MSFC-555

NEURAL NETWORK BURST PRESSURE PREDICTION IN COMPOSITE OVERWRAPPED PRESSURE VESSELS

ERIC v. K. HILL, SETH-ANDREW T. DION, JUSTIN O. KARL, NICHOLAS S. SPIVEY, AND JAMES L. WALKER II*

Aerospace Engineering Department, Embry-Riddle Aeronautical University
Daytona Beach, FL 32114
*Non-Destructive Evaluation Branch, NASA Marshall Space Flight Center, AL 35812

Abstract

Acoustic emission data were collected during the hydroburst testing of eleven 15 inch diameter filament wound composite overwrapped pressure vessels. A neural network burst pressure prediction was generated from the resulting AE amplitude data. The bottles shared commonality of graphite fiber, epoxy resin, and cure time. Individual bottles varied by cure mode (rotisserie versus static oven curing), types of inflicted damage, temperature of the pressurant, and pressurization scheme. Three categorical variables were selected to represent undamaged bottles, impact damaged bottles, and bottles with lacerated hoop fibers. This categorization along with the removal of the AE data from the disbonding noise between the aluminum liner and the composite overwrap allowed the prediction of burst pressures in all three sets of bottles using a single backpropagation neural network. Here the worst case error was 3.38 percent.

Keywords: acoustic emission, amplitude distribution, backpropagation, burst pressure prediction, composites, filament wound, graphite/epoxy, neural networks, nondestructive evaluation, pressure vessel.

Introduction

Acoustic Emission

Acoustic emission (AE) is a nondestructive evaluation method that involves instrumenting a specimen with piezoelectric transducers and recording parametric representations of the waveform data from flaw growth activity in order to perform a structural integrity analysis. Analysis of the AE data allows for the determination of failure mechanisms that are active in the specimen. Consequently, it also contains information concerning the structural integrity.

Burst Pressure Prediction

The prediction of burst pressures in both damaged and undamaged filament wound composite pressure vessels has been previously accomplished using linear multivariate statistical analysis and backpropagation neural networks [1-3]. The goal of this research was to utilize a backpropagation neural network to make burst pressure predictions on 15 inch (380 mm) diameter graphite/epoxy filament wound composite overwrapped pressure vessels (COPVs otherwise known as bottles) that were varied in the method of cure, type of damage, temperature, and pressurization scheme. What made this research different from its predecessors was that the disbonding of the composite overwrap from the aluminum liner generated multiple hit AE data (noise) which had nothing to do with the structural integrity of the vessels. This precluded a straightforward solution similar to those obtained previously until the noise data were eliminated.

Neural Networks

Artificial neural networks are a diverse set of robust mathematical tools used to classify data into clusters, recognize patterns, process signals, and do predictive modeling and forecasting. Here an unsupervised SOM neural network was used to classify the composite failure mechanisms that occur during pressurization. The backpropagation architecture is a feed-forward design that was subsequently employed for making supervised burst pressure predictions.

Kohonen Self Organizing Map (SOM)

In composite structures, the amplitude frequencies [of occurrence] generated during damage progression can be grouped and classified into failure mechanisms. For small data sets these mechanisms can be seen as "humps" in the AE amplitude distributions. Figure 1 shows the amplitude distribution for bottle SN002, an impact damaged graphite/epoxy COPV used for training the backpropagation network, which appears to have four humps. This number of failure mechanisms (four) was confirmed by classifying the AE amplitude data with a Kohonen self-organizing map (SOM) neural network.

