1988

Predicting Burst Pressures in Filament Wound Composite Pressure Vessels Using Acoustic Emission Data

Frederick R. Kalloo

Embry-Riddle Aeronautical University - Daytona Beach

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PREDICTING BURST PRESSURES
IN FILAMENT WOUND COMPOSITE PRESSURE VESSELS
USING ACOUSTIC EMISSION DATA

BY
FREDERICK R. KALLOO

A THESIS PRESENTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE IN AERONAUTICAL ENGINEERING

EMBRY-RIDDLE AERONAUTICAL UNIVERSITY

1988
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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY
SUPERVISION BY Mr. Frederick R. Kalloo
ENTITLED "Predicting Burst Pressures in Filament Wound Composite
Pressure Vessels Using Acoustic Emission Data"
BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF Master of Science in Aeronautical Engineering

[Signatures]

Recommendation Concurred by Examining Committee:

[Signatures]
ABSTRACT

This work presents a statistical method for predicting the burst pressures in filament wound composite pressure vessels by analyzing acoustic emission data obtained during hydroproof testing. First the acoustic emission data is plotted in the form of amplitude distributions. Then, by using statistical models with characteristics similar to Rayleigh and Gaussian distributions, failure mechanism percentages are found, at which point multiple regression analysis is used to predict burst pressures. Next, the predicted burst pressures are compared to the actual burst pressures and the significance of the data is analyzed using standard statistical theories. The research shows that the predicted burst pressures are within ± 1% of the actual burst pressures. However, future experiments are required to clarify whether or not the Rayleigh and Gaussian models provide the best fit to the amplitude distributions. Finally, the problem of locating and isolating the acoustic emission sensors to remove extraneous noise must be studied.
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CHAPTER 1

INTRODUCTION

What are filament wound composite (FWC) pressure vessels? How are they made and what are they used for? To answer these questions one must first look at a class of composite materials known as fibrous composites. A fibrous composite consist of fibers, from materials such as carbon, graphite, and boron, held together by a resin. The layer of resin used to hold the fibers together is known as a matrix. The flat arrangement of a layer of fibers and resin is referred to as a lamina. Figure 1.1 is an example of a lamina with unidirectional fibers.

The manufacture of FWC pressure vessels begins with filament winding. This process consist of passing a fiber through a liquid resin and then winding it on a spindle called a mandrel. To obtain the required strength and stiffness, the fibers are wrapped in helical and hoop directions as shown in Fig. 1.2. Finally, the layers of wound fibrous composite including the mandrel are cured, after which the mandrel is removed [1]. The pressure vessel thus formed is found to be of high strength and lightweight.

The high tensile strength to density ratio of the fibrous composites used in FWC pressure vessels makes them especially useful in weight sensitive applications like aircraft and space vehicles. Fibrous composites made of the materials mentioned earlier (carbon, boron, and graphite) have tensile strength to density ratios on the order of $49 - 54 \times 10^5$ in., while structural steels have ratios on the order of $26$ to $36 \times 10^5$ in.). Hence, FWC pressure vessels have been used to replace metal pressure vessels in applications such as rocket motor cases and missile fuel tanks.

Filament wound composite (FWC) pressure vessels, however, do not
FIGURE 1.1
LAMINA WITH UNIDIRECTIONAL FIBERS

FIGURE 1.2
FILAMENT WOUND COMPOSITE PRESSURE VESSEL
exhibit the same elastic-plastic behavior as metal pressure vessels. In pressurization tests of FWC pressure vessels (referred to in industry as hydroproofing) there have been instances in which a vessel has been successfully pressurized to the maximum expected operating pressure (MEOP) on the first cycle and then failed below MEOP on the very next pressurization cycle. This failure occurs because some irreversible damage, mostly matrix cracking, typically appears during the first pressurization cycle.

The very nature of composite materials results in complex deformation and fracture modes. Generally speaking, for FWC pressure vessels, matrix cracking, delaminations, and fiber breaks have been identified as the three principal types of damage that can occur under pressurization [2-4]. The purpose of the matrix is to transmit the load to the fibers and to hold them in place, while the fibers are the main load bearing constituents. Hence, fiber breaks are the most critical of the failure modes in determining burst pressure strength. Unfortunately, normal hydroproofing can occasionally result in significant fiber breakage.

Acoustic emission (AE) techniques have been used successfully to determine the nature and extent of these failure mechanisms as they occur during pressurization [3,4]. AE data have shown that matrix cracking occurs almost from the start of pressurization and continues throughout the hydroproof cycle. This is the least damaging of the failure mechanisms. As higher pressures are reached, delaminations begin to occur in the regions where the interlaminar shear stresses are greatest. In some cases, this failure mechanism will provide stress relief so that the burst pressure strength actually increases rather than decreases. Finally, at 70-80% of burst pressure, major fiber breaks begin to occur and are sources of large amplitude burst type emissions [3].

