the 1.08 percent RMS error for the whole test set. Despite the generally acceptable RMS error level, the trained net has failed to capture the physical behavior as is indicated by the large percentage errors in several properties. The reasons for such poor performance are still under investigation. One possible explanation is the sheer volume of the number of input variables (31). This probably could be alleviated by choosing clusters of input/output variables that strongly interact and training them separately as opposed to a single neural net. Another alternative is to choose n nets with m input variables to 1 output variable mapping instead of a single m input variables to n output variables mapping.

Computational Efficiency

In the second stage, ICAN generates the 625 test sets using four minutes and forty-three seconds of VAX CPU time while the neural network simulator requires one minute and forty-three seconds. Although both programs perform extensive input and output, this probably has little impact since the VAX utilizes memory mapped I/O. Based upon these timings, the neural network performs its calculations roughly 2.5 times faster than ICAN. Reducing the size of the hidden layer in the neural network to five nodes has resulted in a network which performs its calculations about 3.2 times quicker than ICAN when applied to difficult stage two problems. In stage three, with all constituent properties varying, the neural network performs about 1.8 time faster than ICAN. This improvement factor could probably be increased beyond 2.0 by decreasing the size of the hidden layer and investing additional time in network training. Training costs, however, have been significant for Stage 3 simulations. Approximately nineteen hours of CRAY/XMP-4 super computer CPU time was consumed. This contrasts with a few minutes of DEC/VAX CPU time for training one of the single variable simulators in stage one. The latter half of the training on the CRAY reduced the RMS error on the test set by only one tenth of a percent, so ten hours of training time would probably have been adequate. The training time is, of course, a function of the training algorithm, which in this case was "plain vanilla" delta error back propagation. More advanced training algorithms would greatly reduce the needed CPU time. After training is completed, the calculation is relatively simple, and it takes place at a fixed rate for all problems.

The principle computational advantages of the neural network implementation would not be evidenced unless it were implemented on multiple parallel processors. Except for the limited gains resulting from vectorization of DO-loops, comparable parallelism could be obtained with ICAN only through a major restructuring of the source code, a process conceivably involving months of effort. In fact, it is highly doubtful that comparable parallelism could ever be accomplished with an algorithmic ICAN implementation. However, one of the advantages of ICAN is that it can be integrated with a Finite element code to which it supplies with needed element material properties. Even the modest improvement in CPU times by a factor of two or three pays good dividends when multiplied by the usually large number of finite elements in a model and by the iterations through nonlinear simulation runs.

Future Efforts

The results of this project do show enough promise to the hypothesis that neural networks may be utilized to simulate the micromechanical behavior of composites necessary to integrated composite structural analysis. Future efforts will be directed toward clustering concepts at both input and output data for better training and predictive capabilities as well as applying neural network simulations to composites analysis problems where existing techniques do not provide results for their category of problems as efficiently as ICAN does for its category. That investigation will also include implementation and testing of a parallel processing scheme.

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Table 1 Single Variable Results.

	RMS error results
Fiber Volume Ratio	1.175 %
Void Volume Ratio	0.181 %
Temperature	0.408 %
Moisture	0.354 %

Table 2 Four Variable Results.

Constituents Description	RMS error results
S-Glass fiber with Epoxy Matrix	1.069 %
AS Graphite fiber with Low Modulus, Low Strength Matrix	0.975 %
P-75 Fiber with High Modulus, High Strength Matrix	1.066 %

Table 3 (a) Description of Ply Properties.

1.	Elastic Moduli	E_{l11}	psi
2.		E_{l22}	psi
3.		E_{l33}	psi
4.	Shear Moduli	G_{l12}	psi
5.		G_{l23}	psi
6.		G_{l13}	psi
7.	Poisson's Ratios	ν_{l12}	psi
8.		ν_{l23}	psi
9.		ν_{l13}	psi
10.	Therm. Exp. Coef.	α_{l11}	ppm/°F
11.		α_{l22}	ppm/°F
12.		α_{l33}	ppm/°F
13.	Density	ρ_l	lb/in^3
14.	Heat Capacity	C_l	BTU/lb
15.	Heat Conductivity	K_{l11}	$BTU \cdot in/hr/ft^2/°F$
16.		K_{l22}	$BTU \cdot in/hr/ft^2/°F$
17.		K_{l33}	$BTU \cdot in/hr/ft^2/°F$
18.	Strengths	S_{l11T}	psi
19.		S_{l11C}	psi
20.		S_{l22T}	psi
21.		S_{l22C}	psi
22.		S_{l12S}	psi
23.	Moist. Diffusivity	D_{l11}	in^2/sec
24.		D_{l22}	in^2/sec
25.		D_{l33}	in^2/sec
26.	Moist. Expansion	β_{l11}	in/in/1% moist.
27.	Coefficient	β_{l22}	in/in/1% moist.
28.		β_{l33}	in/in/1% moist.
29.	Flexural Moduli	E_{l11F}	psi
30.		E_{l22F}	psi
31.	Flexural Strengths	S_{23}	psi
32.		S_{F11}	psi
33.		S_{F22}	psi
34.		S_{sb}	psi
35.	Ply Thickness	t_l	inches
36.	Interply Thickness	δ_c	inches
37.	Interfiber Spacing	δ_f	inches