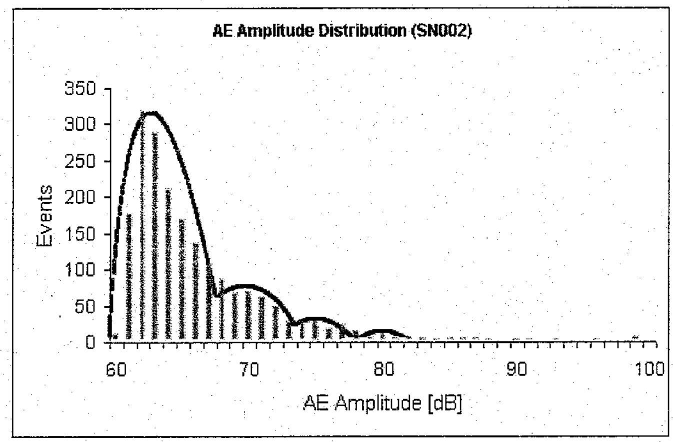

Figure 1 AE amplitude distribution for COPV SN002

Backpropagation

The backpropagation neural network is a feed-forward, supervised neural network, that is to say, it does not return a feedback signal to itself during each training pass, and it is necessary to train the network on a known solution before applying it to a new case. This is called supervised learning. A backpropagation neural network is typically constructed with an input layer, one or more hidden layers (each composed of multiple neurons) for mapping, and an output layer.

Experimental Procedure

Pressure Vessels

Eleven 15-inch diameter filament wound COPVs were wet wound on a filament winder. The bottles were thin-walled aluminum cylinders overwrapped with graphite fibers and epoxy resin. The winding sequence was 3 inner hoop plies, followed by 2 helical layers, and then 2 outer hoop plies. Eight of the bottles were rotated at slow speeds (rotisserie style) during oven curing; three were oven cured without rotation. Four of the COPVs were tested at ambient temperature, while the remaining seven experienced cryogenic temperatures. Due to the nature of piezoelectric materials, it was thought that the large variation in temperatures would have a significant effect on transducer output voltage, as well as adding to the brittle nature of the composite material.

Varying amounts of artificial damage were inflicted on the bottles in the form of impacts from both blunt and sharp tups, as well as with the cutting of hoop fibers: five tows were cut in the mid hoop ply and five in the first outer hoop ply. The strain rate was also varied non-systematically in that the pressurization scheme used on each bottle test varied in both duration and number of pressurization ramps/holds; thus, no two bottles were pressurized alike.

The amount of diversity in some of these variables and the small number of bottles would not allow for statistical analysis of the effects of each variable. Therefore, neural networks were employed as the primary method of data analysis. Table 1 summarizes the test variables along with the failure or burst pressures.

Table 1 Summary of graphite/epoxy COPV variables and burst pressures

S/N	Damage	Cure Type	Test Temperature	Burst Pressure [psig]
002	Impacted	Static	Cryogenic	1880
003	Impacted	Rotisserie	Cryogenic	2004
005	None	Rotisserie	Ambient	2960
009	None	Static	Cryogenic	2544
010	None	Static	Cryogenic	2460
013	None	Rotisserie	Ambient	2874
014	None	Rotisserie	Cryogenic	2390
018	Lacerated	Rotisserie	Ambient	2864
020	Impacted	Rotisserie	Cryogenic	1967
025	Lacerated	Rotisserie	Cryogenic	2393
026	Lacerated	Rotisserie	Ambient	2675

AE Data Collection

Acoustic emission data were successfully collected from all seven of the bottles in the test set. A multi-channel Physical Acoustics Corporation (PAC) AE analyzer was used to record the acoustic emission flaw growth data from seven AE channels, each representing a transducer at a unique location on the test bottles. This data acquisition unit also allowed for a separate parametric input, which was used to record a ±5.0 volt signal representative of the pressure in the test specimen. Figure 2 shows a schematic diagram of the test setup.

Six PAC AE transducers were mounted equidistant around the circumference of the top and bottom hoop winds on each bottle. The seventh transducer was mounted near the upper polar boss on the helically wound portion of the bottles. In the ambient temperature tests, hot melt glue was used to bond each transducer and provide acoustical coupling between the transducer and the specimen. For the cryogenic tests, high-aqueous vacuum grease and a mechanical housing were used to couple the transducers to the bottles. The data sampling threshold was set to record all acoustic emission hits that had an amplitude of 60 dB or greater.