Since each of the three principal failure mechanisms possesses a somewhat unique amplitude signature, it was postulated that the percentage of occurrences of each of these failure modes could be used to predict the burst pressures of FWC pressure vessels. The subject of this research was to prove
the feasibility of this hypothesis. Multiple regression analysis, a statistical tool used to establish the functional relationship between several variables, was used to correlate the actual burst pressures with the failure mechanism percentages of the bottles [5]. Appendix C provides further details concerning the data and model used in multiple regression analysis. The ability to accurately predict the burst pressure of FWC pressure vessels from a low pressure test, i.e., before major irreversible damage has occurred, could be used as an economic, effective method of quality control.
CHAPTER 2

ACOUSTIC EMISSION PARAMETERS

Some of the parameters used to quantify acoustic emission are events, counts, amplitude, duration, and energy. These parameters are described in Fig. 2.1(a). Here an adjustable threshold voltage is shown superimposed over an AE event. Notice that the event (stress wave signature) itself is a very complex, damped, sinusoidal voltage versus time trace. The threshold voltage is set above the noise level of the signal. An event begins when the voltage first exceeds this arbitrary threshold. It ends when the signal goes back below the threshold for a specified period of dead time (approximately 200 μs). The AE count is the number of times the signal makes a positive and negative excursion across the threshold for a given event; e.g., the event shown has six counts. The peak amplitude and duration are shown in Fig. 2.1(b) along with the energy, which is a measure of the AE event envelope.

The event shown in Fig. 2.1 is typical of a matrix crack transverse to the hoop direction in an ASTM standard (D-2585) 5.75 inch diameter test bottle (Fig. 2.2). This is a thin walled pressure vessel. Here the AE event duration is short, and the counts, amplitude, and energy are low. On the other hand a delamination may be thought of as a series of overlapping disbond events; consequently the durations are very long in comparison to transverse matrix cracks and fiber breaks. Fiber breaks can be characterized as medium to high amplitude, short duration events. These concepts are summarized in Table 2.1. Although, all of the above mentioned parameters are useful in providing information on AE, this research uses only the number of events occurring and the amplitude level of that occurrence to predict burst pressure.
Figure 2.1
AE Quantification Parameters
Figure 2.2
ASTM Standard 5.75-in, Diameter Test Bottle
<table>
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<tr>
<th>ACoustic Emission Parameters</th>
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<td>Medium</td>
<td>Medium-High</td>
</tr>
<tr>
<td>Short</td>
<td>Short-Medium</td>
</tr>
</tbody>
</table>

**Table 2.1**
Characterizing failure mechanisms using acoustic emission parameters.
CHAPTER 3
AMPLITUDE DISTRIBUTIONS

The form of AE data output used in this analysis was the number of events \( N_e \) versus amplitude \( A \) curve, or amplitude distribution plot, as shown in Fig. 3.1. From experiment it has been observed [4] that the low amplitude, high event hump labeled 1 in the amplitude distribution (Fig. 3.1(a)) is due to matrix cracking transverse to the hoop direction. The lower event, higher amplitude, humps are due to matrix cracking along the hoop direction, fiber breaks, and delaminations (Fig. 3.1(b)), respectively.

In studying the amplitude distribution plots generated by acoustic emission data, the complex subject of wave propagation in composites must be considered briefly. Some of the key aspects that directly influence the acoustic emission data are (1) geometric spreading, (2) losses due to material absorption, and (3) dispersion of the acoustic emission stress waves. All three of these factors result in a loss in signal amplitude as explained in Appendix D [2]. This means that a 96 dB stress wave from a delamination in the dome region might be sensed as a 92 dB signal by the time it propagates to the nearest AE transducer on the equator of the bottle, whereas an identical 96 dB event occurring immediately adjacent to the transducer would be properly sensed as a 96 dB event. Therefore, a statistical spread is expected in the amplitude peak. A similar phenomena would be expected for each of the other failure mechanisms as well; thus, the humps in the amplitude distribution.

From Fig. 3.1 it can be seen that the various humps in the amplitude distribution can be statistically modeled by either Rayleigh or Gaussian type
Figure 3.1
Amplitude Distributions
Figure 3.3
Gaussian Distribution
Figure 3.2
Rayleigh Distribution (Skewed Right)
curves (Fig. 3.2 and 3.3). Since each of the three principal failure mechanisms produces a unique hump in the amplitude distribution, it was postulated that the percentage of occurrences of each of the failure modes could be used to predict the actual burst pressures of FWC pressure vessels. Dividing the total number of events occurring under each hump by the total number of overall events occurring during the entire loading cycle gives the percentages of each failure mechanism.

Logically, it would seem that the accuracy of the burst pressure prediction would depend upon how well each amplitude distribution (Fig. 3.1) can be separated into its characteristic failure modes. Since both the Rayleigh and Gaussian distributions have distinct shapes (Figs. 3.2 and 3.3) the amplitude distribution can be statistically separated into the most probable failure mode bands. The final accuracy of the burst pressure prediction equation was determined by comparing the actual and predicted burst pressures from a series of eleven FWC (ASTM standard 5.75 inch) pressure vessels.
CHAPTER 4

THEORY OF RAYLEIGH AND GAUSSIAN DISTRIBUTIONS

For a Rayleigh distribution the relative frequency is given by the expression

\[ f(A) = 2b(A-A_0)e^{-b(A-A_0)^2}, \]  

(1)

where

- \( A_0 \) = initial or threshold value of amplitude \( A \)
- \( b \) = constant.

