# A Study on the Crack Growth of AA2219 Aluminium Alloy material using Acoustic Emission Signal Analysis

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## Abstract

The crack growth in the engineering materials usually precedes the occurrence of a significant amount of plasticity at the crack tip. The plastic deformation and crack opening of the metallic materials usually produce intense acoustic emission. The paper reports on an experimental study carried out to determine the characteristics of the acoustic emission signals emitted from AA2219 Aluminium material during crack opening. Unsupervised pattern recognition analysis of acoustic emission signals captured during the tensile loading of a compact tension specimen is carried out to segregate the genuine AE signals from all the data acquired during tension test. 3 classes of signals segregated through the K-means cluster algorithm has been analyzed in detail. The variation in the magnitude of AE parameters of different clusters is distinct. The signature of crack growth based on the AE parameters viz. amplitude, duration, energy and counts has been obtained through the study.

Key words: Acoustic Emission (AE), AA2219 Aluminium alloy, Pattern recognition, Amplitude, Energy, Counts etc.

## Introduction

AA2219 aluminum alloy is widely used for aerospace applications due to its good mechanical properties like good strength-to-weight ratio and fatigue resistance. It is used for the fabrication of launch vehicle components such as propellant tanks, engine casings and structural components like heat shield and Interstages [1]. The pressurized components are normally exposed to a proof test before the actual usage. Various NDT tools are used for detecting the presence of any existing defect in the components before and after the testing. Acoustic emission (AE) NDT technique is widely used for the real time structural integrity evaluation of pressure vessels and structures made of AA2219 alloys. For the critical assessment of the structure it is required to know the characteristics of the various defects occurring in the structure. The initiation/ growth of the cracks during proof testing needs to be monitored. For this, the signature corresponding to the crack grown in the material is to be identified. This paper gives the details of the study conducted on the Pre-cracked compact tension specimen of AA2219 Aluminium alloy. The major challenge for the signature analysis of specimen data is the discrimination of genuine AE signals from noise signals due to the machine operation and also the rubbing of the specimen with pins used for holding the specimen in the machine. Nowadays various signal analysis methods are used for this and the process is very involved. Un-supervisory pattern recognition method by using cluster algorithm is found to be one of the effective method for segregating the genuine AE signals from total data acquired during testing. The characterization of the AE signals corresponding to the crack growth of the material is carried out through the analysis of the variation in the different AE parameters namely amplitude, duration, energy and counts.

## Acoustic Emission Technique

Acoustic emission (AE) is a phenomenon in which elastic or stress waves are emitted from rapid, localized change of strain energy in material [2]. Type of AE waves generated depends on material properties, its mechanical behavior and level of stresses at the source. AE waves can be Elastic, Non-linear elastic, Elastic-plastic and Elastic- viscoplastic. An elastic waves attenuate at short distances and therefore elastic waves are mostly detected and analyzed in acoustic emission testing [3]. The practical application of the AE first emerged in the 1950's, through the research work of Joseph Kaiser (Germany). In 1957 after performing extensive laboratory studies, Clement A. Tatro, suggested to use AE as an NDT method [3]. Currently AE has become one of the most important non-destructive testing techniques, which is widely applied for fatigue crack detection and location in pressure vessels and pipelines, partial discharge sources detection and location in power transformers and rotating machinery, damage assessment in fiber-reinforced polymer-matrix composites, monitoring welding applications and corrosion processes, on-line monitoring of civil-engineering structures etc [4].

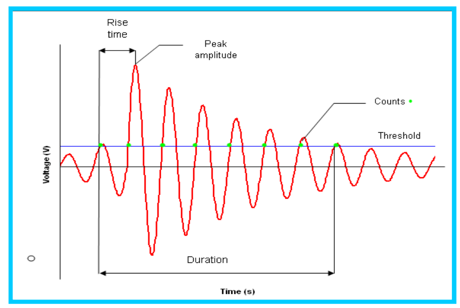


Fig.1. AE Parameters

The sensors used for this technique are piezoelectric sensors, with elements made of special ceramic elements like lead zirconate titanate (PZT). AE waves are detected by AE sensor which converts dynamic motions at the surface of the material into electrical signals. Since the AE signals are weak, they are normally amplified by two amplifiers namely preamplifier and a main amplifier [5]. A few sensors can monitor a relatively large volume and can detect different types of growing damages usually long before the sizes and severity attains the detectable range of other NDT techniques. The most widely used signal measurement parameters in AE signal analysis is given in Fig.1. They are amplitude, duration, energy, counts, rise time, rms etc.

