J Nondestruct Eval (2008) 27: 127–133
DOI 10.1007/s10921-008-0040-6

Artificial Neural Network Prediction of Ultimate Strength of Unidirectional T-300/914 Tensile Specimens Using Acoustic Emission Response

T. Sasikumar · S. Rajendraboopathy · K.M. Usha · E.S. Vasudev

Published online: 30 October 2008

Abstract Acoustic Emission (AE) Monitoring was used to evaluate unidirectional carbon epoxy specimens when tensile loaded with a 100 kN Universal Testing Machine. A series of eighteen samples were loaded to failure to generate AE data for this analysis. After data acquisition, AE response from each test was filtered to include only data collected up to 50% of the actual failure load for further analysis. Amplitude, Duration and Energy are effective parameters utilized to differentiate various failure modes in composites viz., matrix crazing, fiber cut, and delamination with several sub categories such as matrix splitting, fiber/matrix debonding, fiber pull-out etc.

The ultimate strength prediction was performed with an Artificial Neural Network Back propagation algorithm. Peak Amplitude values varying from 35–100 dB were taken as the input to the network. The impact of signal amplitudes due to different failure mechanism to the ultimate strength was mapped using a supervised network having a middle layer with 45 neurons and actual failure loads were supplied as target values during training phase. The network finally trained with twelve specimens was able to predict failure loads of remaining six specimens with in the acceptable error tolerance.

Keywords Artificial neural network · Back propagation · Acoustic emission · Amplitude · Prediction · Composites · Tensile strength

T. Sasikumar (✉)
College of Engineering Guindy, Anna University, Chennai-25, India
e-mail: sasikumar_t2000@yahoo.co.in

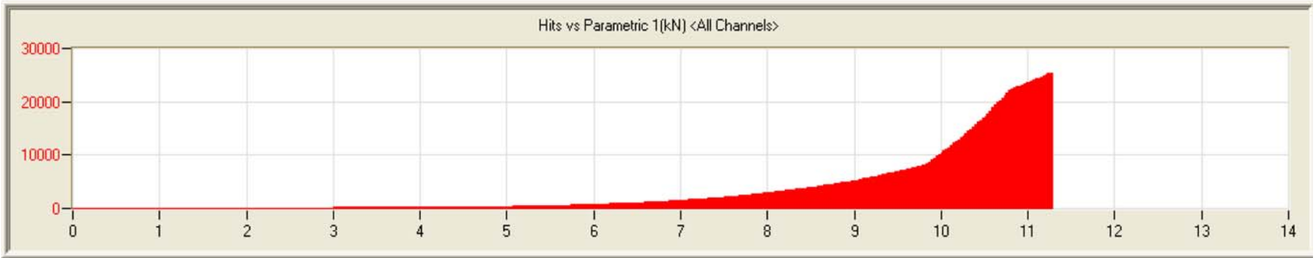
S. Rajendraboopathy
Dept. of Mech. Engg., CEG, Anna University, Chennai-25, India
e-mail: boopathy@annauniv.edu

K.M. Usha
CCTD, CMSE, Vikram Sarabai Space Center, ISRO, Trivandrum-13, India
e-mail: km_usha@vssc.gov.in

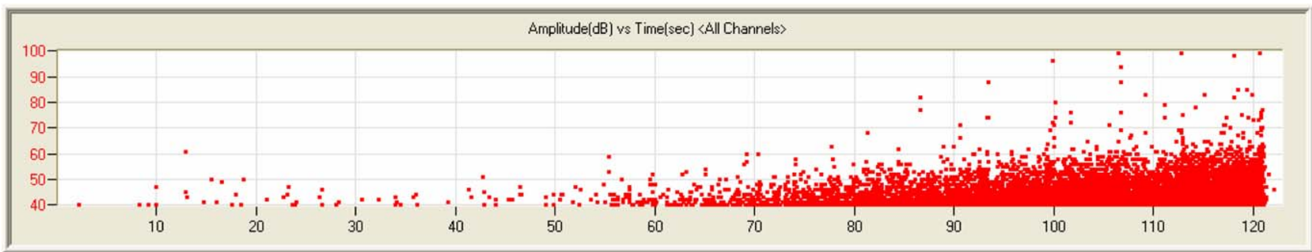
E.S. Vasudev
Vikram Sarabai Space Centre, ISRO, Trivandrum-13, India
e-mail: es_vasudev@vssc.gov.in