If we define \( A_p \) as the value of \( A \) at which the maximum or peak value of \( f(A) \) occurs and \( \bar{A} \) as the average or mean value of \( A \), then the constant \( b \) can be defined in terms of \( A_p \) and \( A_0 \) by setting \( f'(A) = 0 \). From Fig. (3.2) it can be seen that for this zero slope condition \( A = A_p \). Thus, differentiating Eq. (1) gives

\[ f'(A) = 2be^{-b(A-A_0)^2} + 2b(A-A_0)[-2b(A-A_0)]e^{-b(A-A_0)^2} \]

\[ = 2be^{-b(A-A_0)^2} - 4b^2(A-A_0)^2e^{-b(A-A_0)^2} \]

\[ = 2be^{-b(A-A_0)^2}[1 - 2b(A-A_0)^2] = 0. \]

Then because \( 2be^{-b(A-A_0)^2} \neq 0 \),

\[ 1 - 2b(A-A_0)^2 = 0. \]
or

$$b = 1/[2(A_p - A_0)^2] .$$  \hspace{1cm} (2)$$

The constant $b$ can be defined in terms of $\bar{A}$ and $A_0$ by using the mean value theorem:

$$\bar{A} = \frac{\int A f(A) dA}{\int f(A) dA} .$$

The lower integral can be evaluated by substituting $f(A)$ from Eq. (1) and then using the following substitutions, $t = A - A_0$ and $dt = dA$, which yields

$$\int f(A) dA = 2b \int_0^\infty te^{-bt} dt = -e^{-bt} \bigg|_0^\infty = 1 .$$

After substituting for $f(A)$ from Eq. (1), the upper integral can be evaluated using integration by parts. Applying these steps gives

$$\int A f(A)dA = A(-e^{-b(A-A_0)^2}) \bigg|_0^\infty - \int [-e^{-b(A-A_0)^2}]dA .$$

Evaluating the above expressions yields the following result:

$$A = A_0 + \sqrt{\frac{\pi}{4b}}$$  \hspace{1cm} (3)$$

and then solving for $b$ gives

$$b = \frac{\pi}{4(A-A_0)^2} .$$  \hspace{1cm} (4)$$
Next define \( A_{.99} \) as the value of \( A \) at which 99% of the area under the \( f(A) \) curve occurs. We can therefore evaluate \( A_{.99} \) as follows:

\[
0.99 = \int_{A_0}^{A_{.99}} f(A) \, dA = -e^{-b(A-A_0)^2} \bigg|_{A_0}^{A_{.99}}
\]

\[
= -e^{-b(A_{.99}-A_0)^2} \left( -1 \right).
\]

Solving for \( A_{.99} \) gives the result

\[
A_{.99} = A_0 + \left[ \frac{1}{b} \ln\left( \frac{1}{1-0.99} \right) \right]^{1/2}.
\]

(5)

We can write \( \tilde{A} \) in terms of \( A_0 \) and \( A_p \) by substituting Eq. (2) into Eq. (3):

\[
\tilde{A} = A_0 + \left( \sqrt{\frac{b}{2}} \right)(A_p-A_0).
\]

(6)

Let us now define the relative frequency \( f(A) = \frac{N}{N_T} \), where \( N \) is the number of events at a given value of \( A \) and \( N_T \) is the total number of events under the \( f(A) \) curve. The maximum value of \( f(A) \) is equal to \( N_p \) divided by \( N_T \) with \( N_p \) being the peak value, i.e., the number of events occurring at \( A_p \).

Therefore in Eq. (1) we can write the following:

\[
f(A_p) = \frac{N_p}{N_T} = 2b(A_p-A_0)e^{-b(A_p-A_0)^2}.
\]

Substituting Eq. (2) into the above results gives

\[
\frac{N_p}{N_T} = \frac{e^{-1/2}}{A_p-A_0}.
\]

then solving for \( A_p \) yields the following result:
\[ A_p = A_0 + \frac{N_T}{N_p} \cdot \frac{1}{e} . \]  

(7)

Similarly, we can find \( N_{.99} \) from Eq. (1) as follows:

\[ f(A_{.99}) = N_{.99}/N_T = 2b(A_{.99}-A_0)e^{-b(A_{.99}-A_0)^2}. \]

Solving for \( N_{.99} \) yields the desired result:

\[ N_{.99} = 2N_T b(A_{.99}-A_0)e^{-b(A_{.99}-A_0)^2}. \]  

(8)

For a Gaussian distribution the relative frequency \( f(A) \) is given by

\[ f(A) = \left( \frac{e^{-\left(\frac{A-A_0}{2\sigma}\right)^2}}{\sigma \sqrt{2\pi}} \right). \]  

(9)

where \( \mu = \bar{A} \)

\( \sigma = \) standard deviation.

