# Defect Characterisation of GFRP Cross Ply Laminates using Artificial Neural Networks

M. K. Karthik, S. Sivaraman
Assistant Professor,
Department of Aeronautical Engineering,
Hindusthan College of Engg & Technology,
Coimbatore.

P. Balaguru
Assistant Professor,
Department of Aeronautical Engineering,
Raja Lakshmi Engineering College,
Chennai

R. Prabu
Assistant Professor,
Department of Aeronautical Engineering,
KCG College of Technology,
Chennai

***Abstract*— An experimental work has been carried out to characterise the defects of post impacted Glass/Epoxy composite laminates using online acoustic emission (AE) monitoring and artificial neural networks (ANN). The laminates were made from ten-layered glass fibre (200 MIL cloth) with epoxy as the binding medium by hand lay-up technique and cured at a pressure of 100 kg/cm2 under room temperature using a 30 ton capacity compression moulding machine for 24 hours. 25 test specimens (ASTM D3039 standard) were prepared from the cross-ply laminates using water jet cutting machine. 21 specimens were subjected to impact load from three different heights using CEAST Fractovis Drop Impact machine. Both impacted and non-impacted specimens were subjected to uniaxial tension under the acoustic emission monitoring using 30 kN INSTRON 3367 universal testing machine. The dominant AE parameters such as counts, energy, duration, rise time and amplitude are recorded during monitoring. These AE parameters are then used to characterise the defects in composite materials using Fuzzy C-means clustering algorithm associated with Principal Component Analysis. Artificial Neural Network technique is used in the process of getting the results. The acquired results can be used for online health monitoring through which failure of composite components can be identified at the initial stages.**

***Keywords*— Acoustic emission monitoring, artificial neural network, Fuzzy C means clustering, principal component analysis, online health monitoring, Glass/Epoxy, Cross-Ply laminates.***

## 1. INTRODUCTION

Glass Fiber Reinforced Polymer (GFRP) laminates are widely for aerospace applications because of their high strength to weight ratio and corrosion resistance. However one of the major limitations is the effect of impact damage which leads to multiple level delamination through the thickness. To prevent the material from failing structurally we have to identify the defects at earlier stages itself.

Acoustic Emission (AE) [4] can be used a tool for the evaluation of damages in fiber reinforced composites. AE cannot be considered as a non-destructive testing method strictly, because the changes which occur during AE are mostly irreversible. In conventional AE investigation, various AE parameters are analyzed directly as a plot of two or three AE parameters, which is not sufficient for composite materials.

Artificial Neural Network (ANN) [1] analogous to biological neural system is an adaptive computer program which provides solutions to problems like complex data collections. In this approach relationship between input and output parameters are developed through a training process in which sets of inputs are applied to the network and the resulting outputs are compared with the known results. ANN's are trained using either supervised or unsupervised learning models. The trained networks are used to predict the output that would result from a set of inputs which are not included in the training data.

The major challenge with data analysis is the discrimination between the different acoustic emission sources. The objective of the cluster analysis is to separate a set of data into several classes that reflect the internal structure of the data. Indeed, cluster analysis is an important tool for investigating and interpreting data.

In order to improve the cluster analysis process, fuzzy c-means clustering associated with a principal component analysis are proposed in this paper. The fuzzy c-means clustering method (FCM) is an effective unsupervised algorithm for automatic clustering and separating AE patterns composed of multiple features extracted from the random AE waveforms. The five descriptors used are the energy, amplitude, rise time, counts and duration of the AE signals. FCM is applied to the above data and the damage mechanisms[7] such as matrix cracking, fiber matrix debonding and delamination signals.

## 2. PREPARATION OF TEST SPECIMENS

Uni-directional glass fibers (S-Class) of dimension 300x300 mm are cut from the big roll.10 such glass fibers are required for preparing a GFRP laminate. The weight of all the 10 glass fibers is measured using an electronic weighing machine. Epoxy resin equal in weight to that of fiber is weighed and taken separately. The hardener is added to the resin in the ratio of 1:10. The epoxy resin mixture is then mixed thoroughly.

Place the mould on the table. Apply a thin layer of resin on the surface of the lower mould. Next place the first layer of glass and use rollers to squeeze the excess resin. Apply resin over the first layer of glass and place then place the second glass layer and again use the rollers to squeeze the excess resin.