1 Introduction

Fiber Reinforced Plastics (FRP) has been widely used in aviation industry, due to the advantages such as, high strength to weight ratio, good corrosive resistance, and fast on site installation. These weight savings in turn contribute to greater payload capability. With the increased use of composites, continuing research in assessment and quality control of composites must be an ongoing process. The major types of damage mechanism of FRP are matrix crazing, Fiber breakage and delamination [1]. As far as the structural integrity is concerned there is a question being whether or not the proof loading will lower the actual failure load. For metals, assuming the absence of macroscopic flaws, as long as the stress is kept below the proportional limit or yield point, there is little in the way of plastic deformation and therefore no noticeable degradation in the structural integrity. This however, does not hold true for fiber/matrix composites, because fibers are the primary load bearing constituents in composites, the structural integrity begin to degrade as soon as the fibers begin to break. The plot between load from zero to failure and the corresponding acoustic emission event frequency is given in Fig. 1a, b. The only way to avoid such an unintentional structural degradation is to reduce the proof test load [2, 3].



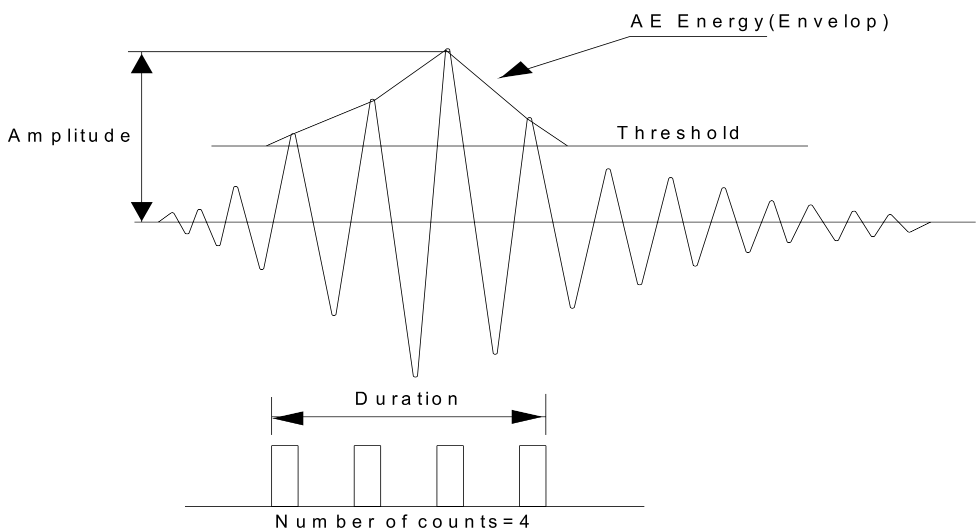
(a)



(b)

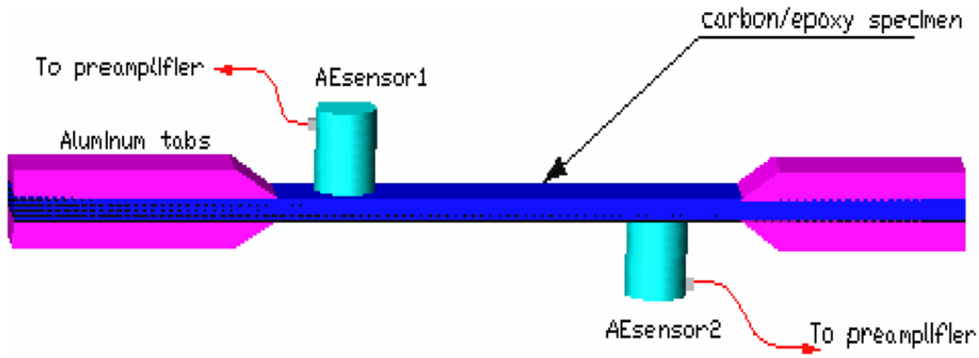
Fig. 1 (**a**) Load vs. hits. (**b**) Amplitude vs. time

