Characterisation of Various Damage Mechanisms of Adhesively-Bonded Bi-Material Double-Lap Joints Using Existing Unsupervised and Supervised Clustering Methods

Ingmar Boshuizen, Daniel Cisneros Acevedo, Matthew Dekkers,
Shadab Eftekhar, Ruben Goetstouwers, Luuk Halsema,
Afonso Tuna, Badhrinarayanan Sambath, and Suyi Wen
Group AB 11, Faculty of Aerospace Engineering, Delft University of Technology, The Netherlands

Abstract

Acoustic Emission (AE) is a non-destructive testing technique to detect damages within a specimen without causing any damage to the material. The signals detected by AE testing can be clustered by unsupervised and supervised methods. The purpose of this paper is to investigate how accurate common unsupervised and supervised clustering methods are in the characterisation of damage mechanisms of an adhesively-bonded bi-material double-lap joint joint using AE techniques. The joint consists of a steel core and CFRP skins which are adhered by a thick adhesive. The AE data were collected by conducting a shear strength test on the joint specimen, the component materials, and the interfaces by tensile loading respectively. The AE data of the component materials and interfaces were then clustered using unsupervised hierarchical clustering method and inputted as a training set to identify different types of damage using supervised decision tree method. Furthermore, images were taken during the shear strength test to aid the analysis of the damage behaviour of the specimen. The results show that the dominant damage mechanism came from the damages in the steel core using AE signals. It was also found that the classification method used in this paper has an accuracy of 98.1%. However, the images show that adhesive failure and debonding failures at the interface were the dominant damage mechanisms. In conclusion, hierarchical clustering and decision tree as common clustering methods cannot be used as a useful tool to detect and characterise different damage mechanisms of a double-lap joint accurately.

Nomenclature

AE	Acoustic Emission
CFRP	Carbon Fibre Reinforced Polymer
FFT	Fast Fourier Transform
GUI	Graphical User Interface
HDT	Hit Definition Time
PCA	Principal Component Analysis
PDT	Peak Definition Time
SHM	Structural Health Monitoring

I. Introduction

Acoustic Emission (AE) is a passive non-destructive testing technique used to detect and diagnose failure mechanisms in engineering structures by detecting the sudden release of strain energy within the structure [?]. This energy is in the form of a wave which is detected by piezoelectric sensors attached to the structure and is converted to an electric signal [?]. By analyzing this signal, information about the type and location of the damage can be obtained. Carbon Fibre Reinforced Polymer (CFRP) composites are increasingly being used, and therefore, it is important to be able to detect and characterize the damages occurring in these structures. This process is called Structural Health Monitoring (SHM) [?].

From the literature review, it was found that most available researches on AE assessment are limited to single-material specimens such as CFRP composites and metals [? ? ? ?]. However, there is a lack of research on the use of AE testing to find damage mechanisms on an adhesively-bonded hybrid double-lap joint. It is more challenging to classify signal clusters associated with each damage mechanism in hybrid joints compared to single-material specimens as both the individual materials and the interfaces have various damage mechanisms, resulting in a higher number of overlapping AE events. These joints are used in large structures such as maritime vehicle and aircraft, where there are economic benefits to detecting the damages beforehand and performing preventive maintenance instead of corrective maintenance. Hence, it is necessary to conduct more research focused on the effective AE damage characterization of adhesively-bonded hybrid double-lap joints. To classify AE signal clusters to characterise the associated damage mechanisms, suitable unsupervised and supervised clustering methods should be used [?]. From the literature study, one supervised and one unsupervised method were chosen for this report. Hierarchical clustering was found to be one of the most efficient unsupervised methods for data clustering and had the best performance in terms of clustering AE signals [? ?]. For the supervised methods, a decision tree was found to be capable of producing accurate results [? ?].

The consequent research to be completed will describe the specific materials and test setup to be explored, the clustering methods used for analysis, present the conclusions and attempting to answer the research question "How accurate are the common clustering methods in AE testing on a double-lap joint configuration made of a composite laminate and steel core, bonded by a thick adhesive?".