Repeat the procedure with alternating layers of glass fiber and resin mixture until all the 10 layers of glass fibers are finished. Place the upper mould over the lower mould and the mould is closed. The mould is placed in the compression moulding machine and cured at a pressure of 100 bar for 24 hours.

Fig.1 GFRP Cross ply laminate after curing from Compression Moulding Machine

The GFRP cross ply laminate will be having a thickness of about 1.8mm. 25 test specimens were cut from the laminate using water jet cutting machine according to ASTM D3039 standard.

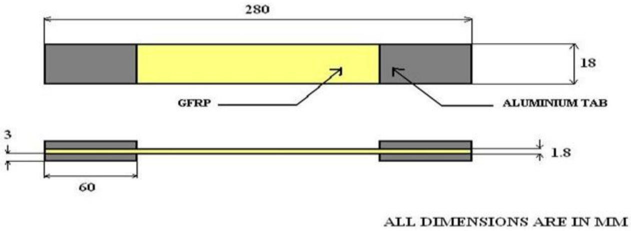


Fig.2 ASTM D3039 Standard

## 3. INTRODUCTION OF IMPACT DAMAGE IN SPECIMEN

The specimens prepared from the laminates are grouped into three groups of seven specimens each. Each group of specimens was subjected to impact[5],[6] using CEAST Fractovis drop impact machine from three different heights of 75mm, 100mm and 125mm respectively. The parameters used during the impact process are: Clamping force – 1000 N, Impactor Striker mass – 1.926 kg, Impactor diameter – 12.7mm. The remaining specimens are kept without impact damage.

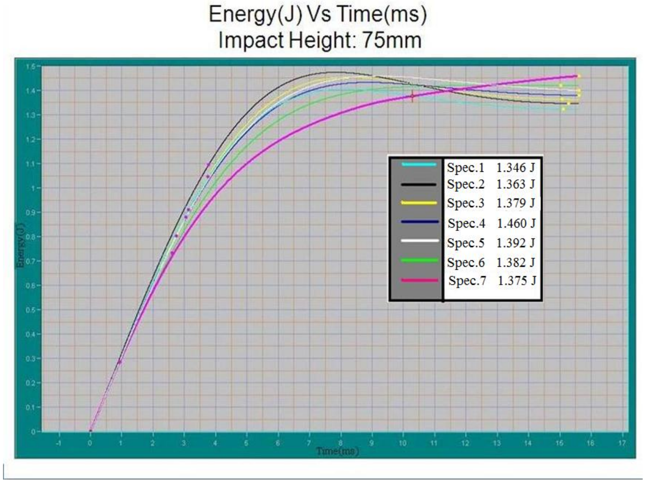


Fig.3 Impact Energy Vs. time

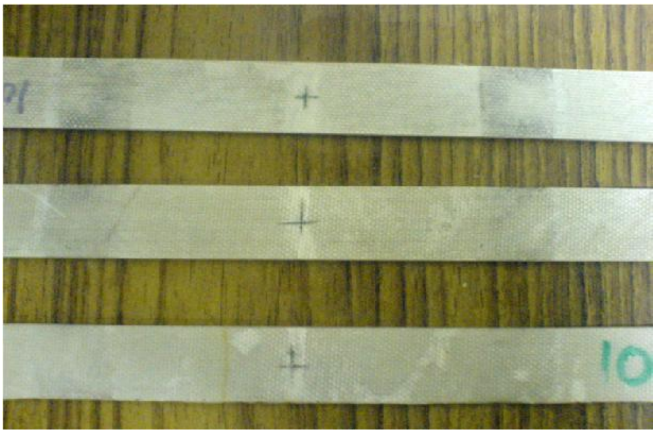

Fig.4 Post impacted specimen

## 4. EXPERIMENTAL PROCEDURE FOR TESTING

The impacted specimens are then subjected to uni-axial tension using 30kN INSTRON 3367 Universal Testing Machine under acoustic emission monitoring. The parameters used for the tensile loading process are: cross head speed – 0.1mm/min, sampling rate – 30pts/min. Aluminum tabs [2] are placed at the ends to provide grip as well for noise reduction during AE monitoring.

