Prediction of composite laminate residual strength based on a neural network approach
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Abstract
In this paper, the problem of tensile strength prediction of composite laminates containing artificially implanted holes is confronted. An approach based on the integration of acoustic emission and load data through neural network is presented. The obtained results show that neural networks can be a useful tool in the monitoring of fracture behavior of composite laminates through acoustic emission detection and analysis.

1. Introduction
The identification of defects and the assessment of defect criticality through nondestructive evaluation (NDE) is a very attractive research topic in the field of composite materials. One of the main obstacles to the further development and diffusion of composite material applications is the lack or scarcity of NDE methods being inexpensive, reliable, non-intrusive and relatively easy to apply.

Acoustic emission (AE), i.e. transient stress waves released in materials undergoing permanent deformation and fracture, has been widely utilized for the study and characterization of metals and composites [1, 2]. AE based NDE and monitoring techniques present the unique advantage over other NDE methodologies of allowing for the "live" sensing of failure processes occurring in a material under loading. This peculiarity of AE testing makes "on-line" decisions on damage development and real-time corrective actions possible.
At present, however, there is a need for a better interpretation of the AE response from composite materials under loading to obtain a reliable prediction of the critical stress before catastrophic failure takes place. In this work, AE monitoring of the fracture behavior of center-hole composite laminates is employed for tensile strength prediction at an early stage of the AE response based on a neural network approach.

2. Acoustic emission from composites

If a virgin composite laminate is tensile tested, AE activity, in terms of total event counts \( N_t \), typically increases with stress or strain in a smooth fashion up to failure. The curve is frequently logarithmic [1]:

\[
N_t = A \sigma^n \tag{1}
\]

where \( \sigma \) is stress and \( A, n \) are two constants to be experimentally evaluated, dependent on the material and the AE system setting.

In a simple tensile test, the stress field is basically uniform within the body, so that AE comes from the whole material volume under control. The presence of cracks, holes or cutouts strongly affects stress distribution, magnifying the stresses at the discontinuity tip. Thus, the crack tip becomes a preferential site of failure development. This results in two effects: (a) the material load carrying capability undergoes a substantial reduction and its residual strength decreases; (b) AE is strongly altered, because an early activity is generated by a small material volume. The latter feature makes AE monitoring a very promising NDE method, provided a correlation is found between AE evolution and residual strength.

Many theoretical and experimental efforts have been devoted to predicting the residual tensile strength of composite laminates containing stress raisers. The most dependable models [3] rely on the "stress intensity factor", \( K_I \), defined as:

\[
K_I = \sigma (\pi C)^m \tag{2}
\]

where \( C \) is the half-dimension of the discontinuity and \( m \) an empirically derived exponent.

Since stress concentrators of different size generate similar stress fields if characterized by the same \( K_I \) value, it has been postulated that failure occurs when \( K_I \) achieves a critical value,
\( K_{IC} \), only dependent on the material under consideration. Indicating residual strength with \( \sigma_c \), from eqn (2):

\[
\sigma_c = \frac{K_{IC}}{(\pi C)^m} \quad (3)
\]

It is natural to infer that also AE depends on the stress intensity factor, rather than on stress. Thus, it has been hypothesized that [4]:

\[
N_t = B K_I \quad (4)
\]

where \( B \) is a constant for a given material and fixed AE setting parameters, independent of the geometry of the stress raiser.

From eqns (2) and (4), for a given applied stress, a higher AE activity is expected when large stress concentrators are present in the material. The main implication of eqn (4) for the present work is that the AE evolution is strictly dependent on the geometry of the stress raiser. Thus, a reliable prediction of material residual strength can be reasonably expected through suitable interpretation of the AE response based on a neural network approach.

### 3. Experimental

Quasi-isotropic \((0/90/\pm 45)_S\) E glass fabric/epoxy prepreg composite laminates were tensile tested. Nominal thickness was 1.3 mm and fiber volume fraction 35%. Tensile strength of the virgin material was 269 N/mm^2. Rectangular specimens, 60 mm by 250 mm, were utilized for tensile tests on center-hole samples. Three different hole diameters were used: 4 mm, 8 mm, and 20 mm. At least 4 valid tests were performed for each experimental condition. 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 composite laminate fracture behavior prediction.