The AE data used was collected from testing, and the data has been analyzed by the use of a in-house developed Graphical User Interface (GUI) in MATLAB. This software is able to extract different features of AE signals, detect the initiation of damage and type of damage for 1D and 2D structural elements, and finally distinguish and classify different damage mechanisms by means of different clustering methods. The reason why MATLAB was chosen is because it contains applications and toolboxes such as Machine Learning and Deep Learning Toolbox and Classifier Learner that enable the implementation of unsupervised and supervised methods easily.

II. Methodology

A. Test Method

AE testing was performed on the joint specimen as shown in Fig.1 and in addition, all materials that compose the specimen including steel, CFRP, and adhesive were tested separately so that the data cluster associated with the damage of each individual material could be captured. The signals, coming from the strain energy, were captured with an AE sensor. The sensor was broadband (measuring movement in a large variety of frequencies) and resonant-type. Furthermore, it was a single-crystal piezoelectric transducer from Vallen Systeme GmbH, AE1045S-VS900M, with a frequency range of 100 − 900 kHz.

During testing, AE signals below the 40 dB threshold were not registered. However, a lower threshold of 35 dB was used for the adhesive material as there are fewer AE events due to its elasticity; otherwise, not enough AE signals would be captured. For the joint, the sensor was placed at the bottom of the steel specimen.

An AMSY-6 Vallen, 8-channels acoustic emission system with a maximum sampling rate of 2 MHz was used to record the AE events. Afterwards, the signals were strengthened with a 34 dB pre-amplifier. In addition, a 1.27 mm/min displacement control rate was used during the test.

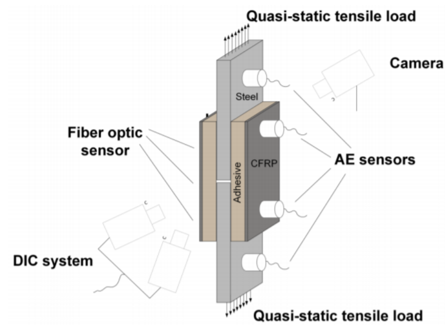

Figure 1 Schematic of the double-lap joint specimen. [?]

While the joint is loaded in tension, the adhesive experiences shear load. Hence, the adhesive was tested in tensile load as well as shear which includes mode I and mode II as demonstrated in Fig.2 while the CFRP was loaded in tension and the steel in shear and tension. The composite skin as seen in Fig.1 was tested in tension, modes I and II separately. During the test, the applied load and displacement of the joint were recorded and images of the side view of the double-lap joint specimen were taken every second.

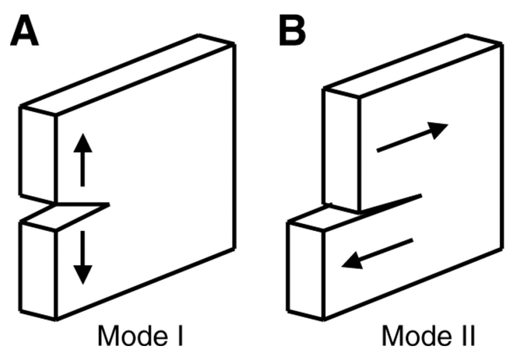

Figure 2 Mode I and Mode II Loading [?]

B. Description of the data

After testing, 23 data sets were received consisting of matrices with voltages. These data sets consisted of the data obtained by the testing from the individual materials as well as for the whole joint. The columns represented different signals and the rows represented points in time. Every signal lasted 1 microsecond, and since every material was tested using a constant control rate, not all matrices have the same amount of columns. This is due to the fact that every material fails at a different time.

C. Extraction and Selection of AE Features

By running the tests, a data file was extracted, where every point of each AE signal was displayed as a voltage. In the file, every column represented a signal, and every row represented a time step. The time difference between the rows was 48.8 nanoseconds. After collecting each signal, AE features including the frequency, duration, counts, rise time, peak amplitude and energy of each signal were extracted. The frequencies were found by using a Fast Fourier Transform (FFT)[**?**]. The duration was found by looking at the points where the signal crossed the threshold until the time between them was larger than the hit definition time (HDT). The number of counts was found by counting the number of times the signal curve approaches the threshold from below as indicated as the green points in Fig.3. The peak amplitude and rise time were found by determining the maximum amplitude of each signal, and determining the time difference between the time at which the maximum amplitude of each signal was reached within the peak definition time (PDT) and the starting time of the signal above a certain threshold voltage for each material as mentioned in Fig.II.A. Finally, the energy was found by integrating the square of the signal over the found duration [**?**].

