Def Sci J, Vol 40, No 1, January 1990, pp 55-70

Acoustic Emission and Signal Analysis

A.K. Rao

Department of Aerospace Engineering, Indian Institute of Science, Bangalore–560 012

ABSTRACT

Acoustic emission (AE) is one of the most recent entries into the field of nondestructive evaluation. Due to the uniqueness of the basic principle and the potential for tackling a wide range of applications, the technique has gone through rapid strides in a very short time. Thus, today, two decades after the first application of the technique, AE is used in various industries, such as petro-chemical, refinery, nuclear, transportation and aerospace. While, some of the applications can be dealt with by current state-of-the-art, through simple methods of measurement and analysis, the entire potential of the technique still remains to be exploited as extraction of complete information contained in the signal is not possible with the adaption of only simple data analysis procedures. Currently several scientists in many countries are involved in evolving and implementing advanced concepts for AE signal analysis. These along with the approach adopted by us are discussed in this paper.

1. SOME ASPECTS OF ACOUSTIC EMISSION

1.1 The Phenomenon

Acoustic emissions are pressure waves generated due to transient release of energy when a material is subjected to mechanical, thermal or chemical changes causing irreversible deformations or changes in atomic arrangement. Cracking of timber, tin cry, noise generated before rock and mine collapses are some of the examples of acoustic emission (AE) which have been intuitively utilized as warning signals. Local dynamic movements such as initiation and propagation of cracks, twinning, slip dislocation movements, phase transformation, and fusion (welding) are

Received 20 January, 1990

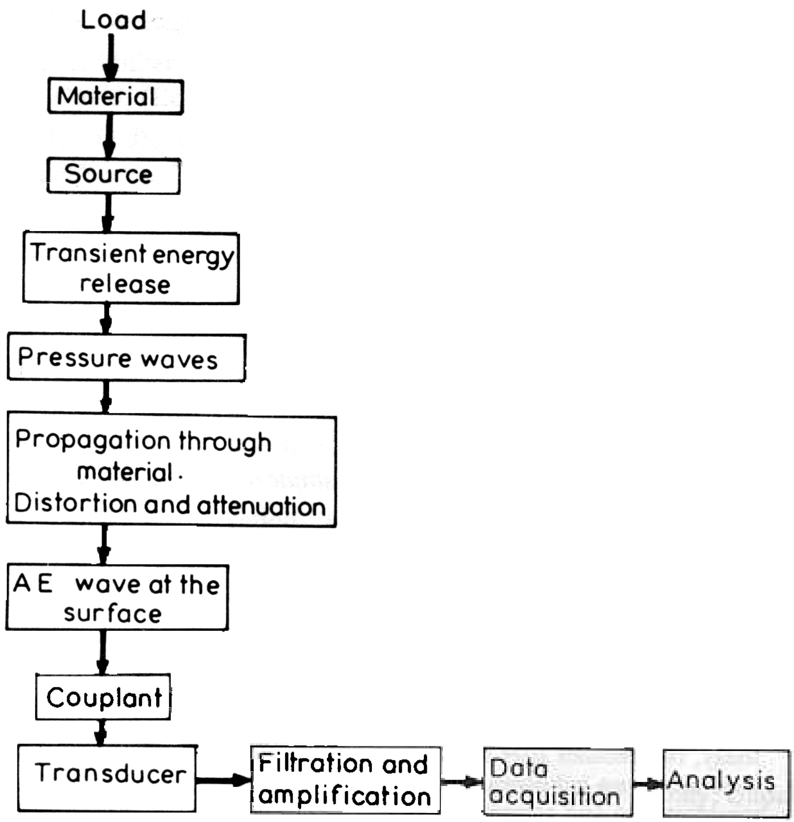

Figure 1. Morphology of AE signals.

typical examples of processes giving rise to AE. The morphology of AE signals is shown in Fig. 1.

The energy released travels as a spherical wavefront and is converted as electrical signal by transducers placed on surface of the material. The volume and characteristics of the AE generated are dependent on the source characteristics, the principal characteristics of the source being its initial severity, current state, local metallurgical structure and current environment. Propagation of the wave through the material is effected by several factors. Macro- and micro-discontinuities and surfaces cause reflections and generation of surface waves. Grain boundaries, inclusion, etc. cause reflection and diffraction. Anisotropic behaviour of the medium causes the wave to propagate with different velocities in different directions and non-ideal elastic behaviour of the medium causes damping and dispersion. Thus the pressure wave that arrives at the transducer is a highly distorted and attenuated version of the source waveform. Further, the transfer functions of the transducer and the couplant between the medium and transducer contribute their own share of distortion. The transducer output is filtered and amplified to eliminate ambient noise and increase the signal-to-noise ratio.