Fig. 2 Typical acoustic emission signal and characteristics

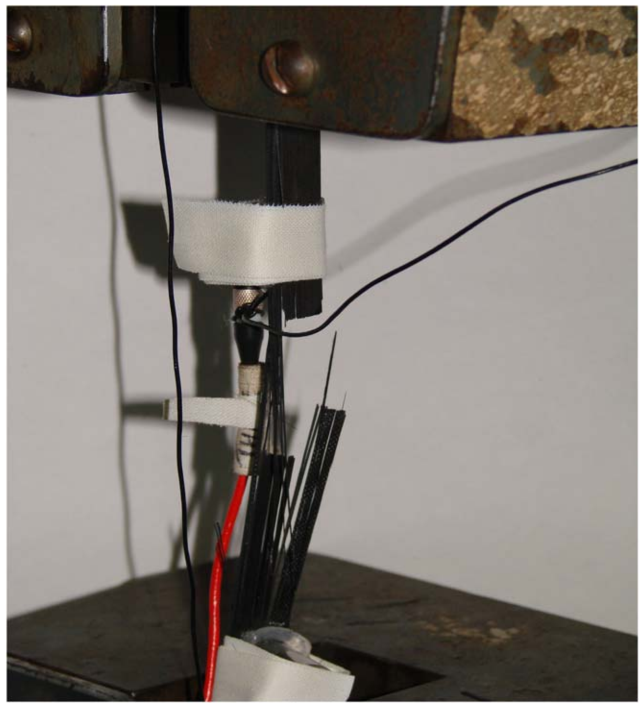


Acoustic Emission (AE) technique is a fast developing NDT tool ideally suited for the integrity evaluation of composite hardware during proof load testing [4]. Acoustic Emission is defined as "the class of phenomena where by transient elastic waves are generated by the rapid release of energy from localized sources with in a material, or the transient waves so generated" [5]. AE signals, once generated will be detected by the AE sensors, which are attached to the material, and sent to the AE data acquisition system for recording and processing. A typical acoustic emission signal Fig. 2 is a complex, damped, sinusoidal voltage vs. time plot. Some of the characteristics such as Amplitude, Duration, Energy, Events and Counts are the key parameters for material characterization and structural integrity evaluation [1, 6]. For a long time amplitude distribution has been utilized for analyzing the failure mechanism in composite materials [7]. Predicting ultimate failure load of composite specimens using AE data was proved earlier by Walker [8].

Artificial Neural Network (ANN) is an information processing system that has certain characteristics similar to biological neural networks. A neural network consists of a large number of simple processing elements called neurons or nodes. Each of these neurons is connected to other neurons by communication links, each with associated weighting. The weighting represents information which is used by the network to solve a problem. A hidden layer neuron has many input paths and combines values of the input paths by a simple summation. The summed input is then modified



(a)



(b)

Fig. 3 (**a**) Specimen with sensors. (**b**) Specimen with sensors after failure

by a transfer function and passed directly to the output path of the processing element. The output path of the processing element can then be connected to input paths of other nodes through connection weightings. Since each connection has a corresponding weighting, these weightings prior to being summed modify the signals on the input lines to a process element. The processing elements are usually organized into groups called layers. Typically a network consists of an input layer, where data are presented to the network, one or more hidden layers for processing, and one output layer for getting the results from the network. It has been demonstrated that AE data could be used along with neural network for predicting ultimate strength of graphite epoxy tensile specimens, Walker [9]. Predicting welded strength of aluminum-lithium specimens with the help of ANN was successfully done by Hill [10].

