ULTRASONIC NDE OF ADHESIVE METAL TO METAL BOND INTEGRITY BASED ON A COMBINED NUMERICAL AND EXPERT SYSTEM APPROACH

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INTRODUCTION

Bonded structures have become increasingly prevalent in the safe and reliable operation of many advanced material components. Concomitant with the wide-spread use of adhesively bonded materials comes the need of nondestructive inspection of the bond line. Since conventional NDE methods offer only partial success in detecting the various possible bondline conditions [1], additional research in the actual energy/bondline interaction is required.

Within the context of ultrasonic pulse-echo measurements a combined numerical and experimental approach is adopted [2] to examine bond specific parameters inherent in transient signals obtained from the material under test. Our strategy is targeted at numerically replicating the underlying physical inspection process by predicting the transducer signal responses of a simulated bonded specimen in the time domain. The interaction of the transducer generated elastic waves with different simulated bonding configurations such as disbonds, weak bonds, and porosity situations can thus be examined within the theoretical limits of model linearity, two-dimensionality of specimen, etc. The resulting synthetic data is subsequently utilized to train a neural network model to extract bondline specific features. The correlation between the experimental and numerical signals permits isolation of individual bondline characteristics which ultimately yield more precise information regarding the assessment of bond strength.

This paper introduces a multilayered specimen as a first step towards developing theoretical bondline models. These models serve as a basis for applying numerical analysis techniques to obtain time-amplitude (A-scan) signals. Preliminary research has shown that such simple models compare well with experimental measurements [3]. By incremental variation of specific model parameters such as bondline thickness and material density, a complete database can be created. After appropriate truncation and scaling, the signals are fed as training data into a 3 layer neural network based on the delta learning rule. The PC-based neural network is then capable of identifying these model variations both in synthetic and experimental data.

Review of Progress in Quantitative Nondestructive Evaluation, Vol. 12
Edited by D.O. Thompson and D.E. Chimenti, Plenum Press, New York, 1993

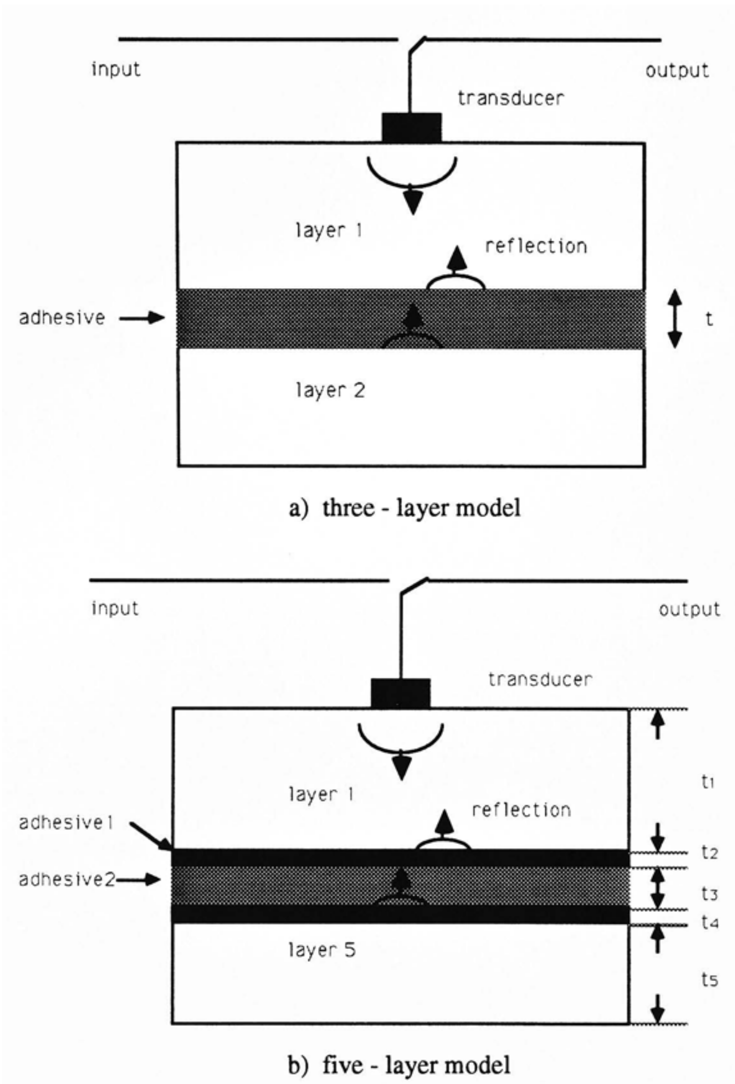

Fig. 1.Two theoretical bondline geometries as a basis for the numerical modeling approach.