Acoustic emission is of two types: continuous and burst-type. Continuous emission, in general, is of low level and is commonly associated with plastic deformation, grain boundary sliding and dislocation movements in crystal lattices. Some of the common examples of burst-type emissions are crack advancement, twinning, phase transformations (for example, martensite formation in carbon steel). Emissions from a material can contain a combination of both of these two types.

The first scientific investigation of AE phenomenon was reported in 1948 by Shockley *et al.*[1]. First pioneering work using electronic instrumentation was done in 1950 by Joseph Kaiser[2] who observed that AE was an irreversible phenomenon, in that repetitive loading does not lead to repetition of emissions.

The work by Shoefield[3] and Tatro[4] in the mid 1950s did much to improve instrumentation and better understanding of AE sources. However, in this decade very little work was reported. In the early 1960s AE caught the attention of many workers. Significant advancements were made in this decade in AE signal processing and instrumentation which hastened its growth as a viable nondestructive evaluation (NDE) method. First commercial equipment was developed and a number of reports on AE applications appeared[5,6]. In the seventies AE technology enjoyed a vigorous growth and today AE literature spreads over thousands of papers, numerous books and monographs. For quick reference bibliographies with abstracts have been brought out[7]. Special technical publications[5,8] reviews by Lord[6,9], Kanji Ono[10] and Wadley and Scurby[12] are valuable references.

1.2 Applications

The first practical application of AE was during the hydrotesting of Polaris missile chambers. Since then it has gained wide recognition as an active NDE tool. One of the first areas of applications is the study of plastic deformation, crack initiation and extension in materials. Currently, AE is being increasingly used to detect and locate flaws in metallic and composite structures and has emerged as a valuable tool in fracture mechanics studies.

In industry, AE technology is used for testing and monitoring a wide variety of structures and components ranging from simple fluid transmission pipelines to large nuclear pressure vessels. Some of the other industrial applications are loose particle detection, leak testing, weld and drill monitoring and corrosion detection in metals.

In the field of rock mechanics AE has emerged as a useful tool for field studies on geologic structures.

1.3 Typical AE Instrumentation

Typical AE equipment consists of signal detection, data (signal) acquisition, processing and analysis units. Most commonly used AE sensors are piezoelectric transducers. Resonant types are used with narrow band instrumentation and nonresonant types with wide band instrumentation. Transducers based on optical interferometry principle using laser beams are currently under study. The transducer is followed by a preamplifier – amplifier combination giving up to 100 dB total amplification. If filtering is desired it is generally included as an interstage in the preamplifier unit itself. To cater for a wide frequency range of experimentation, AE preamplifiers are generally designed for wide bandwidth.

The signal can be displayed on a cathode ray oscilloscope screen to get a preliminary idea of the activity. To characterise the source mechanism, information contained in the signal can be extracted and interpreted either online or off-line. Different options of AE signal analysis are shown in Fig. 2. For off-line analysis and interpretation, the signals can be recorded on analog magnetic recorders; the advantage being the availability of raw signals for analysis. Alternatively, the data can also be stored on digital recorders after digitization. Currently, a number of microcomputer-based integrated real-time AE monitoring systems are commercially available. These systems have software for signal parameter extraction and distribution analysis.

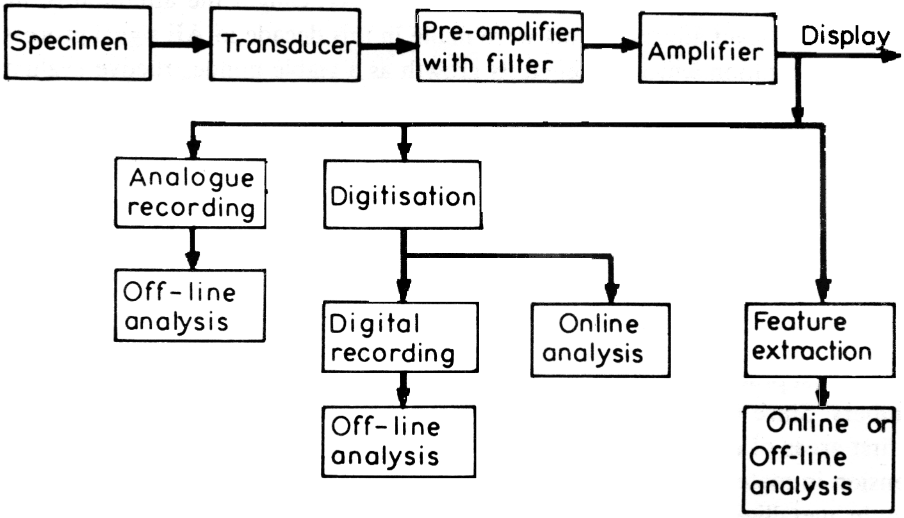

Figure 2. Options for AE analysis systems.