## Pattern Recognition

The pattern recognition techniques are based on the classification of various parameters also called descriptors, into clusters forming patterns [6]. Clustering is the process of grouping the data into classes or clusters, so that objects within a cluster have high similarity in comparison to one another but are very dissimilar to objects in other clusters. Mainly there are two types of pattern recognition method based on the knowledge of dataset. They are unsupervised and supervised pattern recognition methods [7].

Unsupervised Pattern Recognition is the process by which objects are classified in general groups according to their similarity. This process does not require any previous knowledge or database. Objects are classified into groups by comparing their features and determining their similarity. Supervised Pattern Recognition, which involves a learning process and where each new set of data is processed and classified to one of the previously known and predefined groups by comparing its features to a database or using rules derived from the learning process. Applying Supervised Pattern Recognition in AE implies previous knowledge about the number of classes as well as a set of known examples from different AE sources to be used in the classifier design. Different Supervised Algorithms might be used, depending on the complexity of the problem as well as the required speed performance of the classifier. Among the different classifiers the simple minimum distance classifier, the linear classifier and the complex Neural Networks have been used for the classification of AE data. There are several clustering methods that can be used to find clusters of similar records for different applications. Some of the algorithms which use Euclidean distance as a measure of dissimilarity between the pattern classes are Cluster Seeking, Max-Min distance, K-Means, Forgy, Isodata etc. [9].

In this paper, the global k-means clustering algorithm is used. The k-means algorithm is a fast iterative algorithm that has been used in many clustering applications. It is a point-based clustering method that starts with the cluster centers initially placed at arbitrary positions and proceeds by moving at each step the cluster centers in order to minimize the clustering error. The main disadvantage of the method lies in its sensitivity to initial positions of the cluster centers. Therefore, in order to obtain near optimal solutions using the k-means algorithm several runs must be scheduled differing in the initial positions of the cluster centers [11]. This algorithm takes the input parameter, 'k' and partitions a set of 'n' objects into 'k' clusters so that the resulting intra cluster similarity is high but the inter cluster similarity is low. Cluster similarity is measured in regard to the mean value of the objects in a cluster, which can be viewed as the cluster's centroid or center of gravity. The k-means algorithm proceeds as follows. First, it randomly selects k of the objects, each of which initially represents a cluster mean or center. For each of the remaining objects, an object is assigned to the cluster to which it is the most similar, based on the distance between the object and the cluster mean. It then computes the new mean for each cluster. This process iterates until the criterion function converges. Typically, the square-error criterion is used, defined as

$$E = \sum_{i=1}^{k} \sum_{p \varepsilon ci} |p - mi|$$

Where E is the sum of the square error for all objects in the data set; p is the point in space representing a given object; and mi is the mean of cluster Ci(both p and mi are multidimensional). In other words, for each object in each cluster, the distance from the object to its cluster center is squared, and the distances are summed [7].
To extract the best suited class number for discriminating among the different AE mechanisms sources, different criteria is used. The evaluation of clustering results is based on the R criterion defined by Davies and Bouldin (1979) [11]. The criterion relies on the calculation of

$$R_{ij} = D_i + \frac{D_j}{D_{ij}} \quad (i, j = 1 \ldots C)$$

Where $D_i$ and $D_j$ denote the average within-class distance of clusters i and j respectively. $D_{ij}$ denotes the distance between the two clusters i and j and C is the number of clusters.
Denoting by $r_i$
$r_i = \max\{R_{ij}\}$

The criterion is defined as R = $\frac{1}{c}\sum_{i=1}^{c} ri$
Lower the value of R provides better the clustering. The index R is then calculated from the maximum values of Rij divided by the number of clusters.

Another criterion based on the computation of Dj and Djj had been proposed by τ and defined (Bow. 1984) as follows:

$$\tau = \frac{\min(Dij)}{\max(Dk)} \quad i,j,k=1,\ldots\ldots.,C$$

The index τ is calculated from the minimal distance min (Dij) between members of clusters i and j and the maximum distance max (Dk) of members within cluster k. According to above equation the cluster members separate more distinctly for low values of R and high values of τ or the ratio R/τ should be minimum. Comparing the above criteria with those based on within-class scatter matrix they have the advantage to be independent of the number of classes. Therefore, it has been proposed to estimate the number of classes by plotting the criterion value versus the number of clusters and searching for that number which minimizes (maximizes) the criterion value[7,12]:.