The maximum value of \( f(A) \) is given by the following equation:

\[ \text{max } f(A) = N_p/N_T = \frac{e^{-\left(\bar{A}-\bar{A}\right)^2/2\sigma^2}}{\sigma \sqrt{2\pi}}. \]

This can be seen from Fig. 3.3 since \( A_p = \bar{A} = \mu \). Simplifying the above relation we find that

\[ N_p/N_T = 1/(\sigma \sqrt{2\pi}), \]

and solving for \( \sigma \) results in

\[ \sigma = N_T / (N_p \sqrt{2\pi}) . \]  

(10)

The \( Z \) function measures the relative position of \( A \) with respect to \( \bar{A} \) in units of
\( \sigma \). Hence, \( Z \) is defined by

\[
Z = (A - \bar{A})/\sigma. \tag{11}
\]

Solving for \( A \) gives,

\[
A = \bar{A} + Z\sigma
\]

and setting \( A = A_{.99} \) gives the desired result:

\[
A_{.99} = \bar{A} + Z\sigma. \tag{12}
\]

Here the value of \( Z \) can be found from statistical tables for any desired percentage of \( A \).
CHAPTER 5

ANALYSIS OF THE ACOUSTIC EMISSION DATA

The acoustic emission data for this research were obtained from hydroproof testing of eleven FWC pressure vessels. Figure 5.1 is a schematic diagram of the experimental setup. Figure 5.2 is an amplitude distribution plot generated by this system. The original eleven amplitude data plots are shown in Appendix A. The first step in the analysis of this output was to separate the amplitude distribution plots into their characteristic Rayleigh and Gaussian type distributions. The location of $A_{99}$ was approximated by visually superimposing these distributions onto the amplitude distribution plots. Then an estimate of the number of events corresponding to each hump of the curve was made by counting the squares. These estimates were then converted into failure mechanism percentages by dividing them by the total number of events occurring for that test. These results were next tabularized and entered into the MUR (multiple regression) computer program, where a burst pressure prediction equation was formulated. The estimated values of the burst pressure for each bottle were then compared to the actual values of burst pressure.

In order to improve the accuracy of the prediction equation, the original amplitude distributions from the AE equipment were replotted on precision graph paper (Fig. 5.3). Figures A.12 to A.22 in Appendix A show the replotted amplitude data plots. These plots were made ensuring that the total number of events and the characteristic shape remained the same. At some amplitude levels it was necessary to reorder the number of events at that level to keep the total number of events consistent with the original value. This enabled the position of $A_{99}$ to be accurately determined. Repeating the above procedure, failure mechanism percentages were recalculated, a new burst pressure
Figure 5.1
Schematic Diagram of Hydroproof Test
Figure 5.2
Amplitude Distribution Plot
FIGURE 5.3
REPLOTTED AMPLITUDE DISTRIBUTION PLOT
prediction equation was formulated, and the estimated values of the burst pressure for each bottle were compared to the actual values. By this means the multiple correlation coefficient was improved from 0.77289 to 0.99578 while, the accuracy of the predicted burst pressures were improved from ± 13% to within ± 1% of the actual burst pressures.

The final step in analyzing the acoustic emission data was to calculate the value of $A_{.99}$ using the mathematical formulae derived in Chapter 4. These values were then compared to the values found by using the replotted amplitude distributions. This was done to determine how well the mathematical models of the Rayleigh and Gaussian distributions matched the experimental data.
CHAPTER 6

RESULTS AND CONCLUSIONS

The results of this research are given in the MUR computer program output of Fig. 6.1. The complete computer printout is provided in Appendix B. This research has shown that acoustic emission data can be used to predict the burst pressure of FWC pressure vessels within an accuracy of ± 1% of the actual burst pressure. The failure mechanism percentages from the replotted data (MUR input data) for each bottle are shown in Table 6.1. The burst pressure prediction equation obtained by multiple regression analysis of these values was

\[ \text{PRED. DEP. VAR. 1} = 4563.297 - 1433.550 \times V_1 - 3661.750 \times V_2 + 2864.978 \times V_3. \]

In the above equation, PRED. DEP. VAR. 1 is the predicted value of the burst pressure. \( V_1 \) is the failure mechanism percentage calculated from the Rayleigh type distribution. \( V_2 \) and \( V_3 \) are the failure mechanism percentages calculated from the Gaussian type distributions. The percentage errors between the predicted and actual values of the burst pressure are shown in Table 6.2.

The success of this analysis can also be seen from the computed value of 0.99578 for the multiple correlation coefficient. This statistic implies that the acoustic emission data contains 99% of the information necessary to accurately predict the burst pressure. Another important statistic is the Durbin-Watson statistic. The value of 1.71775 computed for this statistic is close to 2.0, which indicates that autocorrelation is not a major problem with the data of Table 6.1. Autocorrelation denotes interdependence between the independent variables in a multiple regression model. Hence, the
FRACTION OF VARIABILITY ACCOUNTED FOR 99157
MULTIPLE CORRELATION COEFFICIENT 99578

-------------------------------- EQUATION --------------------------------
PRED DEP VAR \( 1 = 4563.297 - 1433.550V_1 - 3661.750V_2 + 2864.978V_3 \)

-------------------------------- EQUATION --------------------------------

PREDICTED VS ACTUAL RESULTS

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<td>3282.320</td>
<td>-32.031</td>
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<td>0.826</td>
<td>0.0544</td>
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<tr>
<td>11</td>
<td>3198</td>
<td>3217.211</td>
<td>-19.211</td>
<td>-0.6071</td>
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</table>

STANDARD ERROR OF ESTIMATE 18270E+02 AS A PERCENT OF MEAN = 59256E+00
MEAN ERROR(%) - 0.257
STD DEV (%) 50632
DURBIN-WATSON STATISTIC = 1 71775