1.4 Signals

Acoustic emission bursts are transient in nature and hence are broad in spectral content. But due to resonances of the transducer and the component, AE signal (transducer output) becomes oscillatory. While a signal due to a burst-type emission event can be approximated by decaying sinusoid (Fig. 3(a)), continuous emission events occur so rapidly that a sustained signal (Fig. 3(b)) is observed. Ambient noises limit measurements in the audio range. On the other hand, attenuation problems are encountered in the higher frequency range. So, the usual frequency range of AE experimentation is in the 100 kHz to 5 MHz band. Within this frequency range for sensitivity and to avoid noise, resonant transducers are utilized in association with narrow band filters (for example, 125 to 250 kHz). However, this approach has the disadvantage of loosing signal content at frequencies other than the considered band. There are certain mechanical and hydraulic noises which have broad spectral content like acoustic emission events. In such cases it is desirable to have wide band operation and determine characteristic spectral features of AE bursts which can be used to discriminate them from noise signals[12].

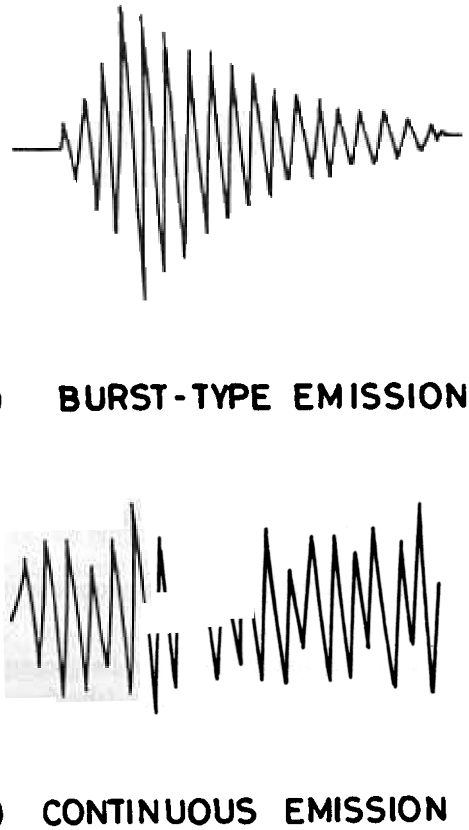

Figure 3. Two types of AE signals.

Figure 4 shows a typical AE signal due to burst-type emission and the parameters commonly used for analysis. These are explained below :

Threshold (V_t) : In burst-type AE, the threshold voltage level V_t is generally set to distinguish signal from noise. An AE event is counted only if the signal crosses the threshold level V_t.

Ring down count (RDC) : Number of times the signal crosses the threshold V_t.

Event duration (ED) : The beginning of an event is marked when the envelope of the signal crosses the threshold V_t and the end is marked when it falls below the threshold. Event duration is the time difference between the beginning and ending of an event.

Peak amplitude (PA) : Highest amplitude attained by signal in an event.

Rise time (RT) : Time taken for signal to reach peak amplitude from the time it first crosses the threshold.

Energy (Ee) : The area under time versus amplitude squared curve for an event.

Fall time (FT) : Difference between the time when peak amplitude occurs and end of event.

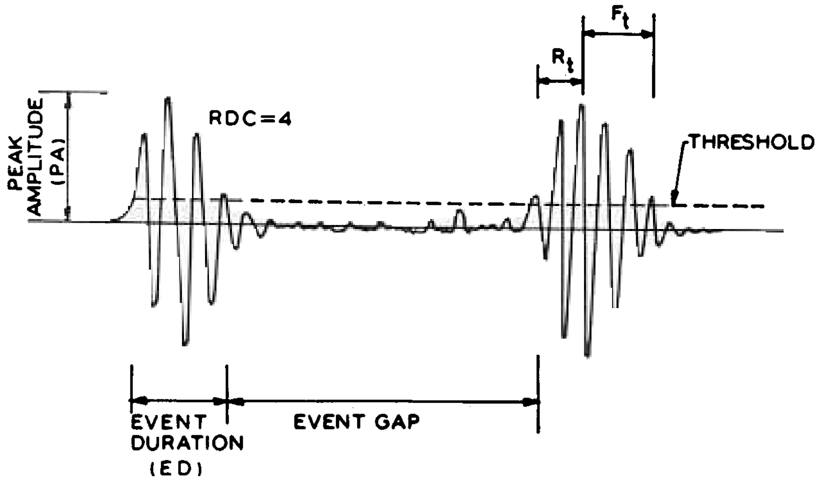

Figure 4. Some AE signal parameters.

Inter event gap : Time between the end of previous event and beginning of current event.

Some frequency domain parameters that can be chosen for analysis are the peak amplitude in the spectrum, dominant frequency (the frequency at which the peak amplitude occurs), energy (the area under the energy density spectrum). Peak amplitudes, dominant frequencies and energies at various sub-bands can also be used as features to study the characteristics of a source.