Pattern recognition was applied on the data of the samples using the commercially available "NOESIS" pattern recognition and neural networks software for AE applications [10]. NOESIS is a WINDOWS based software package, specially designed and optimized for the analysis of Acoustic Emission data. With this software Acoustic Emission users can do the data analysis and evaluation of common AE parameters using extended analysis capabilities through clustering and classification of multidimensional data.

**Experimental Procedure**

As part of the study AA2219 Compact tension specimens were fabricated as shown in Fig.2. The material is in T87 condition. Specimens are 80x80 in size with 16mm thick and with a 45mm long and 4mm wide notch in the centre. Two numbers of 15mm diameter holes were drilled on the specimens for putting the maraging steel pins for holding the specimen in the machine. Pre-cracking was introduced in servo controlled universal testing machine through fatigue loading.

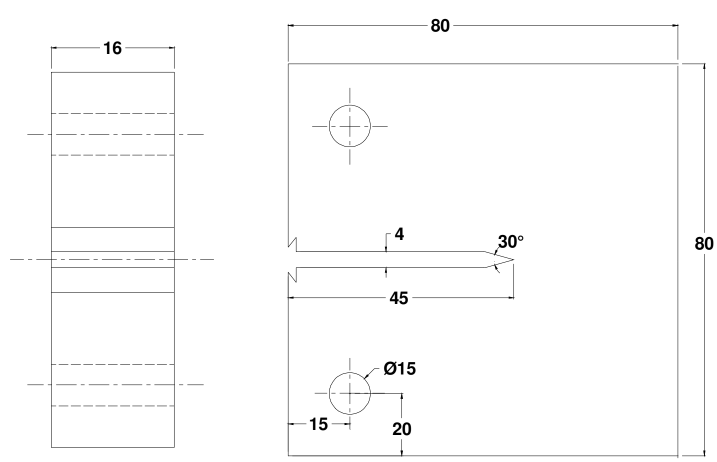



Fig.2.Compact Tension Specimen

The pre-cracked specimens were tested in the Lloyd make Universal Testing Machine (UTM) having maximum capacity of 100KN. Specially made fixtures were used for holding the specimens in the machine. Tensile testing was performed on displacement control at a rate of 1.25 mm/min. The plots of extension, load and time were recorded in the machine itself. Three numbers of Compact tension specimens (CT) were tested.

During the testing Acoustic Emission monitoring was carried out. Two AE sensors of 150kHz resonant frequency (PAC R15) were mounted one each on the top and bottom of the notch. Highly viscous ultrasonic couplant was used to acoustically couple the sensor to the specimen. The sensors were connected to PAC 2/4/6 preamplifiers using 1 meter long cable.

RG58 Belden make Co-axial cables were used to connect the pre-amplifiers to the AE system. Mistras SAMOS board was used for real-time data acquisition during tension testing. Simulated AE signals produced by mechanical pencil-lead breaks (0.5 mm, 2H) near to the sensors were used for sensor calibration. NOESIS pattern recognition software supplied by Physical Acoustic Corporation (PAC), USA was used for the post test data analysis.

## Results & discussion

The amplitude vs time plot of the total data captured from one of the test sample is shown in Fig.3. 7838 numbers of AE signals were registered and it's a combination of genuine AE due to material deformations and the unwanted noise signals due to the rubbing of pins and machine