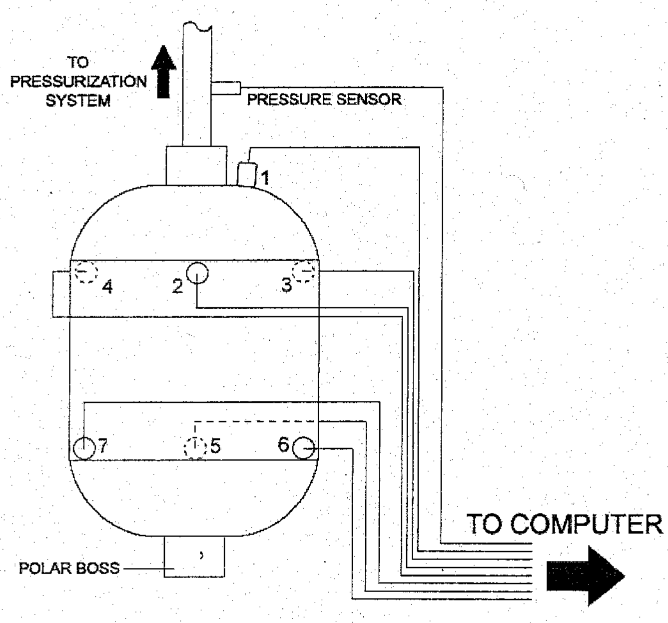

Figure 2 Sensor positioning and test setup

AE Data Filtering

Even though constraints such as amplitude threshold, peak definition time (PDT=100 μs), hit definition time (HDT=500 μs), and hit lockout time (HLT=500 μs) were applied to the acoustic emission sampling, considerable noise and multiple hit data were still present in the raw data sets. HDT is the minimum time that an acoustic emission event must have to be recorded, and the combination of HDT and HLT determines the maximum time for an event before it is considered to be a multiple hit event [4]. These settings work in real-time as data are recorded.

Multiple hit data occur when many acoustic emission waveforms reach the transducer closely spaced in time, one after another (in a condition of buffer overrun or in the cases where HDT and HLT are not properly set). This results in a long artificial waveform that is actually comprised of several smaller waveforms, which will have vastly different AE parameters than single hit data. In this case, the multiple hit data are probably the result of composite disbonding from the aluminum liner, a failure mechanism which should not affect the burst pressure.

In order to remove these multiple hits from the recorded data set, it was determined that any acoustic emission hits having durations longer than 100 ms were to be removed. Rise time, the waveform parameter that represents the time-to-peak of the waveform, was used to further remove suspected multiple hit data. Long rise times typically indicate multiple hits logged together. Thus, any hit with a rise time of greater than 25 ms was also removed from the data set. The AE energy parameter is a measure of the area under the rectified waveform envelope. In the case of these data, many hits were reported by the data acquisition system to have zero energy. These hits were also discarded under the assumption that they were noise.

The final filter applied to the data was to select those data points to be used in the actual burst pressure prediction. After removing all of the data prior to the start of pressurization (the acquisition hardware recorded AE parameter data before pressurization commenced), it was decided that the first 2000 data points would provide a sufficient sample size for the neural network to train on while still taking only those data that were acquired at or below 20 percent of the anticipated burst pressure. In general, damage is inflicted on composite bottles during any pressurization cycle; therefore, the goal was to predict on data taken at low proof pressures.

Using the final edited data set from each bottle, a frequency distribution of the amplitudes was extracted for training and testing of the backpropagation neural network. The histogram representation of an amplitude distribution for bottle S/N 002 can be seen in Figure 1, and the amplitude distributions from the edited data for all eleven bottles are summarized in Table 2. The neural network was trained to analyze the subtle differences in the distributions from each bottle and match them to the damage type and burst pressures provided in the training set.

