Journal of Manufacturing Engineering, December, 2011, Vol. 6, Issue. 4, pp 240-244

DETERMINING THE BURST PRESSURE OF COMPOSITE PRESSURE BOTTLES USING ACOUSTIC EMISSION RESPONSE

Sasikumar T[1], Rajendra Boopathy S[2], Albert Singh S[3], Usha K M[4] and Vasudev E S[5]

[1, 2] Department of Mechanical Engineering, CEG, Anna University, Guindy, Tamilnadu-600 025, India
[3] Bharath Sanchar Nigam Limited, Nagercoil, Tamilnadu-629 001, India
[4, 5] Vikram Sarabhai Space Centre, ISRO, Trivandrum, Kerala- 695022, India

ABSTRACT

Acoustic emission (AE) Nondestructive testing was carried out during the hydrostatic loading of five identical glass fiber reinforced pressure bottles. The AE data acquired upto 50% of the theoretical burst pressure was recorded; the bottles were pressurized till failure. The Amplitude frequency distribution of AE data, maximum dilation and fiber strain at various locations were given as the inputs and the corresponding burst pressures were given as the targeted output for the supervised back propagation neural network. Architecturally 64-16-16-1, net work was able to map the patterns present in the AE signals, which lead to the burst failure of the pressure vessels. The network trained with the data generated from three bottles of the maximum, minimum and average burst pressures was able to predict the burst pressure of the remaining two bottles with a worst case prediction error of 3.49 % well within the desired goal of ±5 percent.

Key Words: *Structural Integrity, Burst Pressure, Acoustic Emission, Neural Network and Composite Pressure Vessels.*

1. Introduction

Proof testing of composite pressure vessels is complicated by the fact that most composite structures do not exhibit the same elastic plastic behavior found in metal structures. Excluding macroscopic discontinuities, as long as the structure is kept below the yield point, there is little plastic deformation, and therefore, no noticeable degradation in the structural integrity of metal structures. But this does not hold true for fiber/matrix composites. Since the fibers are the primary load bearing constituents in composites, the structural integrity begins to degrade as soon as the fiber begins to fail. In a fiber bundle, fiber breakage began to occur at less than 20 % of the ultimate load [1]. While different structures might begin to experience fiber breakage at a higher fraction of the ultimate load, the exponential upturn of the number of fiber breaks with increasing load is typical of composite structures. This means that the common proof testing pressure of 70-80 percent of expected failure pressure used on metal design can significantly damage a composite structure, thereby degrading its structural integrity [2]. To avoid significant fiber breakage and the associated structural degradation during proof testing, a procedure needs to be adopted, that uses a much lower proof loading for composites and would also accurately determine the ultimate strength of the structure. To understand how acoustic emission nondestructive testing can be used to predict burst pressures in filament wounded composite pressure vessels, some background information on Acoustic Emission (AE) must be provided. An AE signal is produced by the rapid release of strain energy, as discontinuity growth occurs in a material [3]. Energy waves are produced and travel outward from the discontinuity growth source. Piezoelectric transducers are placed on the material to convert the stress waves into electric voltage signals which are then used for analysis. Some of the characteristics used to quantify acoustic emission signals are amplitude, counts, events, duration, energy etc. A typical acoustic emission signal is a complex, damped, sinusoidal voltage Vs time plot as shown in Figure (1).

An Artificial neural network is an information processing system that has certain characteristics similar to biological neural networks. A neural network consists of large number of simple processing elements called neurons or nodes [4]. Each of these neurons is connected to other neurons by communication links, each with an associated weighting. The weightings represent information being used by the network to solve a problem. A neuron has many input paths and

*Corresponding Author - E- mail: boopathy@annauniv.edu

combines the 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. The output path of the processing elements can then be connected to the input paths of other nodes through connection weightings. Since each connection has a corresponding weighting, the signals on the input lines to a processing element are modified by these weightings prior to being summed. The processing elements are usually organized in to groups called layers. Typically a network consists of an input layer where data are presented to the network, and one output layer which holds the response of the network, and one or more hidden layers for processing. There are several types of networks, but only the feed forward back propagation network was used in this research.