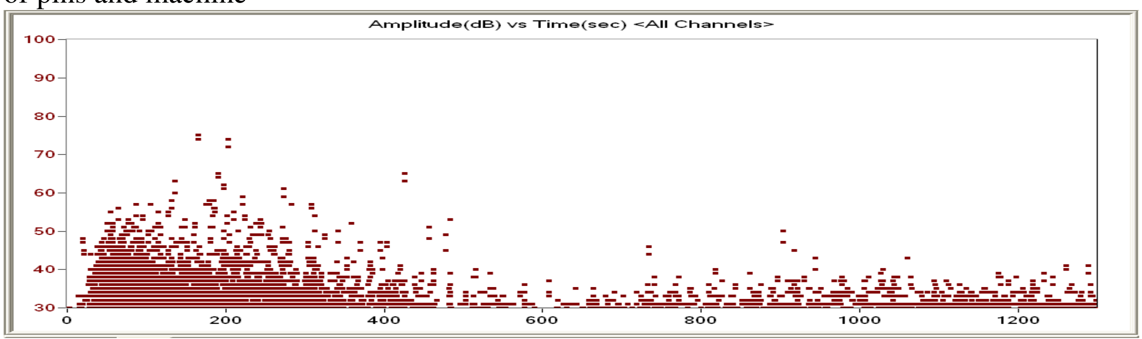



Fig.3. Tension test AE data of Pre-cracked Compact Tension Specimen

operation. There is an increasing trend in AE activity in the initial period and subsequently there is a declining trend in the number of emissions and the amplitude value after reaching the peak level.

The first hits for each AE burst have been filtered out and processed in the NOESIS software. Total 4640 numbers of first hits were separated. The degree of correlation between the AE parameters in the first hits data set has been found out using the dendrogram. A correlation value less than 0.7 indicate presence of various sources [7,12]. AE features selected for the discrimination of different sources are Rise time, Energy, Amplitude, Average Frequency, rms, Reverberation Frequency, Initiation Frequency Partial Power 1, Partial Power 2, Partial Power 3, Frequency Centroid and Peak Frequency.

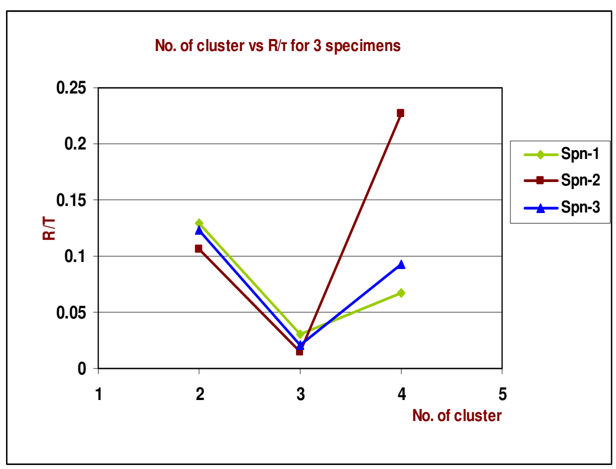
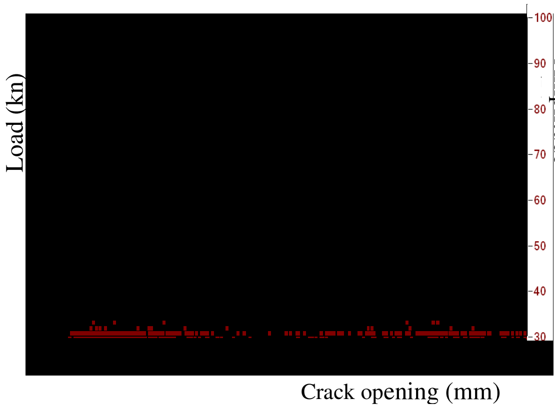



Fig.4. No. of Clusters vs R/t for 3 specimens

The best suited cluster for the data set has been selected through the R criterion defined by Davies and Bouldin and τ criteria defined by Bow. According to the criterion, the cluster members separate more distinctly for low values of R and high values of τ or the ratio R/τ should be minimum[7]. The number of Clusters vs R/τ value for three tested CT specimens are shown in Fig.4. It is found R/τ ratio is minimum for three classes and it shows for all the three specimens there are three distinct sources of emissions.

The load vs crack opening plot with AE amplitude of 3 classes of the AE signals obtained from the specimen is shown in Fig.5. There are 833 Class-1 signals, 1415 Class-2 signals and 2392 Class-3 signals were separated. There is a distinct variation observed in the characteristics of the three different classes of signals obtained from the specimen. The amplitude values are much lower in Class-1 & Class-2 signals and also there is not much variation in the magnitude. Significant increase in the number of emissions and the peak values have been observed in the Class-3 signals.



