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Evaluation of impacted composite laminate residual strength through neural networks

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Abstract

This paper deals with the evaluation of residual tensile strength of composite laminates containing impact damage generated with different impact energies. Sensor fusion of acoustic emission and load data is carried out through neural networks to obtain a prediction of residual tensile strength as early as possible in the loading history of impacted composite laminates. The results show that neural network processing provides an effective monitoring of laminate fracture behavior based on acoustic emission analysis.

Introduction

One of the main disadvantages of composite materials in comparison with metals is their liability to be damaged by low velocity impact. Accordingly, composite laminates can undergo severe strength reduction because of impact damage occuring during fabrication or service [1,2].

Nondestructive evaluation (NDE) methods for composite materials are generally capable of providing information on defects generated during fabrication or service [3,4]. Most of these methods can determine the type and location of damage in the material: it is then necessary to correlate the detected damage with residual mechanical properties. Unfortunately, despite the efforts of researchers [5,6], completely satisfying analytical methods for prediction of strength after impact are not yet available.

A totally different approach is enabled by NDE techniques based on acoustic emission (AE) testing. The detection of AE, i. e. transient stress waves released in materials undergoing permanent deformation and fracture, presents the unique advantage of sensing the failure processes as they occur in the material under loading [4,7]. This allows for on-line decisions on damage development and real-time corrective actions.

There is, however, a need for a better interpretation of AE detected from composite materials under loading to achieve a reliable strength prediction before catastrophic failure. In a previous paper [8], it was reported that while in tensile testing of vergin composite samples the stress field is uniform and AE comes from the whole material volume, the presence of damage affects the stress distribution, magnifying stresses at the tip of the discontinuity. The crack tip becomes a preferential site of failure development inducing two effects: material residual strength decreases and AE is strongly altered bacause an early activity is generated by a small material volume. This feature makes AE monitoring a very promising NDE method, provided a reliable correlation between detected AE and residual strength is found.

In [9] a correlation between AE and residual strength was hypothesized. In [8] a reliable prediction of material residual strength was obtained through neural networks in the case of tensile testing of quasi-isotropic fiberglass composites carrying center holes. In this paper, AE monitoring of the fracture behavior of composite laminates containg impact damage generated with different impact energies is utilized for residual tensile strength prediction at an early stage of the AE response based on a similar neural network approach.

Experimental

Quasi-isotropic $(0/90/\pm45)_S$ E glass fabric/epoxy prepreg composite laminates were fabricated. Nominal thickness was 1.3 mm and fiber volume fraction 35%. Tensile strength of the virgin material was 269 N/mm^2. The laminates, 80 mm in width and 1000 mm in length, were clamped in a circular support, 60 mm in diameter, and struck at their central point by a hemi-spherical tup with a 20 mm diameter and 1 kg mass. Impact energy was varied in the range 2-20 J by varying the drop height. After impact, rectangular specimens, 80 mm by 250 mm, were trimmed to 250 mm length and tensile tested. A total number of 14 valid tests on impacted samples were performed. AE was detected during tensile tests using a 150 kHz resonant sensor; amplification was 58 dB, threshold level 0.5 V, and high-pass filter cut-off freq. 100 kHz. AE event counts, N_t, was the AE count-based parameter considered for impacted composite laminate fracture behavior prediction.

Results and discussion

By plotting the AE N_t recorded during tensile testing of the impacted samples vs. applied stress, typical N_t - σ curves were obtained [9,10] (Fig. 1). Curve trend was very much dependent on impact energy and damage, in agreement with fracture mechanics considerations. In particular, residual strength decreases with increasing impact energy. A more detailed analysis of the features of the AE response of the tested laminates is given in [10].

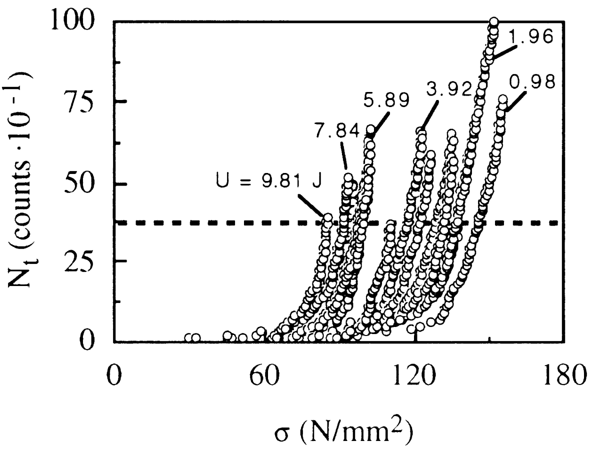

Figure 1: N_t - σ curves for impacted composite laminate samples. U = impact energy in J. Dotted line = minimum value of N_{tmax}.