## 5. DATA ACQUISITION USING AE

When the structure is loaded transient elastic waves are generated due to the rapid release of strain energy within the materials called as acoustic emission. These acoustic emission has various characteristics such as amplitude, rise time, duration, energy, counts, counts to peak, threshold. These characteristics are recorded and used for analysis purpose. An

8-channel acoustic emission setup along with SAMOS E3.10 data acquisition system supplied by physical acoustic corporation was used. AE measurement were made using two

Nano 30 PAC sensors attached to the specimen through high vacuum grease couplant. The signals from the transducer are then passed through PAC 2/4/6 G/A pre-amplifier before reaching the main unit. The input parameters[9] used for AE monitoring are: peak definition time (PDT) – 30µs, hit definition time (HDT) - 300µs , hit lock-out time (HLT) - 600µs. AE wave velocity was found as 3149523.8 m/s by Hsu-Nielson source (pencil lead break test).

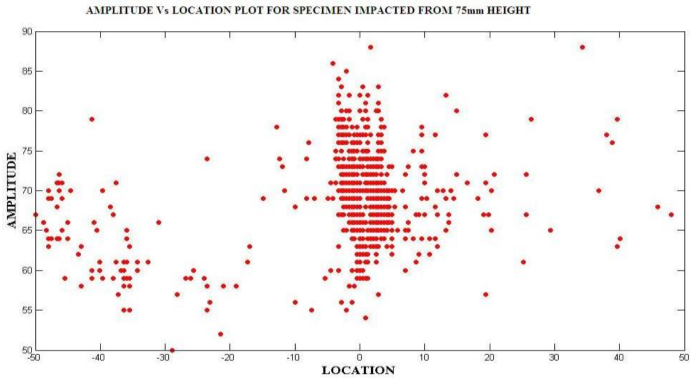


Fig.5 Amplitude Vs Location Plot for the specimen impacted from 75mm height

## 6. CLUSTERING USING ANN

### *6.1 Multivariable Data Clustering:*

Acoustic Emission Signals are used for the investigation of local damage in composite materials. The problem in the analysis of the AE signals is to identify the most critical damage mechanisms. The unsupervised pattern recognition analysis [8] associated with a principal component analysis is a tool that is used for the classification of the monitored AE events. A cluster analysis of the AE data is achieved and the resulting clusters are correlated to the damage mechanisms of the material under investigation.

Different damage mechanisms have been identified on fiber – matrix composite materials from their AE signals. According to the previous studies, the damage mechanisms that are considered according to the collected AE signals are matrix cracking, fiber cut, and delamination signals. Since there are three damage mechanisms that occur within the composites, the classification to make is considered as a three – class problem.

Fuzzy c-means clustering method is thus applied with three clusters. The five descriptors used are the rise time, count, energy, duration, amplitude. Next Principal component analysis is achieved in order to visualize the results in a two – dimension subspace.

### *6.2 Principal Component Analysis*

One of the difficulties in multivariate statistics is the problem of visualizing data that has many variables. Principal Component Analysis is a quantitatively rigorous method for achieving this simplification. The method generates a new set of variables, called principal components [3]. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components as a whole form an orthogonal basis for the space of the data.

The first principal component is a single axis in space. When you project each observation on that axis, the resulting values form a new variable. And the variance of this variable is the maximum among all possible choice of the first axis. The Second principal component is another axis in space, perpendicular to the first. Projecting the observations on this axis generates another new variable. The variance of this variable is the maximum among all possible choices of this second axis.

The full set of principal components is as large as the original set of variables. But it is commonplace for the sum of the variances of the first few principal components to exceed 80% of the total variance of the original data.

### *6.3 Fuzzy C-Means Clustering*

Fuzzy C-means clustering algorithm divides out an input data among a pre-defined number k of classes. The classification criterion is then the minimization of the sum of the squared distances between all the descriptor vectors of a cluster and its center. At the beginning, the coordinates of the cluster centres are initialized and each descriptor vector is assigned to the cluster whose center is the closest.

Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek in 1981 as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters.

The fuzzy logic starts with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster. The initial guess for these cluster centers is most likely incorrect. Additionally it assigns every data point a membership grade for each cluster. By iteratively updating the cluster centers and membership grades for each point, it iteratively moves the cluster centers to the right location within a data set. The iteration is based on minimizing an objective function that represents the distance from any given data point into a cluster center weighted by that data point's membership grade.

