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Artificial neural network a tool for predicting failure strength of composite tensile coupons using acoustic emission technique

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

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Abstract A series of 18 tensile coupons were monitored with an acoustic emission (AE) system, while loading them up to failure. AE signals emitted due to different failure modes in tensile coupons were recorded. Amplitude, duration, energy, counts, etc., are the effective parameters to classify the different failure modes in composites, viz., matrix crazing, fiber cut, and delamination, with several subcategories such as matrix splitting, fiber/matrix debonding, fiber pullout, etc. Back propagation neural network was generated to predict the failure load of tensile specimens. Three different networks were developed with the amplitude distribution data of AE collected up to 30%, 40%, and 50% of the failure loads, respectively. Amplitude frequencies of 12 specimens in the training set and the corresponding failure loads were used to train the network. Only amplitude frequencies of six remaining specimens were given as input to get the output failure load from the trained network. The results of three independent networks were compared, and we found that the network trained with more data was having better prediction performance.

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

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

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

Keywords Back propagation · Acoustic emission · Amplitude · Prediction · Composites · Tensile strength

1 Introduction

Fiber reinforced plastics (FRP) have been widely used in the aviation industry due to their advantages, like 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 of whether or not the proof loading lowers the actual failure load of composite hardware. 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 begins to degrade as soon as the fibers begin to break. The only way to avoid such an unintentional structural degradation is to reduce the proof test load [2, 3].

AE technique is a fast-developing nondestructive testing tool ideally suited for the integrity evaluation of composite

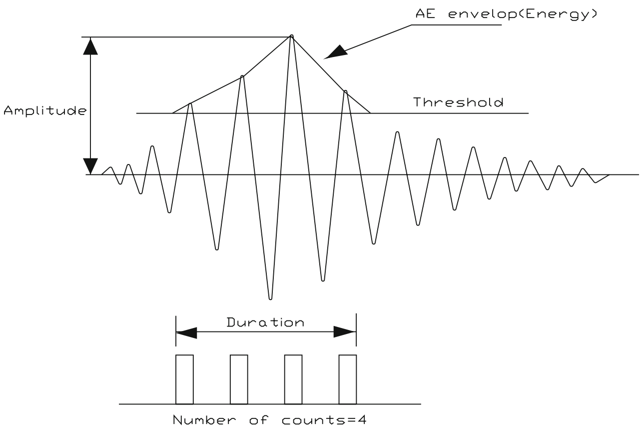


Fig. 1 Typical AE signal and characteristics

hardware during proof load testing. AE 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” [4]. 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 AE signal, Fig. 1, 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, 5]. Very long back itself amplitude distribution has been utilized for analyzing the failure mechanism in composite materials [6]. Predicting ultimate failure load of composite specimens using AE data was proved earlier by Walker and Hill [7].

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 weightage. The weightage represent information that 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 by a transfer function and passed directly to the output path of the processing element, as shown in Fig. 2. 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 get the results from the network [8]. It has been demonstrated that AE data could be used along with neural network for predicting ultimate strength of graphite epoxy tensile specimens and weld strength of aluminum–lithium specimens by researchers Walker and Hill [9, 10], respectively.

2 Apparatus and procedure

Eighteen AE data sets were generated by loading ASTM D-3039 carbon/epoxy unidirectional tensile specimens at a rate of 5 KN/min to failure. INSTRON 5582 type 100 KN capacity UTM was used to do 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 were used. AE transducers were mounted in position using adhesive tapes 30 mm apart from aluminum