THEORETICAL MODELING BASIS

As a starting point in the analysis, generic three- and five layer models are created as shown in Fig. 1. A key feature in these theoretical models is a variable thickness which in the three layer model has been adjusted from 100 to 200 microns in increments of 1 micron. Unlike the three-layer medium, the five layer medium utilizes two transition layers of different material densities.

The numerical procedure employed to obtain the appropriate A-scan signals for a simulated transducer with 1/4 inch aperture and 5 MHz centerfrequency is discussed in a companion paper [4]. A typical numerical A-scan prediction for the five-layer model is shown in Fig. 2. As can be seen, the original transient transducer signal (in the range 0 - 0.5 μsec) interacts with the bondlayer and produces a complex response after a time delay of approximately 1.5 μsec.

In order to isolate and quantify the bond thickness in a variable three layer model, the numerical program was executed 100 times to obtain A-scan predictions ranging from 100 to 200 microns. The signal variations for 4 different thicknesses (100, 150 , 152, and 200 microns) are shown in Figure 3.

Since only the bondline interaction process is of interest, the A-scans shown in Figure 3 are truncated to 64 time sampling points based on a sampling period of 10 nsec and a time history the range between 2.6 and 3.24 μsec as depicted in Figure 4.

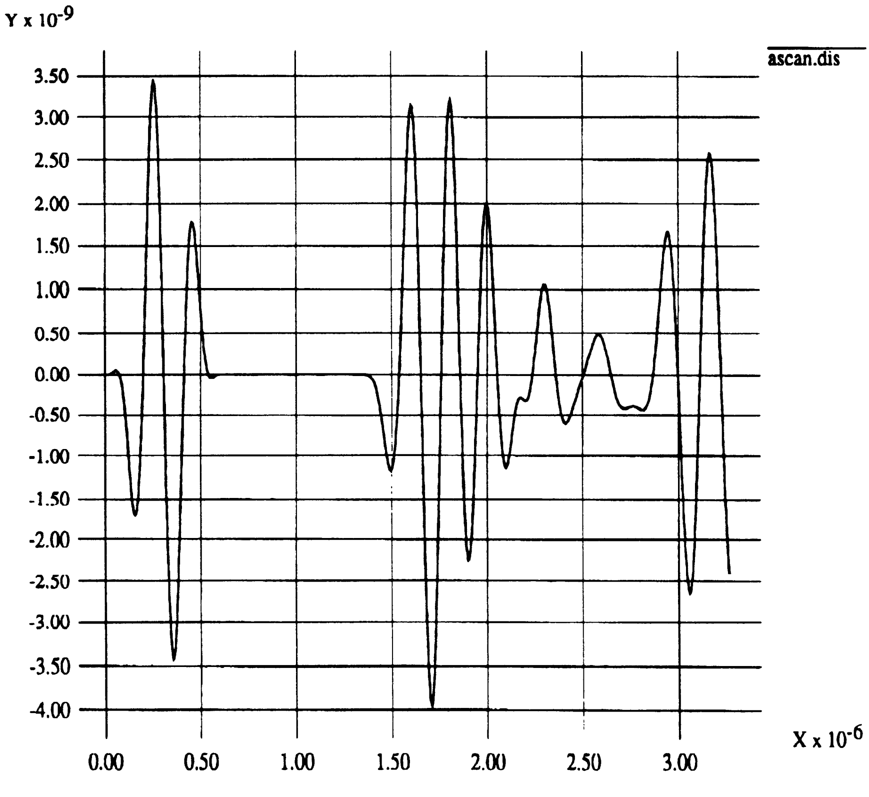

Fig. 2. Numerical A-scan signal prediction for the five-layer bondline model.