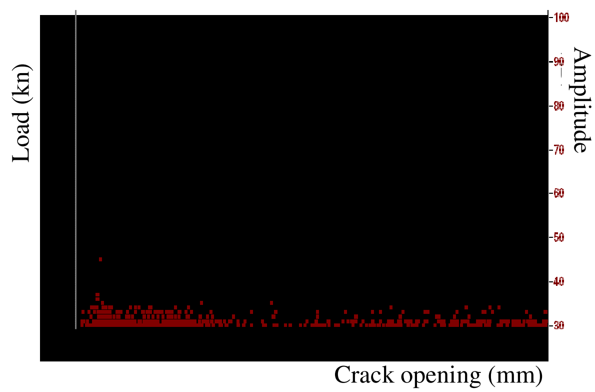
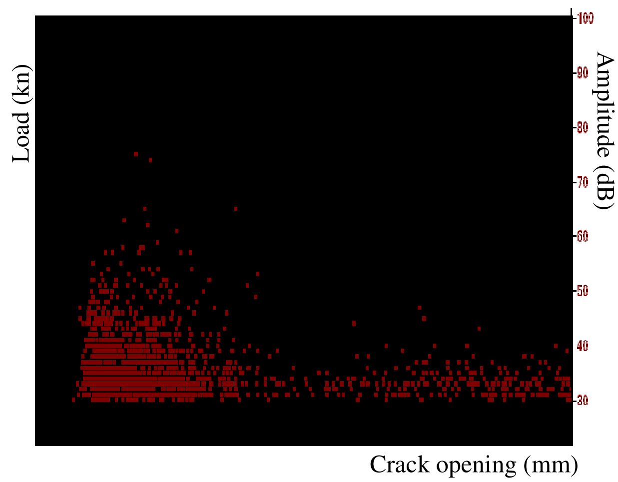
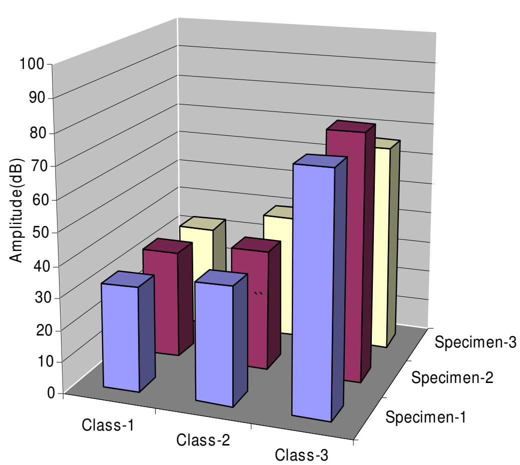
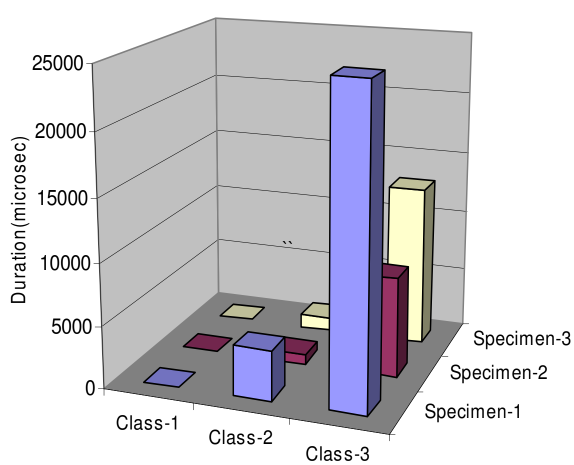




Fig.5. Three (3) distinct classes obtained from the specimens




The features of different AE parameters viz. amplitude, duration, energy & counts obtained for three different samples are shown in histograms in Fig.6. The peak values for Class-1 & Class-2 signals for different parameters are found to be much lower than the class-3 signals. The Class-1 signals are having peak amplitude level less than 35dB and Class-2 signal are having peak amplitude level less than 45dB, while the amplitude levels of Class-3 signals are more than 50dB.