FIGURE 61
MUR COMPUTER OUTPUT
<table>
<thead>
<tr>
<th>BOTTLE NUMBER</th>
<th>FAILURE MECHANISM PERCENTAGES</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( Y_1 )</td>
</tr>
<tr>
<td>043-17-19</td>
<td>0.880</td>
</tr>
<tr>
<td>043-105-80</td>
<td>0.803</td>
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<tr>
<td>043-18-21</td>
<td>0.918</td>
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<tr>
<td>043-11-5</td>
<td>0.871</td>
</tr>
<tr>
<td>043-113-114</td>
<td>0.923</td>
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<tr>
<td>044-33-34</td>
<td>0.676</td>
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<tr>
<td>044-44-58</td>
<td>0.745</td>
</tr>
<tr>
<td>044-101-92</td>
<td>0.731</td>
</tr>
<tr>
<td>044-25-15</td>
<td>0.840</td>
</tr>
<tr>
<td>044-37-42</td>
<td>0.745</td>
</tr>
<tr>
<td>044-2-13</td>
<td>0.843</td>
</tr>
</tbody>
</table>

**TABLE 6.1**
FAILURE MECHANISM PERCENTAGES
<table>
<thead>
<tr>
<th>BOTTLE NUMBER</th>
<th>ACTUAL BURST PRESSURE (psi)</th>
<th>PREDICTED BURST PRESSURE (psi)</th>
<th>PERCENT ERROR</th>
</tr>
</thead>
<tbody>
<tr>
<td>043-17-19</td>
<td>2909.000</td>
<td>2934.157</td>
<td>-.86481</td>
</tr>
<tr>
<td>043-105-80</td>
<td>2858.000</td>
<td>2860.487</td>
<td>-.12204</td>
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<tr>
<td>043-18-21</td>
<td>3028.000</td>
<td>3031.882</td>
<td>-.12821</td>
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<tr>
<td>043-11-5</td>
<td>2949.000</td>
<td>2927.157</td>
<td>.74068</td>
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<td>043-113-114</td>
<td>3085.000</td>
<td>3069.130</td>
<td>.51441</td>
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<tr>
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<td>3106.000</td>
<td>3083.695</td>
<td>.71813</td>
</tr>
<tr>
<td>044-101-92</td>
<td>3223.000</td>
<td>3222.195</td>
<td>.02498</td>
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<td>044-25-15</td>
<td>3282.000</td>
<td>3282.320</td>
<td>-.00976</td>
</tr>
<tr>
<td>044-37-42</td>
<td>3358.000</td>
<td>3357.817</td>
<td>.00544</td>
</tr>
<tr>
<td>044-2-13</td>
<td>3198.000</td>
<td>3217.211</td>
<td>-.60071</td>
</tr>
</tbody>
</table>

**TABLE 6.2**
COMPARISON OF ACTUAL AND PREDICTED BURST PRESSURES
Durbin-Watson statistic gives credence to the hypothesis that the acoustic emission data can be separated into specific amplitude bands corresponding to the various failure mechanisms. Appendix C gives a basic review into the fundamentals of these statistics.

The fact that amplitude distributions had to be replotted in order to obtain good results showed that there was a need for the initial computer output, specifically the amplitude distribution plot, to be more accurately represented. For accurate amplitude distribution plots the resolution of the ordinate (events axis) must be in steps of one (Fig. A.12) rather than in steps of two (Fig. A.1). This need arose from the fact that the plotter used to record the original amplitude data, would plot an odd number of events occurring by going up to the next even number. The latter resulted in distortion of the Rayleigh and Gaussian distributions. For this reason the amplitude distribution data was replotted on precision graph paper with a one to one resolution.

Using Eqs. (2) and (8) of Chapter 4, the location of \( A_{99} \) for the Rayleigh type distribution was calculated. The values of \( A_0 \) and \( A_p \) used in these equations were obtained from the replotted amplitude data. In Table 6.3 the location of \( A_{99} \) obtained from these equations (\( A_{R,99} \)) is compared to that obtained by replotting the amplitude data (\( A_{e,99} \)). Examination of Table 6.3 shows that, in six of the eleven cases, \( A_{e,99} \) is within \( \pm 1 \) decibel of \( A_{R,99} \). The other five cases differed by a minimum of 5 to a maximum of 12 decibels. These differences may be due to rubbing noises in the polar boss region; however, this is not certain.