2 Apparatus and Procedure

Eighteen AE data sets were generated by loading ASTM D-3039 carbon/epoxy tensile specimens at a rate of 5 KN/min to failure. INSTRON 5582 type 100 KN capacity UTM was used to perform the tensile test. While loading, AE activity was monitored with a Physical Acoustic Corporation (PAC) DiSP AE system. A pair of R15 sensors (150 KHz, resonant) and preamplifiers with 40 dB gain are used. AE transducers are mounted in position using adhesive tapes 30 mm apart from aluminum tabs. In order to acquire emissions from complete volume, the sensors were mounted on alternate sides of the specimen as shown in Fig. 3a and b. AE signal transmission between specimen and sensor was ensured through appropriate couplant (silicone vacuum grease). A threshold setting of 35 dB was adopted for the test after estimating background noise. Nielson Hsu

0.5 mm dia, 2 H pencil break was conducted before each test for ensuring proper working of AE channels [11]. The exact material specification of each samples were same, except that they were produced in different curing conditions. Only the portion of AE amplitude frequency data collected up to 50% of the theoretical failure load of first ten specimens were supplied as input to the BP Artificial Neural Network model. 50% amplitude frequency data of remaining eight specimens were used as the test phase for the ultimate strength prediction. Walker has taken only the matrix crazing signals (23 dB to 45 dB) for his weibull analysis and neural network prediction at 25% level [9]. This research has contemplated that the accurate prediction could be possible with AE data recorded during loads up to 50% of the failure load, because significant number of fiber breakage and matrix splitting events, which are adversely affecting the failure load of specimen take place with this limit.

3 AE Characteristics of Failure Mechanisms

As mentioned previously, the three primary failure modes for most composites are matrix crazing, fiber breakage and delamination. Unlike in pressure vessels and flexural tests considerable delamination was not expected in unidirectional tensile test, but fiber splitting can occur. Each of these failure modes has specific magnitudes for various AE characteristics, which makes acoustic emission useful in identifying these failure mechanisms. Amplitude vs. event histogram of one specimen is given in Fig. 4. A typical matrix crazing signal is of long duration with low amplitude and low energy. Matrix crazing occurs throughout the testing cycle and is usually the least damaging of the mechanism [12]. Matrix splitting occurs when matrix cracking occurs along the fibers. This mechanism can bring down the failure load as much as the fiber failure [13]. Duration of this failure is short, energy and amplitude also lesser than fiber breakage. Another failure mode, fiber breakage is typically the most damaging of mechanism, since the fibers are main load bearing constituents of the structure. Fiber breaks have highest amplitudes and energy of the three primary failure mechanisms. Although all the characteristics are useful in providing information on acoustic emission, the research here will use the frequency of hits in each amplitude range (or bin) from 35 dB to 100 dB for failure load prediction. Here event frequencies at 1 dB interval is provided as input for the neural network. Hubele and Hwarng showed that the three-layer back propagation neural network could closely approximate the results obtained from statistical analysis [14]. Neural network approximations also take into account any nonlinearities present, and according to the Kolmogorov theorem, a three-layer neural network should be able to map any continuous function exactly [15]. Statistical methods are capable of predicting the failure strength of specimens, but with neural network prediction accuracy was found to be better.

4 Results and Discussion

Acoustic emission data were collected during loading until failure of each specimen. Table 1 illustrates the ultimate load and corresponding AE hits recorded from testing of each of the specimen. Data acquired till failure is used for post test analysis. After analysis three parameters considered for further studies are amplitude, duration and energy. A series of plots were generated between different AE parameters to illustrate, evaluate and assess the possible correlation between these parameters and failure load, but it was found that there was no significant linearities present between AE data and failure load. Multiple linear regression analysis is performed by Fatzinger [16] using percentage of hits associated with each failure mechanisms have provided a failure load (I-beams) prediction error of 36%, but an optimized Artificial neural network with amplitude frequency provided only 9.5% error. From this research work it was concluded that amplitude frequency along with ANN proved to be better than all other AE parameters. Hence here also the same approach is used.