2. CURRENT METHODS OF SIGNAL ANALYSIS

Some parameters that can be utilised to measure the AE activity were indicated in the previous section. The simplest and most commonly used analysis procedures are estimation of cumulative counts, cumulative events, event and count rates. These kinds of analyses have often been very useful for obtaining warning of impending failures. However, when one is interested in studying the behaviour of a source such as a crack in its early stages, these procedures appear to be deficient[13,14]. In recent times, the random character of AE signals has been well-recognised and statistical methods have found their way into AE signal analysis. These include, signal parametric plots as per event basis with respect to time or load or any other parameter of interest, mean signal parameter plots, distribution plots of each individual signal parameter and distribution plots with respect to time or load. The objective of this type of analysis has been to observe and quantify trends in the individual signal parameters. In the conventional statistical signal analysis language, these are univariate analyses involving a single signal parameter individually and independently. But, if we accept that an AE signal is random in character, a more appropriate approach would be to utilize the information available in each one of the parameters collectively, i.e., to use a multivariate approach than considering a single parameter in its isolation. This is the basis on which we proposed and pursued pattern recognition (PR) in acoustic emission.

An AE signal available for analysis is a distorted version of the source waveform. While the distorted version of the signal, variations in the behaviour of notionally identical sources and statistical aspects of the experimental conditions give a random character to an AE signal, the presence of pseudo AE sources and extraneous noise signals further complicate the situation. Thus in some cases signal recognition itself can become a difficult task. Under these circumstances, the concept of PR which looks for meaningful regularities under otherwise confusing conditions has attracted the attention of some investigators in the AE community.

3. PATTERN CLASSIFICATION OF AE SIGNALS

Pattern recognition by itself is a vast field. Often, the success of using the approach depends upon understanding the data at hand and identifying a suitable method. In the present context, we can start with a formulation that AEs are complaints generated by materials in their own language and suggest the use of syntactic approach for understanding the phenomenon. But, this would be highly involved and too difficult to handle as the basics of the language itself are completely unknown. Thus, we are left with statistical methods, either supervised or unsupervised, the underlying principle being extraction of implicit information from data which has statistical variations and is distorted and noisy. When we focus our attention on the general situations encountered with AE data such as difficulties in generating a training set for analysis, the advantages of unsupervised methods outweigh the supervised methods.

Elsley and Graham[15] first reported the application of PR to AE signal analysis. They used the peak amplitude in each of the seven chosen bands of the frequency spectrum and the time of occurrence of an emission event as features to classify data from bending experiments on graphite epoxy composite coupons. Detection of the inherent classes (clusters) in the emission data was attempted by searching for dense regions, well separated from one another, in the eight-dimensional feature space.

Hutton *et al.*[16] utilized PR to discriminate emission due to crack growth from acoustic noise signals such as rubbing or fretting in fasteners with the objective of automated detection of fatigue crack growth in aircraft structures. Using a combination of time and frequency domain parameters, they compared the performance of commonly used classification techniques like linear discriminant function, empirical Bayes estimation and K-nearest neighbour rule and obtained classification accuracy ranging from 80 to 90 per cent.

Chan *et al.*[17] demonstrated the utility of PR techniques by successful application of K-nearest neighbour rule, empirical Bayesian classification and linear discriminant function for identification of stress corrosion cracking in aluminium, stainless steel and alloy steel. Features were derived from time and frequency domain parameters and statistical properties of the signals.

Michel *et al.*[18] applied the ISODATA algorithm for analysis of acoustic signals generated in sodium-cooled fast breeder reactor. Bae *et al.*[19] also used the ISODATA algorithm to classify AE signals generated during mechanical testing of two types of fibre glass composite materials. They attempted to model the envelope of AE bursts by two different mathematical functions. Parameters obtained through least square fit were used for clustering the data which do not lead to any conclusive results. However, when energies of various sub-frequency bands of 5 MHz width were used as features, four distinct classes resulted.

Chan *et al.*[20] applied linear discriminant function, minimum-distance classification and *K*-nearest neighbour classification for sorting AE signals representing several kinds of welding parameters under controlled shop conditions. Classification experiments were conducted with thirty waveform features, and also with the best features chosen from this set. Results revealed 95 per cent classification accuracy.

Murthy[13] studied the feasibility of PR approach for AE signal classification through several experiments with plain and defective tin and zircalloy specimens. Using a combination of time and frequency domain parameters, a heuristic clustering algorithm was applied to classify signals obtained from a plain specimen and two specimens with different initial crack lengths of tin and zircalloy.

Graham and Elsley[21] used energies in each of the seven chosen frequency bands as detected by a single transducer and the ratios of the energies in these bands as detected by two transducers, as features to classify signals due to fatigue crack growth, crack face rubbing and fretting. They could achieve an accuracy of more than 95 per cent in discriminating fretting against crack growth or crack face rubbing using the ratios of the spectral energies detected by the two transducers. An accuracy of more than 90 per cent was achieved in separating crack growth events from crack face rubbing using spectral energies detected at either transducer separately.