Future research will clarify whether or not the Rayleigh and Gaussian models are accurate descriptors of the amplitude distributions. It may be necessary to increase the sophistication of the mathematical models in order to better fit the experimental data. Experimental details such as isolation of rubbing noises and location of the acoustic emission sensors may also need to be considered. This will allow researchers to be confident that only acoustic emissions from the actual delaminations, fiber breaks, and matrix cracks are
<table>
<thead>
<tr>
<th>BOTTLE NUMBER</th>
<th>$A_p$</th>
<th>$A_0$</th>
<th>$b$</th>
<th>$A_{R,99}$</th>
<th>$A_{e,99}$</th>
<th>DIFFERENCE $A_{R,99} - A_{e,99}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>043-17-19</td>
<td>62</td>
<td>51</td>
<td>0.004</td>
<td>84</td>
<td>72</td>
<td>12</td>
</tr>
<tr>
<td>043-105-80</td>
<td>57</td>
<td>51</td>
<td>0.014</td>
<td>69</td>
<td>70</td>
<td>-1</td>
</tr>
<tr>
<td>043-18-21</td>
<td>58</td>
<td>51</td>
<td>0.010</td>
<td>72</td>
<td>71</td>
<td>1</td>
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<tr>
<td>043-11-5</td>
<td>59</td>
<td>52</td>
<td>0.010</td>
<td>73</td>
<td>72</td>
<td>1</td>
</tr>
<tr>
<td>043-113-114</td>
<td>57</td>
<td>52</td>
<td>0.020</td>
<td>67</td>
<td>75</td>
<td>-8</td>
</tr>
<tr>
<td>044-33-34</td>
<td>57</td>
<td>52</td>
<td>0.020</td>
<td>67</td>
<td>66</td>
<td>1</td>
</tr>
<tr>
<td>044-44-58</td>
<td>60</td>
<td>52</td>
<td>0.008</td>
<td>76</td>
<td>71</td>
<td>5</td>
</tr>
<tr>
<td>044-101-92</td>
<td>58</td>
<td>51</td>
<td>0.010</td>
<td>73</td>
<td>73</td>
<td>0</td>
</tr>
<tr>
<td>044-25-15</td>
<td>57</td>
<td>51</td>
<td>0.014</td>
<td>69</td>
<td>77</td>
<td>-8</td>
</tr>
<tr>
<td>044-37-42</td>
<td>56</td>
<td>52</td>
<td>0.031</td>
<td>64</td>
<td>72</td>
<td>-8</td>
</tr>
<tr>
<td>044-2-13</td>
<td>58</td>
<td>52</td>
<td>0.014</td>
<td>70</td>
<td>71</td>
<td>-1</td>
</tr>
</tbody>
</table>

**TABLE 6.3**
**COMPARISON OF $A_{e\,99}$ AND $A_{R\,99}$**
being recorded. Future research should also include detailed sensitivity and error analyses. The ultimate desire of researchers would be an accurate, completely automated procedure for burst pressure prediction.
APPENDIX A

AMPLITUDE DATA
Ch, A-Dump is OFF

ON-CUMULATIVE INTERVAL SUM VENTS FIRST ARRIVAL VENTS = 636

GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL

FIGURE A.1

Ch, A-Dump is OFF

ON-CUMULATIVE INTERVAL SUM VENTS FIRST ARRIVAL VENTS = 774

GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL

FIGURE A.2
4 Ch, A-Dump is OFF

NON-CUMULATIVE

INTERVAL SUM

EVENTS

FIRST ARRIVAL

EVENTS = 797

GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL

FIGURE A.3

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL

FIGURE A.4
Ch, A-Dump is OFF
ON-CUMULATIVE
INTERVAL SUM
VENTS
FIRST ARRIVAL
VENTS = 735
GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL

FIGURE A.5

Ch, A-Dump is OFF
ON-CUMULATIVE
INTERVAL SUM
VENTS
FIRST ARRIVAL
VENTS = 833
GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL

FIGURE A.6
Ch, A-Dump is OFF

ON-CUMULATIVE
INTERVAL SUM
VENTS
FIRST ARRIVAL
VENTS = 707
GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL
FIGURE A.7

Ch, A-Dump is OFF

ON-CUMULATIVE
INTERVAL SUM
VENTS
FIRST ARRIVAL
VENTS = 565
GRAPH 1 OF 1

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL
FIGURE A.8
Ch, A-Dump is OFF

NON-CUMULATIVE
INTERVAL SUM
EVENTS
FIRST ARRIVAL
EVENTS = 905
GRAPH 1 OF 1

044-25-15 5.75 BOTTLE

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL
FIGURE A.9

Ch, A-Dump is OFF

NON-CUMULATIVE
INTERVAL SUM
EVENTS
FIRST ARRIVAL
EVENTS = 556
GRAPH 1 OF 1

044-37-42 5.75 BOTTLE

NON-CUMULATIVE AMPLITUDE FIRST ARRIVAL
FIGURE A.10

36
Ch, A-Dump is OFF

NON-CUMULATIVE

INTERVAL SUM

EVENTS

FIRST ARRIVAL

EVENTS = 809

GRAPH 1 OF 1

NON-CUMULATIVE+ AMPLITUDE FIRST ARRIVAL

FIGURE A.11
BOTTLE # 043-113-114

FIGURE A.16

42
FIGURE A.17
BOTTLE # 044-25-15

FIGURE A.20
APPENDIX B

COMPLETE MUR OUTPUT
File MUR.DAT
0.880  0.109  0.011  2909.000
0.803  0.171  0.026  2858.000
0.918  0.069  0.013  3028.000
0.871  0.116  0.013  2949.000
0.923  0.060  0.017  3085.000
0.676  0.244  0.080  2921.000
0.745  0.175  0.080  3106.000
0.731  0.163  0.106  3223.000
0.840  0.082  0.078  3282.000
0.745  0.133  0.122  3358.000
0.843  0.090  0.067  3198.000

PROBLEM NO. 1

NO. OF VARIABLES  4  NO. OF DEPENDENT VARIABLES  1
NO. OF OBSERVATION  11
F LEVEL TO ENTER VARIABLE  1.10  F LEVEL TO REMOVE VARIABLES  1.000

VARIABLE  MEAN      STD. DEV.
  1  815909100  082070030
  2  128363600  055617030
  3  055727280  040934320
  4  308327300000  16648130000

SIMPLE CORRELATION COEFFICIENTS. (ROW BY COL.)