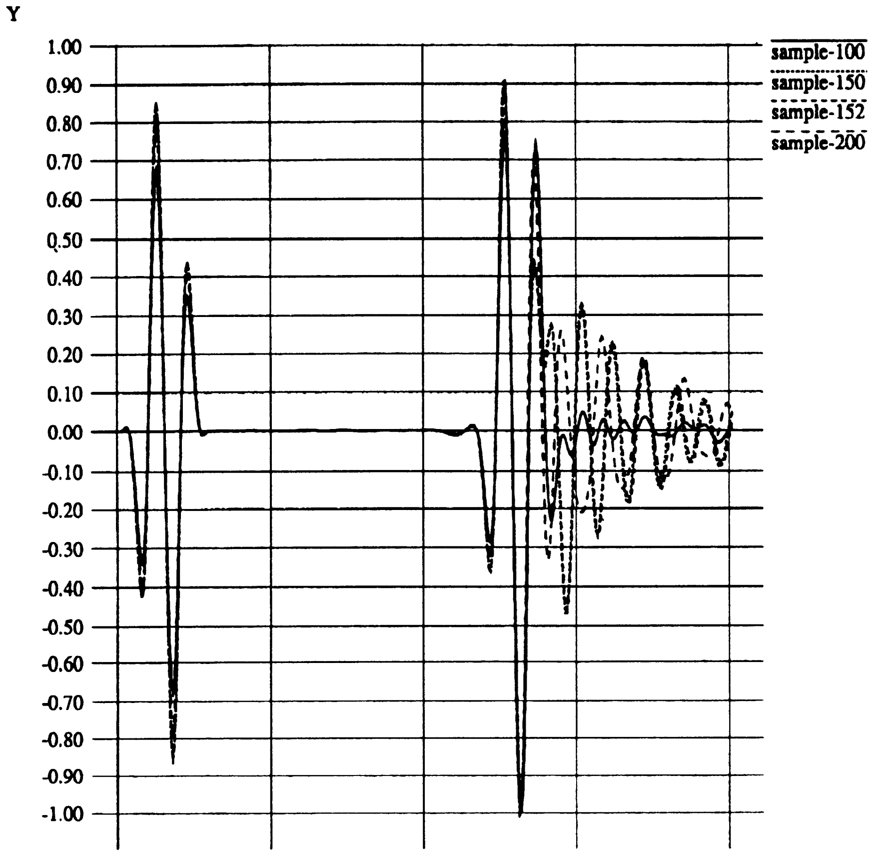

Fig. 3. Four numerically predicted ultrasonic A-scans for the normalized particle displacement fields recorded at the transducer location.