Fig. 2 Artificial neuron model

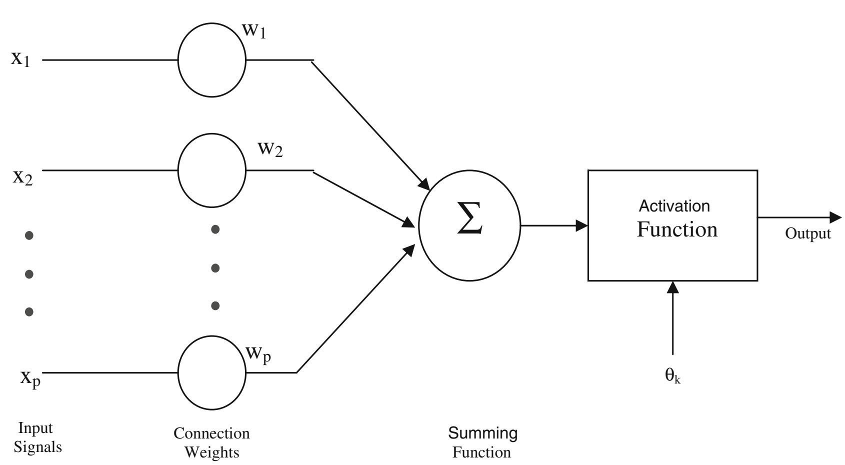
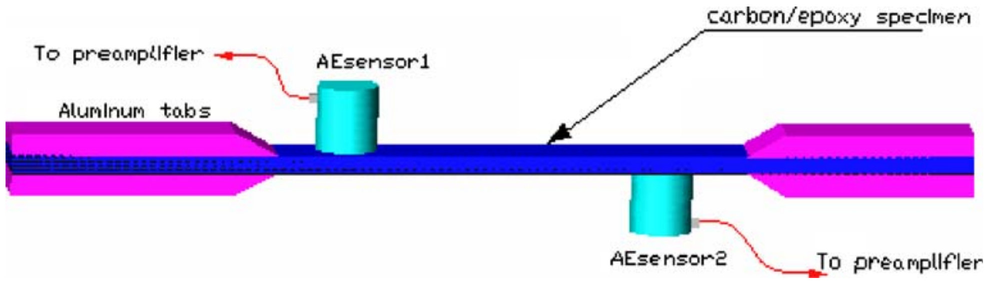


Fig. 3 Specimen with sensors



tabs. In order to acquire emissions from complete volume, the sensors were mounted on alternate sides of the specimen, as shown in Fig. 3. 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. Hsu-Nielson 0.5 mm dia, 2H pencil break was conducted before each test for ensuring proper working of AE channels. The exact material specification of each sample was same, except that they were produced in different curing conditions to widen the failure load band width. Only portions of AE amplitude frequency data collected up to 30%, 40%, and 50% of theoretical failure load of 12 specimens were supplied as input to the individual BP ANN models. Amplitude frequency data of six remaining specimens were used as the test phase for the ultimate strength prediction. Walker has taken only the matrix crazing signals (23 to 45 dB) for his weibull analysis and neural network prediction at 25% level [9]. This research has contemplated that accurate prediction could be possible with high-amplitude hits recorded during loading because a significant number of fiber breakage and matrix splitting events, which produce high-amplitude signals, are adversely affecting the failure load of the specimen.

3 Failure mechanisms analysis

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 matrix splitting can occur. Each of these failure modes has specific magnitudes for various AE characteristics, which makes AE useful in identifying these failure mechanisms. 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 mechanisms [11]. Matrix splitting occurs when matrix cracking occurs along the fibers. This mechanism can bring down the failure load as much as the fiber failure [12]. Duration of this failure is long; energy and amplitude are also lesser than fiber breakage. Another failure mode, fiber breakage, is typically the most damaging mechanism since the fibers are the main load-bearing constituents of the structure. Fiber breaks have the highest amplitudes and energy in the three primary failure mechanisms. These are all consolidated in Table 1.

Table 1 Characteristics of failure modes

AE parameter	Failure modes		
	Matrix crazing	Matrix splitting	Fiber breakage
Amplitude	Low	Medium	High
Duration	Long	Long	Short
Energy	Less	More	More

Table 2 AE hits from specimens and its failure loads

Specimen Numbers	Number of AE hits up to 30% load	Number of AE hits up to 40% load	Number of AE hits up to 50% load	Actual Failure load (kN)
1	117	386	712	10.948
2	173	307	672	11.244
3	257	361	715	11.296
4	134	246	407	10.744
5	151	295	659	11.751
6	139	294	624	10.982
7	128	313	549	11.781
8	138	260	366	11.262
9	82	142	721	10.493
10	385	478	652	11.762
11	146	261	676	12.959
12	179	352	1,083	11.439
13	171	437	625	12.111
14	231	340	625	11.439
15	184	275	544	10.032
16	180	353	742	10.438
17	133	221	531	11.821
18	203	340	694	11.748