By plotting AE \( N_t \) recorded during center-hole sample testing vs. applied stress, typical \( N_t - \sigma \) curves were obtained [4]. Curve trend was very much dependent on hole diameter, in agreement with fracture mechanics considerations. In particular, as qualitatively predicted by eqn (4), AE \( N_t \) at a given stress level was the higher, the larger the hole. Besides, the ultimate stress, i.e. the laminate residual strength, was obviously the lower, the larger the hole diameter.
4. Neural network processing

On the basis of the experimental results, a neural network approach was attempted to obtain the prediction of composite laminate residual strength at an early stage of its loading history. The idea was to feed a pattern vector representing the AE $N_t - \sigma$ curve at the input layer of a network and obtain the value of residual strength at the output layer. If the evaluation of the laminate residual strength were carried out after obtaining the entire AE $N_t - \sigma$ curve, the information would be utterly useless for monitoring applications: the laminate would be broken before any action could be taken. If a correct evaluation could be obtained earlier than the achievement of the ultimate stress, the identification of residual strength would represent a prediction and actions such as laminate repair or substitution could be taken.

A total number of 14 valid tensile tests on center-hole laminate samples were considered for neural network processing: four tests on 4 mm hole diameter samples, four tests on 8 mm hole diameter samples, and six tests on 20 mm hole diameter samples.

For each tensile test, an AE $N_t - \sigma$ 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 $N_t - \sigma$ 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 laminate residual strength and the length of the vector is the total number of AE events at failure, $N_{t_{\text{max}}}$. Curve vectors have different lengths as both residual strength and $N_{t_{\text{max}}}$ vary significantly with hole diameter; besides, a dispersion of data was also observed within each group of samples with the same hole diameter.

Neural network processing was applied to predict composite laminate residual strength. A backpropagation three-layer neural network was utilized to produce a mapping from input vectors to output values [5]: the curve vectors were the input and the sample residual strength was the output. 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 which requires 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: 200. 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 composite laminate diagnostics.

In Fig. 1, the first 200 data points of the AE $N_t - \sigma$ curves, i.e. the patterns presented at the network input layer, are reported.

![Figure 1: $N_t - \sigma$ curves for different hole diameters: first 200 points. Black circles = 20 mm, white circles = 8 mm, small dots = 4 mm.](image)

Five networks with $Q = 200$, 180, 150, 100, and 50 input nodes, respectively, 5 hidden nodes and 1 output node were used for 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. The weights and thresholds of all nodes were randomly initialized between -1 and +1. The learning coefficients were: learning rate $\eta = 0.9$ and 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 1500 and 4000, according to the time to convergence. Epoch size, i.e. the number of training presentations between weight updates, was 16. 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 network recall phase, and the other pattern vectors were used for learning: a total of 14 different learning and recalling procedures were carried out.
In Fig. 2, the ratio of predicted over actual residual strength for different hole diameters 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 very near the actual experimental value. However, data scatter is rather high for all hole diameters for 50 input data points. Data scatter decreases notably for 100 input data points. Then, it decreases slightly with increasing number of data points down to approximately ±5%.

![Figure 2: Ratio of predicted over actual residual strength vs. number of input data points. Q-5-1 neural networks.](image)

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 20 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 2000000 for 9069 input vectors. Training of the 2-20-1 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 plotted vs. normalized AE event counts, $N_t/N_t\max$ (Fig. 3). The value of the actual sample residual strength was reported in the plot as a continuous horizontal line to allow for the evaluation of residual strength prediction error as the composite load history progresses.
Figure 3: Predicted residual strength vs. normalized AE event counts, $N_t/N_{t_{\text{max}}}$, for different hole diameters. Continuous horizontal line = actual residual strength.

Predicted residual strength is affected by a large error in the first part of the AE $N_t - \sigma$ curve up to about $N_t = 0.25 N_{t_{\text{max}}}$, corresponding to $\approx 80\%$ of the actual residual strength. Then, the error decreases with increasing load and is more significant for hole diameter 20 mm than for the lower diameters. However, in all cases, a prediction of residual strength with precision $\geq 95\%$ can be obtained for $N_t \leq 0.60 N_{t_{\text{max}}}$, corresponding to $90\%$ of the actual residual strength.

Figure 4: Ratio of predicted over actual residual strength vs. number of input data points. 2-20-1 neural network.
In Fig. 4, the ratio of predicted over actual residual strength is reported vs. the number of input data points for the 2-20-1 neural network. Examining Figs. 2 and 4, the performance of the Q-5-1 and 2-20-1 neural networks can be compared. Both network configurations provide reasonably accurate results when the number of input data points is $\geq 100$. The main difference between the two network configurations can be appreciated when the number of input data points is $< 100$. In this case, the 2-20-1 network can predict material residual strength with a much higher precision.

5. Conclusions

AE event counts vs. stress curves obtained during tensile testing of center-hole GFRP composite laminates were utilized as input patterns to different neural network configurations to verify their capability to predict material residual strength very early in the AE response evolution and laminate loading history. The results obtained emphasize the usefulness of neural network processing in materials technology problems where analytic solutions are not available.

References