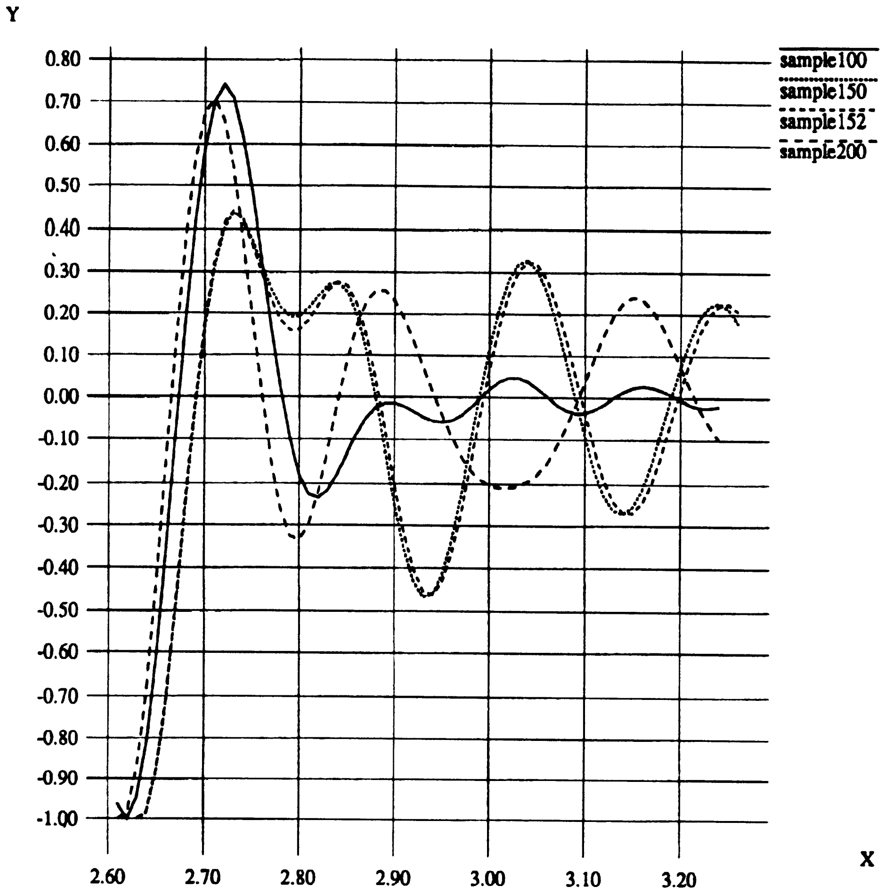

Fig.4. Truncated A-scans for 64 sample points between 2.6 and 3.24 μsec.

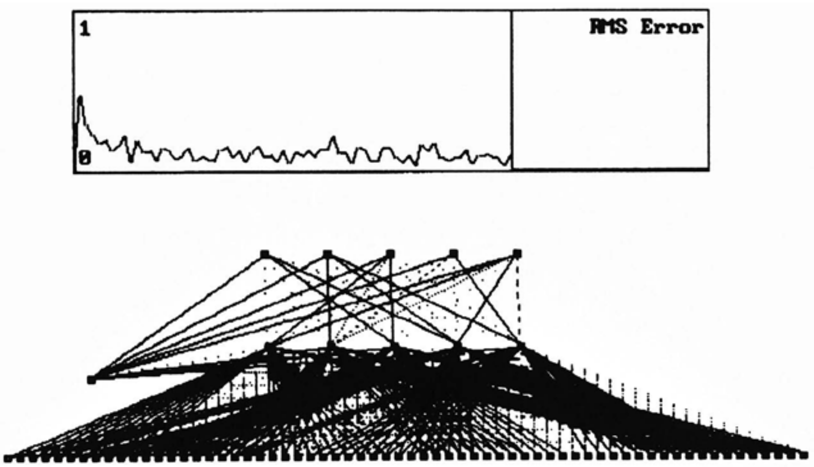

Fig. 5. Realistic neural network to classify synthetic A-scan data as shown in Fig. 4.

thickness condition (microns)	output
100 - 120	(1,0,0,0,0)
121 - 140	(0,1,0,0,0)
141 - 160	(0,0,1,0,0)
161 - 180	(0,0,0,1,0)
181 - 200	(0,0,0,0,1)

Fig. 6. Classification of numerical thickness predictions.

FEATURE EXTRACTION APPROACH

A neural network is employed to determine the thickness information inherent in the A-scan data as shown in Figure 4. The network uses 64 input nodes, 5 hidden nodes and 5 output nodes as seen in Figure 5.

To train the above network, the 100 A-scan signals of 64 sample length each have been applied to the input layer 10 times. The weights in the processor elements are adjusted under supervised learning according to the backpropagation algorithm. The learning process is terminated once the network falls below a predetermined overall Root-Mean -Square(RMS) error or reaches an upper limit as qualitatively displayed in the top graph of Fig. 5. On the basis of the five output nodes, the numerically obtained 100 signals were classified as belonging into 5 separated groups based on their respective thicknesses. Figure 6 summarizes the grouping.

The training process on an IBM compatible personal computer 486/33 MHz system typically takes 10 - 11 minutes. If the signals from the original numerical training set are picked at random and applied as input, the neural network properly classifies the response with 100 % accuracy. On the other hand, the network recalls the appropriate classification bin in 18 out of 20 cases using input signals external to the training set. For instance, a thickness of 141.6 micron is still classified as belonging to a signal associated with the output bin.

air gap size (microns)	condition	output
0 - 20	perfect bond	(1,0,0,0,0)
20 - 40	weak bond I	(0,1,0,0,0)
40 - 60	weak bond II	(0,0,1,0,0)
60 - 80	weak bond III	(0,0,0,1,0)
> 80	disbond	(0,0,0,0,1)

Fig. 7. Grouping for numerical weak bond simulation

WEAK BOND IDENTIFICATION

As a possible weak bond model, one can assume an interfacial layer which is partitioned into two separate layers: one consisting of medium parameters equivalent to a coupling gel [4] and a second layer consisting of air. This air gap is made variable such that for thicknesses between 20 and 80 mircons various degrees of weak bonding are diagnosed. For thicknesses beyond 80 microns a disbond is assumed. Figure 7 summarizes the grouping.

