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Prediction of Failure Load in Glass/Epoxy Laminates from Acoustic Emission Monitoring Using Artificial Neural Network

S. S. Benadict Bensiger and C. Suresh Kumar

Department of Aeronautical Engineering, Lord Jegannath College of Engg. & Tech., Anna University Chennai, India.

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ABSTRACT

The objective of this paper is to predict the failure load of the composite laminates during tensile loading using an online Acoustic Emission (AE) monitoring and Artificial Neural Network. Bidirectional glass/epoxy laminates were subjected to tensile loading. The laminates were made for 12 layers of bi-directional glass mat in an epoxy matrix. The AE data recorded during the tensile testing was used to predict the failure load. The parameters such as amplitude, count, duration, energy, peak to count and rise-time were used for the analysis. Feed forward back propagation neural network model was generated from acoustic emission cumulative counts data taken during loading of bi-directional glass/epoxy tensile specimens. Cumulative counts recorded up to 50% and 75% of the failure load were used as the input data for simulation. The results show that the developed non-destructive method is capable of predicting the failure of composites subjected to tensile loading with an error of 3.5% and 7.6% for cumulative counts of 50% and 75% of loads respectively.

Introduction

Glass fiber reinforced polymer composites are widely used in aircraft, spacecraft, automotive and electronics industries because of their high strength, stiffness, temperature resistance and low weight. An on-line monitoring procedure, capable to predict the failure load in fibre reinforced polymer composite materials will permit to guarantee the structural safety. Acoustic emission (AE) technique is one of the versatile techniques widely used for materials research and online monitoring because of its potential for detection and location of dynamic events. AE is defined as the class of phenomenon whereby transient elastic waves are generated by rapid release of energy from localized sources in a material. The AE occurs as a series of short impulsive packets of energy. The energy thus released from the packet travels as spherical wave front and can be picked up from the surface of materials using highly sensitive transducers. The wave thus picked up by the transducer is converted into an electrical signal, which on suitable processing and analysis can reveal valuable information about the source. Artificial Neural Network (ANN) is one of the best prediction tools. A Neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by using electronic components or is simulated in software on a digital computer. To achieve good performance, neural networks employ a massive interconnection of simple computing cells referred to as “neurons”. Artificial neural networks have been trained to perform complex functions in various fields, including prediction, pattern recognition, identification, control systems, classification, speech, and vision.

A number of studies exist, which are aimed at the prediction of strength of the composite materials. V. Arumugam et al [1] predicted the residual strength of post impacted carbon/epoxy composite laminates using an online acoustic emission (AE) monitoring and artificial neural networks (ANN). The dominant AE parameters such as counts, energy, duration, rise time and amplitude are recorded during monitoring. Cumulative counts corresponding to the amplitude ranges obtained during the tensile testing are used for training the network. S. Rajendraboopathy et al [2] used cumulative counts of acoustic emission parameter to predict the ultimate failure load of the carbon/epoxy laminates. They achieved 5% error margin by giving the cumulative counts as input vectors for the three layer network. Alberto Diaz Diaz et al [3] determined a method for accurately predicting the onset of mode III delamination in multi layered structures. Software called DEILAM and a model of plates called M4-5N were used to evaluate the stresses in the laminate. Two application examples with two materials were considered and in both examples the theoretical predictions were accurate. R.R. Chang and J.M. Chu [4] estimated the failure strength of laminated composite shafts subjected to static bending load and torque. They also found out that the ultimate failure load is generally higher than the first-ply failure load of a laminated composite shaft. James L. Walker and Eric v. K. Hill [5] demonstrated the feasibility of predicting ultimate strength in simple composite structures through a neural network analysis of their acoustic emission (AE) amplitude distribution data. A back propagation neural network was trained to correlate the AE amplitude with the ultimate strengths of the samples. The network was trained using two sets of inputs, the statistical parameters obtained from a Weibull distribution fit of the amplitude distribution data and the event frequency (amplitude) distribution. A. R. Bunsell and D. Valentin [6] proposed a life prediction technique under steady loading for filament wound tubes. J. Baram and M. Rosen [7] indicated that analysis of the amplitude distribution of the acoustic signals emitted during cyclic stress may provide a non-destructive method of predicting fatigue life. Mariappan et al [8] used Nomograph to estimate the shape parameter β and scale parameter θ for Weibull analysis. The values obtained using the Nomograph was found to be

Tele:
E-mail addresses: sanbenadict@gmail.com

closer when compared to its counterparts. N.H. Yang, H. Nayeb-Hashemi and A. Vaziri [9] determined a non-destructive evaluation method for predicting the residual tensile strength of erosion damaged fiber-reinforced composites based on monitoring the acoustic emission (AE) activity of the composite specimens during uniaxial tensile loading. Weibull probability distribution was used for the prediction. In our project we undergone tensile testing in 12 layer glass/epoxy composites and recorded the AE parameters required for the prediction. Feed forward back propagation neural network model was generated from acoustic emission cumulative counts data taken during loading of bi-directional glass/epoxy tensile specimens. Cumulative counts recorded up to 50% and 75% of the failure load were used as the input data for simulation. The results showed that the developed non-destructive method is capable of predicting the failure of composites subjected to tensile loading with an error of 3.5% and 7.6% for cumulative counts of 50% and 75% of loads respectively.