The most important result illustrated in Fig. 1 is that samples displaying different residual strength also show distinct AE N_t - σ curves: the lower the residual strength, the higher the N_t value for a given stress level. AE activity seems to be dependent on residual strength rather than on impact energy. This observation is interesting because it supports the possibility of correlating the AE response with residual strength.

Neural network processing was applied to predict composite laminate residual strength at an early stage of its loading history. A pattern vector representing the AE N_t - σ curve was fed at the input layer of a network in order to obtain the value of residual strength at the output layer. If the evaluation of residual strength were carried out after the entire AE N_t - σ curve is available, the laminate would have already failed and the information would be useless. If a correct evaluation could be obtained at a stress level lower than the ultimate stress, the prediction of residual strength would allow for actions such as laminate repair or substitution.

A total number of 14 valid tensile tests on impacted laminate samples were considered for neural network processing. For each tensile test, an AE N_t - σ experimental curve, consisting in a sequence of data points each identified by an AE event count and its corresponding stress value, was available. As AE event counts increase from 1 to the total number of events at failure by increments of 1 event, the AE N_t - σ curve can be represented by a vector: the components of the curve vector are the stress values for each AE event and the position of the stress value in the vector corresponds to its associated AE event count. The last component of the curve vector is the impacted laminate residual strength and the length of the vector is the total number of AE events at failure, N_{tmax}. Curve vectors have different length as both residual strength and N_{tmax} vary significantly with impact energy.

A backpropagation three-layer neural network was utilized to produce a mapping from input vectors to output values [11]: the curve vectors were the input and the impacted sample residual strength was the output. In order to reduce the number of nodes at the input layer, abridged curve vectors were obtained by selecting one stress value every other ten in the original sequence. The reduced curve vectors to be utilized as inputs to the neural network had 1/10 of the components of the original curve vectors. This did not introduce significant errors in the obtained results.

The number of input nodes should match the number of components in the input vectors. The curve vectors had different lengths and could not be utilized as inputs to the same neural network requiring the same number of input features from all input vectors. Thus, input pattern vectors were constructed by selecting the first Q components of all curve vectors. The maximum Q value was the length of the smallest curve vector in the training set, ie 370 (dotted line in Fig. 1). Lower Q values were also used to verify network performance when a smaller portion of the curve was considered: as matter of fact, the earlier the correct pattern recognition, the more useful the system for impacted composite laminate diagnostics.

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Nine networks with Q = 370, 300, 250, 200, 150, 100, 50, 40, 30 input nodes, respectively, 5 hidden nodes and 1 output node were used for impacted laminate residual strength prediction. The number of hidden nodes was chosen according to a "cascade learning" procedure [6]: hidden units are added one at a time until an acceptable training speed is achieved. Weights and thresholds were randomly initialized between -1 and +1. Learning coefficients were: learning rate between input and hidden layers $\eta = 0.3$, learning rate between hidden and output layers $\eta = 0.15$, momentum $\alpha = 0.4$. The learning rule was the Generalized Delta Rule and the transfer function applied to the nodes was the sigmoid function $f(x) = 1/(1+e^{-x})$ [5]. The number of learning steps for a complete training set was comprised between 42000 and 280000, according to time to convergence and value of Q. Epoch size, ie the number of training presentations between weight updates, was 1. The Q-5-1 neural networks were trained by the "leave-k-out" method, which is particularly useful when dealing with small training sets [7]. One pattern vector (k = 1) was held back in turn for the recall phase, and the other pattern vectors were used for learning: 14 different learning and recalling procedures were carried out.

In Fig. 2, the ratio of predicted over actual residual strength is reported vs. the number of input data points. Vertical bars represent data scatter and symbols indicate mean values. Predicted residual strength mean value is in all cases practically coincident with the actual experimental value. However, data scatter is rather high up to 50 input data points. Data scatter decreases notably for 100 input data points, then it stays constant at +10%/-7%.