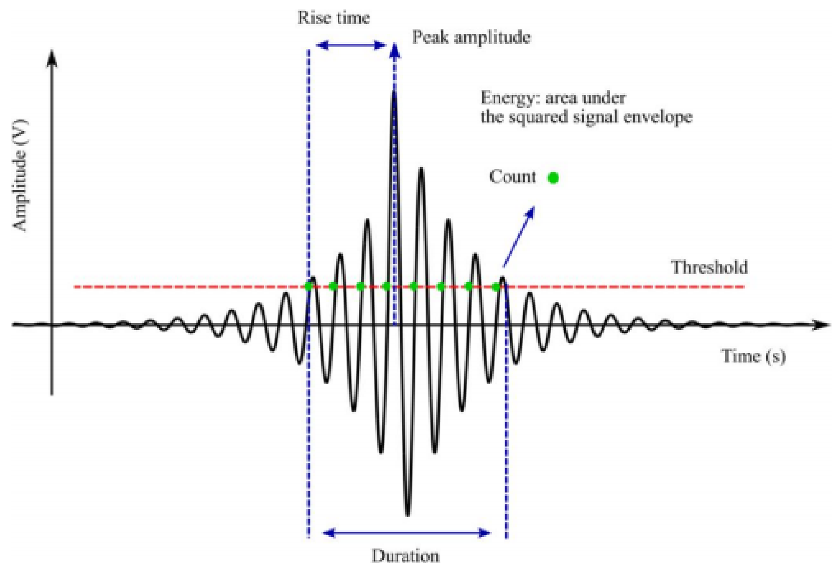

Figure 3 AE features graphically displayed [? , p. 150].

D. Cluster Analysis

Once all the selected AE features were extracted for each material as mentioned in Fig.II.C, a cluster analysis was performed on each of these features to identify distinct AE signals clusters that correspond to damage mechanisms of each individual material and interface, and thereby identifying the damage mechanisms of the double-lap-joint sample. The cluster analysis was performed by using MATLAB. To cluster the AE signals, unsupervised and supervised clustering methods were used. Finally, by implementing these two methods, a user-friendly GUI that can input all the AE data was created to determine the dominant damage mechanism of the joint specimen. Using the GUI, cumulative energy against time graph of the joint specimen was plotted.

1. Hierarchical Clustering

Unsupervised agglomerative hierarchical clustering was used to group different AE signals for each feature and illustrate the clustering results using dendrogram with the use of the Statistics and Machine Learning Toolbox from MATLAB. The procedure of agglomerative hierarchical cluster analysis on each AE feature is described as follows [**?**]:

1) Calculate the Euclidean distance between every pair of AE signals using the pdist function.
2) Find larger clusters by grouping pairs of AE signals that are close together (small Euclidean distance) until a dendrogram plot with Euclidean distance on the y axis was formed using the linkage function.

3) Compute the inconsistency coefficient of links that join different clusters using the inconsistent function.
4) Find the number of distinct clusters by specifying a inconsistency coefficient threshold of 1.3 using the cluster function.

2. Decison Tree

Decision tree is a supervised method to partition the input data set into clustered regions and empty regions that produce outliers and anomalies [**?**]. In this report, it was chosen to recognise the patterns of damage mechanisms of the double-lap joint sample based on known and labelled AE signals of the individual materials and interface, which was then used to make predictions about the response of the AE signals for each chosen AE feature. A correct label was first assigned to each AE signal. In Fig.1 these classifications are highlighted.

An input data matrix was created, whose rows represent the AE signals and columns represent the labels and the six AE feature parameters including frequency, duration, peak amplitude, rise time, energy, and counts. This matrix was inputted to the Classification Learner app in MATLAB as a training set. The following software settings were used: the AE features and the labels were selected as the predictors and the response respectively; no validation was chosen; Principal Component Analysis (PCA) was enabled by selecting 6 numeric components and 'specify number of components' as the component reduction criterion'; and finally the maximum number of splits were chosen to be 2000, the split criterion was the maximum deviance reduction, and "find all" was chosen for the surrogate decision splits. In Section III a confusion matrix which represents the outcome of the classification learner can been seen, which shows how well the currently selected classifier performed for each material. Basically, what the classification learner does is assigning points to certain classes due to algorithmic steps and later checks whether or not those are assigned correctly.