After generating 100 training samples the network is successful in classifying the training patterns exactly. In order to further test its performance, the numerical code was employed to simulate A-scans associated with airgaps of 10.3 and 40.5 microns which differ from the training set. For the first case, the output vector (0.878,0.432,0.002,-0.006,0.003) is classified as a perfect bond and for the second case the output vector (0.032,0.573, 0.865, -0.009, 0.001) is classified as belonging to the weak bond II group.

EXPERIMENTAL TESTING FOR THE TOTAL BOND/DISBOND CLASSIFICATION

A total disbond is modeled experimentally using a single aluminum plate supported at the perimeter. The transducer is placed in the center of the plate to avoid contamination of the A-scan data by reflections from the plate edges. Figure 8 shows the physical dimensions of the experimental configuration.

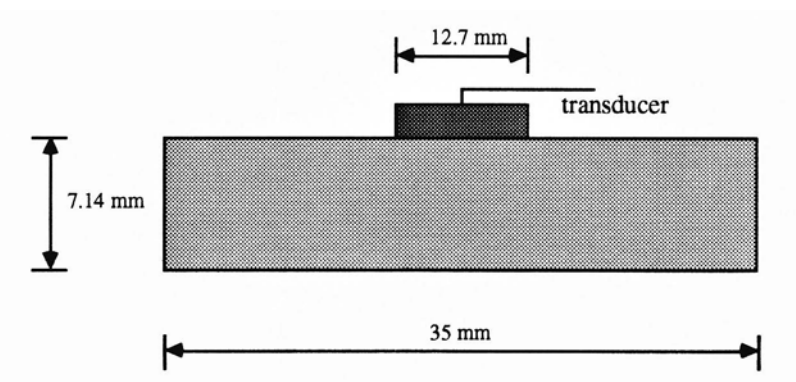

Fig. 8. Single aluminum plate experimental configuration.

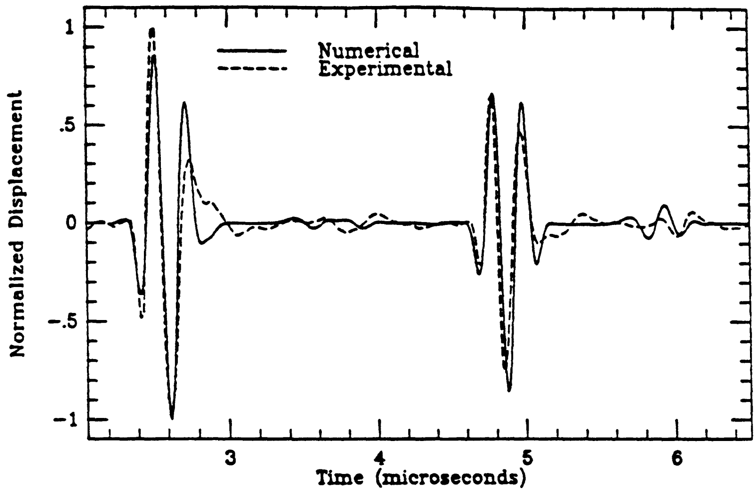

Fig. 9 Numerical and experimental A-scan signal for Fig. 8 geometry.

One quarter inch diameter contact transducer with a center frequency of 5 MHz is used. As training data, the numerically generated signal shown in Fig. 9 (solid line) is the basis for the recognition of experimental signals (dotted line). For this condition a dual output layer approximated the perfect binary pattern (0, 1) as (-0.161, 0.406)

CONCLUSIONS

From these preliminary results, it can be concluded that a neural network performs very well in terms of extracting the thickness characteristics inherent in the transducer input data. If this capability of feature extraction is considered adequate, quantitative information can be prepared from theoretical, computer based simulations. Furthermore it may become possible, based on the work present in this paper, to develop a neural network system that goes beyond the quantitative thickness evaluations, to incorporate a variety of different geometric and material parameters.

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