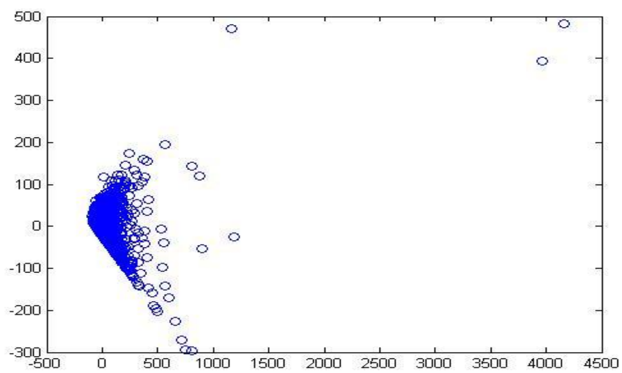


Fig.6 Plot between first and second principal components.

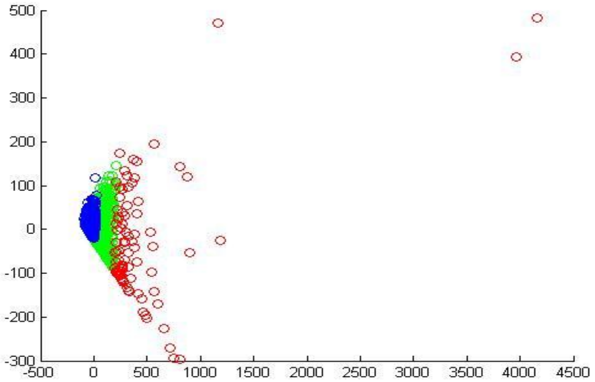


Fig.7 Plot showing the clusters formed using fuzzy c-means clustering

## 7. RESULTS AND DISCUSSION

### 7.1 Impact test results:

Impact test was done using CEAST Fractovis Drop Impact machine at various height and the impact energy for each height is tabulated below,

| IMPACT ENERGY (J) | | | |
|---|---|---|---|
| Spec. No | Impact Energy (J) | Spec. No | Impact Energy (J) |
| 75_2 | 1.346 | 100_5 | 1.838 |
| 75_3 | 1.363 | 100_8 | 1.922 |
| 75_4 | 1.379 | 100_9 | 1.795 |
| 75_8 | 1.460 | 125_2 | 2.15 |
| 75_9 | 1.392 | 125_5 | 2.21 |
| 75_10 | 1.382 | 125_6 | 2.25 |
| 75_11 | 1.375 | 125_7 | 2.25 |
| 100_1 | 1.729 | 125_8 | 2.26 |
| 100_2 | 1.757 | 125_10 | 2.39 |
| 100_3 | 1.826 | 125_11 | 2.31 |
| 100_4 | 1.838 | | |

Table1. Impact Energy Results

### *7.2 Tensile test results:*

The impacted specimens are then subjected to uni axial tensile load using INSTRON 3367 Universal Testing Machine and the failure loads of all the specimens are tabulated below,

| FAILURE LOAD (kN) | | | |
|---|---|---|---|
| Spec. No | Failure Load | Spec. No | Failure Load |
| 75mm2_2 | 3.386 | 100mm5_5 | 2.976 |
| 75mm3_3 | 3.692 | 100mm8_8 | 3.197 |
| 75mm 4_4 | 3.847 | 100mm9_9 | 2.719 |
| 75mm 8_8 | 3.426 | 125mm2_2 | 2.213 |
| 75mm 9_9 | 3.591 | 125mm5_5 | 1.895 |
| 75mm 10_10 | 3.562 | 125mm6_6 | 1.808 |
| 75mm 11_11 | 3.779 | 125mm7_7 | 1.975 |
| 100mm1_1 | 3.042 | 125mm8_8 | 2.215 |
| 100mm2_2 | 2.728 | 125mm10_10 | 1.728 |
| 100mm3_3 | 2.899 | 125mm11_11 | 2.285 |
| 100mm4_4 | 3.118 | | |

Table2. Tensile Failure Loads

### *7.3 AE Data Acquisition results*

During Tensile test, AE setup was used for data acquisition of various AE parameters such as Amplitude, Duration, Rise time, Energy, Counts etc., The AE data obtained during the test should be then clustered and sorted into three different groups, each group representing the failure mechanism of composite. The following tables represent the total number of events recorded during each test and the clustered data representing the failure mechanisms.