Table 3 Test results with 30% load

Specimen No.	Actual failure loads (KN)	Predicted failure loads (KN)	% Error
12	11.439	14.265	24.7
13	12.111	11.057	−8.7
14	11.437	10.829	−5.33
16	10.438	11.999	14.95
17	11.821	13.898	17.57
18	11.748	10.021	−14.70

Although all the characteristics are useful in providing information on AE, the research herein used only amplitude (in the form of frequency in each dB from 35 to 100) for failure load prediction. Here, event frequencies at 1-dB intervals are 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 [13]. 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 [14]. Statistical methods are also capable of predicting the failure strength of specimens [15]; however, neural network prediction accuracy was found to be better.

4 Results and discussions

AE data were collected during loading until failure of each specimen. Table 2 illustrates AE hits recorded while testing of each specimen at different loading levels. Data acquired till failure are used for posttest analysis. After analysis, three parameters chosen for further studies are amplitude, duration, and energy. Multiple linear regression analysis performed by Fatzinger and Hill [16] using percentage of hits associated with each failure mechanisms has provided a failure load (I-beams) prediction error of 36%, but an optimized ANN 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, the same approach was also adopted.

Eighteen tensile coupons were grouped into two sets called training and testing sets. The training set contains 12 specimens inclusive of best and worst failure loads recorded; the six remaining specimens were in the test set. As first, AE hits recording up to 30% of load were taken for failure load prediction. Amplitude frequency at each dB interval (35 to 100 dB) was given as the input vector. A network was constructed with 66 input neurons and only one output (failure load) neuron. The network was trained with different combinations of middle-layer neurons to get the targeted output. The better error convergence was obtained at the network architecture 66-37-1. Transfer function used was hyperbolic tangent and 0.01 and 0.9 are the learning coefficient and momentum, respectively. Then, the network was given, only the amplitude frequency of testing set specimens and their failure loads were predicted by the network as given in Table 3.

We developed a new network with 40% of AE data consisting of the same number of neurons in the input layer and only one neuron in the output layer. The network was optimized with the structure 66-22-1. Transfer function, learning coefficient, and momentum were the same as those used in the previous network. The convergence threshold of 7×10^{-8} was attained at the 22nd epoch size. Prediction results of six specimens in the test set are given in Table 4.

The third network constructed with 50% of AE data was optimized at the architecture 66-45-1, as shown in Fig. 4. Network parameters like learning rate, momentum, bias, transfer function, learning rule, etc., were the same as those followed in the previous two networks. The target threshold 7×10^{-8} was met at the 28th epoch, as shown in Fig. 5. Output results of the network are given in Table 5.

Prediction results of three networks were compared with the actual failure loads, and they were plotted in Fig. 6. This comparison spelled out that the increase in accuracy of the neural network depends on the increase of data quantity. However, an increase in the load of composite hardware above a particular limit will adversely affect the structural integrity, as discussed in the introduction of this manuscript. Therefore, the failure load prediction was restricted with a maximum of 50% loading level. The maximum error tolerance of 1.22% obtained at 50% loading level was found sufficiently nearer to the actual failure load of the specimen.

5 Conclusion

This paper demonstrates the capability of a back-propagation neural network to predict the ultimate strength of carbon/

Table 4 Test results with 40% load

Specimen No.	Actual failure loads (KN)	Predicted failure loads (KN)	% Error
12	11.439	12.825	12.11
13	12.111	11.956	−1.27
14	11.437	11.024	−3.62
16	10.438	11.259	7.86
17	11.821	12.775	8.07
18	11.748	10.323	−12.04