The 18 tensile specimens were divided into two groups. AE hits recorded form the first ten specimens up to 50% load

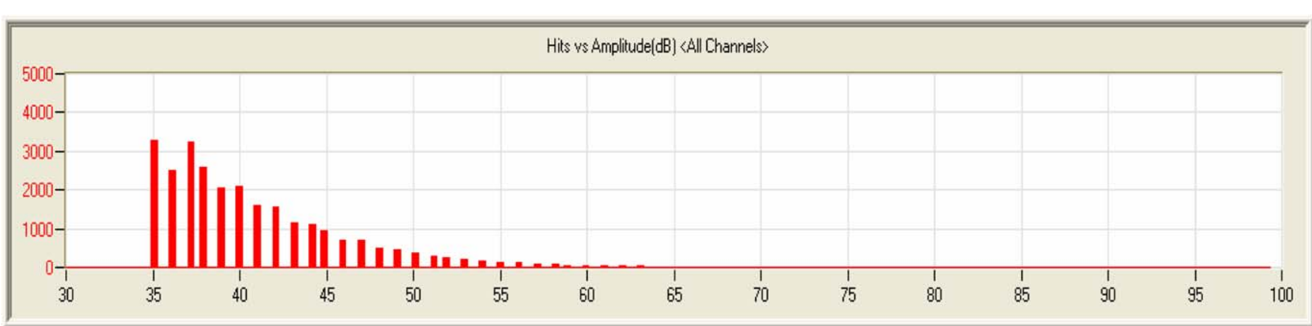


Fig. 4 Amplitude vs. hits histogram

Table 1 AE hits of specimens and corresponding failure loads

Specimen number	Number of AE hits up to failure	Number of hits up to 50% of failure load	Failure load (kN)
1	16345	712	10.948
2	16776	672	11.244
3	17324	715	11.296
4	9727	407	10.744
5	19906	642	11.751
6	30316	659	10.982
7	21918	624	11.781
8	16466	549	11.262
9	10088	366	10.493
10	19115	721	11.762
11	28629	652	12.959
12	20162	676	11.439
13	31087	1083	12.111
14	18714	625	11.439
15	12611	544	10.032
16	17022	742	10.438
17	17203	531	11.821
18	19123	694	11.748

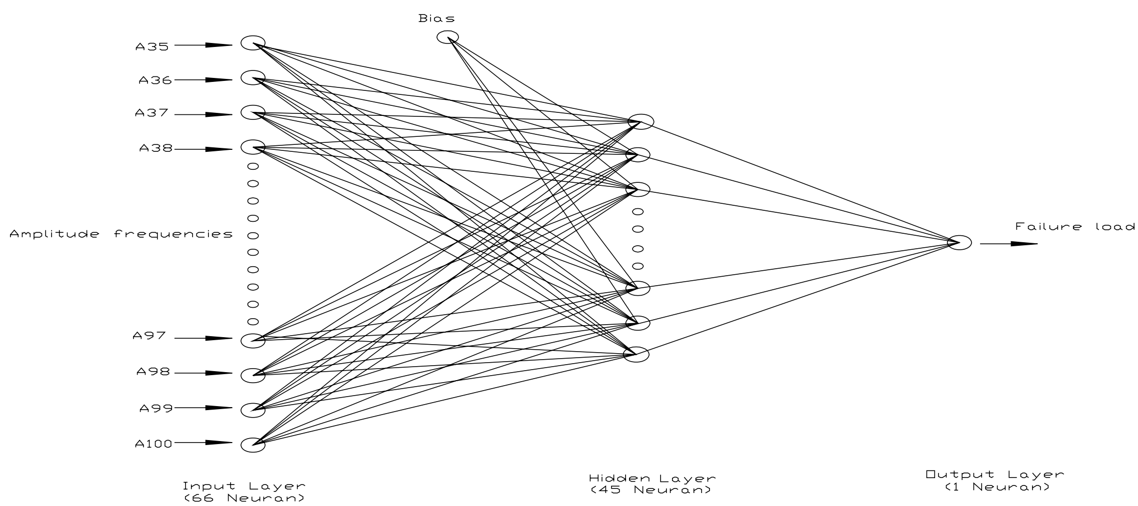


Fig. 5 Neural network for failure load prediction

and corresponding failure loads were used to train the network. AE data of the remaining eight specimens were used for testing the trained network. AE amplitude data was given as the input vector for Back propagation neural network tool in the MATLAB workspace.