Specimen Preparation

A 300 × 300 mm glass/epoxy composites laminates is fabricated by hand lay-up using 12 layers bi-direction glass mat in an epoxy matrix .The laminate was cured at a pressure of 100 kg/cm^2 at room temperature using a 300 ton capacity compression molding machine for 24hrs. ASTM D3039 standard tensile specimen of size 280 × 18 × 2.78 mm^3 were removed from the fabricated laminates using water-jet cutting to avoid machining defects and maintain a good surface finish.

Tensile Testing Procedure

The tensile tests were conducted on specimens using an Instron 3367 (Norwood, MA, United states) Universal Testing Machine at room temperature. The cross head speed was kept at 0.3 mm/min. Damage initiation & accumulation in the specimens during tensile tests is monitored by an eight channel Acoustic Emission monitoring system.

Acoustic Emission Monitoring

An 8 channel AE system supplied by Physical Acoustics Corporation (PAC) (Princeton, NJ, USA) with a sampling rate of 3 MHz and 40 dB pre-amplification is used for this study. Preamplifiers having a bandwidth of 10 kHz-2 MHz are used. The ambient noise was filtered using a threshold of 45 dB. AE measurements were pre-formed using two PAC Nano 30 resonant sensors is kept at 100mm. High vacuum silicon grease was used as couplant.

The amplitude distribution covers the range 0-100 dB (0 dB corresponds to 1 μV at the transducer output). After mounting the transducers, a pencil lead break procedure was used to generate repeatable AE signals for the calibration of each sensor. Velocity and attenuation studies are performed on the laminates. The average wave velocity in the material was found to be 3228 m/s. AE hardware settings are as follows: Peak definition time (PDT) = 30 μs, hit definition time (HDT) = 300 μ/s, hit lockout time (HLT) = 600 μs. These time intervals enables the partition of continuous stress wave into separate hits, in order to analyze them using signal descriptors, such as counts, amplitudes etc. Here, suitable values for PDT, HDT and HLT have been selected.

Artificial Neural Network

Work on artificial neural networks, commonly referred to as “neural networks”, has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations (e.g., pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today.

A neural network is massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: Knowledge is acquired by the network from its environment through learning process and the inter-neuron connection strengths, known as synaptic weights, are used to store the required knowledge.

The procedure used to learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network is an orderly fashion to attain a desired design objective. The modification ofsynaptic weights provides the traditional method for the design of neural networks. Such an approach is the closest to linear adaptive filter theory, which was already well established and successfully applied in many diverse fields. However it is also possible for the neural network to modify its own topology, which is motivated by the fact neurons in the human brain can die and that new synaptic connections can grow.

Artificial neural networks have been trained to perform complex functions in various fields, including prediction, pattern recognition, identification, control systems, classification, speech, and vision. To achieve good performance, neural networks employ a massive interconnection of simple computing cells referred to as “neurons”. A model of a neuron was shown in fig. 1. For modeling an artificial functional model from the biological neuron, three basic components must be taken in account.

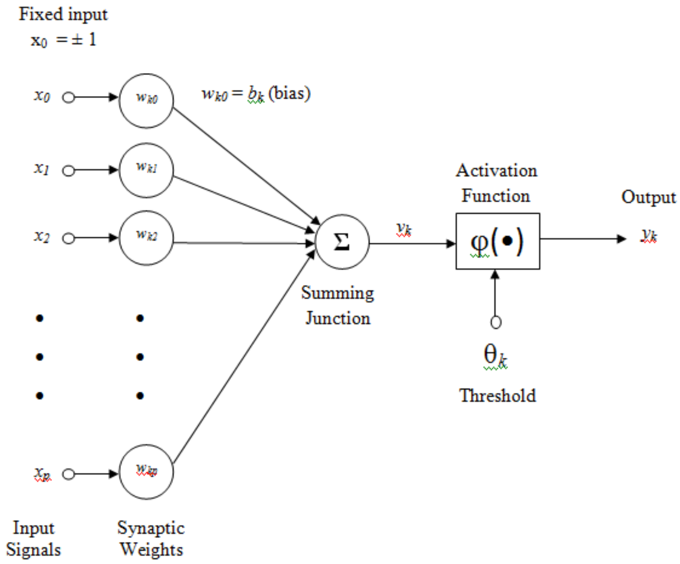

Fig 1: Model of a neuron

First off, the synapses of the biological neuron are modeled as weights. The synapse of the biological neuron is the one which interconnects the neural network and gives the strength of the connection. For an artificial neuron, the weight is a number, and represents the synapse. A negative weight reflects an inhibitory connection, while positive values designate excitatory connections. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Many such input/target pairs are needed to train a network.