Table 3 (b). Neural Net vs ICAN predictions for the properties of S-Glass/Epoxy Composite.

No.	ICAN	NETS	%Error	ICAN	NETS	%Error	ICAN	NETS	%Error
	k_f =.38;k_v=.03;T=200°;M=1%			k_f =.45;k_v=.02;T=100°;M=.5%			k_f =.65;k_v=.01;T=250°;M=.5%		
1	0.49240E+07	0.48980E+07	0.5	0.58250E+07	0.57927E+07	0.6	0.81710E+07	0.82606E+07	-1.1
2	0.89360E+06	0.89155E+06	0.2	0.13060E+07	0.13011E+07	0.4	0.15200E+07	0.15315E+07	-0.8
3	0.89360E+06	0.89198E+06	0.2	0.13060E+07	0.12986E+07	0.6	0.15200E+07	0.15287E+07	-0.6
4	0.33260E+06	0.33152E+06	0.3	0.48750E+06	0.48528E+06	0.5	0.56920E+06	0.57396E+06	-0.8
5	0.21090E+06	0.21068E+06	0.1	0.30330E+06	0.30163E+06	0.6	0.33140E+06	0.33301E+06	-0.5
6	0.33260E+06	0.33163E+06	0.3	0.48750E+06	0.48564E+06	0.4	0.56920E+06	0.57304E+06	-0.7
7	0.28250E+00	0.28367E+00	-0.4	0.27550E+00	0.27537E+00	0.0	0.24900E+00	0.24863E+00	0.1
8	0.45880E+00	0.46083E+00	-0.4	0.42830E+00	0.42859E+00	-0.1	0.35230E+00	0.35068E+00	0.5
9	0.28250E+00	0.28360E+00	-0.4	0.27550E+00	0.27536E+00	0.0	0.24900E+00	0.24877E+00	0.1
10	0.52440E-05	0.50000E-05	4.7	0.46290E-05	0.50000E-05	-8.0	0.36520E-05	0.40000E-05	-9.5
11	0.32280E-04	0.33000E-04	-2.2	0.22210E-04	0.22000E-04	0.9	0.19330E-04	0.19000E-04	1.7
12	0.32280E-04	0.32000E-04	0.9	0.22210E-04	0.22000E-04	0.9	0.19330E-04	0.19000E-04	1.7
13	0.60340E-01	0.60808E-01	-0.8	0.63980E-01	0.64133E-01	-0.2	0.73560E-01	0.73937E-01	-0.5
14	0.24730E+00	0.24920E+00	-0.8	0.20680E+00	0.20748E+00	-0.3	0.21350E+00	0.21455E+00	-0.5
15	0.38780E+01	0.38677E+01	0.3	0.40910E+01	0.40785E+01	0.3	0.55250E+01	0.55457E+01	-0.4
16	0.27080E+01	0.26967E+01	0.4	0.24590E+01	0.24429E+01	0.7	0.42310E+01	0.42510E+01	-0.5
17	0.27080E+01	0.27014E+01	0.2	0.24590E+01	0.24429E+01	0.7	0.42310E+01	0.42491E+01	-0.4