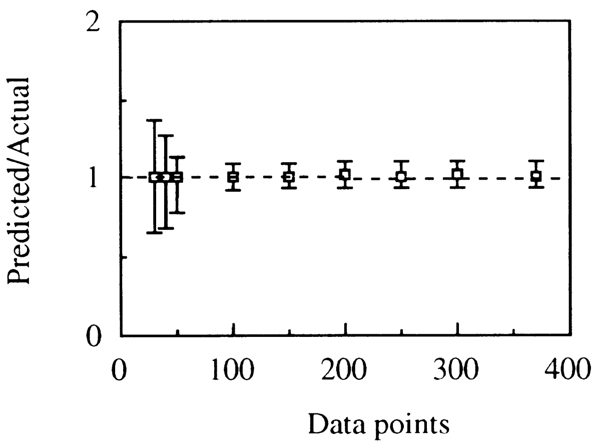

Figure 2: Ratio of predicted over actual residual strength vs. number of input data points. Q-5-1 neural networks.

Another neural network configuration was used for residual strength prediction. Single data points from the experimental curves were utilized as input vectors. The input layer had 2 input nodes for the stress value and its associated AE event count, the hidden layer had 4 nodes, and the output layer 1 node for residual strength prediction. Weights and thresholds initialization, learning coefficients, learning rule, transfer function, and epoch size were the same as for the Q-5-1 networks. The number of learning steps for a complete training set was 114000 for 829 input vectors. Training of the 2-4-1 neural network was obtained by inputting the data points of all experimental curves, except for one curve held back in turn for the recall phase.

The output values obtained from the learned network after sequentially inputting the data points of the held back curve were normalized and plotted vs. normalized AE event counts, $N_t/N_{t\ max}$. In Fig. 3, the upper and lower envelopes of the curves are reported.

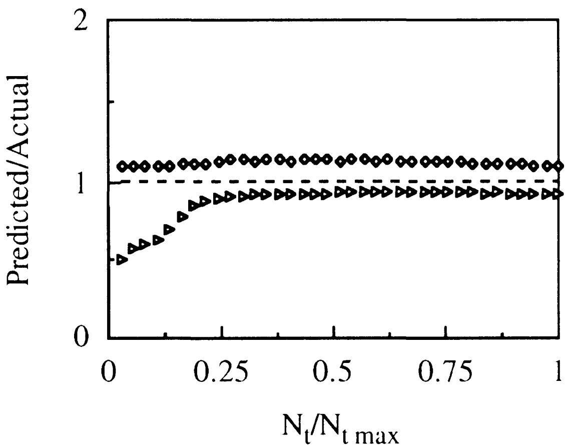

Figure 3: Upper and lower envelopes of the ratio of predicted/actual residual strength vs. normalized AE event counts, $N_t/N_{t\ max}$.

Predicted residual strength is affected by a large error in the first part of the AE N_t - σ curve up to $N_t = 0.20\ N_{tmax}$, corresponding to 80-90% of the actual residual strength and to 20 - 50% of vergin material ultimate strength. Then, the error stays constant with load. A prediction of residual strength with precision +10%/-7% can be obtained.

In Fig. 4, the ratio of predicted over actual residual strength is reported vs. the number of input data points for the 2-4-1 neural network. A prediction of residual strength with precision +10%/-7% can be obtained for input data points ≥ 100.

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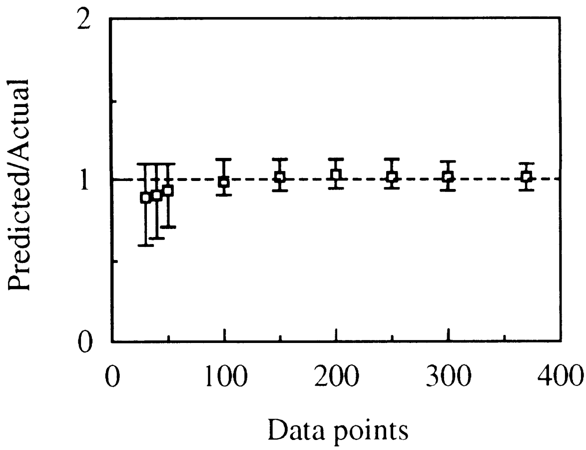

Figure 4: Ratio of predicted over actual residual strength vs. number of input data points. 2-4-1 neural network.

Examining Figs. 2 and 4, the performance of the Q-5-1 and 2-4-1 neural networks can be compared. Both network configurations provide reasonably accurate results when the number of input data points is ≥ 100. The main difference between the two nework configurations can be appreciated when the number of input data points is < 100. In this case, the 2-4-1 network can predict material residual strength with a higher precision in terms of positive error. This avoids the danger of overestimating the actual residual strength and provides a more conservative prediction for low number of input data points.

Conclusions

Experimental curves of AE event counts vs. stress obtained from tensile tests on impacted composite laminates were utilized as input patterns to different neural network configurations. The capability of neural network processing to effectively predict material residual strength at an early stage in the AE response evolution and laminate loading history was verified and critically assessed.

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