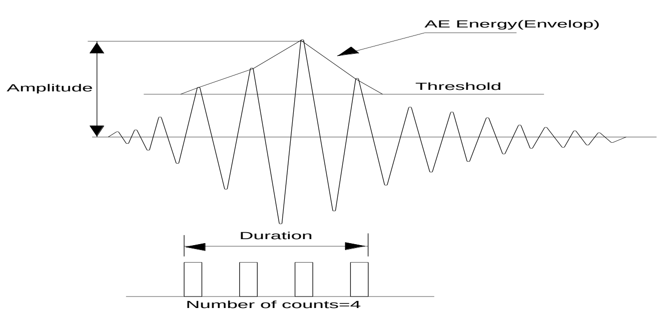

Fig. 1 Acoustic Emission Wave and Parameters

2. Experiment

Research was conducted with a series of five 475mm length and 150mm outer diameter filament wound composite pressure vessels also known as bottles. All the bottles employed E-glass fibers and an epoxy resin and were wet wound over a 4mm thick polypropylene liner which consists of two aluminum alloy end adopters at both the sides. The composite wall thickness of 5mm was contributed by 8 helical layers (54°) and 6 hoop layers (90°)over the liner as shown in Figure(2).

All the bottles were identical in their geometry and the materials they made by. A radiography (X-ray) test was conducted on all the bottles to verify the uniformity in the thickness of the composite walls, and to confirm that all are defect free in their structures. Four R15 AE sensors (150 kHz, resonant) were mounted over the bottle such that two were at both the end domes (fill end, closed end) opposite to each other, and the other two at the middle portion of the hoop winding in opposite directions. The locations of the later two sensors make a 90° angle with the earlier two, so that the entire volume of the bottle was with in the vicinity of the sensors. The Hsu-Nielson pencil break was carried out to check the functioning of the sensors. Preamplifiers were placed in the circuit near the transducer and shielded cables were used to eliminate electromagnetic interference. The Physical Acoustic Corporation (PAC)-DiSP AE work station was employed to acquire the signals during pressurizing the vessels. The Axial and diametrical dilations of the bottles were measured with three linear potentiometers (0-10mm range), of which two were mounted at both the end adapters (fill and closed) and one at the top middle of the diametrical portion of the vessels as shown in Figure (3).

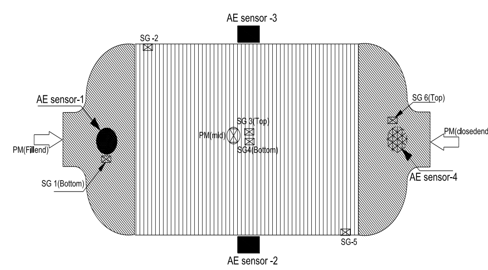

Fig. 2 GFRP Pressure Bottle Sensor Locations

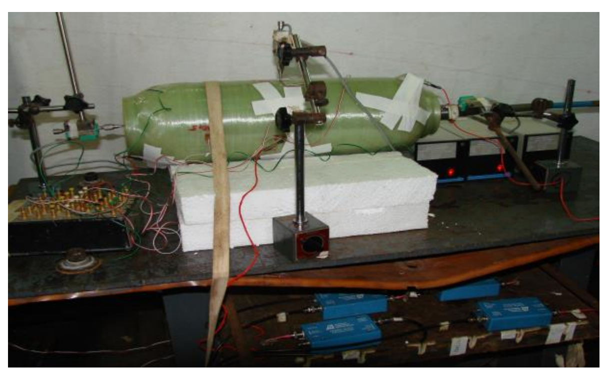

Fig. 3 Pressure Bottle Experimental Setup

In addition to this, six strain gauges (0-18000µ€) were bonded at six identical locations of the five bottles, such that two were on the (helical winding) end domes and four on the (hoop winding) cylindrical portion. All of them were connected with a 30 channel Data Acquisition System (DAQ) for online monitoring, and recording the data during testing. The hydrostatic pressure test was carried out on all the five bottles up to 50% of their theoretical burst pressure100bar (ie, designed burst pressure is 200bar) in a cyclic mode as follows.

Cycle-1: 0 - 50bar (1 minute hold) - 0
Cycle-2: 0 - 100bar (1 minute hold) – 0
Cycle-3: 0 – till burst.
The pressure was brought down to zero after the 100bar to facilitate removal of acoustic emission sensors and the potentiometers to avoid damage during burst cycle. A uniform pressure rate of 20bar/minute was maintained on all the cycles and the burst pressures were recorded from each bottle.