18	0.14290E+06	0.14232E+06	0.4	0.16910E+06	0.16823E+06	0.5	0.23720E+06	0.23977E+06	-1.1
19	0.11550E+06	0.10809E+06	6.4	0.14090E+06	0.13581E+06	3.6	0.11200E+06	0.11311E+06	-1.0
20	0.80220E+04	0.80406E+04	-0.2	0.10830E+05	0.10867E+05	-0.3	0.79070E+04	0.80123E+04	-1.3
21	0.18720E+05	0.18736E+05	-0.1	0.25280E+05	0.25376E+05	-0.4	0.18450E+05	0.18733E+05	-1.5
22	0.69530E+04	0.69347E+04	0.3	0.93900E+04	0.94120E+04	-0.2	0.68530E+04	0.69419E+04	-1.3
23	0.11800E-03	0.11900E-03	-0.8	0.10600E-03	0.10600E-03	0.0	0.68000E-04	0.67000E-04	1.5
24	0.76710E-04	0.77000E-04	-0.4	0.65840E-04	0.66000E-04	-0.2	0.38750E-04	0.38000E-04	1.9
25	0.76710E-04	0.77000E-04	-0.4	0.65840E-04	0.66000E-04	-0.2	0.38750E-04	0.38000E-04	1.9
26	0.17190E-03	0.17800E-03	-3.5	0.16830E-03	0.16900E-03	-0.4	0.54390E-04	0.59000E-04	-8.5
27	0.17230E-02	0.17350E-02	-0.7	0.14480E-02	0.14540E-02	-0.4	0.80580E-03	0.79200E-03	1.7
28	0.17230E-02	0.17370E-02	-0.8	0.14480E-02	0.14500E-02	-0.1	0.80580E-03	0.79300E-03	1.6
29	0.49240E+07	0.49081E+07	0.3	0.58250E+07	0.57886E+07	0.6	0.81710E+07	0.82613E+07	-1.1
30	0.89360E+06	0.89138E+06	0.2	0.13060E+07	0.12986E+07	0.6	0.15200E+07	0.15290E+07	-0.6
31	0.43440E+04	0.43225E+04	0.5	0.56960E+04	0.56752E+04	0.4	0.38340E+04	0.39348E+04	-2.6
32	0.15970E+06	0.15395E+06	3.6	0.19220E+06	0.18973E+06	1.3	0.19020E+06	0.19113E+06	-0.5
33	0.14040E+05	0.14065E+05	-0.2	0.18960E+05	0.19022E+05	-0.3	0.13840E+05	0.14001E+05	-1.2
34	0.10430E+05	0.10393E+05	0.4	0.14090E+05	0.14121E+05	-0.2	0.10280E+05	0.10406E+05	-1.2
35	0.50000E-02	0.50000E-02	0.0	0.50000E-02	0.50000E-02	0.0	0.50000E-02	0.50000E-02	0.0
36	0.15760E-03	0.15800E-03	-0.3	0.11560E-03	0.11700E-03	-1.2	0.35720E-04	0.36000E-04	-0.8
37	0.15760E-03	0.15700E-03	0.4	0.11560E-03	0.11800E-03	-2.1	0.35720E-04	0.35000E-04	2.0