| EVENT DATA HISTORY | | | | |
|---|---|---|---|---|
| Spec. No | TOTAL EVENTS | CLASS-I | CLASS-II | CLASS-III |
| 75_2 | 4084 | 3342 | 705 | 37 |
| 75_3 | 7256 | 6582 | 626 | 48 |
| 75_4 | 1958 | 1720 | 232 | 6 |
| 75_8 | 2690 | 2676 | 13 | 1 |
| 75_9 | 4194 | 3375 | 774 | 45 |
| 75_10 | 3338 | 3018 | 312 | 8 |
| 75_11 | 6932 | 6803 | 124 | 1 |
| 100_1 | 8128 | 5627 | 2414 | 87 |
| 100_2 | 11868 | 11737 | 123 | 8 |
| 100_3 | 3918 | 2907 | 974 | 37 |
| 100_4 | 3866 | 3864 | 1 | 1 |
| 100_5 | 7076 | 6982 | 92 | 2 |
| 100_8 | 2340 | 2336 | 3 | 1 |
| 100_9 | 9334 | 7963 | 1281 | 103 |
| 125_2 | 16323 | 15376 | 946 | 1 |
| 125_5 | 4566 | 2951 | 1552 | 63 |
| 125_6 | 4658 | 3510 | 1098 | 50 |
| 125_7 | 12707 | 12680 | 24 | 3 |
| 125_8 | 7776 | 7752 | 23 | 1 |
| 125_10 | 3398 | 2614 | 698 | 86 |
| 125_11 | 3922 | 3913 | 8 | 1 |

Table3. AE Date Acquisition

### *7.4 Cluster Analysis results:*

Cluster analysis is performed to group the acquired AE data into different clusters. Once the AE data are clustered, then the various AE parameters are analyzed and their ranges are tabulated which are given in the tabular column listed below,

| AE PARAMETER RANGE OF CLASS-I SIGNALS: | | | | | | |
|---|---|---|---|---|---|---|
| Spec. No | TOTAL EVENT | RISE | COUNT | ENERGY | DURATION | AMP |
| 75_2 | 354 | 1-268 | 20-107 | 1-46 | 74-474 | 51-79 |
| 75_3 | 6582 | 1-149 | 20-48 | 2-45 | 68-197 | 52-86 |
| 75_4 | 1720 | 1-121 | 20-53 | 2-39 | 73-203 | 50-84 |
| 75_8 | 2676 | 1-587 | 20-179 | 2-84 | 61-960 | 54-85 |
| 75_9 | 3375 | 1-99 | 20-47 | 2-41 | 75-175 | 52-85 |
| 75_10 | 3018 | 1-247 | 20-64 | 2-51 | 79-271 | 54-85 |
| 75_11 | 6803 | 1-270 | 20-193 | 2-94 | 65-1210 | 51-86 |
| 100_1 | 8128 | 1-136 | 20-41 | 2-47 | 66-167 | 54-86 |
| 100_2 | 11868 | 1-1293 | 20-610 | 2-183 | 63-3197 | 51-95 |
| 100_3 | 3918 | 1-119 | 20-40 | 2-34 | 69-167 | 53-84 |
| 100_4 | 3866 | 1-642 | 20-721 | 2-735 | 69-3134 | 53-91 |
| 100_5 | 7076 | 1-396 | 20-74 | 2-161 | 68-405 | 52-93 |
| 100_8 | 2340 | 1-775 | 20-279 | 2-156 | 78-1565 | 52-81 |
| 100_9 | 9334 | 1-161 | 20-47 | 2-29 | 69-182 | 53-80 |
| 125_2 | 16323 | 1-145 | 20-638 | 2-387 | 59-3063 | 53-86 |
| 125_5 | 4566 | 1-95 | 20-38 | 2-27 | 61-151 | 56-82 |
| 125_6 | 4658 | 1-108 | 20-41 | 2-38 | 71-175 | 57-86 |
| 125_7 | 12707 | 1-713 | 20-189 | 2-313 | 60-1030 | 51-95 |
| 125_8 | 7776 | 1-651 | 20-216 | 2-207 | 64-1232 | 52-94 |
| 125_10 | 3398 | 1-582 | 20-176 | 2-58 | 63-941 | 54-83 |
| 125_11 | 3922 | 1-558 | 20-354 | 2-220 | 73-1904 | 54-89 |