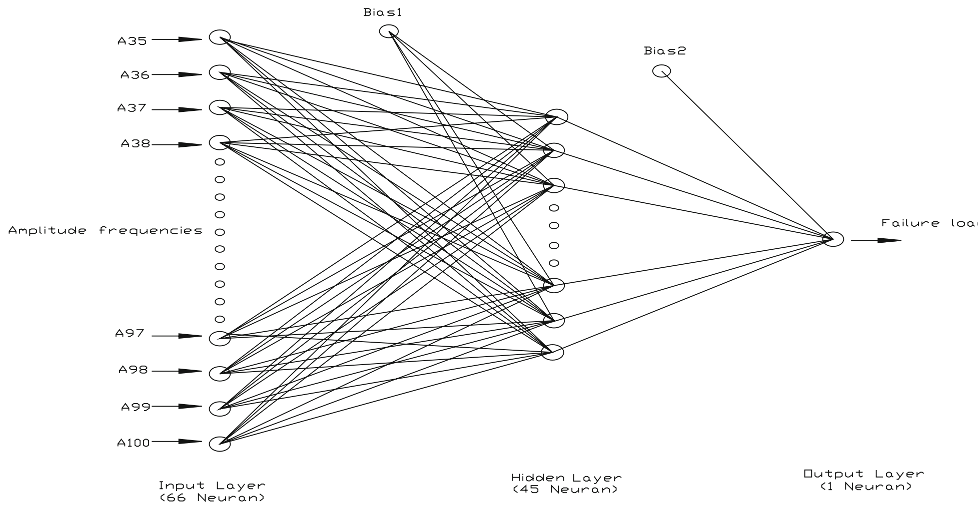


Fig. 4 Neural network for failure load prediction

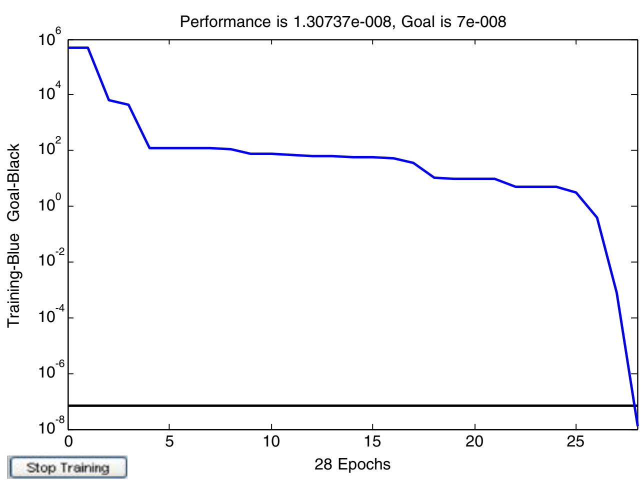


Fig. 5 Error convergence at 28th epochs

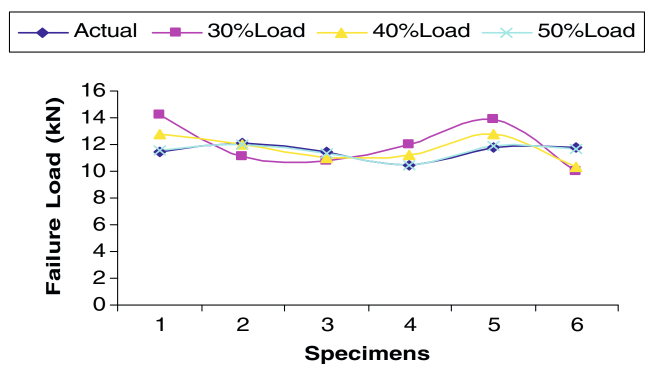


Fig. 6 Results plot with actual failure loads

Table 5 Test results with 50% load

Specimen No.	Actual failure loads (KN)	Predicted failure loads (KN)	% Error
12	11.439	11.57	1.14
13	12.111	12.052	−0.49
14	11.437	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

epoxy tensile specimens. An increase in performance of the network with a higher quantity of AE data was proved very clearly by the comparison done between the results of three independent networks developed. In order to avoid the structural integrity degradation during proof testing, the failure loads of tensile coupons were predicted with 50% and the lover level itself. So that it may be possible to proof test the composite hardware, more sophisticated methods than those that are currently being tested need to be developed (70% to 80% of failure load), and their failure loads could be predicted.

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