Table 4. Prediction of Laminate Properties: Nets vs ICAN

	Property	Symbol	Units	ICAN	NETS	%Error
1.	Density	ρ_c	lb/in^3	0.71300E-01	0.71402E-01	-0.1
2.	Thickness	t_c	inches	0.20000E-01	0.20000E-01	0.0
3.	Stiffness Matrix	C_{11}	psi	0.78030E+07	0.77880E+07	0.2
4.		C_{12}	psi	0.86740E+06	0.87231E+06	-0.6
5.		C_{13}	psi	0.68700E+06	0.69079E+06	-0.6
6.		C_{22}	psi	0.20340E+07	0.20409E+07	-0.3
7.		C_{23}	psi	0.74620E+06	0.75070E+06	-0.6
8.		C_{33}	psi	0.20310E+07	0.20380E+07	-0.3
9.		C_{44}	psi	0.39270E+06	0.39408E+06	-0.4
10.		C_{55}	psi	0.64150E+06	0.64382E+06	-0.4
11.		C_{66}	psi	0.83180E+06	0.83434E+06	-0.3
12.	Thermal Exp.	α_{cxx}	ppm/°F	0.34750E-05	0.40000E-05	-15.1
13.	Coefficients	α_{cyy}	ppm/°F	0.16730E-04	0.17000E-04	-1.6
14.		α_{czz}	ppm/°F	0.17160E-04	0.17000E-04	0.9
15.	Thermal	K_{cxx}	$BTU\cdot in/hr/ft^2/°F$	0.51290E+01	0.51152E+01	0.3
16.	Conductivity	K_{cyy}	$BTU\cdot in/hr/ft^2/°F$	0.35750E+01	0.35732E+01	0.1
17.		K_{czz}	$BTU\cdot in/hr/ft^2/°F$	0.35250E+01	0.35239E+01	0.0
18.	Heat Capacity	H_c	BTU/lb/°F	0.19870E+00	0.19782E+00	0.4
19.	Elastic Moduli	E_{cxx}	psi	0.73560E+07	0.73352E+07	0.3
20.		E_{cyy}	psi	0.17100E+07	0.17160E+07	-0.4
21.		E_{czz}	psi	0.17390E+07	0.17453E+07	-0.4
22.	Shear Moduli	G_{cyz}	psi	0.39270E+06	0.39408E+06	-0.4
23.		G_{czx}	psi	0.64150E+06	0.64382E+06	-0.4
24.		G_{cxy}	psi	0.83180E+06	0.83434E+06	-0.3
25.	Poisson's	ν_{cxy}	in/in	0.34950E+00	0.34924E+00	0.1
26.	Ratios	ν_{cyx}	in/in	0.81240E-01	0.81313E-01	-0.1
27.		ν_{cxz}	in/in	0.20980E+00	0.20953E+00	0.1
28.		ν_{czx}	in/in	0.49620E-01	0.49559E-01	0.1
29.		ν_{cyz}	in/in	0.33990E+00	0.33990E+00	0.0
30.		ν_{czy}	in/in	0.34570E+00	0.34563E+00	0.0
31.	Ref. Plane	Z_{cgc}	in	0.10000E-01	0.10000E-01	0.0

Table 5. Typical Stage Three Results for a S-Glass/Epoxy Composite system. (fvr = 60)

No.	Nets	ICAN	%Error
1:	7622223.500000	7640000.000000	0.232677
2:	1844958.125000	1948000.000000	5.289624
3:	1844958.125000	1948000.000000	5.289624
4:	700597.625000	731500.000000	4.224522
5:	430829.156250	439400.000000	1.950579
6:	700597.625000	731500.000000	4.224522
7:	0.253360	0.260000	2.553899
8:	0.364425	0.373500	2.429699
9:	0.253360	0.260000	2.553899
10:	0.000003	0.000004	10.137203
11:	0.000012	0.000013	4.303826
12:	0.000012	0.000013	4.303826
13:	0.073018	0.071600	1.980679
14:	0.258058	0.189700	36.034887
15:	11.080626	5.000000	121.612511
16:	3.836754	3.013000	27.339996
17:	3.836754	3.013000	27.339996
18:	229083.203125	221800.000000	3.283680
19:	111144.492188	140000.000000	20.611077
20:	18111.642578	8070.000000	124.431754
21:	6862.871582	18830.000000	63.553523
22:	8172.138672	8076.000000	1.190424
23:	0.000080	0.000080	0.000000
24:	0.000045	0.000045	0.177460
25:	0.000045	0.000045	0.177460
26:	0.000102	0.000105	2.205727
27:	0.001206	0.001209	0.253649
28:	0.001206	0.001209	0.253649
29:	7622223.500000	7640000.000000	0.232677
30:	1844958.125000	1948000.000000	5.289624
31:	4842.767578	4851.000000	0.169706
32:	191200.046875	214600.000000	10.903986
33:	12713.559570	14120.000000	9.960626
34:	12258.209961	12110.000000	1.223864
35:	0.005000	0.005000	0.000000
36:	0.000060	0.000052	15.882386
37:	0.000060	0.000052	15.882386