Table 1 Specimen labelling.

Class	Specimen
0	Adhesive
1	CFRP
2	Interface
3	Steel

3. MATLAB GUI Implementation

The GUI is implemented in MATLAB. It allows the user to input an AE data file with different AE features and specifies the threshold voltage, HDT and PDT. By selecting the feature, it clusters the AE signals using hierarchical clustering and decision tree as mentioned in the sections before. Finally, the results are plotted graphically.

III. Results and Discussion

The confusion matrix in Fig. 4 shows the classification and misclassification rates of each damage mechanism event type. This confusion matrix was first trained using the data provided from the GUI of MATLAB. From this data certain features as discussed in subsection II.C of Methodology were extracted and analyzed as discussed in subsubsection II.D.2 Decision Tree. The final decision tree produced an overall accuracy of **98.1%**.

In Fig.4, it can be seen that class 0 and 2 which correspond to AE events of the interface and adhesive specimen have lower classification accuracies (84% and 82%) as there is smaller number of data points available for evaluation compared to class 1 and 3. For instance, class 2 has only 1094 data points. Also, as seen in Fig. 4, class 1 which represents the CFRP specimen has the highest classification rate. The reason of having a classification rate of larger than 99% is that for class 1 the highest number of AE events was extracted.

Figure 4 Confusion Matrix.

While having 408 points for class 0, class 1 had over 200000 events. Therefore class 1 was cut down to 33177 AE Events since the machine learning tool, gave very low classification rates for the other classes. This was due to over-training the model; when having so much data points the computer will prefer classifying the points to class 1 since it did already so many times. Therefore, almost all points would be appointed to class 1, which is incorrect. While stripping the number of data points for class 1, the classification rate of 99 % was not changed.

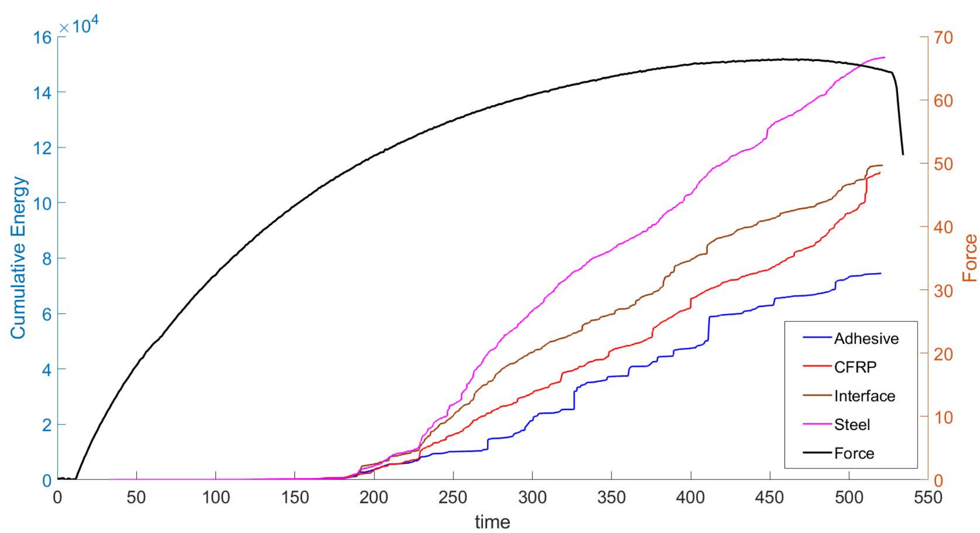

Figure 5 Load and Cumulative Energy versus Time Curves.

The GUI interface was used to plot load and cumulative energy against time curves as presented in Fig.5.