The network consists of 66 neurons in the input layer (one neuron for each 1 dB wide amplitude bin from 35 dB to 100 dB), and one targeted output (failure load) neuron in the output layer as shown in Fig. 5. A summary of the neural network training and testing parameter is provided in Table 2. After considerable experimentation, the optimal learning co-efficient and momentum for this application were found to be 0.01 and 0.9 respectively. The learning rule employed was Levenberg-Marguart algorithm, and the linear transfer function was incorporated into the network. Network with single middle layer consisting of as few as 3 processing elements to as many as 50 processing elements were attempted. The best training results were obtained at 66-45-1 network architecture. The convergence threshold of 7×10^{-8} was attained at 7 epoch size, Fig. 6. The prediction results of 11th to 18th specimens are presented in Table 3, individual failure load prediction errors of all speci-

Table 2 Summery of neural network training and testing parameters

Input layer	66
Middle layer	45
Output layer	1
Bias	Yes
Learning coefficient	0.01
Momentum	0.9
Learning rule	Levenberg-Marguart algorithm
Transfer function	Hyperbolic tangent
Min-Max	Yes
Convergence threshold	7×10^{-8}
Epoch size	7
Input range	0 to 215
Output range	0 to 13
Cycles fixed	100

Table 3 Network testing results of 8 specimens

Specimen number	Actual strength (KN)	Predicted strength (KN)	% Error
11	12.959	11.268	**−13.04**
12	11.439	11.443	0.034
13	12.111	11.569	**−4.47**
14	11.439	11.328	−0.97
15	10.032	10.872	**8.37**
16	10.438	10.421	−0.16
17	11.821	11.852	0.26
18	11.748	11.712	−0.306

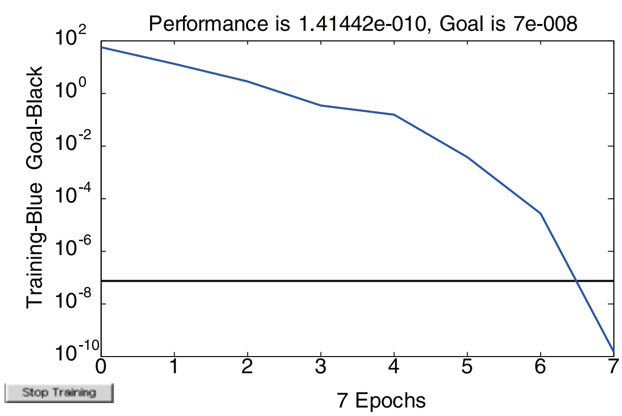


Fig. 6 Error convergence at 7 epoch size

mens except 11, 13 and 15 were within ±1 percent. Since the specimens were prepared in different curing conditions, variation of their failure load was slightly more. Above said three specimen's failure loads lies outside the range at which the network is trained for. It clearly shows the incapability of network to predict the ultimate loads that are outside the training range. Subsequent adding of specimen 11 and specimen 15 which are having two extreme failure loads in this series with training set data of the network could bring down the maximum prediction error to 1.22%. Results are summarized in Table 4.

5 Conclusion

In this project work, AE data was recorded from 18 number of ASTM D-3039 unidirectional carbon/epoxy tensile specimens cured in different temperature while loading to failure. The key parameters of Acoustic emission like amplitude, duration and energy was involved for further analysis, and it was found that amplitude frequency is the most significant parameter to predict failure load of composite hardware in advance.

This paper demonstrates that a back propagation neural network could be used to predict ultimate strength of carbon/epoxy tensile specimens using amplitude distribution data taken up to 50% of the actual failure load as the input vector and their known ultimate strength as the output vector. Only the amplitude frequency of AE data taken up to 50% of the actual failure load was used as input vector for prediction. A single 45 neuron hidden layer of neural network was able to map the descriptive features of the amplitude distribution data to the known failure strengths of the

Table 4 Network testing results of 6 specimens

Specimen number	Actual strength (KN)	Predicted strength (KN)	% Error
12	11.439	11.570	1.14
13	12.111	12.052	−0.49
14	11.439	11.299	**−1.22**
16	10.438	10.479	0.39
17	11.821	11.873	0.44
18	11.748	11.628	−1.02

samples tested. This technique permitted the ultimate tensile strength prediction with an acceptable error tolerance of 1.22 percent.