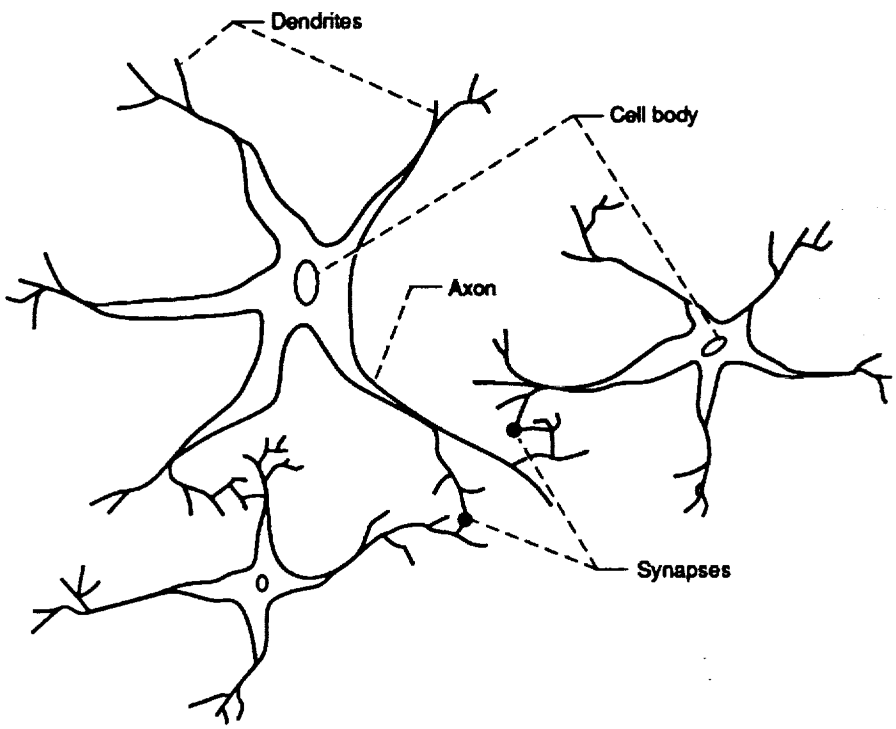

Figure 1.—Neurons.

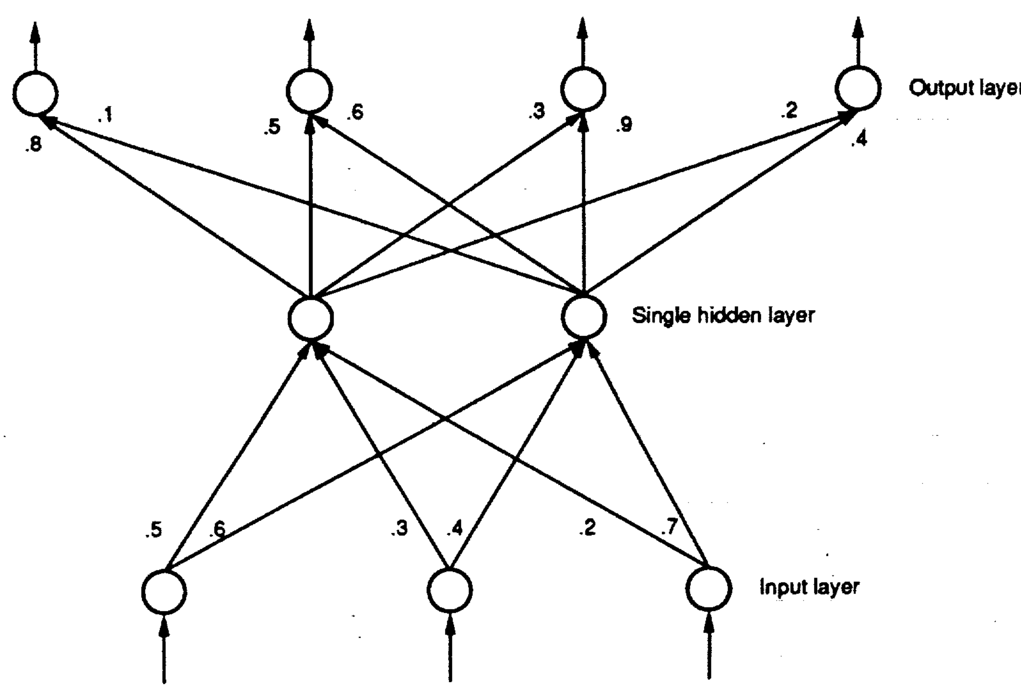

Figure 2.—A simple neural network.

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16. Abstract
Artificial neural networks can provide improved computational efficiency relative to existing methods when an algorithmic description of functional relationships is either totally unavailable or is complex in nature. For complex calculations, significant reductions in elapsed computation time are possible. The primary goal of this project is to demonstrate the applicability of artificial neural networks to composite material characterization. As a test case, a neural network has been trained to accurately predict composite hygral, thermal, and mechanical properties when provided with basic information concerning the environment, constituent materials, and component ratios used in the creation of the composite. A brief introduction on neural networks is provided along with a description of the project itself.

17. Key Words (Suggested by Author(s))
Neural nets; Composite materials; Neurons; Nodes; Networks; Fibers; Void ratio; Moisture; Feed forward control; Parallel processing (computers)

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