The investigations discussed in the preceeding paragraphs indicate that they are more or less feasibility studies with limited scope. The Bayesian scheme, *K*-nearest neighbour rule and linear discriminant functions used by Hutton *et al.*[16] and Chan *et al.*[17,20] are supervised procedures. These procedures require a sufficiently large set of classified training samples truely representative of the various categories of signals representing different sources. In most of the AE signal classification problems, collection of such a training set is either impossible or impracticable due to the non-availability of *a priori* information regarding the sources of the signals.

The unsupervised procedures (clustering) used by Elsley and Graham[15] are heuristic in nature and for practical AE signal analysis problems the computational requirements of these procedures may turn out to be prohibitive. The minimum-distance classification method[20] suffers from the drawback that its success depends on the choice of characteristic prototypes or cluster centres in the given data set. The ISODATA algorithm used by Michel *et al.*[18] and Bae *et al.*[19] requires a number of process parameters that depend on the knowledge about the category structure of data to be specified. In the absence of such information, the investigator has to experiment with various values of the process parameters to arrive at meaningful results.

4. APPLICATION OF AE IN AIRCRAFT COMPONENT MONITORING

Failure of structural members under the action of fluctuating loads is known as 'fatigue failure'. A fatigue failure begins with a small crack. The crack usually nucleates from a point of discontinuity in the material such as change in cross-section or a hole.

Less obvious points at which fatigue cracks are likely to initiate are irregularities caused due to machining, inclusions, etc. A fatigue crack thus nucleated, can grow to critical size due to fluctuating loads in service leading to catastrophe if it is not detected and attended to at some stage before it becomes critical.

Fatigue crack growth in critical aircraft components like aero engine mountings, wing root attachments, undercarriage mountings, etc. during flight can lead to catastrophic failures. Cause of many fatal accidents in the past has been traced to fatigue crack growth. Even in the recent times, failure of critical aircraft structures due to cracks resulting in fatal accidents are not uncommon. So, there is a vital need to continuously monitor these structures to detect the existence of growing fatigue cracks. This demands a dynamic nondestructive testing (NDT) technique which can continuously monitor critical assemblies and give suitable early warning before a propagating crack reaches the limits of criticality.

Many of the conventional NDT techniques like radiography, eddy current and ultrasonics are unsuited for detection of incipient cracks in some aircraft components because of their poor reliability and the laborious process of scanning the entire structure. For example, a crack present in the bottom face of wing spar can easily go unnoticed when the aircraft is on ground by any of the above mentioned techniques. Moreover, these techniques cannot be used in detecting cracks located in inaccessible locations in aircraft components such as wing root attachments, engine mountings, etc. Naturally a dynamic technique such as AE is the obvious answer. But, certain problems prevent the direct usage of the technique in the current state-of-the-art and preforce further investigations. Currently, some investigators in the area are involved in investigation to address this problem.

A major problem with AE technique in the context of in-flight monitoring of critical aircraft components is that of detecting the true AE activity in the presence of various spurious AE sources such as hydraulic noise, jet engine noise, aerodynamic noise, electromagnetic interference, fretting, crack face rubbing, etc.

4.1 AE Monitoring during Fatigue Crack Growth in an Aero Engine Mount

An aero engine mount, a highly stressed structural member of an aircraft which can be treated for all practical purposes as a typical pin joint is considered for the present investigation. The complete experimental programme was planned and carried out towards a Master of Engineering Project[22,23]. A study was carried out on different types of aero engine mountings pertaining to Dart, Orpheus, RD-OF, R11F, Goblin, AI-20 and Avon engines and a typical engine mount of a jet engine pertaining to a fighter aircraft was chosen for the study. In the present context, though different engine mounts differ in finer design details, most of these can be generalised into simple pin joint type of structures. So, a simple version of the mount was designed keeping in view the overall geometric features. Fine curvature and stepping in the fork end of engine mount were avoided. The simplified engine mount which is in two parts, viz., top bracket and bottom bracket secured by a centre pin is shown in Fig. 5. Thus the problem when brought down to the laboratory scale should consist of two noise sources, fretting (friction between pin and the hole periphery) and crack face