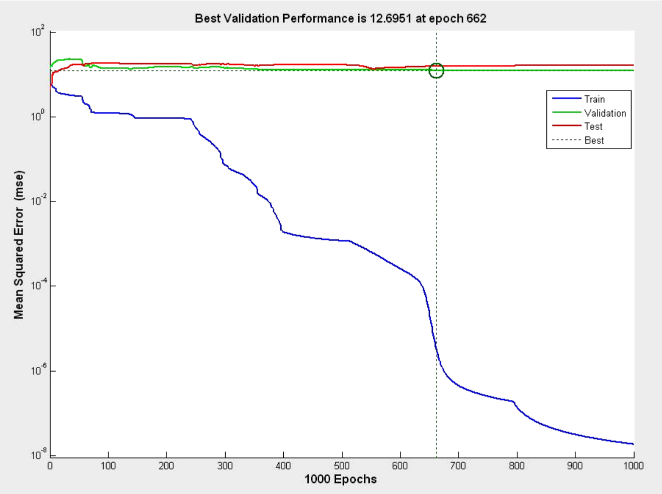

Fig 2: Performance plot

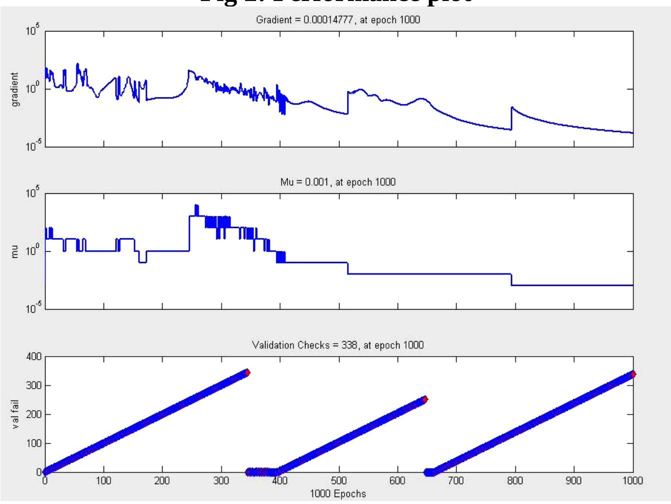

Fig 3: Training state

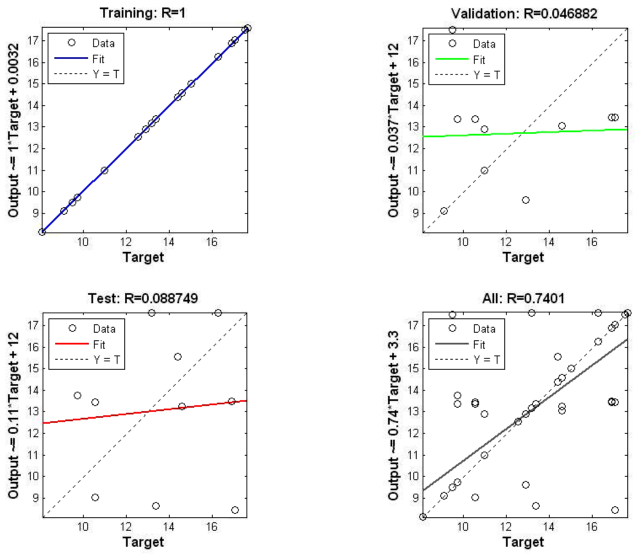

Fig 4: Regression plots

Result And Discussions

Artificial Neural Network (ANN) was used to predict the failure load. Cumulative counts of 8 specimens were used to train the network and cumulative counts recorded for 50% & 75% of the failure loads were used for simulation. Feed forward back propagation was the network type used. MATLAB neural network tool was used for the prediction with cumulative count as input and failure load as target. The back propagation algorithm is one of the best learning procedures which calculate the error by comparing the calculated outputs and target. The error is the difference between the output values and the target values. TRAINLM was the training function used. TRAINLM is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. TRAINLM is often the fastest back propagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.