3. Result and Discussion

A series of five GFRP pressure bottles were pressurized till failure. Acoustic emission (AE) signals were acquired from each bottle up to 50% of their theoretical burst pressure (100bar). The maximum dilation recorded in the three potentiometers (three variables) and also the maximum strain measured from both the hoop fibers and helical fibers (six variables) were taken for further analysis. During proof pressure testing, the filament wound composite pressure vessels have three primary failure mechanisms: matrix cracking, delamination and fiber breaks. The matrix serves to protect the fibers, hold them in place, and transmit the loads to them. Since the fibers are the primary load bearing constituents of the structure, fiber breaks are the most critical failure mechanisms in determining the burst strength. Matrix cracking and delaminations can also occur during hydro proof, changing the expected burst pressure of the vessels, but to a lesser extent than fiber breaks. Acoustic emission technology has proven to be very useful in classifying these failure mechanisms, in that each of the mechanisms possesses a different acoustic emission signature. These acoustic signatures will be used to determine the effect of the various failure mechanisms towards the burst pressure. It has been demonstrated that the AE data and multivariate statistical analysis could be used to predict burst pressure in graphite epoxy pressure vessels [5]. Later it was shown that the AE data could be used along with multivariate statistical analysis in determining equations for ultimate strength prediction in ASTM D-3039 unidirectional graphite epoxy tensile specimens [6]. Subsequently, this problem was solved using the artificial neural network [7]. Dilation of the bottle during proof loading and the strain rate of the fibers are significant parameters which are not utilized so far. In this research work, together with the amplitude frequency data, the maximum dilation and maximum strain were also used to generate the neural network model to predict the burst pressure of the composite pressure vessels.

A back propagation neural network model was generated with 64 input neurons. The variables of each input neuron are given in Table (1).Targeted burst pressure is the only neuron in the output layer of the network. The network was trained with three data sets generated from the bottles for which the high, middle and low burst pressures were recorded. Their actual burst pressures were given as the targeted output of the network. The prediction performance of the network was good enough, within the range of the training bandwidth. This had been proved earlier with tensile specimens [8]; the same was adopted here also. A network with a single middle layer consisting of as few as 10 processing elements (neurons) to as many as 50 processing elements was attempted, and it was found to be difficult to get the error convergence with this limited number (only three) of training data sets. In order to overcome this drawback, the number of connection links in the network has to be increased, so that the number of iterations (cycles) would also be increased [9]. One more hidden layer was introduced and the training was carried out. The best training results were obtained with 64-16-16-1 structured network as shown in Figure (4).

Table 1 Input Variable to the Network

Neuron 1	Dilation on fill end of the bottle
Neuron 2	Dilation on closed end of the bottle
Neuron 3	Diametrical Dilation at hoop winding
Neuron 4-9	Strain gauge readings on the fibers (hoop and helical)
Neuron 10-64	Amplitude frequencies(one neuron for each one dB wide amplitude bin from 46dB to 100dB)

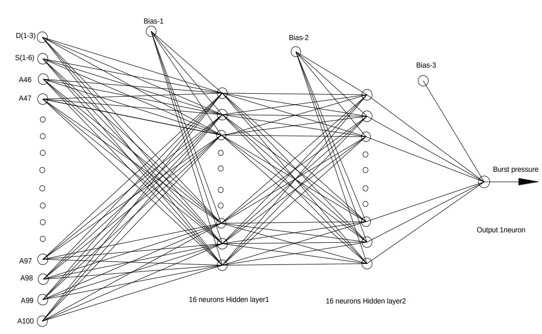

Fig. 4 Network Architecture for Prediction

The convergence threshold of 7×10^{-8} was attained at the 35th epoch as shown in Figure (5). The comparison plot between the actual and desired output of the trained network is given in Figure (6). A summary of the neural network training and testing parameters is given in Table (2).

Table 2: Summery of the Network

Input layers	1
Hidden layers	2
Output layers	1
Neurons in input layer	64
Neurons in hidden layer 1	16
Neurons in hidden layer 2	16
Neurons in 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	35
Input range	0 to 3748
Output range	0 to 299.5