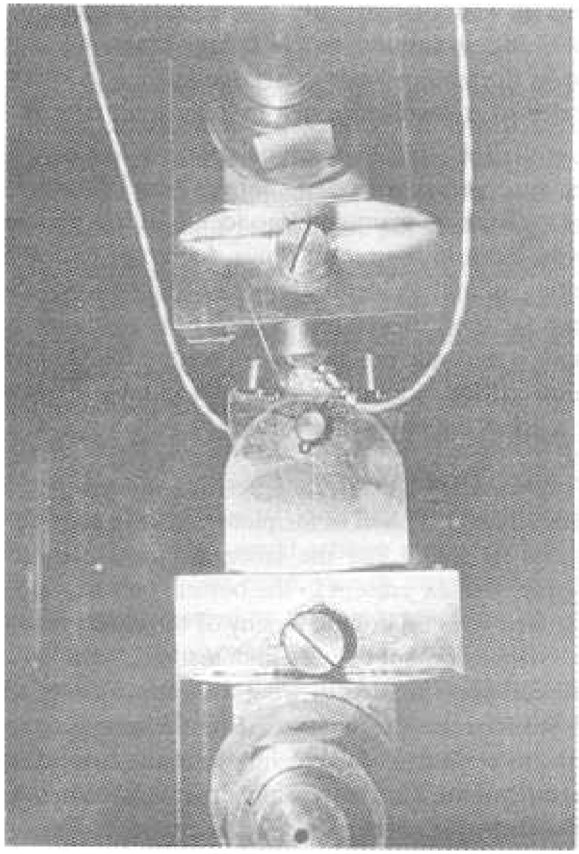

Figure 5. Aero engine mount.

rubbing (rubbing of crack surface due to crack tip plasticity effects), in addition to the true AE activity due to crack growth.

4.2 Experimental Program

Three simulated aero engine mounts were fabricated with EN-24 (SAE 4340) material. To obtain illustrative data for understanding the basic characteristics of the material in relation to AE as well as to decide about the instrument settings, tensile tests were also carried out. Further, the tensile tests also included experiments designed for obtaining fretting data separately. The engine mounts were subjected to constant amplitude fatigue cycling using a servo-hydraulic test system (MTS) (Fig. 6). AE data was picked up by using a 375 kHz resonant transducer, and was recorded on winchester/ floppy diskettes utilising AET-5000 system. The sensors were mounted on opposite faces on the bottom bracket of the engine mount well close to the centre bolt, the likely zone of fatigue crack initiation. Fretting characteristics were obtained from fatigue tests on engine mounts by suppressing the signals due to fretting with the application of grease and use of teflon tape on the pin and noting down the characteristics of the events that were eliminated. Further different load ratios were

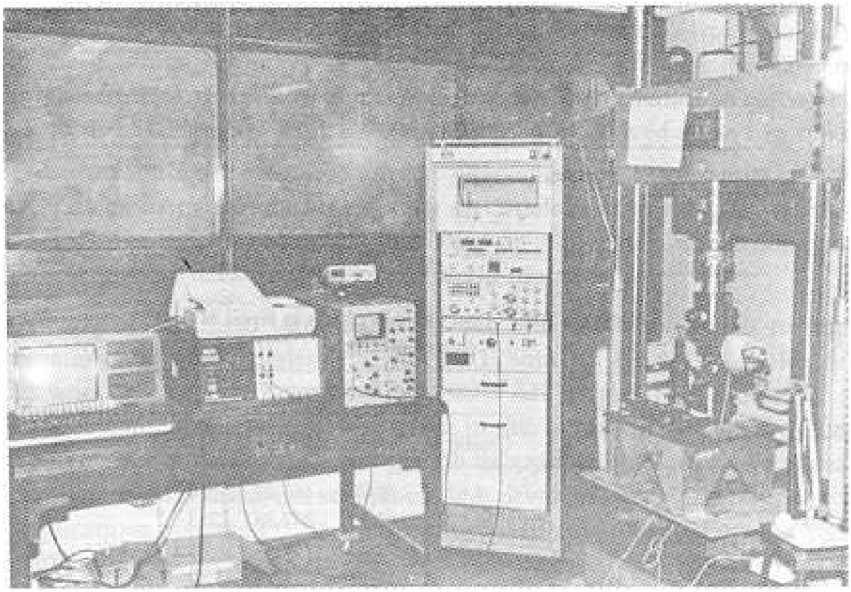

Figure 6. Experimental set-up.

used to obtain conditions of crack propagation and crack face rubbing simultaneously and crack growth alone.

4.3 Classification and Source Characterization

4.3.1 Cluster Analysis of the Data

Each of the above data files was subjected to clustering by threshold-k-means scheme. A four-dimensional pattern vector, with the four time domain parameters RDC, ED, PA and RT as coordinates, was derived from each event data record. Software developed with the city block distance (*l*1 metric) as the similarity measure was used. Number of clusters (k) in each of the data file was assumed to be four corresponding to fretting, crack face rubbing, crack growth and any other possible noise source. The initial threshold for the first stage of the threshold-k-means classifier was computed from the maximum and minimum values of the four chosen features. The results of classification for mounts 14, 17 and 18 are presented in Table 1(a–c) and the results for mounts 11, 12 and 25 are presented in Table 2(a–c).