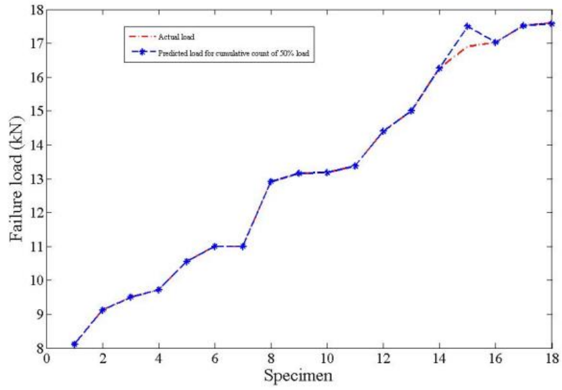

Fig. 5: Actual load and predicted load for cumulative count of 50% load

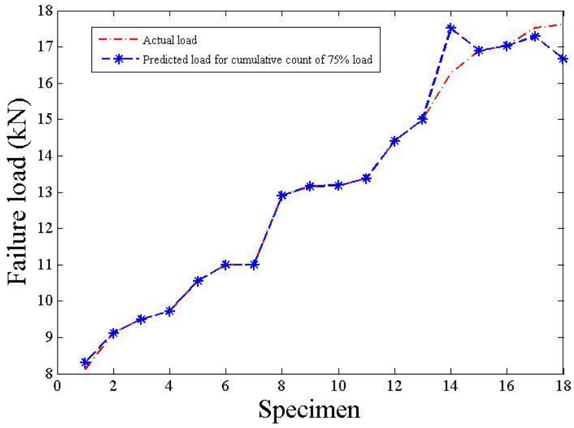

Fig. 6: Actual load and predicted load for cumulative count of 75% load

LEARNGDM was used as the adaption learning function. LEARNGDM is the gradient descent with momentum weight and bias learning function. Hyperbolic tangent sigmoid (TANSIG) transfer function was used as the transfer function. Transfer functions calculate a layer's output from its net input. Four hidden layer and one output layer was used for training the network. The network structured as 20-20-10-5 was able to give the prediction results. 1000 epochs were used as the training parameter. With this trained network failure load can be predicted for the cumulative counts of 50% load of any similar specimen. The performance plot is shown in fig. 2. The regression plot obtained during the training of neural network is shown in fig. 4. The predicted values obtained by the simulation of neural network are tabulated in the table 1. Cumulative counts recorded for 50% & 75% of the failure loads shows the maximum of 3.5% & 7.6% error respectively

Conclusion

Acoustic emission helps in the real time monitoring of the strength of composite materials. AE parameters like amplitude, duration, counts and energy are most significant parameters for prediction of failure load. Cumulative counts recorded for 50% of the failure loads shows the maximum of 3.5% error and the cumulative counts recorded for 75% of the failure loads shows the maximum of 7.6% error.

Table 1: Failure load predicted using Artificial Neural Network

Sp. No.	Actual failure load (kN)	Predicted failure load for Cumulative counts of 50% loads (kN)	% Error	Predicted failure load for Cumulative counts of 75% loads (kN)	% Error
1	8.113	8.113042724	-0.000526606	8.310284862	-2.431712827
2	9.119	9.118999957	4.69735E-07	9.119000054	-5.9516E-07
3	9.5	9.499999886	1.20464E-06	9.500000004	-4.35093E-08
4	9.72	9.720000162	-1.67043E-06	9.719999975	2.59897E-07
5	10.55	10.55000009	-8.94725E-07	10.55000011	-1.01031E-06
6	11	11.0000997	-0.00090638	10.99997386	0.00023764
7	11	11.00005931	-0.000539192	10.99986474	0.001229651
8	12.91	12.91000032	-2.5056E-06	12.90999996	3.29596E-07
9	13.16	13.15999933	5.05542E-06	13.1599998	1.53388E-06
10	13.18	13.18000021	-1.62379E-06	13.17999996	2.94612E-07
11	13.37	13.37000013	-9.52422E-07	13.37000012	-9.05675E-07
12	14.4	14.4	3.03111E-08	14.39999987	9.33366E-07
13	15	14.99999973	1.804E-06	15.00000022	-1.4619E-06
14	16.26	16.26000004	-2.47232E-07	17.50737307	-7.671421112
15	16.9	17.49799005	-3.538402685	16.89999999	3.00166E-08
16	17.03	17.03	2.70452E-08	17.02999997	1.592E-07
17	17.52	17.51999995	2.96255E-07	17.28516077	1.340406575
18	17.61	17.5788343	0.176977259	16.66579942	5.361729587

The plot between actual and predicted loads is shown in fig. 5 & 6. Feed forward back propagation neural network in MATLAB is very useful tool for predicting the failure load of the composite materials. Hence it is proved that the artificial neural network is the best tool for predicting the failure load of composite materials. It is also proven that the cumulative counts from smaller load can be used to predict the failure load.

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