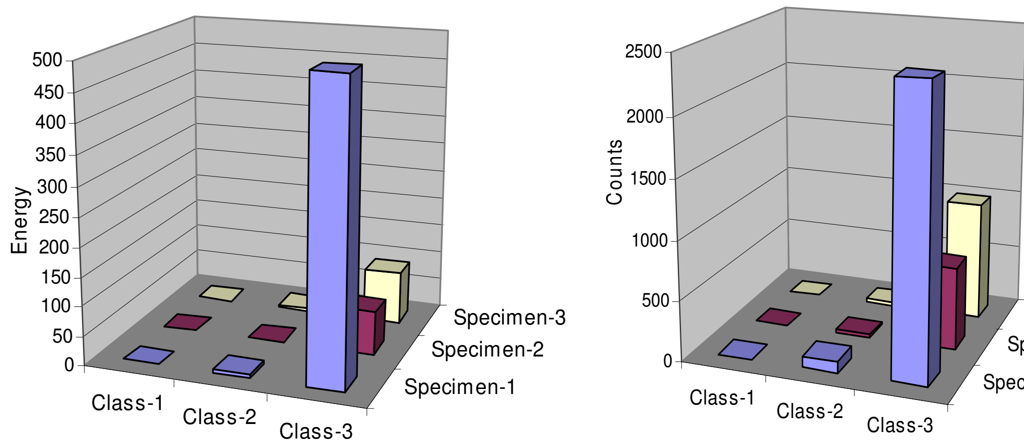



Fig.6. Range of AE parameters for three (3) distinct classes from 3 specimens

The crack propagation on the materials preceded by the formation of the plastic zone in the crack tip. The elastic to plastic deformation on AA2219 material can cause AE and the AE parameters attain its peak magnitude level at the time of initiation of plastic yielding. 2219 material exhibit peak amplitude more than 50dB during the plastic deformation [13]. Such a trend is clearly seen in the Class-3 signals. The magnitude of other two classes is less than 50 dB which confirms the findings. This indicates that the Class-1 & Class-2 signals are associated with mechanical noises during testing and the Class-3 signals correspond to the genuine AE signals during crack growth on the material.

The cumulative AE parameters with respect to the crack opening are shown in Fig.7. AE signals started in the elastic regime and an increasing trend in emissions and the magnitude of AE parameters are seen further. The AE parameters obtained from CT specimen show higher magnitude when compared with the corresponding value obtained during the parent metal yielding. This is due to the increased stress concentration level at the crack tip [14]. AE parameters reach a peak level during crack opening and the corresponding values are: amplitude >70dB, duration >8ms, Energy >100 and Counts >1000.

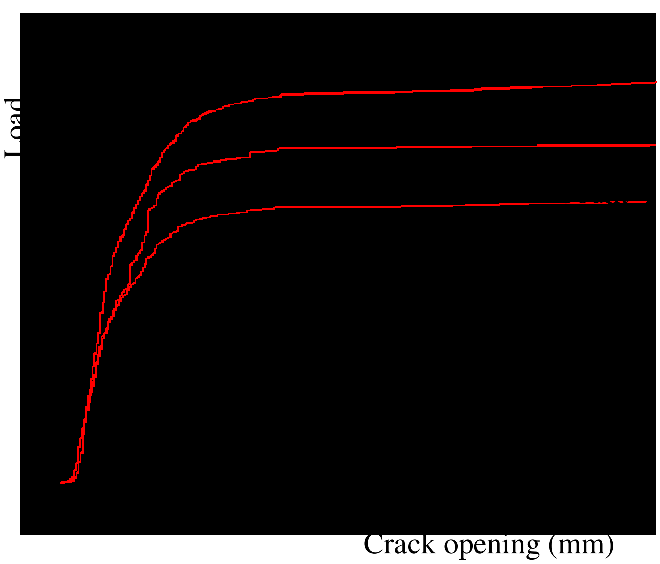



Fig.7. Cumulative AE Parameters Vs Crack opening

**Correlation of crack growth parameters with Hardware data**

The cluster analysis using pattern recognition described above can be used for the structural integrity assessment of a hardware made from the same material. Figs. 8 & 9 show the data of two AA2219 Aluminium tanks during pressure test. The parameters for the

Class-3 signals correspond to crack growth in the specimen which is used for correlating with defect growth in hardware during test. Practically, a scaling up of AE parameters is seen in all hardware under test. Hence, these Class-3 values are considered to be the allowable limit for a structurally integral hardware in the absence of hardware failure data. The allowable values of parameters are marked in all the graphs. Since the parameters do not rise above these levels for the first tank, the structural integrity is evaluated as good during the real time testing itself. In the second case, the parameters have risen above the allowable levels. Though there is no continuous repeated emission from that location, the tank was recommended for a post test complementary NDT test before acceptance. The NDT results indicated no defect growth. Hence this assessment can be considered to be quite conservative. Efforts are on to generate data during failure test of hardware for correlation.