Table 1(a). Classification results for fretting files

File	Test	No. of events	Classification			
			Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 14	Fretting	1798	1306	394	97	1
Mount 17	-do-	123	113	10	4	1
Mount 18	-do-	1007	945	15	4	43

Table 1(b). Classification results in terms of percentage population of clusters

File	Test	No. of events	Classification %			
			Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 14	Fretting	1798	72.6	21.9	5.4	0.05
Mount 17	-do-	123	91.8	8.1	3.2	0.8
Mount 18	-do-	1007	93.8	1.5	0.4	4.3

Table 1(c). Classification results in terms of cluster centres.

File	Cluster centres			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 14	4.62	20.29	63.23	36
	26.02	166.51	347.88	383
	87.24	92.54	94.27	85
	3.96	11.97	18.77	289
Mount 17	2.84	10.1	9.50	2
	12.92	65.9	117.25	213
	92.58	92.7	97.00	97
	1.42	3.9	1.00	1
Mount 18	2.26	13.06	7.00	6.44
	8.45	104.00	196.25	37.44
	96.07	92.00	97.00	90.95
	1.14	7.53	1.00	4.00

Table 2(a). Classification of events obtained for different tests by the threshold-*k*-means method

File	Test	No. of events	Classification			
			Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 11	Crack propagation	1212	521	408	221	
Mount 12	-do-	1437	808	460	152	17
Mount 25	-do-	981	831	140	9	

Table 2(b). Classification results in terms of percentage population of clusters

File	Test	No. of events	Classification (%)			
			Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 11	Crack propagation	1212	43.2	33.6	18.2	5.00
Mount 12	-do-	1437	56.2	32.2	10.5	1.10
Mount 25	-do-	981	84.7	14.2	0.9	0.10

Table 2(c). Classification results in terms of cluster centres

File	Cluster centres			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 11	2.32	15.84	43.15	93.00
	15.86	102.74	226.82	442.34
	77.73	88.41	89.97	95.90
	5.18	11.26	23.61	25.86
Mount 12	3.07	12.96	29.95	70.11
	21.40	95.85	208.25	443.35
	89.98	92.28	90.15	96.70
	5.15	13.86	33.00	13.17
Mount 25	4.40	16.56	43.88	36
	20.70	120.75	421.88	496
	88.41	90.65	92.55	83
	3.40	13.35	32.11	473

4.4 Discussion of Results

The results of the classification carried out on different files can be discussed by dividing them into two categories. The first category consists of files (mounts 14, 17 and 18) which have fretting as the major source. The second category consists of files (mounts 11, 12 and 25) have data recorded during crack growth and so the events generated are due to all the three sources namely fretting, crack growth and crack face rubbing.

To start with, let us take a close look at the first category (Table 1(a–c) to obtain the characteristics of fretting in terms of event parameters. The first file (mount 14) consists of a total of 1798 points. Out of these 1306 have been classified as one cluster which is the most dominant with the cluster centre having the parameter values as RDC = 4.62, ED = 26.02, PA = 87.24 and RT = 3.96. As can also be observed from the table, the second dominant cluster has 394 points with different parameter values. The other two clusters have insignificant number of points. In view of the controlled conditions set up for the experiment, we should have had only one cluster. But the second cluster has 394 points with different characteristics. This may be due to a set of events belonging to fretting which have slightly different characteristics or events which have entered the data due to an unknown source such as noise. So, for all practical purposes we can consider the classification to have yielded one cluster with the fretting characteristics.

Further examination of the most dominant clusters obtained for mounts 17 and 18 indicate that they are very similar to the most dominant cluster obtained for mount 14. So, these clusters can be reasonably identified with the fretting events. In other words, the characteristic parameter vector for fretting can be represented as the mean of the first cluster centres of all the three files (mounts 14, 17 and 18). Thus the representative values of the parameters for fretting are RDC = 3.59, ED = 18.37,

Table 2(c). Classification results in terms of cluster centres

File	Cluster centres			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mount 11	2.32	15.84	43.15	93.00
	15.86	102.74	226.82	442.34
	77.73	88.41	89.97	95.90
	5.18	11.26	23.61	25.86
Mount 12	3.07	12.96	29.95	70.11
	21.40	95.85	208.25	443.35
	89.98	92.28	90.15	96.70
	5.15	13.86	33.00	13.17
Mount 25	4.40	16.56	43.88	36
	20.70	120.75	421.88	496
	88.41	90.65	92.55	83
	3.40	13.35	32.11	473

4.4 Discussion of Results

The results of the classification carried out on different files can be discussed by dividing them into two categories. The first category consists of files (mounts 14, 17 and 18) which have fretting as the major source. The second category consists of files (mounts 11, 12 and 25) have data recorded during crack growth and so the events generated are due to all the three sources namely fretting, crack growth and crack face rubbing.