The graph shows the AE activity of the adhesive, CFRP, interface and steel due to the applied force. The cumulative energy curves for each of the aforementioned groups all show a number of sudden increases during the time interval. Each sudden jump in energy is an indication of a sudden release in the accumulated strain energy of the specimen [**?**]. In other words, it is an indication of a damage mechanism within each specimen. The adhesive contains the largest sudden jumps in cumulative energy. The interface almost exhibits the same pattern of sudden jumps, but less severely. While testing the complete joint, cracks could be seen at the timestamps which match the sudden jumps in the curve in Fig. 5.

In Fig. 5, it can be clearly seen that steel has the largest cumulative energy, suggesting that the dominant damage mechanism of the double-lap joint specimen is caused by the damages in the steel core. However, as indicated in Fig.6 and Fig.7, the main damage mechanisms are adhesive failure, CFRP- and steel- interface failures. There was no clear visual observations of any damages in the steel, which contradicts the results found by the clustering of AE signals. This could suggest that the clustering methods used to derive these results are in fact insufficient to accurately describe the characterization of different damage mechanisms within the double-lap joint specimen.

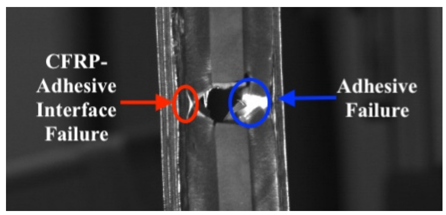

Figure 6 Damages at the centre of the double-lap joint configuration during testing.

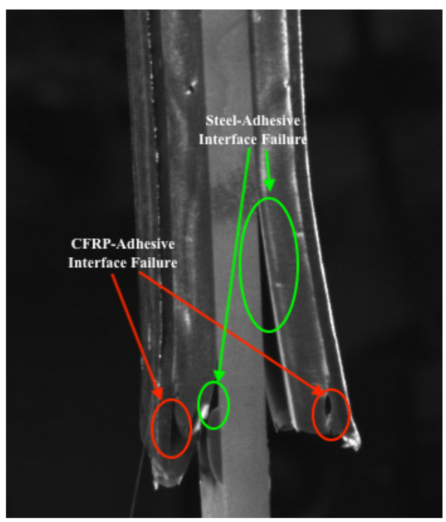

Figure 7 Damages at the bottom of the double-lap joint configuration during testing.

The images that were taken to obtain a visual representation of the damages within the double-lap joint were not clear enough, making it difficult to identify the exact damage mechanism at a certain time frame. This created difficulties in comparing the results obtained from Fig.5 with what was observed from the images at any specific instant of time and therefore it was harder to verify the results based on AE signals. However, one clear distinction can be made from the photos and that is that the adhesive contains the most damage of all materials.

Another improvement that can be made is exploring and comparing the performance of different unsupervised and supervised methods. In this report, only one unsupervised and one supervised method were used and hence, the conclusion would be drawn based on only the performance of these two methods. Hence, to answer the research question, more common clustering methods should be used in order to determine whether methods other than hierarchical clustering and decision tree are also insufficient for the damage characterization of a double-lap joint material.

IV. Conclusion

This paper aimed to ascertain the accuracy of commonly used clustering methods to identify different damage mechanisms in adhesively-bonded hybrid double-lap joints using Acoustic Emission (AE). With this objective, a steel/adhesive/CFRP composite was exposed to a quasi-static tensile load while recording AE events initiated by material failure. In addition, AE signals were captured for each material separately, as well as for the interfaces between the adhesive and the two other materials. This data was used to train the Classifier Learner in MATLAB for cluster analysis. Results of the confusion matrix have shown that this supervised classification method becomes inaccurate when there is a larger number of data points for one material compared to the others. Since a substantial number of AE events was recorded for CFRP, the amount of data points had to be reduced to prevent the Classifier Learner from over training and specifying most as CFRP. At this point in time, due to a coding error, we are unable to conclude whether the classification methods are valid. This error has led to illogical outputs such as a higher perceived cumulative energy for steel with respect to the other materials. Furthermore, it is expected that the confusion matrix will be updated as research continues. Because of this, it is not yet possible to answer the research question or add further recommendations about AE testing to the reader.

Acknowledgements

We thank Milad Saeedifar and Mohamed Saleh for their help and guidance and appreciate all the provided feedback.