Table4. Clustering for Class-1 signals

| AE PARAMETER RANGE OF CLASS-II SIGNALS: | | | | | | |
|---|---|---|---|---|---|---|
| Spec. No | TOTAL EVENT | RISE | COUNT | ENERGY | DURATION | AMP |
| 75_2 | 13 | 11-1153 | 99-313 | 22-134 | 509-1554 | 65-82 |
| 75_3 | 626 | 1-306 | 22-143 | 3-141 | 176-614 | 53-95 |
| 75_4 | 232 | 1-426 | 25-208 | 4-197 | 184-884 | 53-88 |
| 75_8 | 13 | 4-1861 | 146-611 | 29-337 | 973-3099 | 64-87 |
| 75_9 | 774 | 1-242 | 20-90 | 3-84 | 163-436 | 52-91 |
| 75_10 | 312 | 1-723 | 24-235 | 4-137 | 242-1236 | 55-88 |
| 75_11 | 124 | 1-1852 | 41-626 | 7-439 | 344-3199 | 55-90 |
| 100_1 | 2414 | 1-228 | 20-79 | 3-96 | 161-356 | 53-90 |
| 100_2 | 123 | 1-1799 | 94-611 | 16-1381 | 581-2892 | 60-99 |
| 100_3 | 974 | 1-317 | 20-86 | 3-209 | 163-515 | 53-94 |
| 100_4 | 1 | 3914 | 4175 | 357 | 20614 | 94 |
| 100_5 | 92 | 1-1146 | 46-413 | 11-386 | 346-1922 | 62-98 |
| 100_8 | 3 | 1378-1645 | 587-1380 | 232-892 | 3322-7625 | 71-90 |
| 100_9 | 1281 | 1-224 | 21-94 | 3-92 | 170-453 | 55-88 |
| 125_2 | 946 | 1-3038 | 21-1172 | 4-653 | 182-6260 | 56-94 |
| 125_5 | 1552 | 1-172 | 20-89 | 4-231 | 146-377 | 58-99 |
| 125_6 | 1098 | 1-198 | 20-91 | 5-152 | 167-398 | 61-93 |
| 125_7 | 24 | 44-8902 | 147-2261 | 34-1562 | 1053-11232 | 62-99 |
| 125_8 | 23 | 125-3832 | 196-906 | 85-857 | 1370-4757 | 67-99 |
| 125_10 | 698 | 1-159 | 20-64 | 3-57 | 151-334 | 55-85 |
| 125_11 | 8 | 408-3198 | 423-1234 | 194-1156 | 2080-6003 | 75-89 |

Table5. Clustering for Class-2 signals

| AE PARAMETER RANGE OF CLASS-III SIGNALS: | | | | | | |
|---|---|---|---|---|---|---|
| Spec. No | TOTAL EVENT | RISE | COUNT | ENERGY | DURATION | AMP |
| 75_2 | 1 | 3534 | 1399 | 347 | 6093 | 99 |
| 75_3 | 48 | 1-2451 | 74-827 | 18-445 | 626-4371 | 61-90 |
| 75_4 | 6 | 7-917 | 87-309 | 23-336 | 836-1587 | 64-86 |
| 75_8 | 1 | 3977 | 8164 | 5521 | 37650 | 98 |
| 75_9 | 45 | 4-1507 | 36-411 | 9-249 | 399-1992 | 57-89 |
| 75_10 | 8 | 2-1700 | 251-755 | 55-650 | 1765-3342 | 70-88 |
| 75_11 | 1 | 875 | 4402 | 16668 | 20003 | 99 |
| 100_1 | 87 | 1-1916 | 33-753 | 7-980 | 321-3759 | 58-98 |
| 100_2 | 8 | 449-3676 | 809-2048 | 306-2430 | 4068-8331 | 78-99 |
| 100_3 | 37 | 3-695 | 64-268 | 16-434 | 495-1456 | 60-93 |
| 100_4 | 1 | 7676 | 12534 | 59731 | 55511 | 99 |
| 100_5 | 2 | 2742-2920 | 3583-4590 | 9546-13911 | 17274-21423 | 99 |
| 100_8 | 1 | 210 | 4603 | 12446 | 25162 | 99 |
| 100_9 | 103 | 1-1300 | 45-824 | 12-259 | 399-4628 | 63-88 |
| 125_2 | 1 | 9538 | 6849 | 30456 | 29851 | 99 |
| 125_5 | 63 | 1-864 | 55-586 | 26-513 | 355-2429 | 66-99 |
| 125_6 | 50 | 1-567 | 45-379 | 14-700 | 361-1775 | 67-92 |
| 125_7 | 3 | 1680-8259 | 8513-14070 | 3497-25678 | 38737-59937 | 82-99 |
| 125_8 | 1 | 2576 | 3646 | 2220 | 17309 | 98 |
| 125_10 | 86 | 2-550 | 28-239 | 11-113 | 313-1379 | 62-86 |
| 125_11 | 1 | 9943 | 7739 | 30357 | 34005 | 99 |