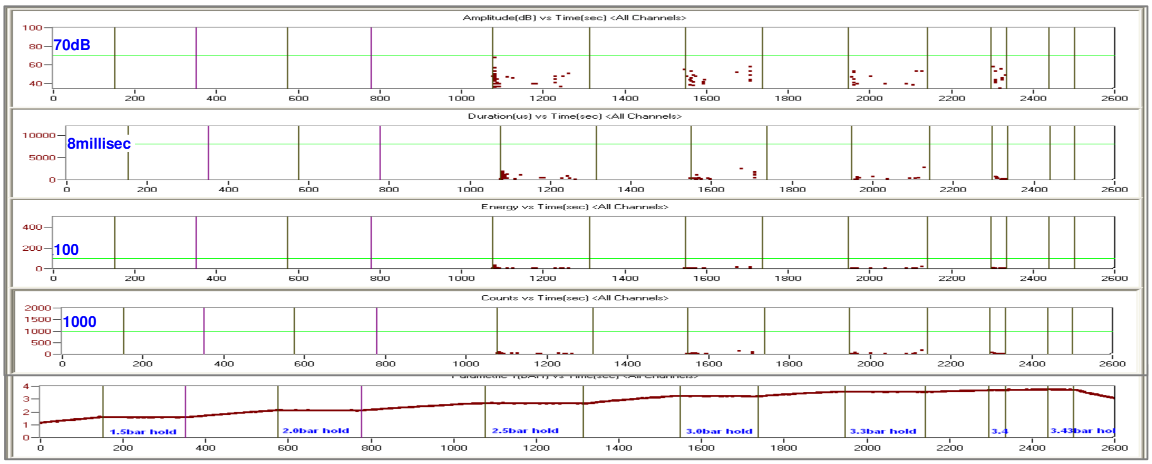


Fig.8. AE data of AA2219 tank cleared based on real time testing

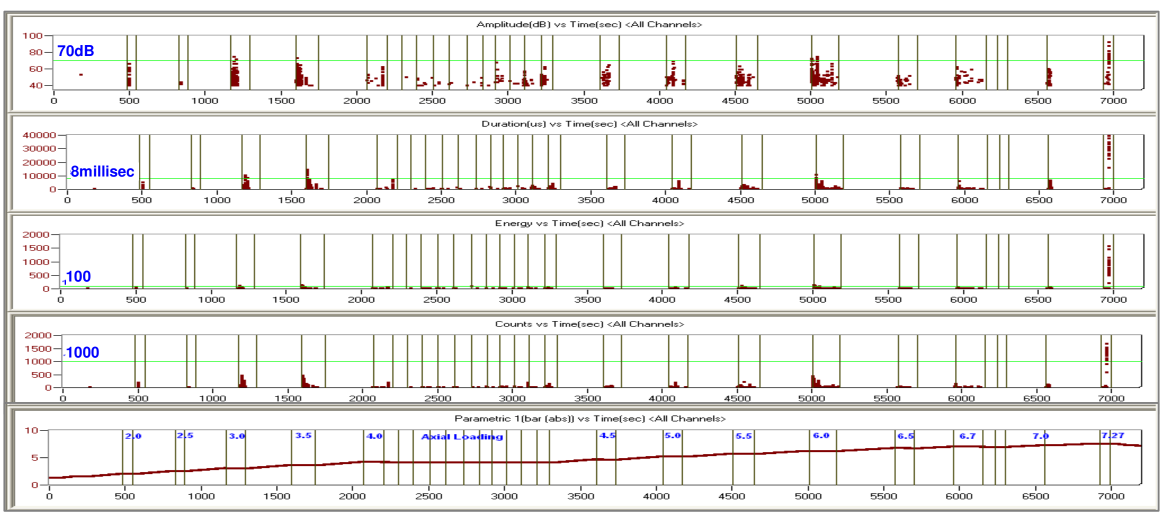


Fig.9.AE data of AA2219 tank recommended for post NDT

## Conclusion

AE signature corresponding to crack opening of the AA2219 material has been obtained through the specimen study. The pattern recognition method is found to be an effective tool for the segregation of the genuine AE signals from the total data. The distinct features of the various AE parameters corresponding to crack growth can be used for evolving a real time AE criterion for the assessment of AA2219 Aluminium alloy components during test.

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