Table 2 Finalized amplitude distribution frequencies (with **categorical variables** in **bold**)

S/N	**Amplitude Distribution Frequency Data**	**Burst Pressure [psig]**
002	**0 1 0** 2 11 177 319 289 212 171 139 109 87 69 70 63 50 29 29 30 19 24 16 7 13 68 6 3 6 5 5 3 1 4 3 1 3 1 0 3 2 0 7 0	1880
003	**0 1 0** 2 66 452 461 268 171 130 89 76 44 37 40 25 35 20 13 17 11 4 10 7 2 4 1 2 4 2 0 0 0 1 0 2 0 0 0 0 0 0 1 4 1	2004
005	**0 0 1** 1 169 148 121 115 95 123 88 81 78 62 59 74 53 53 58 61 47 46 52 58 38 48 43 34 29 31 28 21 21 21 10 7 7 4 6 7 0 3 1 0 0	2960
009	**0 0 1** 1 39 360 452 285 177 119 88 82 70 46 42 31 40 28 32 20 13 9 8 8 6 4 6 7 7 3 1 4 3 3 0 2 0 0 0 1 0 0 0 4 0	2544
010	**0 0 1** 1 47 337 400 298 194 114 112 75 58 58 55 34 44 32 29 20 19 10 8 8 5 10 8 4 1 1 2 6 2 1 1 0 1 1 0 1 1 1 1 1 0	2460
013	**0 0 1** 1 71 401 380 254 169 96 76 67 61 42 44 49 42 29 23 33 16 16 16 21 15 15 12 9 7 4 10 8 7 3 0 3 0 0 1 0 0 0 0 0 0	2874

014	**0 0 1** 1 67 477 475 309 193 98 66 54 29 47 22 25 24 13 2 10 9 10 7 4 9 4 4 1 2 3 1 3 4 0 5 3 1 1 1 0 1 0 2 1 3	2390
018	**1 0 0** 3 225 222 211 176 160 136 137 99 98 80 85 67 54 2 44 40 23 19 21 15 15 5 2 6 4 2 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0	2864
020	**0 1 0** 16 212 369 301 230 179 147 99 95 65 47 42 30 35 25 12 12 8 13 7 10 5 4 0 5 1 7 4 2 3 1 2 0 1 2 0 0 0 0 5 4	1967
025	**1 0 0** 3 30 224 309 294 216 176 132 102 99 76 63 39 48 36 26 19 18 15 12 10 13 8 6 5 0 3 0 0 1 0 2 5 0 1 1 1 1 0 0 7 2	2393
026	**1 0 0** 3 13 108 166 199 199 205 173 167 135 103 107 86 66 58 47 29 29 35 15 16 5 8 8 5 1 3 2 3 3 1 0 1 1 1 0 1 0 0 0 1 0	2675

Results

Network Architecture

The backpropagation neural network used herein [4] had the architecture shown in Figure 3. The input for each bottle consisted of a 1 x 44 dimensional vector with 3 entries representing the damage categories (001 undamaged; 010 impacted; and 100 lacerated) plus 41 integers representing the frequency distribution of amplitudes from 60 dB to 100 dB (Table 2). The actual burst pressure was also supplied as an input for error calculation at the output.

Each neuron in the hidden layer contains a hyperbolic tangent activation or transfer function that can be used to approximate the shape of the amplitude distributions. A large number of neurons can be used together to approximate compound and/or discontinuous curves that will fit the training data well, but if trained too closely, the backpropagation neural network may not predict accurately on the test data. Too few neurons in the hidden layer will result in loosely fit curves that will not correspond well to the training or test data. Using this approach, it was found that 11 neurons in the hidden layer offered the network that would best fit both the training and the test data.