1.0000 R( 1, 1)  -.8931 R( 1, 2)  -.7915 R( 1, 3)  -.1717 R( 1, 4)
1.0000 R( 2, 2)  .4319 R( 2, 3)  -.2879 R( 2, 4)
1.0000 R( 3, 3)  .7354 R( 3, 4)
1.0000 R( 4, 4)

TRIAL NUMBER  1
PURE CONST. B(0)  =  .308327E+04
COEFFICIENTS
  .00000E+00 B(1)  .00000E+00 B(2)  .00000E+00 B(3)

STANDARD ERROR OF COEFFICIENTS
  .00000E+00  .00000E+00  .87588E+03

STANDARD ERROR OF ESTIMATE  .16648E+03 AS A PERCENT OF MEAN  =  .53995E+0

TRIAL NUMBER  2
VARIABLE GOING IN  =  3  F LEVEL  =  10.6006
PURE CONST. B(0)  =  .291660E+04
COEFFICIENTS
  .00000E+00 B(1)  .00000E+00 B(2)  .29909E+04 B(3)

STANDARD ERROR OF COEFFICIENTS
  .00000E+00  .00000E+00  .87588E+03

STANDARD ERROR OF ESTIMATE  .11891E+03 AS A PERCENT OF MEAN  =  .38567E+0
TRIAL NUMBER 3  
VARIABLE GOING IN = 2   F LEVEL = 427.7234

PURE CONST. B(0) = 312975E+04

COEFFICIENTS
.00000E+00 B(1) -.22282E+04 B(2) .42985E+04 B(3)

STANDARD ERROR OF COEFFICIENTS
.00000E+00 .10272E+03 .13957E+03

STANDARD ERROR OF ESTIMATE .17090E+02 AS A PERCENT OF MEAN = .55249E+00

TRIAL NUMBER 4  
VARIABLE GOING IN = 1   F LEVEL = .0000

PURE CONST. B(0) = 456330E+04

COEFFICIENTS
-.14336E+04 B(1) -.36617E+04 B(2) .28650E+04 B(3)

STANDARD ERROR OF COEFFICIENTS
.26136E+06 .26136E+06 .26136E+06

STANDARD ERROR OF ESTIMATE .12270E+02 AS A PERCENT OF MEAN = .59256E+00

FRACTION OF VARIABILITY ACCOUNTED FOR .99157
MULTIPLE CORRELATION COEFFICIENT .99578

EQUATION
PRED.DEP.VAR.1 = 4563.297 - 1433.550*V1 - 3661.750*V2 + 2864.978*V3

PREDICTED VS. ACTUAL RESULTS

<table>
<thead>
<tr>
<th>OBSERVATION</th>
<th>ACTUAL</th>
<th>PREDICTED</th>
<th>DEVIATION</th>
<th>PERCENT ERROR</th>
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<td>.71813</td>
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<td>-.00976</td>
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<td>3358.00000</td>
<td>3357.81700</td>
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<td>.00544</td>
</tr>
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<td>-19.21069</td>
<td>-.60071</td>
</tr>
</tbody>
</table>

STANDARD ERROR OF ESTIMATE .18270E+02 AS A PERCENT OF MEAN = .59256E+00

MEAN ERROR(%) -.00257
STD. DEV. (%) .50632

DURBIN-WATSON STATISTIC = 1.71775
MULTIPLE REGRESSION ANALYSIS

The following is a short review of important statistical concepts used in this research. The next four sections are extracted verbatim from Chatterjee and Price's book *Regression Analysis by Example* [1].

DESCRIPTION OF THE DATA AND MODEL

The data consists of \( n \) observations on a dependent or response variable \( y \) and \( p \) independent (explanatory) variables \( x_1, x_2, \ldots, x_p \). The observations are usually represented as follows:

<table>
<thead>
<tr>
<th>Observation number</th>
<th>( y )</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>\ldots</th>
<th>( x_p )</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>( y_1 )</td>
<td>( x_{11} )</td>
<td>( x_{21} )</td>
<td>( x_{31} )</td>
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<td>( x_{p1} )</td>
</tr>
<tr>
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<td>( y_2 )</td>
<td>( x_{12} )</td>
<td>( x_{22} )</td>
<td>( x_{32} )</td>
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<td>( x_{p2} )</td>
</tr>
<tr>
<td>3</td>
<td>( y_3 )</td>
<td>( x_{13} )</td>
<td>( x_{23} )</td>
<td>( x_{33} )</td>
<td></td>
<td>( x_{p3} )</td>
</tr>
<tr>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td></td>
<td>( \vdots )</td>
</tr>
<tr>
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<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td>( \vdots )</td>
<td></td>
<td>( \vdots )</td>
</tr>
<tr>
<td>( n )</td>
<td>( y_n )</td>
<td>( x_{1n} )</td>
<td>( x_{2n} )</td>
<td>( x_{3n} )</td>
<td></td>
<td>( x_{pn} )</td>
</tr>
</tbody>
</table>

The relationship between \( y \) and \( x_1, x_2, \ldots, x_p \) is formulated as a linear model

\[
y = B_0 + B_1 x_{11} + B_2 x_{21} + \ldots + B_p x_{p1} + u_i,
\]

where \( B_0, B_1, B_2, \ldots, B_p \) are constants referred to as the model partial regression coefficients (or simply as the regression coefficients) and \( u_i \) is a
random disturbance. It is assumed that for any set of fixed values of $x_1, x_2, \ldots, x_p$ that fall within the range of the data, the linear Equation (3.1) provides an acceptable approximation to the true relationship between $y$ and the $x$'s. In other words, $y$ is approximately a linear function of the $x$'s, and $u_i$ measures the discrepancy in that approximation for the $i$th observation. In particular the $u$'s contain no systematic information for determining $y$ that is not already captured in the $x$'s. It is assumed that $u$'s are random quantities, independently distributed with zero means and constant variance $\sigma^2$.