Table6. Clustering for Class-3 signals

*7.5 Defect Characterization results:*

After performing cluster analysis on the data acquired using Acoustic emission monitoring system during the tensile test performed on the specimen impacted at various energy levels, we obtain three different classes of signals [10] which can be distinguished from each other with the help of AE parameters like, Rise time, Count Energy, Duration and Amplitude. The summary of cluster analysis is given below,

| TYPES OF SIGNAL | AE PARAMETERS | | | | |
|---|---|---|---|---|---|
| | RISE | COUNT | ENERGY | DUR | AMP |
| CLASS-I | 1 – 120 | 20 – 50 | 2 – 45 | 68 – 203 | 52 – 85 |
| | 1 – 600 | 20 – 200 | 2 – 200 | 65 – 1500 | 51 – 90 |
| CLASS-II | 1 – 200 | 20 – 100 | 3 – 125 | 150 – 450 | 55 – 90 |
| | 1 – 2500 | 100 – 1200 | 50 – 1000 | 500 – 6000 | 60 – 100 |
| CLASS-III | 1 – 1000 | 55 – 850 | 18 – 500 | 350 – 4500 | 65 – 90 |
| | >2500 | >6000 | >10000 | >25000 | >99 |

Table7. Defect Characterization Results

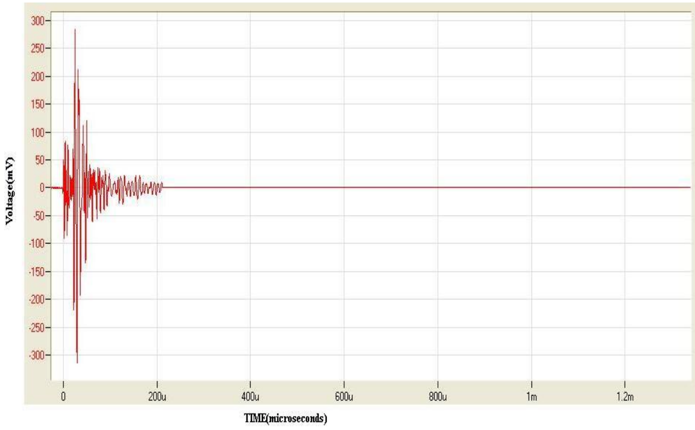


Fig.8 AE Characteristic Signal for Matrix Cracking Failure mode.

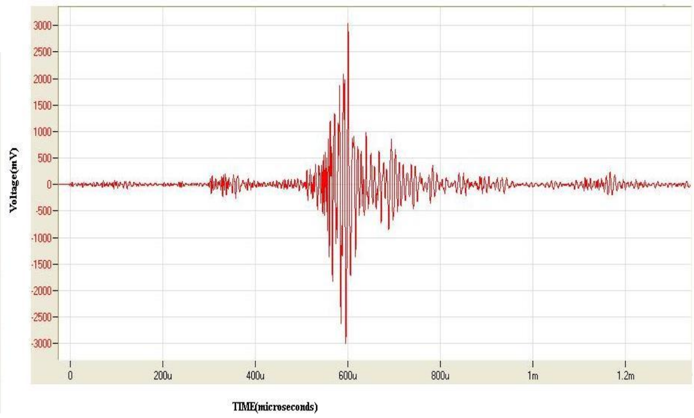


Fig.9 AE Characteristic Signal for Delamination Failure mode.