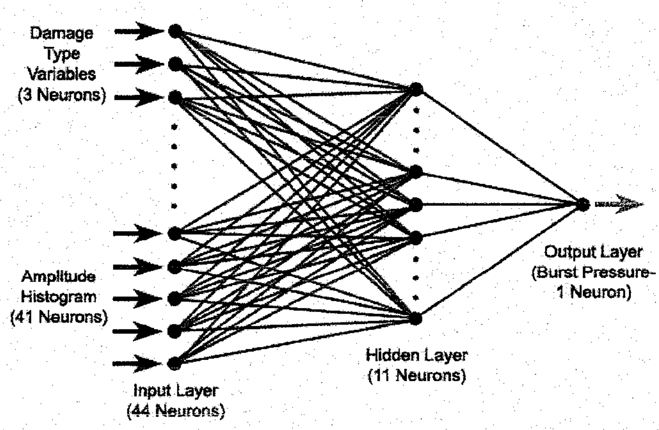

Figure 3 Network architecture

Training the Network

The backpropagation neural network, generated using Neuralware's NeuralWorks Professional II Plus software package, was trained on a total of seven COPVs, including bottles from each of the three damage categories (Table 3). The training set was chosen so that a high and low burst pressure COPV from each damage category was included. The undamaged category also included a midrange burst pressure bottle. Thus, the epoch size was seven or the total number of bottles in the training set.

After numerous experimental iterations, the optimum network architecture and input parameters were determined [4]. The learning rule was the normalized cumulative delta, and the optimal learning coefficient for the network was found to be 0.30 with a momentum of 0.40.

This relatively large learning coefficient allowed the network to train very quickly and to learn in only 71 cycles. Because the network trained so quickly, bias neurons were not employed to speed up the training process. Transition points and learning coefficient ratios were not important either because the default transition point of 5000 cycles was never reached, while the F' offset was set at 0.10.

A root mean square (RMS) error value on the seven COPVs in the training set is computed by the software after every training cycle to determine how well the network has trained. Here the RMS error convergence was set at seven percent. This means that training was considered complete when the network training curve was within an RMS error of seven percent of the training data. It was found that a higher convergence criterion left the network too loosely fit to the training data, and a lower convergence criterion forced tighter fitting of the training data but poorer fitting of the test data.

Burst Pressure Predictions

Finally, the trained network was used to predict burst pressures for both the training and test sets. Table 3 shows a summary of the prediction results on all the COPVs. The maximum prediction error in the seven bottle training set was -2.78 percent, and the maximum error in the four bottle test set was 3.38 percent. All of these values were well within the goal of predicting the burst pressures to within a ±5 percent error.

Table 3 Summary of training and test results

S/N	Damage	Purpose	Burst Pressure [psig]	Predicted Burst Pressure [psig]	Error [%]
002	Impacted	Train	1880	1827.597	-2.78
003	Impacted	Train	2004	1964.115	-1.99
005	None	Test	2760	2853.188	3.38
009	None	Train	2544	2584.266	1.58
010	None	Test	2460	2432.273	-1.12
013	None	Train	2874	2791.009	-2.88
014	None	Train	2390	2358.271	-1.32
018	Lacerated	Train	2864	2869.181	0.18
020	Impacted	Test	1967	1999.875	1.67
025	Lacerated	Train	2393	2369.740	-0.97
026	Lacerated	Test	2675	2643.174	-1.19

Conclusions

The worst case prediction error of 3.38 percent was very low, and the network trained quickly in spite of the many test variables involved. If there were any variations in the amplitude distribution data due to cure mode, temperature, and pressurization scheme, they were automatically taken into account by the backpropagation neural network. The fact that network training was accomplished in only 71 cycles attests to the effectiveness of preprocessing or editing the AE data to remove the multiple hit data and other noises.

References

1. E.v.K. Hill, J.L. Walker II, and G.H. Rowell, Materials Evaluation, **54**, 1996, pp. 744-748.
2. J.L. Walker, S.S. Russell, G.L. Workman, and E.v.K. Hill, Materials Evaluation, **55**, 1997, pp. 903-907.
3. M.E. Fisher and E.v.K. Hill, Materials Evaluation, **56**, 1998, pp. 1395-1401.
4. S.-A. T. Dion, MSAE Thesis, Embry-Riddle Aeronautical U., Daytona Beach, 2006.