The regression coefficient $B_j$ may be interpreted as the increment in $y$ corresponding to a unit increase in $x_j$ when all other variables are held constant. Clearly this interpretation holds independently of the actual values of the $x$'s.

The $B$'s are estimated by minimizing the sum of squared residuals which is known as the method of least squares.

**MULTIPLE CORRELATION COEFFICIENT**

After fitting the linear model to a given body of data, an assessment is made of the adequacy of fit. The most widely used measure is the multiple correlation coefficient $R$, or more frequently the square of the multiple correlation coefficient $R^2$. There are several equivalent ways in which $R^2$ can be defined and interpreted. We define $R^2$ as

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

and interpret it as the proportion of total variability which is explained by the regression equation. $R^2$ has a range between 0 and 1. When the model fits the
data well, it is clear that the value of $R^2$ is close to unity. With a good fit, the observed and predicted values will be close to each other, and $\sum(y_i - \hat{y}_i)^2$ will be small. Then $R^2$ will be near to unity. On the other hand, if there is no relationship between the independent variable and the dependent variables and the linear model gives a poor fit, the best predicted value for an observation $y_i$ would be $\bar{y}$; that is, in the absence of any relationship, the best estimate is the sample mean for in that case the sample mean minimizes the sum of squared deviations. So in the absence of any linear relationship, $R^2$ will be near zero. The value of $R^2$ is therefore used as a summary measure to judge the fit of the linear model to a given body of data.

AUTOCORRELATION

One of the standard assumptions in the regression model is that the error terms $u_i$ and $u_j$, associated with the $i$th and $j$th observations, are uncorrelated. Correlation in the error terms suggests that there is additional explanatory information in the data that has not been exploited in the current model. When the observations have a natural sequential order, the correlation is referred to as autocorrelation.

Autocorrelation may occur for several reasons. Adjacent residuals tend to be similar in both temporal and spatial dimensions. Successive residuals in economic time series tend to be positively correlated. Large positive errors are followed by other positive errors, and large negative errors are followed by other negative errors. Observations sampled from adjacent experimental plots or areas tend to have residuals that are correlated since they are affected by similar external conditions.

The symptoms of autocorrelation may also appear as the result of a variable having been omitted from the right-hand side of the regression equation. If successive values of the omitted variable are correlated, the errors
from the estimated model will appear to be correlated. When the variable is added to the equation, the apparent problem of autocorrelation can be completely eliminated.

The presence of autocorrelation has several effects on the analysis. These are summarized as follows:

1. Least square estimates are unbiased but are not efficient in the sense that they no longer have minimum variance.

2. The estimate of \( \sigma^2 \) and the standard errors of the regression coefficients may be seriously understated; that is, from the data the estimated standard errors would be much smaller than they actually are, giving a spurious impression of accuracy.

3. The confidence intervals and the various tests of significance commonly employed would no longer be strictly valid.

The presence of autocorrelation can be a problem of serious concern for the preceding reasons and should not be ignored.

**DURBIN–WATSON STATISTIC**

The Durbin–Watson statistic \( d \) is the basis of a very popular test of autocorrelation in regression analysis. The closer the sample value of \( d \) to 2, the firmer the evidence that there is no autocorrelation present in the error. Evidence of autocorrelation is indicated by the deviation of \( d \) from the numerical value of 2. When the residual plots and Durbin–Watson statistic indicate the presence of correlated errors the estimated regression equation should be refitted taking the autocorrelation into account.
APPENDIX D

WAVE PROPAGATION THROUGH FILAMENT WOUND COMPOSITES
WAVE PROPAGATION THROUGH FILAMENT WOUND COMPOSITES

The following excerpts are taken from Hamstad's report "Quality Control and Nondestructive Evaluation Techniques for Composites - Part VI: Acoustic Emission - A State-of-the-Art Review".

Geometric Spreading

Geometric spreading is the loss in signal amplitude due to the fact that, as the wave travels away from the point AE source in a two or three dimensional medium, the total area of material through which the wave front is passing increases.

Losses Due To Material Absorption

Losses due to material absorption of the stress-wave energy result in attenuation of the amplitude of the wave as it propagates. This attenuation is more severe for stress waves at higher frequencies and in viscoelastic materials such as epoxy. Analytically, this loss of energy by heat can be expressed by an exponential dependence on distance of propagation (the exponent depends on frequency).

Dispersion

Dispersion of AE stress waves in composites refers to propagation of different frequency components at different speeds. The net result of dispersion is a spreading in the time domain of the stress wave as a function of distance travelled. This results in a decrease in peak signal amplitude but not energy in the AE burst.
BIBLIOGRAPHY