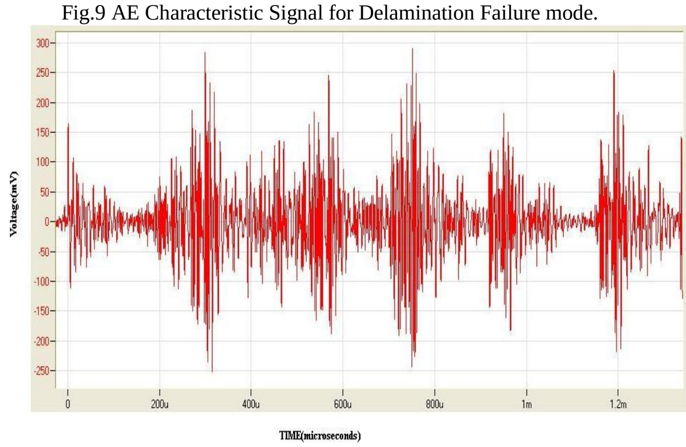


Fig.10 AE Characteristic Signal for Fiber failure mode

## 7. CONCLUSION AND FUTURE SCOPE:

This experimental work was conducted with the aim of creating a database which contains the AE data for a variety of parameters such as impact load, bending load, fatigue load, compression load, and artificial introduction of defects into laminates so as to understand the initiation and growth pattern of various defects. Once these data are collected for different types of mechanical properties, the data can be kept in a centralized place. Using these centralized data online health monitoring can be performed so as to identify the defects in the initial stages itself and necessary actions can be taken to prevent the failure of structures.

Though this experimental work is limited only with impacted specimens subjected to uni-axial tensile loading, the same process followed in this experiment can be used for all the testing of other mechanical properties and recorded in a centralized place through which only online health monitoring[11] can be achieved.

## REFERENCES

[1] H.N.Bar, M.R.Bhat, and C.R.L.Murthy "Identification of failure modes in GFRP using PVDF sensors: ANN approach" in Composite structures 65, 2004, pp. 231 – 237.

[2] C.R. Ramirez-Jimenez, N. Papadakis, N. Reynolds, T.H. Gan, P. Purnell, M. Pharaoh, "Identification of failure modes in glass/polypropylene composites by means of the primary frequency content of the acoustic emission event" in Composites Science and Technology, 64, 2004, pp.1819–1827.

[3] N. Godina, S. Hugueta, R. Gaertnera, L. Salmon, "Clustering of acoustic emission signals collected during tensile tests on unidirectional glass/polyester composite using supervised and unsupervised classifiers" in NDT&E International, 37, 2004, pp. 253 – 264.

[4] S. Hugueta, N. Godina, R. Gaertnera, L. Salmon, D. Villard "Use of acoustic emission to identify damage modes in glass fiber reinforced polyester" in Composites Science and Technology, 62, 2002, pp. 1433 – 1444.

[5] Steve.E.Watkins, Farhad Akhavan, Rohit dua, Donald C Wunch, "Impact Induced Damage Characterization Of Composite Plates using Neural Networks" in Smart Mater. Struct., 16, 2007, pp. 515 – 524.

[6] Carlo Santulli, "Post-impact damage characterisation on natural fibre reinforced composites using acoustic emission" in NDT&E International, 34, 2001, pp. 531 – 536.

[7] Bradford H Parker, "Acoustic emission monitoring of low velocity impact damage in graphite/epoxy laminates during tensile loading" in NASA Technical Memorandum 4339, 1992.

[8] N.Godin, S.Huguet, R.Gaertner, "Integration of kohonen's self-organising map and k-means algorithm for the segmentation of the AE data collected during tensile tests on cross-ply laminates" in NDT&E International, 38, 2005, pp. 299 – 309.

[9] SAMOS AE System User's Manual, Rev 2, Part#: 7030 – 1001, 2005

[10] R. de Oliveira, A.T. Marques, "Damage Mechanisms Identification in FRP using Acoustic Emission and Artificial Neural Networks" in Material Science Forum, 514-516, 2006, pp. 789 – 793.

[11] Victor giurgiutiu, "Active sensors for health monitoring of aging aerospace structures" in SPIE's 7th International Symposium on smart structures and materias and 5th International Symposium on non destructive evaluation and health monitoring of aging infrastructure, 2000, paper # 3985-103.