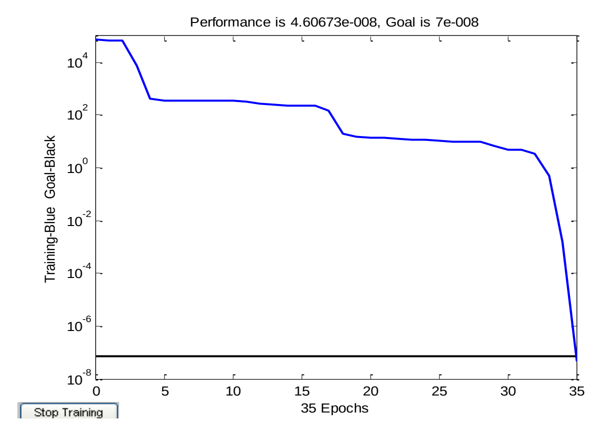

Fig. 5 Error Convergence at 35th Epoch

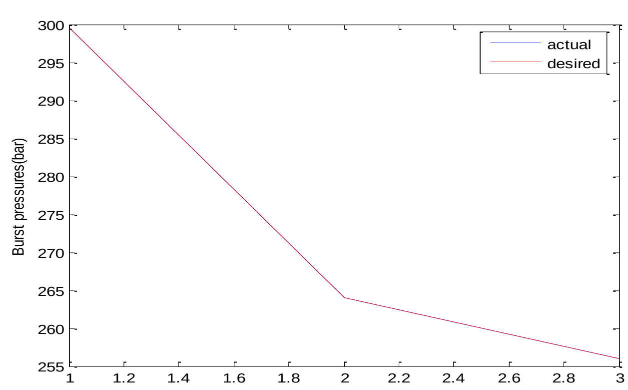

Fig. 6 Results Comparison of Training Sets

The prediction capability of an optimized network was examined by giving only the input data (Amplitude frequencies, Dilations, Strain values) of the remaining two bottles. Burst pressures, predicted by the network and the percentage errors are listed in Table (3). The worst case prediction error of 3.497% occurred in bottle-5, but was less than the ±5 % error margin. The burst pressure prediction of composite pressure bottles within the ±5% acceptable error margin was achieved with a minimum number (only three) of training data sets. The subsequent adding of more data in the training set may enable the network to reduce the error margin remarkably.

Table 3: Results of the Network

S. No	Specification	Actual burst pressure (bar)	Predicted burst pressure (bar)	Percentage error
1.	Bottle-1(training)	263.6	263.5998	0
2.	Bottle-2(training)	299.5	299.4998	0
3.	Bottle-3(training)	256.0	256.0001	0
4.	Bottle-4(test)	260.1	256.3001	-1.46
5.	Bottle-5(test)	274.0	283.5820	3.497

4. Conclusion

i. Acoustic emission signals emitted by different failure modes of composite pressure vessels like matrix crazing, fiber breaks and delaminations during hydrostatic proof testing were mapped by the two middle layer back propagation neural networks and their contribution to the overall burst pressure of the bottles were saved as the weightings.

ii. The double hidden layer network was able to predict the burst pressure of the GFRP pressure bottles within the acceptable error margin (±5%) along with the amplitude frequencies recorded only upto 50 % of its theoretical burst pressure (or) 38% of actual burst pressure; however the number of data sets used for training was the minimum (only three).

iii. The dilation of the bottles (axial, diametrical) and the strain values measured from the fibers (helical, hoop) proved to be valuable inputs for the network towards burst pressure prediction; those have been overlooked by other researchers.

It may be possible to proof test composite pressure vessels more sophisticatedly (may be 50% of theoretical burst pressure) than is being tested currently (70% to 80% of the theoretical burst pressure). Thus, the unintentional degradation of structural integrity of composite pressure vessels while proof testing could be minimized.

References

1. *Eric V K Hill, James L Walker and Ginger H Rowell (1996), "Burst Pressure Prediction in Graphite/Epoxy Pressure Vessels using Neural Networks and Acoustic Emission Amplitude Data", Material Evaluation, Vol.54, 744-748*

2. *Marcus E Fisher and Eric V K Hill (1998), "Neural Network Burst Pressure Prediction in Fiber Glass Epoxy Pressure Vessels using Acoustic Emission", Material Evaluation, Vol. 56, 1395-1401.*

3. *American society for Testing Materials (ASTM E 1316), "Standard Terminology for Non- Destructive Examinations, in Annual Book of ASTM standards, Non-Destructive Testing, ASTM, Philadelphia", Vol.3.*

4. *Sivanandam and Sumathi S (2007), "Introduction to Neural Networks Using MATLAB 6.0", The Mc Graw-Hill Publishing Company ltd., New Delhi.*

5. *Kalloo and Frederick R (1988), "Predicting Burst Pressure in Filament Wound Composite Vessels using Acoustic Emission Data", M.S Thesis, Embry-Riddle Aeronautical University.*

6. *Walker and James L (1990), "Composite Structure Ultimate Strength Prediction from Acoustic Emission Amplitude Data", M.S Thesis, Embry-Riddle Aeronautical University.*

7. *Walker, James L and Eric V K Hill (1991), "Composite Ultimate Strength Prediction from Acoustic Emission Amplitude data", Third conference on Non-destructive evaluation for Aerospace requirements, Huntsville, Alabama, June 4-6.*

8. *Sasikumar T and Rajendra Boopathy S (2008), "Artificial Neural Network Prediction of Ultimate Strength of Unidirectional T300/914 Tensile Specimens using Acoustic Emission Response", Journal of Non-destructive Evaluation, Vol.12, 127-133.*

9. *Sathish kumar (2004), "Neural Networks- A class room Approach", Tata Mc Graw-Hill publishing company Ltd., New Delhi.*

Acknowledgements

The authors would like to thank Mr.M.Enamuthu, Deputy Director, Composite Entity, ISRO who permitted us to publish this work. The continuous support provided by Mr.V.Francis, senior technician, Pressure test facility is cordially acknowledged. A special word of thanks to Mr V.J.James, Section Head, for his timely help to conduct the test.