To start with, let us take a close look at the first category (Table 1(a–c) to obtain the characteristics of fretting in terms of event parameters. The first file (mount 14) consists of a total of 1798 points. Out of these 1306 have been classified as one cluster which is the most dominant with the cluster centre having the parameter values as RDC = 4.62, ED = 26.02, PA = 87.24 and RT = 3.96. As can also be observed from the table, the second dominant cluster has 394 points with different parameter values. The other two clusters have insignificant number of points. In view of the controlled conditions set up for the experiment, we should have had only one cluster. But the second cluster has 394 points with different characteristics. This may be due to a set of events belonging to fretting which have slightly different characteristics or events which have entered the data due to an unknown source such as noise. So, for all practical purposes we can consider the classification to have yielded one cluster with the fretting characteristics.

Further examination of the most dominant clusters obtained for mounts 17 and 18 indicate that they are very similar to the most dominant cluster obtained for mount 14. So, these clusters can be reasonably identified with the fretting events. In other words, the characteristic parameter vector for fretting can be represented as the mean of the first cluster centres of all the three files (mounts 14, 17 and 18). Thus the representative values of the parameters for fretting are RDC = 3.59, ED = 18.37, PA = 91.02 and RT = 2.71 which can be used to identify the other two sources, viz., crack growth and crack face rubbing. The centre of the fourth cluster for mount 18 with 43 points seems to be resembling the fretting events except for a slightly higher value of ED. Since the procedure has been implemented for $k = 4$, it is highly probable that this cluster has resulted because of split of the first cluster (representing fretting events).

The second set of files (mounts 11, 12 and 25) represents data collected during crack growth. The results of classification are shown in Table 2(a–c). The first important feature that can be noticed in this set is that each file has more than one significant cluster. Out of these, the characteristic features (cluster centres in Table 2(c)) of the first cluster are identical to the fretting features obtained in the previous section and can be identified as events due to fretting. Thus, we are left with two significant clusters for identifying the other two sources, viz., crack growth and crack face rubbing. Out of these, cluster 2 for all the three files is very similar to one another in all the four parameters. In other words, these cluster centres are very near to each other in the four-dimensional feature space and the events represented by them can be attributed to the same category, crack growth or crack face rubbing. Similarly, cluster 3 for mounts 11 and 12 seems to be representing the same category of events. But, cluster 3 for mount 25 seems to be quite distinct. However, it has insignificant number of points (less than 1 per cent of the total number).

5. CONCLUSIONS

Acoustic emission is a highly potential NDE tool which can cover a wide range of applications. Methods and techniques have been established over the past few years to locate and evaluate defects in relatively simple situations. But, its successful utilization in areas like in-flight monitoring still poses problems. This is primarily due to deficiencies in AE signal analysis in the current state-of-the-art. Presently used signal analysis techniques like the one-dimensional histogram analysis of the signal parameters and study of cumulative activity are of limited use in complex situations like in-flight monitoring where a major problem is to identify true AE activity due to sources such as crack growth in the midst of various AE-like noises. The present study indicated that this problem can be tackled through pattern recognition.

We attempted a practical application by classifying data taken from carefully designed experiments in the laboratory oriented towards in-flight monitoring. The data could not only be successfully classified but the characteristic features of each of the individual sources also emerged out very clearly.

ACKNOWLEDGEMENTS

The studies at the Indian Institute of Science reported here have been carried out by the author's co-workers, Dr. C.R.L. Murthy, Mr. M.A. Majeed and Mr. M.R. Bhat in particular. The experimental work by the group presented here, has been carried out under a research grant by the Structures Panel of the AR&DB, for the project 'Acoustic Emission Techniques for Structural Integrity Evaluation and Inspection (ANT)'.

18. Michel, V., Bernard, D. & Max, B., Pattern recognition techniques in sodium cooled fast breeder reactor's acoustic signal analysis, Proceedings of the IEEE Conference on Pattern Recognition, 1980.

19. Bae, P., Chaari, A., Gaillard, P. & Chretien, J.F., Pattern recognition techniques for characterisation and classification of acoustic emission signals, Proceedings of the IEEE Conference on Pattern Recognition, 1980.

20. Chan, R.W.Y., Hay Robert, D., Victor Caron, Hone, Michel & Sharp Douglas, R., *Journal of Acoustic Emission,* **4** (4), (1985), 115-123.

21. Graham, L.J. & Elsley, R.K., *Journal of Acoustic Emission,* **2** (2), (1983).

22. Pathak, S.C. & Murthy, C.R.L., *Journal of Acoustic Emission,* **4** (2/3), (1985), 532-534.

23. Pathak, S.C., Acoustic Emission Studies for Detection and Monitoring Incipient Cracks in Simulated Aero Engine Mount Under Fatigue, ME Project Report, (Dept. of Aerospace Engg., Indian Institute of Science, Bangalore), 1985.