Results of this work indicate that it may be possible to proof test more sophisticated composites structures at lower loads (may be 50% of ultimate load) than are currently being tested (70% to 80% of ultimate load) and predicting their failure strength. This will minimize unintentional damage of the hardware while proof testing.

Acknowledgements The authors thank Mr. M. Enamuthu, Deputy Director, Composite Entity, VSSC, for kind permission to publish the experimental work carried out at VSSC, Vatiyoorkavu, Trivandrum. The testing support provided by Mr. Ravikiran, Material testing lab., CMSE, VSSC is cordially thanked. A special words of thanks to Mr. V.J. James, section head, for his timely help to conduct the testing.

References

1. Ativitavas, N., Pothisiri, T., Fowler, T.J.: Identification of fiber reinforced plastic failure mechanisms from acoustic emission data using neural networks. J. Compos. Mater. **40**(3), 193–226 (2006)
2. Hill, E.K., Walker, J.L., Rowell, G.H.: Burst pressure prediction in graphite/epoxy pressure vessels using neural networks and acoustic emission amplitude data. Mater. Eval. **54**(6), 744–748 (1996)
3. Fisher, M.E., Hill, E.K.: Neural network burst pressure prediction in fiber glass epoxy pressure vessels using acoustic emission. Mater. Eval. **56**, 1395–1401 (1998)
4. Gammell, P.M.: New application of acoustic emission to material testing. In: Thompson, D.O., Chimenti, D.E. (eds.) Review of Progress in Quantitative Nondestructive Evaluation, vol. 14, pp. 2051–2058. Plenum, New York (1995)
5. Miller, R.K., McIntire, P.: Acoustic Emission, 2nd edn. Nondestructive Testing Handbook, vol. 5. ASNT, Columbus (1987)
6. Chelladurai, T., Krishnamurthy, R., Acharya, A.R.: An approach for the integrity assessment of M250 maraging steel pressurized systems. J. Acoust. Emiss. **8**(1–2), 88–92 (1989)
7. Pollock, A.A.: Acoustic emission amplitude distributions. Int. Adv. Nondestr. Test. **7**, 215–239 (1981)
8. Walker, J.L., Hill, E.K.: Amplitude distribution modeling and ultimate strength prediction of ASTM D-3039 graphite/epoxy tensile specimens. In: Proceeding from the Fourth International Symposium on Acoustic Emission from Composite Materials (AECM-4), pp. 115–131. The American Society for Nondestructive Testing, Columbus (1992)
9. Walker, J.L., Hill, E.K.: Back propagation neural network for predicting ultimate strength of unidirectional graphite/epoxy tensile specimens. Adv. Perform. Mater. **3**, 75–83 (1996)
10. Hill, E.K., Isreal, P.L., Knotts, G.L.: Neural network prediction of aluminum-lithium weld strength from acoustic emission amplitude data. Mater. Eval. **51**(9), 1040–1045, 1051 (1993)
11. Hsu, N.N., Simmons, J.A., Hardy, S.C.: An approach to acoustic emission signal analysis-theory and experiments. Mater. Eval. **35**(10), 101–106 (1977)
12. Prosser, W.H., et al.: Advanced waveform based A6 detection of matrix crazing in composites. Mater. Eval. **53**(9), 1052–1058 (1995)
13. Ely, T.M., Hill, E.K.: Longitudinal splitting and fiber breakage characterization in graphite epoxy using acoustic emission data. Mater. Eval. **Feb.**, 288–294 (1995)
14. Hubele, N.F., Hwarng, H.B.: A neural network model and multiple linear regression. In: Dagli, C.H., Fernandez, B.R., Ghosh, J., Kumara, R.T.S. (eds.) Intelligent Engineering Systems through Artificial Neural Networks, vol. 4, pp. 199–203. ASME, New York (1994)
15. Fausett, L.V.: Fundamentals of Neural Networks: Architectures, Algorithms and Applications. Prentice Hall, Englewood Cliffs (1994), pp. 328–330.
16. Fatzinger Jr, E.C., Hill, E.K.: Low proof load prediction of fiber glass/epoxy resin I-beam using acoustic emission. J. Test. Eval. **33**(5), 340–347 (2005)